MOSEK Optimization Toolbox for MATLAB

Release 9.2.29

MOSEK ApS

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Chapter 1

Introduction

The **MOSEK** Optimization Suite 9.2.29 is a powerful software package capable of solving large-scale optimization problems of the following kind:

- linear,
- conic:
  - conic quadratic (also known as second-order cone),
  - involving the exponential cone,
  - involving the power cone,
  - semide nite,
- convex quadratic and quadratically constrained,
- integer.

In order to obtain an overview of features in the **MOSEK** Optimization Suite consult the product introduction guide.

The most widespread class of optimization problems is *linear optimization problems*, where all relations are linear. The tremendous success of both applications and theory of linear optimization can be ascribed to the following factors:

- The required data are simple, i.e. just matrices and vectors.
- Convexity is guaranteed since the problem is convex by construction.
- Linear functions are trivially di erentiable.
- There exist very e cient algorithms and software for solving linear problems.
- Duality properties for linear optimization are nice and simple.

Even if the linear optimization model is only an approximation to the true problem at hand, the advantages of linear optimization may outweigh the disadvantages. In some cases, however, the problem formulation is inherently nonlinear and a linear approximation is either intractable or inadequate. *Conic optimization* has proved to be a very expressive and powerful way to introduce nonlinearities, while preserving all the nice properties of linear optimization listed above.

The fundamental expression in linear optimization is a linear expression of the form

$$Ax - b \geq 0.$$

In conic optimization this is replaced with a wider class of constraints

$$Ax - b \in \mathcal{K}$$

where $\mathcal{K}$ is a *convex cone*. For example in 3 dimensions $\mathcal{K}$ may correspond to an ice cream cone. The conic optimizer in **MOSEK** supports a number of di erent types of cones $\mathcal{K}$, which allows a surprisingly large number of nonlinear relations to be modeled, as described in the **MOSEK** Modeling Cookbook, while preserving the nice algorithmic and theoretical properties of linear optimization.

1.1 Why the Optimization Toolbox for MATLAB?

The Optimization Toolbox for MATLAB provides access to most of the functionality of MOSEK from a MATLAB environment. In addition the toolbox includes functions that replace functions from the MATLAB optimization toolbox available from MathWorks.

The Optimization Toolbox for MATLAB provides access to:

- Linear Optimization (LO)
- Conic Quadratic (Second-Order Cone) Optimization (CQO, SOCO)
- Power Cone Optimization
- Conic Exponential Optimization (CEO)
- Convex Quadratic and Quadratically Constrained Optimization (QO, QCQO)
- Semide nite Optimization (SDO)
- Mixed-Integer Optimization (MIO)

as well as to additional functions for:

- problem analysis,
- sensitivity analysis,
- infeasibility diagnostics.

Chapter 2

Contact Information

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Website	mosek.com	
Email		
	sales@mosek.com	Sales, pricing, and licensing
	support@mosek.com	Technical support, questions and bug reports
	info@mosek.com	Everything else.
Mailing Address		
	MOSEK ApS	
	Fruebjergvej 3	
	Symbion Science Park, Box 16	
	2100 Copenhagen O	
	Denmark	

You can get in touch with MOSEK using popular social media as well:

Blogger	https://blog.mosek.com/
Google Group	https://groups.google.com/forum/#!forum/mosek
Twitter	https://twitter.com/mosektw
Linkedin	https://www.linkedin.com/company/mosek-aps
Youtube	https://www.youtube.com/channel/UCvIyectEVLP31NXeD5mIbEw

In particular Twitter is used for news, updates and release announcements.

Chapter 3

License Agreement

Before using the MOSEK software, please read the license agreement available in the distribution at <MSKHOME>/mosek/9.2/mosek-eula.pdfor on the MOSEK website https://mosek.com/products/license-agreement.

MOSEK uses some third-party open-source libraries. Their license details follows.

zlib

MOSEK includes the *zlib* library obtained from the zlib website. The license agreement for*zlib* is shown in Listing 3.1.

Listing 3.1: *zlib* license.

```
zlib.h -- interface of the 'zlib' general purpose compression library
version 1.2.7, May 2nd, 2012

Copyright (C) 1995-2012 Jean-loup Gailly and Mark Adler

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Jean-loup Gailly        Mark Adler
jloup@gzip.org          madler@alumni.caltech.edu
```

fplib

MOSEK includes the oating point formatting library developed by David M. Gay obtained from the netlib website. The license agreement for*fplib* is shown in Listing 3.2.

Listing 3.2: *fplib* license.

```
/***************************************************************
 *
```

(continues on next page)

(continued from previous page)

```
 * The author of this software is David M. Gay.
 *
 * Copyright (c) 1991, 2000, 2001 by Lucent Technologies.
 *
 * Permission to use, copy, modify, and distribute this software for any
 * purpose without fee is hereby granted, provided that this entire notice
 * is included in all copies of any software which is or includes a copy
 * or modification of this software and in all copies of the supporting
 * documentation for such software.
 *
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 * OF THIS SOFTWARE OR ITS FITNESS FOR ANY PARTICULAR PURPOSE.
 *
 ***************************************************************/
```

Zstandard

MOSEK includes the *Zstandard* library developed by Facebook obtained from github/zstd. The license agreement for*Zstandard* is shown in Listing 3.3.

Listing 3.3: *Zstandard* license.

```
BSD License

For Zstandard software

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ANY THEORY OF LIABILITY, WHETHER IN CONTRACT, STRICT LIABILITY, OR TORT
(INCLUDING NEGLIGENCE OR OTHERWISE) ARISING IN ANY WAY OUT OF THE USE OF THIS
SOFTWARE, EVEN IF ADVISED OF THE POSSIBILITY OF SUCH DAMAGE.
```

Chapter 4

Installation

In this section we discuss how to install and setup the MOSEK Optimization Toolbox for MATLAB.

Important: Before running this MOSEK interface please make sure that you:

- Installed MOSEK correctly. Some operating systems require extra steps. See the Installation guide for instructions and common troubleshooting tips.
- Set up a license. See the Licensing guide for instructions.

Compatibility

The Optimization Toolbox for MATLAB can be used with MATLAB version R2015a or newer on all 64-bit platforms.

Locating files in the MOSEK Optimization Suite

The relevant les of the Optimization Toolbox for MATLAB are organized as reported in Table 4.1.

Table 4.1: Relevant les for the Optimization Toolbox for MATLAB.

Relative Path	Description	Label
<MSKHOME>/mosek/9.2/toolbox/r2015a	Toolbox	<TOOLBOXDIR>
<MSKHOME>/mosek/9.2/toolbox/r2015aom	Toolbox (without overloading)	<TOOLBOXOMDIR>
<MSKHOME>/mosek/9.2/toolbox/examples	Examples	<EXDIR>
<MSKHOME>/mosek/9.2/toolbox/data	Additional data	<MISCDIR>

where <MSKHOME> is the folder in which the MOSEK Optimization Suite has been installed.

Setting up the paths

To use Optimization Toolbox for MATLAB the path to the toolbox directory must be added via the addpath command in MATLAB. Use the command

```
addpath <MSKHOME>/mosek/9.2/toolbox/r2015a
```

or, if you do not want to overload functions such as *linprog* and *quadprog* from the MATLAB Optimization Toolbox with their MOSEK versions, then write

```
addpath <MSKHOME>/mosek/9.2/toolbox/r2015aom
```

On the Windows platform the relevant paths are

```
addpath <MSKHOME>\mosek\9.2\toolbox\r2015a
addpath <MSKHOME>\mosek\9.2\toolbox\r2015aom
```

Alternatively, the path to Optimization Toolbox for MATLAB may be set from the command line or it can be added to MATLAB permanently using the con guration le startup.m or from the FileSet Path menu item. We refer to MATLAB documentation for details.

4.1 Testing the installation

You can verify that Optimization Toolbox for MATLAB works by executing

```
mosekdiag
```

in MATLAB. This should produce a message similar to this:

```
>> mosekdiag
Matlab version    : 9.2.0.538062 (R2017a)
Architecture      : GLNXA64
mosekopt path     : /home/user/somepath/toolbox/r2015a/mosekopt.mexa64
MOSEK version     : 9.0.97
Test linear solve: Success
mosekopt works OK. You can use MOSEK in MATLAB.
```

or to:

```
mosekopt: /home/user/somepath/toolbox/r2015a/mosekopt.mexa64
Found MOSEK version : major(9), minor(0), revision(97)
mosekopt is working correctly.
```

If you only want to use Optimization Toolbox for MATLAB then warnings about non-availability of the command-line interface can be ignored.

More advanced debug information can be obtained with:

```
mosekopt('debug(10)')
```

4.2 Troubleshooting

Missing library files such as libmosek64.9.0.dylib or similar

If you are using Mac OS and get an error such as

```
Library not loaded: libmosek64.9.0.dylib
Referenced from:
/Users/.../mosek/9.0/toolbox/r2015a/mosekopt.mexmaci64
Reason: image not found.

Error in callmosek>doCall (line 224)
[res,sol] = mosekopt('minimize info',prob,param);
```

then most likely you did not run the MOSEK installation script install.py found in the bin directory. See also the Installation guide for details.

Windows, invalid MEX-file, cannot find shared libraries

If you are using Windows and get an error such as

```
Invalid MEX-file <MSKHOME>\Mosek\9.0\toolbox\r2015a\mosekopt.mexw64: The specified module␣
↪could not be found.
```

then MATLAB cannot load the MOSEK shared libraries, because the folder containing them is not in the system search path for DLLs. This can happen if MOSEK was installed manually and not using the MSI installer. The solution is to add the path <MSKHOME>\mosek\9.2\tools\platform\<PLATFORM>\bin to the system environment variable PATH. This can also be done per MATLAB session by using the setenv command in MATLAB before using MOSEK, for example:

```
setenv('PATH', [getenv('PATH') ';C:\Users\username\mosek\9.0\tools\platform\win64x86\bin']);
```

See also the Installation guide for details.

MATLAB String type is not supported

From R2017a MATLAB provides a new string type (with double quotes). It is not supported by the Optimization Toolbox for MATLAB and may cause confusing error messages. For example the following will give an error:

```
mosekopt("minimize", prob)

Return code - 1200 [MSK_RES_ERR_IN_ARGUMENT] [A function argument is incorrect.]
```

Always use old-fashioned character arrays (strings in single quotes).

MOSEK does not see new license le

If you updated your license le but MOSEK does not detect it then restart MATLAB. MOSEK is caching the license and it will not notice the change in the license le on disk.

Unde ned Function or Variable mosekopt

If you get the MATLAB error message

```
Undefined function or variable ' mosekopt'
```

you have not added the path to the Optimization Toolbox for MATLAB correctly as described above.

Invalid MEX- le

For certain versions of Windows and MATLAB, the path to MEX les cannot contain spaces. Therefore, if you have installed MOSEK in C:\Program Files\Mosek and get a MATLAB error similar to:

```
Invalid MEX-file <MSKHOME>\Mosek\9.0\toolbox\r2015a\mosekopt.mexw64
```

try installing MOSEK in a di erent directory, for example C:\Users\< someuser>\ .

Output Arguments not assigned

If you encounter an error like

```
Error in ==> mosekopt at 1
function [r,res] = mosekopt(cmd,prob,param,callback)

Output argument "r" (and maybe others) not assigned during call to
"C:\Users\username\mosek\9.0\toolbox\r2015a\mosekopt.m>mosekopt".
```

then a mismatch between 32 and 64 bit versions of MOSEK and MATLAB is likely. From MATLAB type

```
which mosekopt
```

which (for a successful installation) should point to a MEX le,

```
<MSKHOME>\mosek\9.0\toolbox\r2015a\mosekopt.mexw64
```

and not to a MATLAB .m le,

```
<MSKHOME>\mosek\9.0\toolbox\r2015a\mosekopt.m
```

Security exception in MacOS 10.15+ (Catalina)

If an attempt to run MOSEK on Mac OS 10.15 (Catalina) and later produces security exceptions (developer cannot be verified and similar) then use xattr to remove the quarantine attribute from all MOSEK executables and binaries. This can be done in one go with

```
xattr -dr com.apple.quarantine mosek
```

where mosekis the folder which contains the full MOSEK installation or MOSEK binaries. See https://themosekblog.blogspot.com/2019/12/macos-1015-catalina-mosek-installation.html for more information. If that does not help, use the system settings to allow running arbitrary unveri ed applications.

Source code example

Below is the most basic code sample that de nes and solves a trivial optimization problem

$$\begin{array}{ll} \text{minimize} & x \\ \text{subject to} & 2.0 \leq x \leq 3.0. \end{array}$$

For simplicity the example does not contain any error or status checks.

Listing 5.1: Hello World! in MOSEK

```
prob.a  =  sparse(0,1)  % 0 linear constraints, 1 variable
prob.c  =  [1.0]'       % Only objective coefficient
prob.blx=  [2.0]'       % Lower bound(s) on variable(s)
prob.bux=  [3.0]'       % Upper bound(s) on variable(s)

% Optimize
[r, res] = mosekopt('minimize', prob);

% Print answer
res.sol.itr.xx
```

Chapter 6

Optimization Tutorials

In this section we demonstrate how to set up basic types of optimization problems. Each short tutorial contains a working example of formulating problems, de ning variables and constraints and retrieving solutions.

6.1 Linear Optimization

The simplest optimization problem is a purely linear problem. A *linear optimization problem* is a problem of the following form:

Minimize or maximize the objective function

$$\sum_{j=0}^{n-1} c_j x_j + c^f$$

subject to the linear constraints

$$l_k^c \leq \sum_{j=0}^{n-1} a_{kj} x_j \leq u_k^c, \quad k = 0, \ldots, m-1,$$

and the bounds

$$l_j^x \leq x_j \leq u_j^x, \quad j = 0, \ldots, n-1.$$

The problem description consists of the following elements:

- m and n the number of constraints and variables, respectively,
- x the variable vector of length n,
- c the coe cient vector of length n

$$c = \begin{bmatrix} c_0 \\ \vdots \\ c_{n-1} \end{bmatrix},$$

- c^f xed term in the objective,
- A an $m \times n$ matrix of coe cients

$$A = \begin{bmatrix} a_{0,0} & \cdots & a_{0,(n-1)} \\ \vdots & \cdots & \vdots \\ a_{(m-1),0} & \cdots & a_{(m-1),(n-1)} \end{bmatrix},$$

Listing 6.2: Script implementing problem (6.1) using *mosekopt*.

```
function lo2()
clear prob;

% Specify the c vector.
prob.c  = [3 1 5 1]';

% Specify a in sparse format.
subi   = [1 1 1 2 2 2 2 3 3];
subj   = [1 2 3 1 2 3 4 2 4];
valij  = [3 1 2 2 1 3 1 2 3];

prob.a = sparse(subi,subj,valij);

% Specify lower bounds of the constraints.
prob.blc = [30 15  -inf]';

% Specify  upper bounds of the constraints.
prob.buc = [30 inf 25 ]';

% Specify lower bounds of the variables.
prob.blx = zeros(4,1);

% Specify upper bounds of the variables.
prob.bux = [inf 10 inf inf]';

% Perform the optimization.
[r,res] = mosekopt('maximize',prob);

% Show the optimal x solution.
res.sol.bas.xx
```

Please note that

- A MATLAB structure named *prob* containing all the relevant problem data is de ned.
- All elds of this structure are optional except prob.a which is required to be a **sparse** matrix. The dimension of this matrix determine the number of constraints and variables in the problem.
- Di erent parts of the solution can be accessed as described in Sec. 7.1.

Example: Linear optimization using linprog

MOSEK also provides a function *linprog* with a function of the same name from the MATLAB Optimization Toolbox. Consult Sec. 10.1 for details.

Listing 6.3: Script implementing problem (6.1) using *linprog*.

```
f     = - [3 1 5 1]';                          % minus because we maximize
A     = [[-2 -1 -3 -1]; [0 2 0 3]];
b     = [-15  25]';
Aeq   = [3 1 2 0];
beq   = 30;
l     = zeros(4,1);
u     = [inf 10 inf inf]';

% Example of setting options for linprog
% Get default options
opt = mskoptimset('');
% Turn on diagnostic output
opt = mskoptimset(opt,'Diagnostics','on');
```

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```
% Set a MOSEK option, in this case turn basic identification off.
opt = mskoptimset(opt,'MSK_IPAR_INTPNT_BASIS','MSK_OFF');
% Modify a MOSEK parameter with double value
opt = mskoptimset(opt,'MSK_DPAR_INTPNT_TOL_INFEAS',1e-12);

[x,fval,exitflag,output,lambda] = linprog(f,A,b,Aeq,beq,l,u,opt);

x
fval
exitflag
output
lambda
```

6.2 Quadratic Optimization

MOSEK can solve quadratic and quadratically constrained problems, as long as they are convex. This class of problems can be formulated as follows:

$$\begin{array}{lrcccl} \text{minimize} & & & \frac{1}{2}x^T Q^o x + c^T x + c^f & & \\ \text{subject to} & l_k^c & \leq & \frac{1}{2}x^T Q^k x + \sum_{j=0}^{n-1} a_{k,j} x_j & \leq & u_k^c, \quad k = 0, \ldots, m-1, \\ & l_j^x & \leq & x_j & \leq & u_j^x, \quad j = 0, \ldots, n-1. \end{array} \tag{6.2}$$

Without loss of generality it is assumed that Q^o and Q^k are all symmetric because

$$x^T Q x = \frac{1}{2} x^T (Q + Q^T) x.$$

This implies that a non-symmetric Q can be replaced by the symmetric matrix $\frac{1}{2}(Q + Q^T)$.

The problem is required to be convex. More precisely, the matrixQ^o must be positive semi-de nite and the kth constraint must be of the form

$$l_k^c \leq \frac{1}{2} x^T Q^k x + \sum_{j=0}^{n-1} a_{k,j} x_j \tag{6.3}$$

with a negative semi-de nite Q^k or of the form

$$\frac{1}{2} x^T Q^k x + \sum_{j=0}^{n-1} a_{k,j} x_j \leq u_k^c.$$

with a positive semi-de nite Q^k. This implies that quadratic equalities are not allowed. Specifying a non-convex problem will result in an error when the optimizer is called.

A matrix is positive semide nite if all the eigenvalues of Q are nonnegative. An alternative statement of the positive semide nite requirement is

$$x^T Q x \geq 0, \quad \forall x.$$

If the convexity (i.e. semide niteness) conditions are not met **MOSEK** will not produce reliable results or work at all.

6.2.1 Example: Quadratic Objective

We look at a small problem with linear constraints and quadratic objective:

$$\begin{array}{lrl} \text{minimize} & & x_1^2 + 0.1x_2^2 + x_3^2 - x_1 x_3 - x_2 \\ \text{subject to} & 1 \leq & x_1 + x_2 + x_3 \\ & 0 \leq & x. \end{array} \tag{6.4}$$

The matrix formulation of (6.4) has:

$$Q^o = \begin{bmatrix} 2 & & \\ & 2 & 0 \\ & 0 & 0.2 \\ & 1 & 0 \end{bmatrix} \begin{bmatrix} 3 \\ 1 \\ 2 \end{bmatrix}; c = \begin{bmatrix} 2 \\ 0 \\ 1 \\ 0 \end{bmatrix} \begin{bmatrix} 3 \\ 5 \end{bmatrix}; A = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix};$$

with the bounds:

$$l^c = 1; u^c = 1; l^x = \begin{bmatrix} 2 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 3 \\ 5 \end{bmatrix} \text{ and } u^x = \begin{bmatrix} 2 \\ 1 \\ 1 \\ 1 \end{bmatrix} \begin{bmatrix} 3 \\ 5 \end{bmatrix}$$

Please note the explicit $\frac{1}{2}$ in the objective function of (6.2) which implies that diagonal elements must be doubled in Q, i.e. $Q_{11} = 2$ even though 1 is the coe cient in front of x_1^2 in (6.4).

Using mosekopt

In Listing 6.4 we show how to usemosekopt to solve problem (6.4). This is the preferred way.

Listing 6.4: How to solve problem (6.4) usingmosekopt

```
function qo2()

clear prob;

% c vector.
prob.c = [0 -1 0]'; 

% Define the data.

% First the lower triangular part of q in the objective
% is specified in a sparse format. The format is:
%
%    Q(prob.qosubi(t),prob.qosubj(t)) = prob.qoval(t), t=1,...,4

prob.qosubi = [ 1  3 2  3]';
prob.qosubj = [ 1  1 2  3]';
prob.qoval  = [ 2 -1 0.2 2]';

% a, the constraint matrix
subi  = ones(3,1);
subj  = 1:3;
valij = ones(3,1);

prob.a = sparse(subi,subj,valij);

% Lower bounds of constraints.
prob.blc  = [1.0]';

% Upper bounds of constraints.
prob.buc  = [inf]';

% Lower bounds of variables.
prob.blx  = sparse(3,1);

% Upper bounds of variables.
prob.bux = [];      % There are no bounds.

[r,res] = mosekopt('minimize',prob);

% Display return code.
fprintf('Return code: %d\n',r);
```

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```
% Display primal solution for the constraints.
res.sol.itr.xc'

% Display primal solution for the variables.
res.sol.itr.xx'
```

This sequence of commands looks much like the one that was used to solve the linear optimization example using *mosekopt* except that the de nition of the Q matrix in prob. *mosekopt* requires that Q is speci ed in a sparse format. Indeed the vectors qosubi , qosubj , and qoval are used to specify the coe cients of Q in the objective using the principle

$$Q_{\texttt{qosubi(t)},\texttt{qosubj(t)}} = \texttt{qoval(t)}, \text{for} \quad t = 1, \ldots, \text{length}(\texttt{qosubi}).$$

An important observation is that due to Q being symmetric, only the lower triangular part of Q should be speci ed.

Using mskqpopt

In Listing 6.5 we show how to use *mskqpopt* to solve problem (6.4).

Listing 6.5: Function solving problem (6.4) using *mskqpopt*.

```
function qo1()

% Set up Q.
q     = [[2 0 -1];[0 0.2 0];[-1 0 2]];

% Set up the linear part of the problem.
c     = [0 -1 0]';
a     = ones(1,3);
blc   = [1.0];
buc   = [inf];
blx   = sparse(3,1);
bux   = [];

% Optimize the problem.
[res] = mskqpopt(q,c,a,blc,buc,blx,bux);

% Show the primal solution.
res.sol.itr.xx
```

It should be clear that the format for calling *mskqpopt* is very similar to calling *msklpopt* except that the Q matrix is included as the rst argument of the call. Similarly, the solution can be inspected by viewing the res.sol eld.

6.2.2 Example: Quadratic constraints

In this section we show how to solve a problem with quadratic constraints. Please note that quadratic constraints are subject to the convexity requirement (6.3).

Consider the problem:

$$\begin{array}{lrcl} \text{minimize} & & & x_1^2 + 0.1x_2^2 + x_3^2 - x_1x_3 - x_2 \\ \text{subject to} & 1 & \leq & x_1 + x_2 + x_3 - x_1^2 - x_2^2 - 0.1x_3^2 + 0.2x_1x_3, \\ & & & x \geq 0. \end{array}$$

This is equivalent to

$$\begin{array}{lrcl} \text{minimize} & \frac{1}{2}x^TQ^ox + c^Tx & & \\ \text{subject to} & \frac{1}{2}x^TQ^0x + Ax & \geq & b, \\ & x \geq 0, & & \end{array} \tag{6.5}$$

where

$$Q^o = \begin{bmatrix} 2 & 0 & -1 \\ 0 & 0.2 & 0 \\ -1 & 0 & 2 \end{bmatrix}, c = \begin{bmatrix} 0 & -1 & 0 \end{bmatrix}^T, A = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}, b = 1.$$

$$Q^0 = \begin{bmatrix} -2 & 0 & 0.2 \\ 0 & -2 & 0 \\ 0.2 & 0 & -0.2 \end{bmatrix}.$$

The linear parts and quadratic objective are set up the way described in the previous tutorial.

Setting up quadratic constraints

Listing 6.6: Script implementing problem (6.5).

```
function qcqo1()
clear prob;

% Specify the linear objective terms.
prob.c      = [0, -1, 0];

% Specify the quadratic terms of the constraints.
prob.qcsubk = [1     1    1   1  ]';
prob.qcsubi = [1     2    3   3  ]';
prob.qcsubj = [1     2    3   1  ]';
prob.qcval  = [-2.0 -2.0 -0.2 0.2]';

% Specify the quadratic terms of the objective.
prob.qosubi = [1     2    3    3  ]';
prob.qosubj = [1     2    3    1  ]';
prob.qoval  = [2.0   0.2  2.0 -1.0]';

% Specify the linear constraint matrix
prob.a      = [1 1 1];

% Specify the lower bounds
prob.blc    = [1];
prob.blx    = zeros(3,1);

[r,res]     = mosekopt('minimize',prob);

% Display the solution.
fprintf('\nx:');
fprintf(' %-.4e',res.sol.itr.xx');
fprintf('\n||x||: %-.4e',norm(res.sol.itr.xx));
```

6.3 Conic Quadratic Optimization

Conic optimization is a generalization of linear optimization, allowing constraints of the type

$$x^t \in \mathcal{K}_t,$$

where x^t is a subset of the problem variables and $\mathcal{K}_t$ is a convex cone. Since the set $\mathbb{R}^n$ of real numbers is also a convex cone, we can simply write a compound conic constraint $x \in \mathcal{K}$ where $\mathcal{K} = \mathcal{K}_1 \times \cdots \times \mathcal{K}_l$ is a product of smaller cones and x is the full problem variable.

MOSEK can solve conic quadratic optimization problems of the form

$$\begin{array}{lccccc} \text{minimize} & & & c^T x + c^f & & \\ \text{subject to} & l^c & \leq & Ax & \leq & u^c, \\ & l^x & \leq & x & \leq & u^x, \\ & & & x \in \mathcal{K}, & & \end{array}$$

where the domain restriction, $x \in \mathcal{K}$, implies that all variables are partitioned into convex cones

$$x = (x^0, x^1, \ldots, x^{p-1}), \quad \text{with } x^t \in \mathcal{K}_t \subseteq \mathbb{R}^{n_t}.$$

In this tutorial we describe how to use the two types of quadratic cones de ned as:

- Quadratic cone:

$$\mathcal{Q}^n = \left\{ x \in \mathbb{R}^n : x_0 \geq \sqrt{\sum_{j=1}^{n-1} x_j^2} \right\}.$$

- Rotated quadratic cone:

$$\mathcal{Q}_r^n = \left\{ x \in \mathbb{R}^n : 2x_0 x_1 \geq \sum_{j=2}^{n-1} x_j^2, \quad x_0 \geq 0, \quad x_1 \geq 0 \right\}.$$

For other types of cones supported by **MOSEK** see Sec. 6.4, Sec. 6.5, Sec. 6.6. Di erent cone types can appear together in one optimization problem.

For example, the following constraint:

$$(x_4, x_0, x_2) \in \mathcal{Q}^3$$

describes a convex cone in $\mathbb{R}^3$ given by the inequality:

$$x_4 \geq \sqrt{x_0^2 + x_2^2}.$$

Furthermore, each variable may belong to one cone at most. The constraint $x_i - x_j = 0$ would however allow x_i and x_j to belong to di erent cones with same e ect.

6.3.1 Example CQO1

Consider the following conic quadratic problem which involves some linear constraints, a quadratic cone and a rotated quadratic cone.

$$\begin{array}{lrcl} \text{minimize} & x_4 + x_5 + x_6 & & \\ \text{subject to} & x_1 + x_2 + 2x_3 & = & 1, \\ & x_1, x_2, x_3 & \geq & 0, \\ & x_4 \geq \sqrt{x_1^2 + x_2^2}, & & \\ & 2x_5 x_6 \geq x_3^2 & & \end{array} \tag{6.6}$$

The linear constraints are speci ed as if the problem was a linear problem whereas the cones are speci ed using two index lists cones.subptr and cones.sub and list of cone-type identi ers cones.type . The elements of all the cones are listed in cones.sub , and cones.subptr speci es the index of the rst element in cones.sub for each cone.

Listing 6.7 demonstrates how to solve the example (6.6) using **MOSEK**.

Listing 6.7: Script implementing problem (6.6).

```
function cqo1()

clear prob;

[r, res] = mosekopt('symbcon');
% Specify the non-conic part of the problem.

prob.c   = [0 0 0 1 1 1];
prob.a   = sparse([1 1 2 0 0 0]);
prob.blc = 1;
```

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```
prob.buc = 1;
prob.blx = [0 0 0 -inf -inf -inf];
prob.bux = inf*ones(6,1);

% Specify the cones.

prob.cones.type   = [res.symbcon.MSK_CT_QUAD, res.symbcon.MSK_CT_RQUAD];
prob.cones.sub    = [4, 1, 2, 5, 6, 3];
prob.cones.subptr = [1, 4];
% The field 'type' specifies the cone types, i.e., quadratic cone
% or rotated quadratic cone. The keys for the two cone types are MSK_CT_QUAD
% and MSK_CT_RQUAD, respectively.
%
% The fields 'sub' and 'subptr' specify the members of the cones,
% i.e., the above definitions imply that
%   x(4) >= sqrt(x(1)^2+x(2)^2) and 2 * x(5) * x(6) >= x(3)^2.

% Optimize the problem.

[r,res]=mosekopt('minimize',prob);

% Display the primal solution.

res.sol.itr.xx'
```

6.4 Power Cone Optimization

Conic optimization is a generalization of linear optimization, allowing constraints of the type

$$x^t \in \mathcal{K}_t,$$

where x^t is a subset of the problem variables and $\mathcal{K}_t$ is a convex cone. Since the set $\mathbb{R}^n$ of real numbers is also a convex cone, we can simply write a compound conic constraint $x \in \mathcal{K}$ where $\mathcal{K} = \mathcal{K}_1 \times \cdots \times \mathcal{K}_l$ is a product of smaller cones and x is the full problem variable.

MOSEK can solve conic optimization problems of the form

$$\begin{array}{lccccc} \text{minimize} & & & c^T x + c^f & & \\ \text{subject to} & l^c & \leq & Ax & \leq & u^c, \\ & l^x & \leq & x & \leq & u^x, \\ & & & x \in \mathcal{K}, & & \end{array}$$

where the domain restriction, $x \in \mathcal{K}$, implies that all variables are partitioned into convex cones

$$x = (x^0, x^1, \ldots, x^{p-1}), \quad \text{with } x^t \in \mathcal{K}_t \subseteq \mathbb{R}^{n_t}.$$

In this tutorial we describe how to use the power cone. The primal power cone of dimension n with parameter $0 < \alpha < 1$ is defined as:

$$\mathcal{P}_n^{\alpha,1-\alpha} = \left\{ x \in \mathbb{R}^n : x_0^\alpha x_1^{1-\alpha} \geq \sqrt{\sum_{i=2}^{n-1} x_i^2}, \; x_0, x_1 \geq 0 \right\}.$$

In particular, the most important special case is the three-dimensional power cone family:

$$\mathcal{P}_3^{\alpha,1-\alpha} = \left\{ x \in \mathbb{R}^3 : x_0^\alpha x_1^{1-\alpha} \geq |x_2|, \; x_0, x_1 \geq 0 \right\}.$$

For example, the conic constraint $(x, y, z) \in \mathcal{P}_3^{0.25,0.75}$ is equivalent to $x^{0.25} y^{0.75} \geq |z|$, or simply $xy^3 \geq z^4$ with $x, y \geq 0$.

MOSEK also supports the dual power cone:

$$\left(\mathcal{P}_n^{\alpha,1-\alpha}\right)^* = \left\{ x \in \mathbb{R}^n : \left(\frac{x_0}{\alpha}\right)^\alpha \left(\frac{x_1}{1-\alpha}\right)^{1-\alpha} \geq \sqrt{\sum_{i=2}^{n-1} x_i^2},\ x_0, x_1 \geq 0 \right\}.$$

For other types of cones supported by MOSEK see Sec. 6.3, Sec. 6.5, Sec. 6.6. Di erent cone types can appear together in one optimization problem.

Furthermore, each variable may belong to one cone at most. The constraint $x_i - x_j = 0$ would however allow x_i and x_j to belong to di erent cones with same e ect.

6.4.1 Example POW1

Consider the following optimization problem which involves powers of variables:

$$\begin{array}{lrcl} \text{maximize} & x^{0.2}y^{0.8} + z^{0.4} - x & & \\ \text{subject to} & x + y + \frac{1}{2}z & = & 2, \\ & x, y, z & \geq & 0. \end{array} \tag{6.7}$$

With $(x, y, z) = (x_0, x_1, x_2)$ we convert it into conic form using auxiliary variables as bounds for the power expressions:

$$\begin{array}{lrcl} \text{maximize} & x_3 + x_4 - x_0 & & \\ \text{subject to} & x_0 + x_1 + \frac{1}{2}x_2 & = & 2, \\ & (x_0, x_1, x_3) & \in & \mathcal{P}_3^{0.2,0.8}, \\ & (x_2, x_5, x_4) & \in & \mathcal{P}_3^{0.4,0.6}, \\ & x_5 & = & 1. \end{array} \tag{6.8}$$

The linear constraints are speci ed as if the problem was a linear problem. The cone elements are speci ed using two index lists cones.subptr and cones.sub . Cone-type identi ers appear in cones. type , and the cone parameters α are in cones.conepar . The elements of all the cones are listed in cones.sub , and cones.subptr speci es the index of the rst element in cones.sub for each cone.

Listing 6.8 demonstrates how to solve the example (6.7) using MOSEK. The solution is

```
[ 0.06389298  0.78308564  2.30604283 ]
```

Listing 6.8: Script implementing problem (6.7).

```
function pow1()

clear prob;

[r, res] = mosekopt('symbcon');
% Specify the non-conic part of the problem.

prob.c   = [-1 0 0 1 1 0];
prob.a   = [1 1 0.5 0 0 0];
prob.blc = [2.0];
prob.buc = [2.0];
prob.blx = [-inf -inf -inf -inf -inf 1.0];
prob.bux = [ inf  inf  inf  inf  inf 1.0];

% Specify the cones.
prob.cones.type   = [res.symbcon.MSK_CT_PPOW res.symbcon.MSK_CT_PPOW];
prob.cones.conepar= [0.2 0.4];
prob.cones.sub    = [1 2 4 3 6 5];
prob.cones.subptr = [1 4];
% The field 'type' specifies the cone types, in this case power cones.
%
% The fields 'sub' and 'subptr' specify the members of the cones,
% i.e., the above definitions imply that
```

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```
%   (x(1), x(2), x(4))  and (x(3), x(6), x(5))
% are cones.
%
% The field 'conepar' specifies the alpha cone parameters (exponents)

% Optimize the problem.

[r,res]=mosekopt('maximize',prob);

% Display the primal solution.

res.sol.itr.xx'
```

6.5 Conic Exponential Optimization

Conic optimization is a generalization of linear optimization, allowing constraints of the type

$$x^t \in \mathcal{K}_t,$$

where x^t is a subset of the problem variables and $\mathcal{K}_t$ is a convex cone. Since the set $\mathbb{R}^n$ of real numbers is also a convex cone, we can simply write a compound conic constraint $x \in \mathcal{K}$ where $\mathcal{K} = \mathcal{K}_1 \times \cdots \times \mathcal{K}_l$ is a product of smaller cones and x is the full problem variable.

MOSEK can solve conic optimization problems of the form

$$\begin{array}{lrcccl} \text{minimize} & & & c^T x + c^f & & \\ \text{subject to} & l^c & \leq & Ax & \leq & u^c, \\ & l^x & \leq & x & \leq & u^x, \\ & & & x \in \mathcal{K}, & & \end{array}$$

where the domain restriction, $x \in \mathcal{K}$, implies that all variables are partitioned into convex cones

$$x = (x^0, x^1, \ldots, x^{p-1}), \quad \text{with } x^t \in \mathcal{K}_t \subseteq \mathbb{R}^{n_t}.$$

In this tutorial we describe how to use the primal exponential cone defined as:

$$K_{\exp} = \left\{ x \in \mathbb{R}^3 : x_0 \geq x_1 \exp(x_2/x_1),\ x_0, x_1 \geq 0 \right\}.$$

MOSEK also supports the dual exponential cone:

$$K^*_{\exp} = \left\{ s \in \mathbb{R}^3 : s_0 \geq -s_2 e^{-1} \exp(s_1/s_2),\ s_2 \leq 0, s_0 \geq 0 \right\}.$$

For other types of cones supported by **MOSEK** see Sec. 6.3, Sec. 6.4, Sec. 6.6. Different cone types can appear together in one optimization problem.

For example, the following constraint:

$$(x_4, x_0, x_2) \in K_{\exp}$$

describes a convex cone in $\mathbb{R}^3$ given by the inequalities:

$$x_4 \geq x_0 \exp(x_2/x_0),\ x_0, x_4 \geq 0.$$

Furthermore, each variable may belong to one cone at most. The constraint $x_i - x_j = 0$ would however allow x_i and x_j to belong to different cones with same effect.

6.5.1 Example CEO1

Consider the following basic conic exponential problem which involves some linear constraints and an exponential inequality:

$$\begin{array}{lrcl} \text{minimize} & x_0 + x_1 & & \\ \text{subject to} & x_0 + x_1 + x_2 & = & 1, \\ & x_0 & \geq & x_1 \exp(x_2/x_1), \\ & x_0, x_1 & \geq & 0. \end{array} \tag{6.9}$$

The conic form of (6.9) is:

$$\begin{array}{lrcl} \text{minimize} & x_0 + x_1 & & \\ \text{subject to} & x_0 + x_1 + x_2 & = & 1, \\ & (x_0, x_1, x_2) & \in & K_{\exp}, \\ & x & \in & \mathbb{R}^3. \end{array} \tag{6.10}$$

The linear constraints are speci ed as if the problem was a linear problem whereas the cones are speci ed using two index lists cones.subptr and cones.sub and list of cone-type identi ers cones.type . The elements of all the cones are listed in cones.sub , and cones.subptr speci es the index of the rst element in cones.sub for each cone.

Listing 6.9 demonstrates how to solve the example (6.9) using **MOSEK**.

Listing 6.9: Script implementing problem (6.9).

```
function ceo1()

clear prob;

[r, res] = mosekopt('symbcon');
% Specify the non-conic part of the problem.

prob.c   = [1 1 0];
prob.a   = sparse([1 1 1]);
prob.blc = 1;
prob.buc = 1;
prob.blx = [-inf -inf -inf];
prob.bux = [ inf  inf  inf];

% Specify the cones.

prob.cones.type   = [res.symbcon.MSK_CT_PEXP];
prob.cones.sub    = [1, 2, 3];
prob.cones.subptr = [1];
% The field 'type' specifies the cone types, in this case an exponential
% cone with key MSK_CT_PEXP.
%
% The fields 'sub' and 'subptr' specify the members of the cones,
% i.e., the above definitions imply that
%   x(1) >= x(2)*exp(x(3)/x(2))

% Optimize the problem.

[r,res]=mosekopt('minimize',prob);

% Display the primal solution.

res.sol.itr.xx'
```

6.6 Semidefinite Optimization

Semide nite optimization is a generalization of conic optimization, allowing the use of matrix variables belonging to the convex cone of positive semide nite matrices

$$\mathcal{S}^r_+ = \left\{ X \in \mathcal{S}^r : z^T X z \geq 0, \quad \forall z \in \mathbb{R}^r \right\},$$

where $\mathcal{S}^r$ is the set of $r \times r$ real-valued symmetric matrices.

MOSEK can solve semide nite optimization problems of the form

$$\begin{array}{llcccll} \text{minimize} & & & \sum_{j=0}^{n-1} c_j x_j + \sum_{j=0}^{p-1} \langle \overline{C}_j, \overline{X}_j \rangle + c^f & & & \\ \text{subject to} & l_i^c & \leq & \sum_{j=0}^{n-1} a_{ij} x_j + \sum_{j=0}^{p-1} \langle \overline{A}_{ij}, \overline{X}_j \rangle & \leq & u_i^c, & i = 0, \ldots, m-1, \\ & l_j^x & \leq & x_j & \leq & u_j^x, & j = 0, \ldots, n-1, \\ & & & x \in \mathcal{K}, \overline{X}_j \in \mathcal{S}^{r_j}_+, & & & j = 0, \ldots, p-1 \end{array}$$

where the problem has p symmetric positive semidefinite variables $\overline{X}_j \in \mathcal{S}_+^{r_j}$ of dimension r_j with symmetric coefficient matrices $\overline{C}_j \in \mathcal{S}^{r_j}$ and $\overline{A}_{i,j} \in \mathcal{S}^{r_j}$. We use standard notation for the matrix inner product, i.e., for $A, B \in \mathbb{R}^{m\times n}$ we have

$$\langle A, B\rangle := \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} A_{ij}B_{ij}.$$

We demonstrate the setup of semidefinite variables and the matrices $\overline{C}$, $\overline{A}$ on the following examples:

- Sec. 6.6.1: A problem with one semidefinite variable and linear and conic constraints.
- Sec. 6.6.2: A problem with two semidefinite variables with a linear constraint and bound.

6.6.1 Example SDO1

We consider the simple optimization problem with semidefinite and conic quadratic constraints:

$$\begin{array}{lll} \text{minimize} & \left\langle \begin{bmatrix} 2 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix}, \overline{X} \right\rangle + x_0 & \\ \text{subject to} & \left\langle \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \overline{X} \right\rangle + x_0 & = \quad 1, \\ & \left\langle \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \overline{X} \right\rangle + x_1 + x_2 & = \quad 1/2, \\ & x_0 \geq \sqrt{{x_1}^2 + {x_2}^2}, & \overline{X} \succeq 0, \end{array} \tag{6.11}$$

The problem description contains a 3-dimensional symmetric semidefinite variable which can be written explicitly as:

$$\overline{X} = \begin{bmatrix} \overline{X}_{00} & \overline{X}_{10} & \overline{X}_{20} \\ \overline{X}_{10} & \overline{X}_{11} & \overline{X}_{21} \\ \overline{X}_{20} & \overline{X}_{21} & \overline{X}_{22} \end{bmatrix} \in \mathcal{S}_+^3,$$

and a conic quadratic variable $(x_0, x_1, x_2) \in \mathcal{Q}^3$. The objective is to minimize

$$2(\overline{X}_{00} + \overline{X}_{10} + \overline{X}_{11} + \overline{X}_{21} + \overline{X}_{22}) + x_0,$$

subject to the two linear constraints

$$\begin{array}{rcl} \overline{X}_{00} + \overline{X}_{11} + \overline{X}_{22} + x_0 & = & 1, \\ \overline{X}_{00} + \overline{X}_{11} + \overline{X}_{22} + 2(\overline{X}_{10} + \overline{X}_{20} + \overline{X}_{21}) + x_1 + x_2 & = & 1/2. \end{array}$$

Setting up the linear and conic part

The linear and conic parts (constraints, variables, objective, cones) are set up using the methods described in the relevant tutorials; Sec. 6.1, Sec. 6.3, Sec. 6.5, Sec. 6.4. Here we only discuss the aspects directly involving semidefinite variables.

Appending semidefinite variables

The dimensions of semidefinite variables are passed in `prob.bardim`.

Coefficients of semidefinite terms.

Every term of the form $(\overline{A}_{i,j})_{k,l}(\overline{X}_j)_{k,l}$ is determined by four indices (i, j, k, l) and a coefficient value $v = (\overline{A}_{i,j})_{k,l}$. Here i is the number of the constraint in which the term appears, j is the index of the semidefinite variable it involves and (k, l) is the position in that variable. This data is passed in the structure `bara`. Note that only the lower triangular part should be specified explicitly, that is one always has $k \geq l$.

Semidefinite terms $(\overline{C}_j)_{k,l}(\overline{X}_j)_{k,l}$ of the objective are specified in the same way in `barc` but only include (j, k, l) and v.

Source code

Listing 6.10: Code implementing problem (6.11).

```
function sdo1()
[r, res] = mosekopt( 'symbcon');

prob.c          = [1, 0, 0];

prob.bardim     = [3];
prob.barc.subj  = [1, 1, 1, 1, 1];
prob.barc.subk  = [1, 2, 2, 3, 3];
prob.barc.subl  = [1, 1, 2, 2, 3];
prob.barc.val   = [2.0, 1.0, 2.0, 1.0, 2.0];

prob.blc = [1, 0.5];
prob.buc = [1, 0.5];

% It is a good practice to provide the correct
% dimmension of A as the last two arguments
% because it facilitates better error checking.
prob.a          = sparse([1, 2, 2], [1, 2, 3], [1, 1, 1], 2, 3);
prob.bara.subi  = [1, 1, 1, 2, 2, 2, 2, 2, 2];
prob.bara.subj  = [1, 1, 1, 1, 1, 1, 1, 1, 1];
prob.bara.subk  = [1, 2, 3, 1, 2, 3, 2, 3, 3];
prob.bara.subl  = [1, 2, 3, 1, 1, 1, 2, 2, 3];
prob.bara.val   = [1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0];

prob.cones.type     = [res.symbcon.MSK_CT_QUAD];
prob.cones.sub      = [1, 2, 3];
prob.cones.subptr   = [1];

[r,res] = mosekopt( 'minimize info' ,prob);

X = zeros(3);
X([1,2,3,5,6,9]) = res.sol.itr.barx;
X = X + tril(X,-1)' ;

x = res.sol.itr.xx;
```

The solution x is returned in res.sol.itr.xx and the numerical values of $\overline{X}_j$ are returned in res.sol.itr.barx ; the lower triangular part of each $\overline{X}_j$ is stacked column-by-column into an array, and each array is then concatenated forming a single array res.sol.itr.barx representing $\overline{X}_1; \ldots; \overline{X}_p$. Similarly, the dual semide nite variables $\overline{S}_j$ are recovered through res.sol.itr.bars .

6.6.2 Example SDO2

We now demonstrate how to de ne more than one semide nite variable using the following problem with two matrix variables and two types of constraints:

$$\begin{array}{lrcl} \text{minimize} & \langle C_1; \overline{X}_1 \rangle + \langle C_2; \overline{X}_2 \rangle & & \\ \text{subject to} & \langle A_1; \overline{X}_1 \rangle + \langle A_2; \overline{X}_2 \rangle & = & b; \\ & (\overline{X}_2)_{01} & & k; \\ & \overline{X}_1; \overline{X}_2 & & 0: \end{array} \tag{6.12}$$

In our example $\dim(\overline{X}_1) = 3$, $\dim(\overline{X}_2) = 4$, $b = 23$, $k = 3$ and

$$C_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 6 \end{bmatrix}; A_1 = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 0 & 0 \\ 1 & 0 & 2 \end{bmatrix};$$

$$C_2 = \begin{bmatrix} 1 & -3 & 0 & 0 \\ -3 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, A_2 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -3 \end{bmatrix},$$

are constant symmetric matrices.

Note that this problem does not contain any scalar variables, but they could be added in the same fashion as in Sec. 6.6.1.

For explanations of data structures used in the example see Sec. 6.6.1. Note that the elbardim is used to specify that we have two semide nite variables of dimensions 3 and 4.

The code representing the above problem is shown below.

Listing 6.11: Implementation of model (6.12).

```
% Sample data
C1 = [ 1 0 0; 0 0 0; 0 0 6 ];
A1 = [ 1 0 1; 0 0 0; 1 0 2 ];
C2 = [ 1 -3 0 0; -3 2 0 0; 0 0 1 0; 0 0 0 0 ];
A2 = [ 0 1 0 0; 1 -1 0 0; 0 0 0 0; 0 0 0 -3 ];
b = 23;
k = -3;

% The scalar part, as in linear optimization examples
prob.c = [];
prob.a = sparse([], [], [], 2, 0);          % 2 constraints, no scalar variables
prob.blc = [b -inf];                        % Bounds
prob.buc = [b k];

% Dimensions of PSD variables
prob.bardim = [3, 4];

% Coefficients in the objective
[r1,c1,v1] = find(tril(C1));
[r2,c2,v2] = find(tril(C2));

prob.barc.subj = [repmat(1,length(v1),1);                % Which PSD variable (j)
                  repmat(2,length(v2),1)];
prob.barc.subk = [r1; r2];                               % Which matrix entry and value ((k,l)-
↪>v)
prob.barc.subl = [c1; c2];
prob.barc.val = [v1; v2];

% Coefficients in the constraints
[r1,c1,v1] = find(tril(A1));
[r2,c2,v2] = find(tril(A2));

prob.bara.subi = [ones(length(v1)+length(v2),1);         % Which constraint (i)
                  2];
prob.bara.subj = [repmat(1,length(v1),1);
                  repmat(2,length(v2),1);
                  2];                                    % Which PSD variable (j)
prob.bara.subk = [r1; r2; 2];                            % Which matrix entry and value ((k,l)-
↪>v)
prob.bara.subl = [c1; c2; 1];
prob.bara.val = [v1; v2; 0.5];

% Solve with log output
[r, res] = mosekopt('write(test.ptf) minimize echo(10)', prob);

% Retrieve the result assuming primal and dual feasible
X1 = zeros(3);
X1([1,2,3,5,6,9]) = res.sol.itr.barx(1:6);
X1 = X1 + tril(X1,-1)';
```

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```
X2 = zeros(4);
X2([1,2,3,4,6,7,8,11,12,16]) = res.sol.itr.barx(7:16);
X2 = X2 + tril(X2,-1)';

X1
X2
```

The numerical values of $\overline{X}_j$ are returned in res.sol.itr.barx ; the lower triangular part of each $\overline{X}_j$ is stacked column-by-column into an array, and each array is then concatenated forming a single array res.sol.itr.barx representing $\overline{X}_1, \ldots, \overline{X}_p$. Similarly, the dual semide nite variables $\overline{S}_j$ are recovered through res.sol.itr.bars .

6.7 A□ne conic constraints (new)

Optimization Toolbox for MATLAB can solve conic optimization problems in another format:

$$\begin{array}{lrcccl} \text{minimize} & & & c^T x + c^f & & \\ \text{subject to} & l^c & \leq & Ax & \leq & u^c, \\ & l^x & \leq & x & \leq & u^x, \\ & & & Fx + g \in \mathcal{K}, & & \end{array}$$

where $F \in \mathbb{R}^{k \times n}$ and $g \in \mathbb{R}^k$ specify an *affine conic constraint* of length (dimension) k. Usually $\mathcal{K}$ will be a product of basic cones corresponding to individual constraints.

In this tutorial we demonstrate how to use the a ne conic format. It supports all types of basic cones available in **MOSEK** and can be combined with semide nite variables as in Sec. 6.6.

6.7.1 Example AFFCO1

Consider the following simple optimization problem:

$$\begin{array}{lrcl} \text{maximize} & x_1^{1/3} + (x_1 + x_2 + 0.1)^{1/4} & & \\ \text{subject to} & (x_1 - 0.5)^2 + (x_2 - 0.6)^2 & \leq & 1, \\ & x_1 - x_2 & \leq & 1. \end{array} \tag{6.13}$$

Adding auxiliary variables we convert this problem into an equivalent conic form:

$$\begin{array}{lrcl} \text{maximize} & t_1 + t_2 & & \\ \text{subject to} & (1, x_1 - 0.5, x_2 - 0.6) & \in & \mathcal{Q}^3, \\ & (x_1, 1, t_1) & \in & \mathcal{P}_3^{1/3,2/3}, \\ & (x_1 + x_2 + 0.1, 1, t_2) & \in & \mathcal{P}_3^{1/4,3/4}, \\ & x_1 - x_2 & \leq & 1. \end{array} \tag{6.14}$$

Note that each of the vectors constrained to a cone is in a natural way an a ne combination of the problem variables.

We rst set up the linear part of the problem, including the number of variables, objective and all bounds precisely as in Sec. 6.1. Cones will be de ned using the *cones* structure. We construct the matrices F, g for each of the three cones. For example, the constraint $(1, x_1 - 0.5, x_2 - 0.6) \in \mathcal{Q}^3$ is written in matrix form as

$$\begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ t_1 \\ t_2 \end{bmatrix} + \begin{bmatrix} 1 \\ -0.5 \\ -0.6 \end{bmatrix} \in \mathcal{Q}^3.$$

Below we set up the matrices and de ne the cone type as a quadratic cone of length 3:

```
% The quadratic cone
FQ = sparse([zeros(1,4); speye(2) zeros(2,2)]);
gQ = [1 -0.5 -0.6]';
cQ = [res.symbcon.MSK_CT_QUAD 3];
```

Next we demonstrate how to do the same for the second of the power cone constraints. Its a ne representation is:

$$\begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ t_1 \\ t_2 \end{bmatrix} + \begin{bmatrix} 0.1 \\ 1 \\ 0 \end{bmatrix} \in \mathcal{P}_3^{1/4,3/4}.$$

The power cone is de ned by its type, length, number of additional parameters (always equal to 2) and the exponents $\alpha, 1-\alpha$ appearing in the cone de nition. In fact any pair of positive real numbers *proportional* to $(\alpha, 1-\alpha)$ may be used. They will be normalized to add up to 1:

```
% The power cone for (x_1+x_2+0.1, 1, t_2) \in POW3^(1/4,3/4)
FP2 = sparse([1 1 zeros(1,2); zeros(1,4); zeros(1,2) 0 1]);
gP2 = [0.1 1 0]';
cP2 = [res.symbcon.MSK_CT_PPOW 3 2 1.0 3.0];
```

Once a ne conic descriptions of all cones are ready it remains to stack them vertically into the matrix F and vector g and concatenate the cone descriptions in one list. Below is the full code for problem (6.14).

Listing 6.12: Script implementing conic version of problem (6.13).

```
function affco1()

[rcode, res] = mosekopt('symbcon echo(0)');
prob = [];

% Variables [x1; x2; t1; t2]
prob.c = [0, 0, 1, 1];

% Linear inequality x_1 - x_2 <= 1
prob.a = sparse([1, -1, 0, 0]);
prob.buc = 1;
prob.blc = [];

% The quadratic cone
FQ = sparse([zeros(1,4); speye(2) zeros(2,2)]);
gQ = [1 -0.5 -0.6]';
cQ = [res.symbcon.MSK_CT_QUAD 3];

% The power cone for (x_1, 1, t_1) \in POW3^(1/3,2/3)
FP1 = sparse([1 0 zeros(1,2); zeros(1,4); zeros(1,2) 1 0]);
gP1 = [0 1 0]';
cP1 = [res.symbcon.MSK_CT_PPOW 3 2 1/3 2/3];

% The power cone for (x_1+x_2+0.1, 1, t_2) \in POW3^(1/4,3/4)
FP2 = sparse([1 1 zeros(1,2); zeros(1,4); zeros(1,2) 0 1]);
gP2 = [0.1 1 0]';
cP2 = [res.symbcon.MSK_CT_PPOW 3 2 1.0 3.0];

% All cones
prob.f = [FQ; FP1; FP2];
prob.g = [gQ; gP1; gP2];
prob.cones = [cQ cP1 cP2];

[r, res] = mosekopt('maximize', prob);

res.sol.itr.pobjval
res.sol.itr.xx(1:2)
```

6.7.2 Example AFFCO2

Consider the following simple linear dynamical system. A point in $\mathbb{R}^n$ moves along a trajectory given by $z(t) = z(0)\exp(At)$, where $z(0)$ is the starting position and $A = \mathbf{Diag}(a_1, \ldots, a_n)$ is a diagonal matrix with $a_i < 0$. Find the time after which $z(t)$ is within euclidean distance d from the origin. Denoting the coordinates of the starting point by $z(0) = (z_1, \ldots, z_n)$ we can write this as an optimization problem in one variable t:

$$\begin{array}{lrcl} \text{minimize} & t & & \\ \text{subject to} & \sqrt{\sum_i (z_i \exp(a_i t))^2} & \leq & d, \end{array}$$

which can be cast into conic form as:

$$\begin{array}{lrcl} \text{minimize} & t & & \\ \text{subject to} & (d, z_1 y_1, \ldots, z_n y_n) & \in & \mathcal{Q}^{n+1}, \\ & (y_i, 1, a_i t) & \in & K_{\exp},\ i = 1, \ldots, n, \end{array} \tag{6.15}$$

with variable vector $x = [t, y_1, \ldots, y_n]^T$.

We assemble all conic constraints in the form

$$Fx + g \in \mathcal{Q}^{n+1} \times (K_{\exp})^n.$$

For the conic quadratic constraint this representation is

$$\begin{bmatrix} 0 & 0_n^T \\ 0_n & \mathbf{Diag}(z_1, \ldots, z_n) \end{bmatrix} \begin{bmatrix} t \\ y \end{bmatrix} + \begin{bmatrix} d \\ 0_n \end{bmatrix} \in \mathcal{Q}^{n+1}.$$

For the i-th exponential cone we have

$$\begin{bmatrix} 0 & e_i^T \\ 0 & 0_n \\ a_i & 0_n \end{bmatrix} \begin{bmatrix} t \\ y \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \in K_{\exp},$$

where e_i denotes a vector of length n with a single 1 in position i.

Listing 6.13: Script implementing problem (6.15).

```
function t = firstHittingTime(n, z, a, d)

[rcode, res] = mosekopt('symbcon echo(0)');
prob = [];

% Variables [t, y1, ..., yn]
prob.a = sparse(0, n+1);
prob.c = [1 zeros(1,n)];

% Quadratic cone
FQ = diag([0; z]);
gQ = [d; zeros(n,1)];

% All exponential cones
FE = sparse([1:3:3*n    3:3:3*n], ...
            [2:n+1      ones(1,n)], ...
            [ones(1,n)  a']);
gE = repmat([0; 1; 0], n, 1);

% Assemble input data
prob.f = [FQ; FE];
prob.g = [gQ; gE];
prob.cones = [res.symbcon.MSK_CT_QUAD n+1 repmat([res.symbcon.MSK_CT_PEXP 3], 1, n)];

% Solve
[r, res] = mosekopt('minimize', prob);
t = res.sol.itr.xx(1)
```

6.8 Geometric Programming

Geometric programs (GP) are a particular class of optimization problems which can be expressed in special polynomial form as positive sums of generalized monomials. More precisely, a geometric problem in canonical form is

$$\begin{array}{lll} \text{minimize} & f_0(x) & \\ \text{subject to} & f_i(x) \leq 1, & i = 1, \ldots, m, \\ & x_j > 0, & j = 1, \ldots, n, \end{array} \tag{6.16}$$

where each $f_0, \ldots, f_m$ is a *posynomial*, that is a function of the form

$$f(x) = \sum_k c_k x_1^{\alpha_{k1}} x_2^{\alpha_{k2}} \cdots x_n^{\alpha_{kn}}$$

with arbitrary real α_{ki} and $c_k > 0$. The standard way to formulate GPs in convex form is to introduce a variable substitution

$$x_i = \exp(y_i).$$

Under this substitution all constraints in a GP can be reduced to the form

$$\log(\sum_k \exp(a_k^T y + b_k)) \leq 0 \tag{6.17}$$

involving a *log-sum-exp* bound. Moreover, constraints involving only a single monomial in x can be even more simply written as a linear inequality:

$$a_k^T y + b_k \leq 0$$

We refer to the **MOSEK** Modeling Cookbook and to *[BKVH07]* for more details on this reformulation. A geometric problem formulated in convex form can be entered into **MOSEK** with the help of exponential cones.

6.8.1 Example GP1

The following problem comes from *[BKVH07]*. Consider maximizing the volume of a $h \times w \times d$ box subject to upper bounds on the area of the oor and of the walls and bounds on the ratios h/w and d/w:

$$\begin{array}{lrl} \text{maximize} & hwd & \\ \text{subject to} & 2(hw + hd) & \leq A_{\text{wall}}, \\ & wd & \leq A_{\text{floor}}, \\ & \alpha & \leq h/w \leq \beta, \\ & \gamma & \leq d/w \leq \delta. \end{array} \tag{6.18}$$

The decision variables in the problem are h, w, d. We make a substitution

$$h = \exp(x), w = \exp(y), d = \exp(z)$$

after which (6.18) becomes

$$\begin{array}{ll} \text{maximize} & x + y + z \\ \text{subject to} & \log(\exp(x + y + \log(2/A_{\text{wall}})) + \exp(x + z + \log(2/A_{\text{wall}}))) \leq 0, \\ & y + z \leq \log(A_{\text{floor}}), \\ & \log(\alpha) \leq x - y \leq \log(\beta), \\ & \log(\gamma) \leq z - y \leq \log(\delta). \end{array} \tag{6.19}$$

Next, we demonstrate how to implement a log-sum-exp constraint (6.17). It can be written as:

$$\begin{array}{l} u_k \geq \exp(a_k^T y + b_k), \quad (\text{equiv. } (u_k, 1, a_k^T y + b_k) \in K_{\exp}), \\ \sum_k u_k = 1. \end{array} \tag{6.20}$$

This presentation requires one extra variable u_k for each monomial appearing in the original posynomial constraint. It is natural to express the cone membership using an a ne conic constraint (see Sec. 6.7). In this case:

$$\begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ \log(2/A_{\text{wall}}) \\ 0 \\ 1 \\ \log(2/A_{\text{wall}}) \end{bmatrix} \in K_{\exp} \times K_{\exp}.$$

We can now use this function to assemble all constraints in the model. The linear part of the problem is entered as in Sec. 6.1.

Listing 6.14: Source code solving problem (6.19).

```
[r,res] = mosekopt('symbcon');

% Input data
Awall = 200;
Afloor = 50;
alpha = 2;
beta = 10;
gamma = 2;
delta = 10;

% Objective
prob = [];
prob.c = [1, 1, 1, 0, 0]';

% Linear constraints:
% [ 0  0  0  1  1 ]                    == 1
% [ 0  1  1  0  0 ]                    <= log(Afloor)
% [ 1 -1  0  0  0 ]                    in [log(alpha), log(beta)]
% [ 0 -1  1  0  0 ]                    in [log(gamma), log(delta)]
%
prob.a = [ 0  0  0  1  1;
           0  1  1  0  0;
           1 -1  0  0  0;
           0 -1  1  0  0 ];

prob.blc = [ 1; -inf;        log(alpha); log(gamma) ];
prob.buc = [ 1; log(Afloor); log(beta);  log(delta) ];

prob.blx = [ -inf; -inf; -inf; -inf; -inf];
prob.bux = [ inf; inf; inf; inf; inf];

% The conic part FX+g \in Kexp x Kexp
%   x  y  z  u  v
% [ 0  0  0  1  0 ]    0
% [ 0  0  0  0  0 ]    1               in Kexp
% [ 1  1  0  0  0 ]    log(2/Awall)
%
% [ 0  0  0  0  1 ]    0
% [ 0  0  0  0  0 ]    1               in Kexp
% [ 1  0  1  0  0 ] +  log(2/Awall)
%
%
prob.f = sparse([0 0 0 1 0;
                 0 0 0 0 0;
                 1 1 0 0 0;
                 0 0 0 0 1;
                 0 0 0 0 0;
```

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```
                    1 0 1 0 0]);

prob.g = [ 0; 1; log(2/Awall); 0; 1; log(2/Awall)];

prob.cones = [ res.symbcon.MSK_CT_PEXP, 3, res.symbcon.MSK_CT_PEXP, 3 ];

% Optimize and print results
[r,res]=mosekopt( 'maximize',prob);
exp(res.sol.itr.xx(1:3))
```

6.9 Integer Optimization

An optimization problem where one or more of the variables are constrained to integer values is called a (mixed) integer optimization problem. MOSEK supports integer variables in combination with linear, quadratic and quadratically constrtained and conic problems (except semide nite). See the previous tutorials for an introduction to how to model these types of problems.

6.9.1 Example MILO1

We use the example

$$\begin{array}{lll} \text{maximize} & x_0 + 0.64x_1 & \\ \text{subject to} & 50x_0 + 31x_1 & 250; \\ & 3x_0 \quad 2x_1 & 4; \\ & x_0; x_1 \quad 0 & \text{and integer} \end{array} \tag{6.21}$$

to demonstrate how to set up and solve a problem with integer variables. It has the structure of a linear optimization problem (see Sec. 6.1) except for integrality constraints on the variables. Therefore, only the speci cation of the integer constraints requires something new compared to the linear optimization problem discussed previously.

The complete source for the example is listed in Listing 6.15.

Listing 6.15: How to solve problem (6.21).

```
function milo1()
clear prob
prob.c          = [1 0.64];
prob.a          = [[50 31];[3 -2]];
prob.blc        = [-inf -4];
prob.buc        = [250 inf];
prob.blx        = [0 0];
prob.bux        = [inf inf];

% Specify indexes of variables that are integer
% constrained.

prob.ints.sub = [1 2];

% Optimize the problem.
[r,res] = mosekopt( 'maximize',prob);

try
  % Display the optimal solution.
  res.sol.int
  res.sol.int.xx     '
catch
  fprintf( 'MSKERROR: Could not get solution')
end
```

Please note that compared to a linear optimization problem with no integer-constrained variables:

- The prob.ints.sub eld is used to specify the indexes of the variables that are integer-constrained.
- The optimal integer solution is returned in the res.sol.int MATLAB structure.

MOSEK also provides a wrapper for the *intlinprog* function found in the MATLAB optimization toolbox. This function solves linear problems wth integer variables; see the reference section for details.

6.9.2 Specifying an initial solution

It is a common strategy to provide a starting feasible point (if one is known in advance) to the mixed-integer solver. This can in many cases reduce solution time.

It is not necessary to specify the whole solution. **MOSEK** will attempt to use it to speed up the computation. **MOSEK** will rst try to construct a feasible solution by xing integer variables to the values provided by the user (rounding if necessary) and optimizing over the continuous variables. The outcome of this process can be inspected via information items *"MSK_IINF_MIO_CONSTRUCT_SOLUTION"* and *"MSK_DINF_MIO_CONSTRUCT_SOLUTION_OBJ"*, and via the Construct solution objective entry in the log. We concentrate on a simple example below.

$$\begin{array}{ll} \text{maximize} & 7x_0 + 10x_1 + x_2 + 5x_3 \\ \text{subject to} & x_0 + x_1 + x_2 + x_3 \leq 2.5 \\ & x_0, x_1, x_2 \in \mathbb{Z} \\ & x_0, x_1, x_2, x_3 \geq 0 \end{array} \tag{6.22}$$

Solution values can be set using the appropriate elds in the problem structure.

Listing 6.16: Implementation of problem (6.22) specifying an initial solution.

```
% Specify start guess for the integer variables.
prob.sol.int.xx  = [1 1 0 nan]';
```

The log output from the optimizer will in this case indicate that the inputted values were used to construct an initial feasible solution:

```
Construct solution objective       : 1.950000000000e+01
```

The same information can be obtained from the API:

Listing 6.17: Retrieving information about usage of initial solution

```
  res.info.MSK_IINF_MIO_CONSTRUCT_SOLUTION
  res.info.MSK_DINF_MIO_CONSTRUCT_SOLUTION_OBJ
```

6.9.3 Example MICO1

Integer variables can also be used arbitrarily in conic problems (except semide nite). We refer to the previous tutorials for how to set up a conic optimization problem. Here we present sample code that sets up a simple optimization problem:

$$\begin{array}{ll} \text{minimize} & x^2 + y^2 \\ \text{subject to} & x \geq e^y + 3.8, \\ & x, y \text{ integer.} \end{array} \tag{6.23}$$

The canonical conic formulation of (6.23) suitable for Optimization Toolbox for MATLAB is

$$\begin{array}{lll} \text{minimize} & t & \\ \text{subject to} & (t, x, y) \in \mathcal{Q}^3 & (t \geq \sqrt{x^2 + y^2}) \\ & (x - 3.8, 1, y) \in K_{\exp} & (x - 3.8 \geq e^y) \\ & x, y \text{ integer}, & \\ & t \in \mathbb{R}. & \end{array} \tag{6.24}$$

Listing 6.18: Implementation of problem (6.24).

```
[rcode, res] = mosekopt('symbcon echo(0)');
symbcon = res.symbcon;
clear prob

% The full variable is [t; x; y]
prob.c        = [1 0 0];
prob.a        = sparse(0,3);   % No constraints

% Conic part of the problem
prob.f = sparse([ eye(3);
                  0 1 0;
                  0 0 0;
                  0 0 1 ]);
prob.g = [0 0 0 -3.8 1 0]';
prob.cones = [symbcon.MSK_CT_QUAD 3 symbcon.MSK_CT_PEXP 3];

% Specify indexes of variables that are integers
prob.ints.sub = [2 3];

% It is as always possible (but not required) to input an initial solution
% to start the mixed-integer solver.
prob.sol.int.xx = [0, 9, -1];

% Optimize the problem.
[r,res] = mosekopt('minimize',prob);

% The integer solution (x,y)
res.sol.int.xx(2:3)
```

Note that the conic constraints are described using the format $Fx + g \in \mathcal{K}$, that is as *affine conic constraints*. See Sec. 6.7 for details.

Error and solution status handling were omitted for readability.

6.10 Problem Modification and Reoptimization

Often one might want to solve not just a single optimization problem, but a sequence of problems, each di ering only slightly from the previous one. This section demonstrates how to modify and re-optimize an existing problem.

The example we study is a simple production planning model.

Problem modi cations regarding variables, cones, objective function and constraints can be grouped in categories:

- add/remove,
- coe cient modi cations,
- bounds modi cations.

Especially removing variables and constraints can be costly. Special care must be taken with respect to constraints and variable indexes that may be invalidated.

Depending on the type of modi cation, **MOSEK** may be able to optimize the modi ed problem more e ciently exploiting the information and internal state from the previous execution. After optimization, the solution is always stored internally, and is available before next optimization. The former optimal solution may be still feasible, but no longer optimal; or it may remain optimal if the modi cation of the objective function was small. This special case is discussed in Sec. 14.3.

In general, **MOSEK** exploits dual information and availability of an optimal basis from the previous execution. The simplex optimizer is well suited for exploiting an existing primal or dual feasible solution. Restarting capabilities for interior-point methods are still not as reliable and e ective as those for the simplex algorithm. More information can be found in Chapter 10 of the book *[Chv83]*.

6.10.1 Example: Production Planning

A company manufactures three types of products. Suppose the stages of manufacturing can be split into three parts: Assembly, Polishing and Packing. In the table below we show the time required for each stage as well as the profit associated with each product.

Product no.	Assembly (minutes)	Polishing (minutes)	Packing (minutes)	Profit ($)
0	2	3	2	1.50
1	4	2	3	2.50
2	3	3	2	3.00

With the current resources available, the company has 100,000 minutes of assembly time, 50,000 minutes of polishing time and 60,000 minutes of packing time available per year. We want to know how many items of each product the company should produce each year in order to maximize profit?

Denoting the number of items of each type by x_0, x_1 and x_2, this problem can be formulated as a linear optimization problem:

$$\begin{array}{lrcrcrl} \text{maximize} & 1.5x_0 & + & 2.5x_1 & + & 3.0x_2 & \\ \text{subject to} & 2x_0 & + & 4x_1 & + & 3x_2 & \leq 100000, \\ & 3x_0 & + & 2x_1 & + & 3x_2 & \leq 50000, \\ & 2x_0 & + & 3x_1 & + & 2x_2 & \leq 60000, \end{array} \tag{6.25}$$

and

$$x_0, x_1, x_2 \geq 0.$$

Code in Listing 6.19 loads and solves this problem.

Listing 6.19: Setting up and solving problem (6.25)

```
% Specify the c vector.
prob.c = [1.5 2.5 3.0]';

% Specify a in sparse format.
subi = [1 1 1 2 2 2 3 3 3];
subj = [1 2 3 1 2 3 1 2 3];
valij = [2 4 3 3 2 3 2 3 2];

prob.a = sparse(subi,subj,valij);

% Specify lower bounds of the constraints.
prob.blc = [-inf -inf -inf]';

% Specify upper bounds of the constraints.
prob.buc = [100000 50000 60000]';

% Specify lower bounds of the variables.
prob.blx = zeros(3,1);

% Specify upper bounds of the variables.
prob.bux = [inf inf inf]';

% Perform the optimization.
param.MSK_IPAR_OPTIMIZER = MSK_OPTIMIZER_FREE_SIMPLEX;
[r,res] = mosekopt('maximize',prob,param);

% Show the optimal x solution.
res.sol.bas.xx
```

6.10.2 Changing the Linear Constraint Matrix

Suppose we want to change the time required for assembly of product 0 to 3 minutes. This corresponds to setting $a_{0,0} = 3$, which is done by directly modifying the A matrix of the problem, as shown below.

```
prob.a(1,1) = 3.0;
```

The problem now has the form:

$$\begin{array}{lrcrcrcl} \text{maximize} & 1.5x_0 & + & 2.5x_1 & + & 3.0x_2 & & \\ \text{subject to} & 3x_0 & + & 4x_1 & + & 3x_2 & \leq & 100000, \\ & 3x_0 & + & 2x_1 & + & 3x_2 & \leq & 50000, \\ & 2x_0 & + & 3x_1 & + & 2x_2 & \leq & 60000, \end{array} \tag{6.26}$$

and

$$x_0, x_1, x_2 \geq 0.$$

After this operation we can reoptimize the problem.

6.10.3 Appending Variables

We now want to add a new product with the following data:

Product no.	Assembly (minutes)	Polishing (minutes)	Packing (minutes)	Profit ($)
3	4	0	1	1.00

This corresponds to creating a new variable x_3, appending a new column to the A matrix and setting a new term in the objective. We do this in Listing 6.20

Listing 6.20: How to add a new variable (column)

```
prob.c       = [prob.c;1.0];
prob.a       = [prob.a,sparse([4.0 0.0 1.0]')];
prob.blx     = [prob.blx; 0.0];
prob.bux     = [prob.bux; inf];
```

After this operation the new problem is:

$$\begin{array}{lrcrcrcrcl} \text{maximize} & 1.5x_0 & + & 2.5x_1 & + & 3.0x_2 & + & 1.0x_3 & & \\ \text{subject to} & 3x_0 & + & 4x_1 & + & 3x_2 & + & 4x_3 & \leq & 100000, \\ & 3x_0 & + & 2x_1 & + & 3x_2 & & & \leq & 50000, \\ & 2x_0 & + & 3x_1 & + & 2x_2 & + & 1x_3 & \leq & 60000, \end{array} \tag{6.27}$$

and

$$x_0, x_1, x_2, x_3 \geq 0.$$

6.10.4 Appending Constraints

Now suppose we want to add a new stage to the production process called *Quality control* for which 30000 minutes are available. The time requirement for this stage is shown below:

Product no.	Quality control (minutes)
0	1
1	2
2	1
3	1

This corresponds to adding the constraint

$$x_0 + 2x_1 + x_2 + x_3 \leq 30000$$

to the problem. This is done as follows.

Listing 6.21: Adding a new constraint.

```
prob.a       = [prob.a;sparse([1.0 2.0 1.0 1.0])];
prob.blc     = [prob.blc; -inf];
prob.buc     = [prob.buc; 30000.0];
```

Again, we can continue with re-optimizing the modi ed problem.

6.10.5 Changing bounds

One typical reoptimization scenario is to change bounds. Suppose for instance that we must operate with limited time resources, and we must change the upper bounds in the problem as follows:

Operation	Time available (before)	Time available (new)
Assembly	100000	80000
Polishing	50000	40000
Packing	60000	50000
Quality control	30000	22000

That means we would like to solve the problem:

$$\begin{array}{lrcrcrcrcl} \text{maximize} & 1.5x_0 & + & 2.5x_1 & + & 3.0x_2 & + & 1.0x_3 & & \\ \text{subject to} & 3x_0 & + & 4x_1 & + & 3x_2 & + & 4x_3 & \leq & 80000, \\ & 3x_0 & + & 2x_1 & + & 3x_2 & & & \leq & 40000, \\ & 2x_0 & + & 3x_1 & + & 2x_2 & + & 1x_3 & \leq & 50000, \\ & x_0 & + & 2x_1 & + & x_2 & + & x_3 & \leq & 22000. \end{array} \tag{6.28}$$

In this case all we need to do is rede ne the upper bound vector for the constraints, as shown in the next listing.

Listing 6.22: Change constraint bounds.

```
prob.buc     = [80000 40000 50000 22000]';
prob.sol     = res.sol;
[r,res] = mosekopt('maximize',prob,param);
res.sol.bas.xx
```

Again, we can continue with re-optimizing the modi ed problem.

6.10.6 Advanced hot-start

In order to exploit the possibility of hot-starting the simplex algorithms it is necessary to pass the old basic solution when the modi ed problem is re-optimized. Without this operation the optimizer will simply start from scratch. Any subset of the basic solution may be provided, but to achieve the best results all elds of res.sol.bas should be present, that isxx,xc,y,slx,sux,slc,suc,skx,skc .

Listing 6.23: Passing the full basic solution.

```
% Reoptimize with changed coefficient
% Use previous solution to perform very simple hot-start.
% This part can be skipped, but then the optimizer will start
% from scratch on the new problem, i.e. without any hot-start.
prob.sol = [];
prob.sol.bas = res.sol.bas;
[r,res] = mosekopt('maximize',prob,param);
res.sol.bas.xx
```

If the dimensions of the problem (number of variables, constraints) have changed, the lengths of all elds have to be adjusted to be compatible with the reformulated problem. For example, here is an adjustment when adding a new variable:

Listing 6.24: Adjusting lengths in the solution elds related to variables.

```
% Reoptimize with a new variable and hot-start
% All parts of the solution must be extended to the new dimensions.
prob.sol = [];
prob.sol.bas = res.sol.bas;
prob.sol.bas.xx  = [prob.sol.bas.xx; 0.0];
prob.sol.bas.slx = [prob.sol.bas.slx; 0.0];
prob.sol.bas.sux = [prob.sol.bas.sux; 0.0];
prob.sol.bas.skx = [prob.sol.bas.skx; 'UN'];
[r,res] = mosekopt('maximize',prob,param);
res.sol.bas.xx
```

If the optimizer used the data from the previous run to hot-start the optimizer for reoptimization, this will be indicated in the log:

```
Optimizer  - hotstart               : yes
```

When performing re-optimizations, instead of removing a basic variable it may be more e cient to x the variable at zero and then remove it when the problem is re-optimized and it has left the basis. This makes it easier for MOSEK to restart the simplex optimizer.

A more advanced discussion of hot-start is presented in Sec. 9.2.

For a more in-depth treatment see the following sections:

- *Case studies* for more advanced and complicated optimization examples.
- *Problem Formulation and Solutions* for formal mathematical formulations of problems MOSEK can solve, dual problems and infeasibility certi cates.

Chapter 7

Solver Interaction Tutorials

In this section we cover the interaction with the solver.

7.1 Accessing the solution

This section contains important information about the status of the solver and the status of the solution, which must be checked in order to properly interpret the results of the optimization.

7.1.1 Solver termination

The optimizer provides a **response code** of type *rescode*, relevant for error handling. It indicates if any errors occurred in any phase of optimization (including processing input data). It will also indicate system-related errors (such as an out of memory error, licensing error etc.). Finally, it will also indicate if the optimizer terminated correctly, but for a non-standard reason, for example because it reached a time limit or met another criterion set by the user. Such termination codes are not errors. The expected value for a typical successful optimization without any special settings is *"MSK_RES_OK"*.

If a runtime error causes the program to crash during optimization, the rst debugging step is to enable logging and check the log output. See Sec. 7.3.

If the optimization completes successfully, the next step is to check the solution status, as explained below.

7.1.2 Available solutions

MOSEK uses three kinds of optimizers and provides three types of solutions:

- **basic solution** from the simplex optimizer,
- **interior-point solution** from the interior-point optimizer,
- **integer solution** from the mixed-integer optimizer.

Under standard parameters settings the following solutions will be available for various problem types:

Table 7.1: Types of solutions available from **MOSEK**

	Simplex optimizer	Interior-point optimizer	Mixed-integer optimizer
Linear problem	res.sol.bas	res.sol.itr	
Nonlinear continuous problem		res.sol.itr	
Problem with integer variables			res.sol.int

For linear problems the user can force a speci c optimizer choice making only one of the two solutions available. For example, if the user disables basis identi cation, then only the interior point solution will be available for a linear problem. Numerical issues may cause one of the solutions to be unknown even if another one is feasible.

Not all components of a solution are always available. For example, there is no dual solution for integer problems and no dual conic variables from the simplex optimizer.

The user will always need to specify which solution should be accessed.

7.1.3 Problem and solution status

Assuming that the optimization terminated without errors, the next important step is to check the problem and solution status. There is one for every type of solution, as explained above.

Problem status

Problem status (prosta) determines whether the problem is certi ed as feasible. Its values can roughly be divided into the following broad categories:

- feasible the problem is feasible. For continuous problems and when the solver is run with default parameters, the feasibility status should ideally be "MSK_PRO_STA_PRIM_AND_DUAL_FEAS"
- primal/dual infeasible the problem is infeasible or unbounded or a combination of those. The exact problem status will indicate the type of infeasibility.
- unknown the solver was unable to reach a conclusion, most likely due to numerical issues.

Solution status

Solution status (solsta) provides the information about what the solution values actually contain. The most important broad categories of values are:

- optimal ("MSK_SOL_STA_OPTIMAL") the solution values are feasible and optimal.
- certi cate the solution is in fact a certi cate of infeasibility (primal or dual, depending on the solution).
- unknown/unde ned the solver could not solve the problem or this type of solution is not available for a given problem.

Problem and solution status can be found in the elds prosta and solsta of a solution structure solution , for instance res.sol.itr.prosta , res.sol.itr.solsta for the interior-point solution.

The solution status determines the action to be taken. For example, in some cases a suboptimal solution may still be valuable and deserve attention. It is the user's responsibility to check the status and quality of the solution.

Typical status reports

Here are the most typical optimization outcomes described in terms of the problem and solution statuses. Note that these do not cover all possible situations that can occur.

Table 7.2: Continuous problems (solution status for interior-point and basic solution)

Outcome	Problem status	Solution status
Optimal	"MSK_PRO_STA_PRIM_AND_DUAL_FEAS"	"MSK_SOL_STA_OPTIMAL"
Primal infeasible	"MSK_PRO_STA_PRIM_INFEAS"	"MSK_SOL_STA_PRIM_INFEAS_CER"
Dual infeasible (unbounded)	"MSK_PRO_STA_DUAL_INFEAS"	"MSK_SOL_STA_DUAL_INFEAS_CER"
Uncertain (stall, numerical issues, etc.)	"MSK_PRO_STA_UNKNOWN"	"MSK_SOL_STA_UNKNOWN"

Table 7.3: Integer problems (solution status for integer solution, others unde ned)

Outcome	Problem status	Solution status
Integer optimal	"MSK_PRO_STA_PRIM_FEAS"	"MSK_SOL_STA_INTEGER_OPTIMAL"
Infeasible	"MSK_PRO_STA_PRIM_INFEAS"	"MSK_SOL_STA_UNKNOWN"
Integer feasible point	"MSK_PRO_STA_PRIM_FEAS"	"MSK_SOL_STA_PRIM_FEAS"
No conclusion	"MSK_PRO_STA_UNKNOWN"	"MSK_SOL_STA_UNKNOWN"

7.1.4 Retrieving solution values

After the meaning and quality of the solution (or certi cate) have been established, we can query for the actual numerical values. They can be accessed using:

- res.sol.itr.pobjval , res.sol.itr.dobjval the primal and dual objective value.
- res.sol.itr.xx solution values for the variables.
- res.sol.itr.y , res.sol.itr.slx and so on dual values for the linear constraints

and many other elds of the *solution* structure (replace itr with bas or int for other solution types). Note that if the optimization failed then the res.sol eld may not exist and attempting to access it will cause an error.

7.1.5 Source code example

Below is a source code example with a simple framework for assessing and retrieving the solution to a conic optimization problem.

Listing 7.1: Sample framework for checking optimization result.

```
function response(inputfile)

  cmd = sprintf('read(%s)', inputfile)
  % In this example we read the problem from file
  [r, res] = mosekopt(cmd)

  % Read was successful
  if strcmp(res.rcodestr, 'MSK_RES_OK')

      prob = res.prob;
      param = []

      % (Optionally) Uncomment the next line to get solution status Unknown
      % param.MSK_IPAR_INTPNT_MAX_ITERATIONS = 1

      % Perform the optimization.
      [r, res] = mosekopt('minimize', prob, param);

      % Expected result: The solution status of the interior-point solution is optimal.

      % Check if we have non-error termination code or OK
      if isempty(strfind(res.rcodestr, 'MSK_RES_ERR'))

          solsta = strcat('MSK_SOL_STA_', res.sol.itr.solsta)

          if strcmp(solsta, 'MSK_SOL_STA_OPTIMAL')
              fprintf('An optimal interior-point solution is located:\n');
              res.sol.itr.xx

          elseif strcmp(solsta, 'MSK_SOL_STA_DUAL_INFEASIBLE_CER')
              fprintf('Dual infeasibility certificate found.');

          elseif strcmp(solsta, 'MSK_SOL_STA_PRIMAL_INFEASIBLE_CER')
              fprintf('Primal infeasibility certificate found.');

          elseif strcmp(solsta, 'MSK_SOL_STA_UNKNOWN')
              % The solutions status is unknown. The termination code
              % indicates why the optimizer terminated prematurely.
              fprintf('The solution status is unknown.\n');
              fprintf('Termination code: %s (%d) %s.\n', res.rcodestr, res.rcode, res.rmsg);
          else
```

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```
            fprintf('An unexpected solution status is obtained.');
          end

      else
          fprintf('Error during optimization: %s (%d) %s.\n', res.rcodestr, res.rcode, res.
↪rmsg);
      end

  else
      fprintf('Could not read input file, error: %s (%d) %s.\n', res.rcodestr, res.rcode, res.
↪rmsg)
  end

end
```

7.2 Errors and exceptions

Response codes

The function *mosekopt* and its variants return a **response code** (and its human-readable description), informing if optimization was performed correctly, and if not, what error occurred. The expected response, indicating successful execution, is always *"MSK_RES_OK"*. Typical errors include:

- referencing a nonexisting variable (for example with too large index),
- incompatible dimensions of input data matrices,
- NaN in the input data,
- duplicate conic variable,
- error in the optimizer.

Some errors in data preprocessing, such as incorrect command or wrong parameter value will result in *mosekopt* exiting without assigning output; the error message will just be printed out. For this reason it may be a good idea to call *mosekopt* in a try-catch block. A full list of response codes, error, warning and termination codes can be found in the *API reference*. For example, the following code

```
prob.a = sparse(0,1);
prob.c = [NaN];
[r, res] = mosekopt('minimize', prob);
res
```

will produce as output:

```
res =

   rcode: 1470
    rmsg: 'The objective vector c contains an invalid value for variable '' (0).'
rcodestr: 'MSK_RES_ERR_NAN_IN_C'
```

Optimizer errors and warnings

The optimizer may also produce warning messages. They indicate non-critical but important events, that will not prevent solver execution, but may be an indication that something in the optimization problem might be improved. Warning messages are normally printed to a log stream (see Sec. 7.3). A typical warning is, for example:

```
MOSEK warning 53: A numerically large upper bound value  6.6e+09 is specified for constraint
↪'C69200' (46020).
```

Warnings can also be suppressed by setting the *MSK_IPAR_MAX_NUM_WARNINGS* parameter to zero, if they are well-understood.

Error and solution status handling example

Below is a source code example with a simple framework for handling major errors when assessing and retrieving the solution to a conic optimization problem.

Listing 7.2: Sample framework for checking optimization result.

```
function response(inputfile)

  cmd = sprintf('read(%s)', inputfile)
  % In this example we read the problem from file
  [r, res] = mosekopt(cmd)

  % Read was successful
  if strcmp(res.rcodestr, 'MSK_RES_OK')

      prob = res.prob;
      param = []

      % (Optionally) Uncomment the next line to get solution status Unknown
      % param.MSK_IPAR_INTPNT_MAX_ITERATIONS = 1

      % Perform the optimization.
      [r, res] = mosekopt('minimize', prob, param);

      % Expected result: The solution status of the interior-point solution is optimal.

      % Check if we have non-error termination code or OK
      if isempty(strfind(res.rcodestr, 'MSK_RES_ERR'))

          solsta = strcat('MSK_SOL_STA_', res.sol.itr.solsta)

          if strcmp(solsta, 'MSK_SOL_STA_OPTIMAL')
              fprintf('An optimal interior-point solution is located:\n');
              res.sol.itr.xx

          elseif strcmp(solsta, 'MSK_SOL_STA_DUAL_INFEASIBLE_CER')
              fprintf('Dual infeasibility certificate found.');

          elseif strcmp(solsta, 'MSK_SOL_STA_PRIMAL_INFEASIBLE_CER')
              fprintf('Primal infeasibility certificate found.');

          elseif strcmp(solsta, 'MSK_SOL_STA_UNKNOWN')
              % The solutions status is unknown. The termination code
              % indicates why the optimizer terminated prematurely.
              fprintf('The solution status is unknown.\n');
              fprintf('Termination code: %s (%d) %s.\n', res.rcodestr, res.rcode, res.rmsg);
          else
            fprintf('An unexpected solution status is obtained.');
          end

      else
          fprintf('Error during optimization: %s (%d) %s.\n', res.rcodestr, res.rcode, res.
↪rmsg);
      end

  else
      fprintf('Could not read input file, error: %s (%d) %s.\n', res.rcodestr, res.rcode, res.
↪rmsg)
```

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```
  end

end
```

7.3 Input/Output

7.3.1 Stream logging

By default the solver prints a log output analogous to the one produced by the command-line version of MOSEK. Logging may be turned o using the command echo(0) , for example:

```
[r, res] = mosekopt('minimize echo(0)', prob);
```

Log output may be redirected to a le using the command log , for example:

```
[r, res] = mosekopt('minimize log(fileName.txt)', prob);
```

Note that in recent versions of MATLAB the log is not displayed on screen until optimization is completed, which may be an inconvenience for longer tasks. The log written to a le does not have this issue.

Note also that leaving log output on can lead to a dramatic slowdown, visible especially on very small problems.

It is also possible to register a user-de ned callback function that will receive and handle all log output, see the *callback* argument of *mosekopt*.

7.3.2 Log verbosity

The logging verbosity can be controlled by setting the relevant parameters, as for instance

- *MSK_IPAR_LOG*,
- *MSK_IPAR_LOG_INTPNT*,
- *MSK_IPAR_LOG_MIO*,
- *MSK_IPAR_LOG_CUT_SECOND_OPT*,
- *MSK_IPAR_LOG_SIM*, and
- *MSK_IPAR_LOG_SIM_MINOR*.

Each parameter controls the output level of a speci c functionality or algorithm. The main switch is *MSK_IPAR_LOG* which a ect the whole output. The actual log level for a speci c functionality is determined as the minimum between *MSK_IPAR_LOG* and the relevant parameter. For instance, the log level for the output produce by the interior-point algorithm is tuned by the *MSK_IPAR_LOG_INTPNT*; the actual log level is de ned by the minimum between *MSK_IPAR_LOG* and *MSK_IPAR_LOG_INTPNT*.

Tuning the solver verbosity may require adjusting several parameters. It must be noticed that verbose logging is supposed to be of interest during debugging and tuning. When output is no more of interest, the user can easily disable it globally with *MSK_IPAR_LOG*. Larger values of *MSK_IPAR_LOG* do not necessarily result in increased output.

By default MOSEK will reduce the amount of log information after the rst optimization on a given problem. To get full log output on subsequent re-optimizations set *MSK_IPAR_LOG_CUT_SECOND_OPT* to zero.

7.3.3 Saving a problem to a file

An optimization problem can be dumped to a le using the command write . The le format will be determined from the lename's extension. Supported formats are listed in Sec. 16 together with a table of problem types supported by each.

For instance the problem can be written to an OPF le with

```
[r, res] = mosekopt('write(dump.opf)', prob);
```

All formats can be compressed withgzip by appending the .gz extension, for example

```
[r, res] = mosekopt('write(dump.task.gz)', prob);
```

When using MATLAB-like functions the le name can be set using the options structure, for example:

```
opt.Write = 'problem.opf';
linprog(f,A,b,[],[],[],[],opt);
```

Some remarks:

- The problem is written to the le as it is represented in the underlying *optimizer task*, that is including any auxiliary variables introduced by the MATLAB-to-C interface, if applicable.
- Unnamed variables are given generic names. It is therefore recommended to use meaningful variable names if the problem le is meant to be human-readable.
- The task format is **MOSEK**'s native le format which contains all the problem data as well as solver settings.

7.3.4 Reading a problem from a file

A problem saved in any of the supported le formats can be read directly into a *prob* structure using the command read. Afterwards the problem can be optimized, modi ed, etc.

```
[r, res] = mosekopt('read(dump.opf.gz)');
prob = res.prob;
```

7.4 Setting solver parameters

MOSEK comes with a large number of parameters that allows the user to tune the behavior of the optimizer. The typical settings which can be changed with solver parameters include:

- choice of the optimizer for linear problems,
- choice of primal/dual solver,
- turning presolve on/o ,
- turning heuristics in the mixed-integer optimizer on/o ,
- level of multi-threading,
- feasibility tolerances,
- solver termination criteria,
- behaviour of the license manager,

and more. All parameters have default settings which will be suitable for most typical users.
The API reference contains:

- *Full list of parameters*
- *List of parameters grouped by topic*

Setting parameters

Each parameter is identified by a unique name and it can accept either integers, floating point values, symbolic strings or symbolic values. Parameters are set in the structure *param* and passed as a separate argument to *mosekopt*.

Some parameters can accept symbolic strings or symbolic values from a fixed set. The set of accepted values for every parameter is provided in the API reference.

For example, the following piece of code sets up parameters which choose and tune the interior point optimizer before solving a problem.

Listing 7.3: Parameter setting example.

```
% Set log level (integer parameter)
param.MSK_IPAR_LOG = 1;
% Select interior-point optimizer... (integer parameter)
param.MSK_IPAR_OPTIMIZER = 'MSK_OPTIMIZER_INTPNT';
% ... without basis identification (integer parameter)
param.MSK_IPAR_INTPNT_BASIS = 'MSK_BI_NEVER';
% Set relative gap tolerance (double parameter)
param.MSK_DPAR_INTPNT_CO_TOL_REL_GAP = 1.0e-7;

% Use in mosekopt
[r,resp] = mosekopt('minimize', prob, param);
```

7.5 Retrieving information items

After the optimization the user has access to the solution as well as to a report containing a large amount of additional *information items*. For example, one can obtain information about:

- **timing**: total optimization time, time spent in various optimizer subroutines, number of iterations, etc.
- **solution quality**: feasibility measures, solution norms, constraint and bound violations, etc.
- **problem structure**: counts of variables of different types, constraints, nonzeros, etc.
- **integer optimizer**: integrality gap, objective bound, number of cuts, etc.

and more. Information items are numerical values of integer, long integer or double type. The full list can be found in the API reference:

- *Double*
- *Integer*
- *Long*

Certain information items make sense, and are made available, also *during* the optimization process. They can be accessed from a callback function, see Sec. 7.6 for details.

Remark

For efficiency reasons, not all information items are automatically computed after optimization. To force all information items to be updated use the parameter *MSK_IPAR_AUTO_UPDATE_SOL_INFO*.

Retrieving the values

Values of information items are only returned if the info command is used in *mosekopt*. They are available in the field res.info.

Each information item is identified by a unique name. The example below reads two pieces of data from the solver: total optimization time and the number of interior-point iterations.

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```
end

% Decide if to terminate the optimization
% Terminate when cputime > handle.maxtime
if info.MSK_DINF_INTPNT_TIME > handle.maxtime
  r = 1;
else
  r = 0;
end
```

Assuming that we have de ned some problem prob the callback function is attached as follows:

Listing 7.6: Attaching the data callback function to the model.

```
% Define user defined handle.
[r,res]              = mosekopt('echo(0) symbcon');
data.maxtime         = 100.0;
data.symbcon         = res.symbcon;

callback.iter        = 'callback_handler';        % Defined in callback_handler.m
callback.iterhandle = data;

% Perform the optimization.
[r,res] = mosekopt('minimize echo(0)',prob,[],callback);
```

7.7 MOSEK OptServer

MOSEK provides an easy way to o oad optimization problem to a remote server. This section demonstrates related functionalities from the client side, i.e. sending optimization tasks to the remote server and retrieving solutions.

Setting up and con guring the remote server is described in a separate manual for the OptServer.

7.7.1 Synchronous Remote Optimization

In synchronous mode the client sends an optimization problem to the server and blocks, waiting for the optimization to end. Once the result has been received, the program can continue. This is the simplest mode all it takes is to provide the address of the server before starting optimization. The rest of the code remains untouched.

Note that it is impossible to recover the job in case of a broken connection.

Source code example

Listing 7.7: Using the OptServer in synchronous mode.

```
function opt_server_sync(inputfile, addr)
clear prob;
clear param;
clear optserver;

% We read some problem from a file or set it up here
cmd = sprintf('read(%s)', inputfile);
[r,res] = mosekopt(cmd);
prob = res.prob;

% OptServer data
% "host" should be 'http://server:port`
optserver.host = addr;
```

(continues on next page)

Chapter 8

Debugging Tutorials

This collection of tutorials contains basic techniques for debugging optimization problems using tools available in MOSEK: optimizer log, solution summary, infeasibility report, command-line tools. It is intended as a first line of technical help for issues such as: Why do I get solution status *unknown* and how can I fix it? Why is my model infeasible while it shouldn't be? Should I change some parameters? Can the model solve faster? etc.

The major steps when debugging a model are always:

- Consult the log output. It is enabled by default, but if neccessary switch it on explicitly with:

```
[r, res] = mosekopt('minimize echo(10)', prob);
```

- Run the optimization and analyze the log output, see Sec. 8.1. In particular:
  - check if the problem setup (number of constraints/variables etc.) matches your expectation.
  - check solution summary and solution status.
- Dump the problem to disk if necessary to continue analysis. See Sec. 7.3.3.
  - use a human-readable text format, such as *.opf if you want to check the problem structure by hand. Assign names to variables and constraints to make them easier to identify.

```
[r, res] = mosekopt('write(dump.opf)', prob);
```

  - use the MOSEK native format *.task.gz when submitting a bug report or support question.

```
[r, res] = mosekopt('write(dump.task.gz)', prob);
```

- Fix problem setup, improve the model, locate infeasibility or adjust parameters, depending on the diagnosis.

See the following sections for details.

8.1 Understanding optimizer log

The optimizer produces a log which splits roughly into four sections:

1. summary of the input data,
2. presolve and other pre-optimize problem setup stages,
3. actual optimizer iterations,
4. solution summary.

In this tutorial we show how to analyze the most important parts of the log when initially debugging a model: input data (1) and solution summary (4). For the iterations log (3) see Sec. 13.3.4 or Sec. 13.4.8.

8.1.1 Input data

If MOSEK behaves very far from expectations it may be due to errors in problem setup. The log le will begin with a summary of the structure of the problem, which looks for instance like:

```
Problem
  Name                   :
  Objective sense        : max
  Type                   : CONIC (conic optimization problem)
  Constraints            : 20413
  Cones                  : 2508
  Scalar variables       : 20414
  Matrix variables       : 0
  Integer variables      : 0
```

This can be consulted to eliminate simple errors: wrong objective sense, wrong number of variables etc. Note that Fusion, and third-party modeling tools can introduce additional variables and constraints to the model. In the remaining MOSEK APIs the problem dimensions should match exactly what the user speci ed.

If this is not su cient a bit more information can be obtained by dumping the problem to a le (see Sec. 8) and using the anapro option of any of the command line tools. This will produce a longer summary similar to:

```
** Variables
scalar: 20414     integer: 0        matrix: 0
low: 2082         up: 5014          ranged: 0         free: 12892       fixed: 426

** Constraints
all: 20413
low: 10028        up: 0             ranged: 0         free: 0           fixed: 10385

** Cones
QUAD: 1           dims: 2865: 1
RQUAD: 2507       dims: 3: 2507

** Problem data (numerics)
|c|               nnz: 10028        min=2.09e-05      max=1.00e+00
|A|               nnz: 597023       min=1.17e-10      max=1.00e+00
blx               fin: 2508         min=-3.60e+09     max=2.75e+05
bux               fin: 5440         min=0.00e+00      max=2.94e+08
blc               fin: 20413        min=-7.61e+05     max=7.61e+05
buc               fin: 10385        min=-5.00e-01     max=0.00e+00
```

Again, this can be used to detect simple errors, such as:

- Wrong type of cone was used or it has wrong dimension.
- The bounds for variables or constraints are incorrect or incomplete.
- The model is otherwise incomplete.
- Suspicious values of coe cients.
- For various data sizes the model does not scale as expected.

Finally saving the problem in a human-friendly text format such as LP or OPF (see Sec. 8) and analyzing it by hand can reveal if the model is correct.

Warnings and errors

At this stage the user can encounter warnings which should not be ignored, unless they are well-understood. They can also serve as hints as to numerical issues with the problem data. A typical warning of this kind is

```
MOSEK warning 53: A numerically large upper bound value  2.9e+08 is specified for variable
 ' absh[107] '  (2613).
```

Warnings do not stop the problem setup. If, on the other hand, an error occurs then the model will become invalid. The user should make sure to test for errors/exceptions from all API calls that set up the problem and validate the data. See Sec. 7.2 for more details.

8.1.2 Solution summary

The last item in the log is the solution summary.

Continuous problem

Optimal solution

A typical solution summary for a continuous (linear, conic, quadratic) problem looks like:

```
Problem status  : PRIMAL_AND_DUAL_FEASIBLE
Solution status : OPTIMAL
Primal.  obj: 8.7560516107e+01    nrm: 1e+02    Viol.  con: 3e-12    var: 0e+00    cones: 3e-11
Dual.    obj: 8.7560521345e+01    nrm: 1e+00    Viol.  con: 5e-09    var: 9e-11    cones: 0e+00
```

It contains the following elements:

- Problem and solution status. For details see Sec. 7.1.3.
- A summary of the primal solution: objective value, in nity norm of the solution vector x, maximal violations of constraints, variable bounds and cones. The violation of a linear constraint such as $a^T x \quad b$ is $\max(a^T x \quad b; 0)$. The violation of a conic constraint $x \ 2 \ K$ is the distance $\mathrm{dist}(x; K)$.
- The same for the dual solution.

The features of the solution summary which characterize a very good and accurate solution and a well-posed model are:

- Status: The solution status is OPTIMAL
- Duality gap: The primal and dual objective values are (almost) identical, which proves the solution is (almost) optimal.
- Norms: Ideally the norms of the solution and the objective values should not be too large. This of course depends on the input data, but a huge solution norm can be an indicator of issues with the scaling, conditioning and/or well-posedness of the model. It may also indicate that the problem is borderline between feasibility and infeasibility and sensitive to small perturbations in this respect.
- Violations: The violations are close to zero, which proves the solution is (almost) feasible. Observe that due to rounding errors it can be expected that the violations are proportional to the norm (nrm:) of the solution. It is rarely the case that violations are exactly zero.

Solution status UNKNOWN

A typical example with solution status UNKNOWN due to numerical problems will look like:

```
Problem status  : UNKNOWN
Solution status : UNKNOWN
Primal.  obj: 1.3821656824e+01    nrm: 1e+01    Viol.  con: 2e-03    var: 0e+00    cones: 0e+00
Dual.    obj: 3.0119004098e-01    nrm: 5e+07    Viol.  con: 4e-16    var: 1e-01    cones: 0e+00
```

Note that:

- The primal and dual objective are very di erent.
- The dual solution has very large norm.
- There are considerable violations so the solution is likely far from feasible.

Follow the hints in Sec. 8.2 to resolve the issue.

Solution status UNKNOWN with a potentially useful solution

Solution status UNKNOWN does not necessarily mean that the solution is completely useless. It only means that the solver was unable to make any more progress due to numerical difficulties, and it was not able to reach the accuracy required by the termination criteria (see Sec. 13.3.2). Consider for instance:

```
Problem status  : UNKNOWN
Solution status : UNKNOWN
Primal.  obj: 3.4531019648e+04    nrm: 1e+05    Viol.  con: 7e-02    var: 0e+00    cones: 0e+00
Dual.    obj: 3.4529720645e+04    nrm: 8e+03    Viol.  con: 1e-04    var: 2e-04    cones: 0e+00
```

Such a solution may still be useful, and it is always up to the user to decide. It may be a good enough approximation of the optimal point. For example, the large constraint violation may be due to the fact that one constraint contained a huge coefficient.

Infeasibility certificate

A primal infeasibility certificate is stored in the dual variables:

```
Problem status  : PRIMAL_INFEASIBLE
Solution status : PRIMAL_INFEASIBLE_CER
Dual.    obj: 2.9238975853e+02    nrm: 6e+02    Viol.  con: 0e+00    var: 1e-11    cones: 0e+00
```

It is a Farkas-type certificate as described in Sec. 12.2.2. In particular, for a good certificate:

- The dual objective is positive for a minimization problem, negative for a maximization problem. Ideally it is well bounded away from zero.
- The norm is not too big and the violations are small (as for a solution).

If the model was not expected to be infeasible, the likely cause is an error in the problem formulation. Use the hints in Sec. 8.1.1 and Sec. 8.3 to locate the issue.

Just like a solution, the infeasibility certificate can be of better or worse quality. The infeasibility certificate above is very solid. However, there can be less clear-cut cases, such as for example:

```
Problem status  : PRIMAL_INFEASIBLE
Solution status : PRIMAL_INFEASIBLE_CER
Dual.    obj: 1.6378689238e-06    nrm: 6e+05    Viol.  con: 7e-03    var: 2e-04    cones: 0e+00
```

This infeasibility certificate is more dubious because the dual objective is positive, but barely so in comparison with the large violations. It also has rather large norm. This is more likely an indication that the problem is borderline between feasibility and infeasibility or simply ill-posed and sensitive to tiny variations in input data. See Sec. 8.3 and Sec. 8.2.

The same remarks apply to dual infeasibility (i.e. unboundedness) certificates. Here the primal objective should be negative a minimization problem and positive for a maximization problem.

8.1.3 Mixed-integer problem

Optimal integer solution

For a mixed-integer problem there is no dual solution and a typical optimal solution report will look as follows:

```
Problem status  : PRIMAL_FEASIBLE
Solution status : INTEGER_OPTIMAL
Primal.  obj: 6.0111122960e+06    nrm: 1e+03    Viol.  con: 2e-13    var: 2e-14    itg: 5e-15
```

The interpretation of all elements is as for a continuous problem. The additional field itg denotes the maximum violation of an integer variable from being an exact integer.

Feasible integer solution

If the solver found an integer solution but did not prove optimality, for instance because of a time limit, the solution status will be PRIMAL_FEASIBLE

```
Problem status  : PRIMAL_FEASIBLE
Solution status : PRIMAL_FEASIBLE
Primal.  obj: 6.0114607792e+06    nrm: 1e+03    Viol.  con: 2e-13    var: 2e-13    itg: 4e-15
```

In this case it is valuable to go back to the optimizer summary to see how good the best solution is:

```
31       35       1        0        6.0114607792e+06     6.0078960892e+06     0.06        4.1

Objective of best integer solution : 6.011460779193e+06
Best objective bound               : 6.007896089225e+06
```

In this case the best integer solution found has objective value 6.011460779193e+06, the best proved lower bound is 6.007896089225e+06 and so the solution is guaranteed to be within 0.06% from optimum. The same data can be obtained as information items through an API. See also Sec. 13.4 for more details.

Infeasible problem

If the problem is declared infeasible the summary is simply

```
Problem status  : PRIMAL_INFEASIBLE
Solution status : UNKNOWN
Primal.  obj: 0.0000000000e+00    nrm: 0e+00    Viol.  con: 0e+00    var: 0e+00    itg: 0e+00
```

If infeasibility was not expected, consult Sec. 8.3.

8.2 Addressing numerical issues

The suggestions in this section should help diagnose and solve issues with numerical instability, in particular UNKNOWN solution status or solutions with large violations. Since numerically stable models tend to solve faster, following these hints can also dramatically shorten solution times.

We always recommend that issues of this kind are addressed by reformulating or rescaling the model, since it is the modeler who has the best insight into the structure of the problem and can fix the cause of the issue.

8.2.1 Formulating problems

Scaling

Make sure that all the data in the problem are of comparable orders of magnitude. This applies especially to the linear constraint matrix. Use Sec. 8.1.1 if necessary. For example a report such as

```
|A|               nnz: 597023       min=1.17e-6      max=2.21e+5
```

means that the ratio of largest to smallest elements in A is 10^{11}. In this case the user should rescale or reformulate the model to avoid such spread which makes it difficult for **MOSEK** to scale the problem internally. In many cases it may be possible to change the units, i.e. express the model in terms of rescaled variables (for instance work with millions of dollars instead of dollars, etc.).

Similarly, if the objective contains very different coefficients, say

$$\text{maximize } 10^{10}x + y$$

then it is likely to lead to inaccuracies. The objective will be dominated by the contribution from x and y will become insignificant.

Removing huge bounds

Never use a very large number as replacement for ∞. Instead define the variable or constraint as unbounded from below/above. Similarly, avoid artificial huge bounds if you expect they will not become tight in the optimal solution.

Avoiding linear dependencies

As much as possible try to avoid linear dependencies and near-linear dependencies in the model. See Example 8.3.

Avoiding ill-posedness

Avoid continuous models which are ill-posed: the solution space is degenerate, for example consists of a single point (technically, the Slater condition is not satis ed). In general, this refers to problems which are borderline between feasible and infeasible. See Example 8.1.

Scaling the expected solution

Try to formulate the problem in such a way that the expected solution (both primal and dual) is not very large. Consult the solution summary Sec. 8.1.2 to check the objective values or solution norms.

8.2.2 Further suggestions

Here are other simple suggestions that can help locate the cause of the issues. They can also be used as hints for how to tune the optimizer if xing the root causes of the issue is not possible.

- Remove the objective and solve the feasibility problem. This can reveal issues with the objective.
- Change the objective or change the objective sense from minimization to maximization (if applicable). If the two objective values are almost identical, this may indicate that the feasible set is very small, possibly degenerate.
- Perturb the data, for instance bounds, very slightly, and compare the results.
- For linear problems: solve the problem using a di erent optimizer by setting the parameter *MSK_IPAR_OPTIMIZER* and compare the results.
- Force the optimizer to solve the primal/dual versions of the problem by setting the parameter *MSK_IPAR_INTPNT_SOLVE_FORM* or *MSK_IPAR_SIM_SOLVE_FORM*. **MOSEK** has a heuristic to decide whether to dualize, but for some problems the guess is wrong an explicit choice may give better results.
- Solve the problem without presolve or some of its parts by setting the parameter *MSK_IPAR_PRESOLVE_USE*, see Sec. 13.1.
- Use di erent numbers of threads (*MSK_IPAR_NUM_THREADS*) and compare the results. Very di erent results indicate numerical issues resulting from round-o errors.

If the problem was dumped to a le, experimenting with various parameters is facilitated with the **MOSEK** Command Line Tool or **MOSEK** Python Console Sec. 8.4.

8.2.3 Typical pitfalls

Example 8.1 (Ill-posedness) A toy example of this situation is the feasibility problem

$$(x-1)^2 \leq 1, \ (x+1)^2 \leq 1$$

whose only solution is $x = 0$ and moreover replacing any 1 on the right hand side by $1-\varepsilon$ makes the problem infeasible and replacing it by $1+\varepsilon$ yields a problem whose solution set is an interval (fully-dimensional). This is an example of ill-posedness.

Example 8.2 (Huge solution)**.** If the norm of the expected solution is very large it may lead to numerical issues or infeasibility. For example the problem

$$(10^{-4}, x, 10^3) \in \mathcal{Q}_r^3$$

may be declared infeasible because the expected solution must satisfy $x \geq 5 \cdot 10^9$.

Example 8.3 (Near linear dependency)**.** Consider the following problem:

$$\begin{array}{lrcrcrcrcl}
\text{minimize} & & & & & & & & & \\
\text{subject to} & x_1 & + & x_2 & & & & & = & 1, \\
 & & & & & x_3 & + & x_4 & = & 1, \\
 & -\ x_1 & & & -\ & x_3 & & & = & -1+\varepsilon, \\
 & & - & x_2 & & & - & x_4 & = & -1, \\
 & x_1, & & x_2, & & x_3, & & x_4 & \geq & 0.
\end{array}$$

If we add the equalities together we obtain:

$$0 = \varepsilon$$

which is infeasible for any $\varepsilon \neq 0$. Here infeasibility is caused by a linear dependency in the constraint matrix coupled with a precision error represented by the ε. Indeed if a problem contains linear dependencies then the problem is either infeasible or contains redundant constraints. In the above case any of the equality constraints can be removed while not changing the set of feasible solutions. To summarize linear dependencies in the constraints can give rise to infeasible problems and therefore it is better to avoid them.

Example 8.4 (Presolving very tight bounds)**.** Next consider the problem

$$\begin{array}{lrcl}
\text{minimize} & & & \\
\text{subject to} & x_1 - 0.01x_2 & = & 0, \\
 & x_2 - 0.01x_3 & = & 0, \\
 & x_3 - 0.01x_4 & = & 0, \\
 & x_1 & \geq & -10^{-9}, \\
 & x_1 & \leq & 10^{-9}, \\
 & x_4 & \geq & 10^{-4}.
\end{array}$$

Now the **MOSEK** presolve will, for the sake of e ciency, x variables (and constraints) that have tight bounds where tightness is controlled by the parameter *MSK_DPAR_PRESOLVE_TOL_X*. Since the bounds

$$-10^{-9} \leq x_1 \leq 10^{-9}$$

are tight, presolve will set $x_1 = 0$. It easy to see that this implies $x_4 = 0$, which leads to the incorrect conclusion that the problem is infeasible. However a tiny change of the value 10^{-9} makes the problem feasible. In general it is recommended to avoid ill-posed problems, but if that is not possible then one solution is to reduce parameters such as *MSK_DPAR_PRESOLVE_TOL_X* to say 10^{-10}. This will at least make sure that presolve does not make the undesired reduction.

8.3 Debugging infeasibility

This section contains hints for debugging problems that are unexpectedly infeasible. It is always a good idea to remove the objective, i.e. only solve a feasibility problem when debugging such issues.

8.3.1 Numerical issues

Infeasible problem status may be just an artifact of numerical issues appearing when the problem is badly-scaled, barely feasible or otherwise ill-conditioned so that it is unstable under small perturbations of the data or round-o errors. This may be visible in the solution summary if the infeasibility certi cate has poor quality. See Sec. 8.1.2 for how to diagnose that and Sec. 8.2 for possible hints. Sec. 8.2.3 contains examples of situations which may lead to infeasibility for numerical reasons.

We refer to Sec. 8.2 for further information on dealing with those sort of issues. For the rest of this section we concentrate on the case when the solution summary leaves little doubt that the problem solved by the optimizer actually is infeasible.

8.3.2 Locating primal infeasibility

As an example of a primal infeasible problem consider minimizing the cost of transportation between a number of production plants and stores: Each plant produces a xed number of goods, and each store has a xed demand that must be met. Supply, demand and cost of transportation per unit are given in Fig. 8.1.

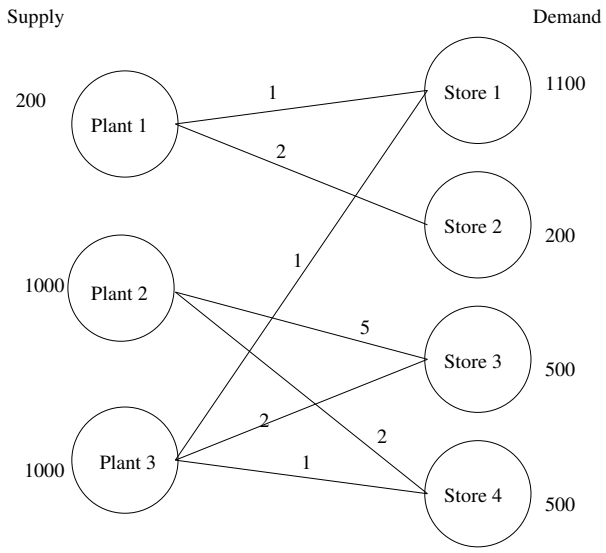

Fig. 8.1: Supply, demand and cost of transportation.

The problem represented in Fig. 8.1 is infeasible, since the total demand

$$2300 = 1100 + 200 + 500 + 500$$

exceeds the total supply

$$2200 = 200 + 1000 + 1000$$

If we denote the number of transported goods from plant i to store j by x_{ij}, the problem can be formulated as the LP:

$$\begin{array}{lllllllllllllllll}
\text{minimize} & & x_{11} & + & 2x_{12} & + & 5x_{23} & + & 2x_{24} & + & x_{31} & + & 2x_{33} & + & x_{34} & & \\
\text{subject to} & s_0: & x_{11} & + & x_{12} & & & & & & & & & & & \leq & 200, \\
& s_1: & & & & & x_{23} & + & x_{24} & & & & & & & \leq & 1000, \\
& s_2: & & & & & & & & & x_{31} & + & x_{33} & + & x_{34} & \leq & 1000, \\
& d_1: & x_{11} & & & & & & & + & x_{31} & & & & & = & 1100, \\
& d_2: & & & x_{12} & & & & & & & & & & & = & 200, \\
& d_3: & & & & & x_{23} & + & & & & & x_{33} & & & = & 500, \\
& d_4: & & & & & & & x_{24} & + & & & & & x_{34} & = & 500, \\
& & & & & & & & & & & & & & x_{ij} & \geq & 0.
\end{array} \tag{8.1}$$

Solving problem (8.1) using **MOSEK** will result in an infeasibility status. The infeasibility certi cate is contained in the dual variables an can be accessed from an API. The variables and constraints with nonzero solution values form an infeasible subproblem, which frequently is very small. See Sec. 12.1.2 or Sec. 12.2.2 for detailed speci cations of infeasibility certi cates.

A short infeasibility report can also be printed to the log stream. It can be turned on by setting the parameter *MSK_IPAR_INFEAS_REPORT_AUTO* to *"MSK_ON"*. This causes **MOSEK** to print a report on variables and constraints which are involved in infeasibility in the above sense, i.e. have nonzero values in the certi cate. The parameter *MSK_IPAR_INFEAS_REPORT_LEVEL* controls the amount of information presented in the infeasibility report. The default value is 1. For the above example the report is

```
MOSEK PRIMAL INFEASIBILITY REPORT.

Problem status: The problem is primal infeasible

The following constraints are involved in the primal infeasibility.

Index    Name      Lower bound      Upper bound      Dual lower       Dual upper
0        s0        NONE             2.000000e+002    0.000000e+000    1.000000e+000
2        s2        NONE             1.000000e+003    0.000000e+000    1.000000e+000
3        d1        1.100000e+003    1.100000e+003    1.000000e+000    0.000000e+000
4        d2        2.000000e+002    2.000000e+002    1.000000e+000    0.000000e+000

The following bound constraints are involved in the infeasibility.

Index    Name      Lower bound      Upper bound      Dual lower       Dual upper
8        x33       0.000000e+000    NONE             1.000000e+000    0.000000e+000
10       x34       0.000000e+000    NONE             1.000000e+000    0.000000e+000
```

The infeasibility report is divided into two sections corresponding to constraints and variables. It is a selection of those lines from the problem solution which are important in understanding primal infeasibility. In this case the constraints s0, s2, d1, d2 and variables x33, x34 are of importance because of nonzero dual values. The columns Dual lower and Dual upper contain the values of dual variables s_l^c, s_u^c, s_l^x and s_u^x in the primal infeasibility certi cate (see Sec. 12.1.2).

In our example the certi cate means that an appropriate linear combination of constraints s0, s1 with coe cient $s_u^c = 1$, constraints d1 and d2 with coe cient $s_u^c - s_l^c = 0 - 1 = -1$ and lower bounds on x33 and x34 with coe cient $-s_l^x = -1$ gives a contradiction. Indeed, the combination of the four involved constraints is $x_{33} + x_{34} \leq -100$ (as indicated in the introduction, the di erence between supply and demand).

It is also possible to extract the infeasible subproblem with the command-line tool. For an infeasible problem called infeas.lp the command:

```
mosek -d MSK_IPAR_INFEAS_REPORT_AUTO MSK_ON infeas.lp -info rinfeas.lp
```

will produce the le rinfeas.bas.inf.lp which contains the infeasible subproblem. Because of its size it may be easier to work with than the original problem le.

Returning to the transportation example, we discover that removing the fth constraint $x_{12} = 200$ makes the problem feasible. Almost all undesired infeasibilities should be xable at the modeling stage.

8.3.3 Locating dual infeasibility

A problem may also be *dual infeasible*. In this case the primal problem is usually unbounded, meaning that feasible solutions exists such that the objective tends towards in nity. For example, consider the problem

$$\begin{array}{ll} \text{maximize} & 200y_1 + 1000y_2 + 1000y_3 + 1100y_4 + 200y_5 + 500y_6 + 500y_7 \\ \text{subject to} & y_1 + y_4 \leq 1,\ y_1 + y_5 \leq 2,\ y_2 + y_6 \leq 5,\ y_2 + y_7 \leq 2, \\ & y_3 + y_4 \leq 1,\ y_3 + y_6 \leq 2,\ y_3 + y_7 \leq 1 \\ & y_1, y_2, y_3 \leq 0 \end{array}$$

which is dual to (8.1) (and therefore is dual infeasible). The dual infeasibility report may look as follows:

```
MOSEK DUAL INFEASIBILITY REPORT.

Problem status: The problem is dual infeasible

The following constraints are involved in the infeasibility.

Index    Name             Activity         Objective        Lower bound      Upper bound
5        x33              -1.000000e+00                     NONE             2.000000e+00
6        x34              -1.000000e+00                     NONE             1.000000e+00

The following variables are involved in the infeasibility.

Index    Name             Activity         Objective        Lower bound      Upper bound
0        y1               -1.000000e+00    2.000000e+02     NONE             0.000000e+00
2        y3               -1.000000e+00    1.000000e+03     NONE             0.000000e+00
3        y4               1.000000e+00     1.100000e+03     NONE             NONE
4        y5               1.000000e+00     2.000000e+02     NONE             NONE

Interior-point solution summary
  Problem status  : DUAL_INFEASIBLE
  Solution status : DUAL_INFEASIBLE_CER
  Primal.  obj: 1.0000000000e+02    nrm: 1e+00    Viol.  con: 0e+00    var: 0e+00
```

In the report we see that the variables y1, y3, y4, y5 and two constraints contribute to infeasibility with non-zero values in the Activity column. Therefore

$$(y_1, \ldots, y_7) = (-1, 0, -1, 1, 1, 0, 0)$$

is the dual infeasibility certi cate as in Sec. 12.1.2. This just means, that along the ray

$$(0, 0, 0, 0, 0, 0, 0) + t(y_1, \ldots, y_7) = (-t, 0, -t, t, t, 0, 0), \ t > 0,$$

which belongs to the feasible set, the objective value $100t$ can be arbitrarily large, i.e. the problem is unbounded.

In the example problem we could

- Add a lower bound on y3. This will directly invalidate the certi cate of dual infeasibility.
- Increase the objective coe cient of y3. Changing the coe cients su ciently will invalidate the inequality $c^T y^* > 0$ and thus the certi cate.

8.3.4 Suggestions

Primal infeasibility

When trying to understand what causes the unexpected primal infeasible status use the following hints:

- Remove the objective function. This does not change the infeasibility status but simpli es the problem, eliminating any possibility of issues related to the objective function.
- Remove cones, semide nite variables and integer constraints. Solve only the linear part of the problem. Typical simple modeling errors will lead to infeasibility already at this stage.
- Consider whether your problem has some obvious necessary conditions for feasibility and examine if these are satis ed, e.g. total supply should be greater than or equal to total demand.
- Verify that coe cients and bounds are reasonably sized in your problem.
- See if there are any obvious contradictions, for instance a variable is bounded both in the variables and constraints section, and the bounds are contradictory.
- Consider replacing suspicious equality constraints by inequalities. For instance, instead of $x_{12} = 200$ see what happens for $x_{12} \geq 200$ or $x_{12} \leq 200$.

- Relax bounds of the suspicious constraints or variables.
- For integer problems, remove integrality constraints on some/all variables and see if the problem solves.
- Form an **elastic model**: allow to violate constraints at a cost. Introduce slack variables and add them to the objective as penalty. For instance, suppose we have a constraint

$$\begin{array}{ll} \text{minimize} & c^T x, \\ \text{subject to} & a^T x \leq b. \end{array}$$

  which might be causing infeasibility. Then create a new variable y and form the problem which contains:

$$\begin{array}{ll} \text{minimize} & c^T x + y, \\ \text{subject to} & a^T x \leq b + y. \end{array}$$

  Solving this problem will reveal by how much the constraint needs to be relaxed in order to become feasible. This is equivalent to inspecting the infeasibility certi cate but may be more intuitive.
- If you think you have a feasible solution or its part, x all or some of the variables to those values. Presolve will propagate them through the model and potentially reveal more localized sources of infeasibility.
- Dump the problem in OPF or LP format and verify that the problem that was passed to the optimizer corresponds to the problem expressed in the high-level modeling language, if any such was used.

Dual infeasibility

When trying to understand what causes the unexpected dual infeasible status use the following hints:

- Verify that the objective coe cients are reasonably sized.
- Check if no bounds and constraints are missing, for example if all variables that should be nonnegative have been declared as such etc.
- Strengthen bounds of the suspicious constraints or variables.
- Form an series of models with decreasing bounds on the objective, that is, instead of objective

$$\text{minimize } c^T x$$

  solve the problem with an additional constraint such as

$$c^T x = -10^5$$

  and inspect the solution to gure out the mechanism behind arbitrarily decreasing objective values. This is equivalent to inspecting the infeasibility certi cate but may be more intuitive.
- Dump the problem in OPF or LP format and verify that the problem that was passed to the optimizer corresponds to the problem expressed in the high-level modeling language, if any such was used.

Please note that modifying the problem to invalidate the reported certi cate does *not* imply that the problem becomes feasible the reason for infeasibility may simply *move*, resulting a problem that is still infeasible, but for a di erent reason. More often, the reported certi cate can be used to give a hint about errors or inconsistencies in the model that produced the problem.

8.4 Python Console

The **MOSEK** Python Console is an alternative to the **MOSEK** Command Line Tool. It can be used for interactive loading, solving and debugging optimization problems stored in les, for example **MOSEK** task les. It facilitates debugging techniques described in Sec. 8.

8.4.1 Usage

The tool requires Python 2 or 3. The MOSEK interface for Python must be installed following the installation instructions for Python API or Python Fusion API. In the basic case it should be su cient to execute the script

```
python setup.py install --user
```

in the directory containing the MOSEK Python module.

The Python Console is contained in the le mosekconsole.py in the folder with MOSEK binaries. It can be copied to an arbitrary location. The le is also available for download here (mosekconsole.py) .

To run the console in interactive mode use

```
python mosekconsole.py
```

To run the console in batch mode provide a semicolon-separated list of commands as the second argument of the script, for example:

```
python mosekconsole.py "read data.task.gz; solve form=dual; writesol data"
```

The script is written using the MOSEK Python API and can be extended by the user if more speci c functionality is required. We refer to the documentation of the Python API.

8.4.2 Examples

To read a problem from data.task.gz , solve it, and write solutions to data.sol , data.bas or data.itg :

```
read data.task.gz; solve; writesol data
```

To convert between le formats:

```
read data.task.gz; write data.mps
```

To set a parameter before solving:

```
read data.task.gz; param INTPNT_CO_TOL_DFEAS 1e-9; solve"
```

To list parameter values related to the mixed-integer optimizer in the task le:

```
read data.task.gz; param MIO
```

To print a summary of problem structure:

```
read data.task.gz; anapro
```

To solve a problem forcing the dual and switching o presolve:

```
read data.task.gz; solve form=dual presolve=no
```

To write an infeasible subproblem to a le for debugging purposes:

```
read data.task.gz; solve; infsub; write inf.opf
```

8.4.3 Full list of commands

Below is a brief description of all the available commands. Detailed information about a speci c command cmdand its options can be obtained with

```
help cmd
```

Table 8.1: List of commands of the MOSEK Python Console.

Command	Description
help [command]	Print list of commands or info about a speci c command
log filename	Save the session to a le
intro	Print MOSEK splashscreen
testlic	Test the license system
read filename	Load problem from le
reread	Reload last problem le
solve [options]	Solve current problem
write filename	Write current problem to le
param [name [value]]	Set a parameter or get parameter values
paramdef	Set all parameters to default values
paramdiff	Show parameters with non-default values
info [name]	Get an information item
anapro	Analyze problem data
hist	Plot a histogram of problem data
histsol	Plot a histogram of the solutions
spy	Plot the sparsity pattern of the A matrix
truncate epsilon	Truncate small coe cients down to 0
resobj [fac]	Rescale objective by a factor
anasol	Analyze solutions
removeitg	Remove integrality constraints
removecones	Remove all cones and leave just the linear part
infsub	Replace current problem with its infeasible subproblem
writesol basename	Write solution(s) to le(s) with given basename
delsol	Remove all solutions from the task
optserver [url]	Use an OptServer to optimize
exit	Leave

Chapter 9

Advanced Numerical Tutorials

9.1 Converting a quadratically constrained problem to conic form

MOSEK employs the following form of quadratic problems:

$$\begin{array}{lrcccl} \text{minimize} & & & \frac{1}{2}x^T Q^o x + c^T x + c^f & & \\ \text{subject to} & l_k^c & \leq & \frac{1}{2}x^T Q^k x + \sum_{j=0}^{n-1} a_{k,j} x_j & \leq & u_k^c, \quad k = 0, \ldots, m-1, \\ & l_j^x & \leq & x_j & \leq & u_j^x, \quad j = 0, \ldots, n-1. \end{array} \tag{9.1}$$

A conic quadratic constraint has the form

$$x \in \mathcal{Q}^n$$

in its most basic form where

$$\mathcal{Q}^n = \left\{ x \in \mathbb{R}^n : x_1 \geq \sqrt{\sum_{j=2}^{n} x_j^2} \right\}.$$

A quadratic problem such as (9.1), if convex, can be reformulated in conic form. This is in fact the reformulation **MOSEK** performs internally. It has many advantages:

- elegant duality theory for conic problems,
- reporting accurate dual information for quadratic inequalities is hard and/or computational expensive,
- it certi es that the original quadratic problem is indeed convex,
- modeling directly in conic form usually leads to a better model*[And13]* i.e. a faster solution time and better numerical properties.

In addition, there are more types of conic constraints that can be combined with a quadratic cone, for example semide nite cones.

MOSEK o ers a function that performs the conversion from quadratic to conic quadratic form explicitly. Note that the reformulation is not unique. The approach followed by **MOSEK** is to introduce additional variables, linear constraints and quadratic cones to obtain a larger but equivalent problem in which the original variables are preserved.

In particular:

- all variables and constraints are kept in the problem,
- each quadratic constraint and quadratic terms in the objective generate one rotated quadratic cone,
- each quadratic constraint will contain no coe cients and upper/lower bounds will be set to $\infty, -\infty$ respectively.

This allows the user to recover the original variable and constraint values, as well as their dual values, with no conversion or additional e ort.

9.1.1 Quadratic Constraint Reformulation

Let us assume we want to convert the following quadratic constraint

$$l \leq \frac{1}{2}x^T Qx + \sum_{j=0}^{n-1} a_j x_j \leq u$$

to conic form. We rst check whether $l = -\infty$ or $u = \infty$, otherwise either the constraint can be dropped, or the constraint is not convex. Thus let us consider the case

$$\frac{1}{2}x^T Qx + \sum_{j=0}^{n-1} a_j^T x_j \leq u. \tag{9.2}$$

Introducing an additional variable w such that

$$w = u - \sum_{j=0}^{n-1} a_j^T x_j \tag{9.3}$$

we obtain the equivalent form

$$\begin{array}{lcl} \frac{1}{2}x^T Qx & \leq & w, \\ u - \sum_{j=0}^{n-1} a_j x_j & = & w. \end{array}$$

If Q is positive semide nite, then there exists a matrix F such that

$$Q = FF^T \tag{9.4}$$

and therefore we can write

$$\begin{array}{lcl} \|Fx\|^2 & \leq & 2w, \\ u - \sum_{j=0}^{n-1} a_j^T x_j & = & w. \end{array}$$

Introducing an additional variable $z = 1$, and setting $y = Fx$ we obtain the conic formulation

$$\begin{array}{ll} (w, z, y) & \in \mathcal{Q}_r, \\ z = 1 & \\ y = Fx & \\ w = u - a^T x. & \end{array} \tag{9.5}$$

Summarizing, for each quadratic constraint involving t variables, **MOSEK** introduces

1. a rotated quadratic cone of dimension $t + 2$,
2. two additional variables for the cone roots,
3. t additional variables to map the remaining part of the cone,
4. t linear constraints.

A quadratic term in the objective is reformulated in a similar fashion. We refer to *[And13]* for a more thorough discussion.

Example

Next we consider a simple problem with quadratic objective function:

$$\begin{array}{ll} \text{minimize} & \frac{1}{2}(13x_0^2 + 17x_1^2 + 12x_2^2 + 24x_0x_1 + 12x_1x_2 - 4x_0x_2) - 22x_0 - 14.5x_1 + 12x_2 + 1 \\ \text{subject to} & -1 \leq x_0, x_1, x_2 \leq 1 \end{array}$$

We can specify it in the human-readable OPF format.

```
[comment]
An example of small QO problem from Boyd and Vandenberghe, "Convex Optimization", page 189 ex␣
↪4.3
The solution is (1,0.5,-1)
[/comment]

[variables]
x0 x1 x2
[/variables]

[objective min]
0.5 (13 x0^2  + 17 x1^2 + 12 x2^2 + 24 x0 * x1 + 12 x1 * x2 - 4 x0 * x2 ) - 22 x0 - 14.5 x1 +␣
↪12 x2 + 1
[/objective]

[bounds]
[b] -1 <= * <= 1 [/b]
[/bounds]
```

The objective function is convex, the minimum is attained for $x^\star = (1, 0.5, -1)$. The conversion will introduce rst a variable x_3 in the objective function such that $x_3 \geq 1/2x^T Qx$ and then convert the latter directly in conic form. The converted problem follows:

$$\begin{array}{ll} \text{minimize} & -22x_0 - 14.5x_1 + 12x_2 + x_3 + 1 \\ \text{subject to} & 3.61x_0 + 3.33x_1 - 0.55x_2 - x_6 = 0 \\ & +2.29x_1 + 3.42x_2 - x_7 = 0 \\ & 0.81x_1 - x_8 = 0 \\ & -x_3 + x_4 = 0 \\ & x_5 = 1 \\ & (x_4, x_5, x_6, x_7, x_8) \in \mathcal{Q}_\nabla \\ & -1 \leq x_0, x_1, x_2 \leq 1 \end{array}$$

We obtain the reformulation as follows:

```
% prob is a quadratic problem
[r, res] = mosekopt('toconic prob', prob)
probConic = res.prob
mosekopt('write(conic.opf)', probConic)
```

and the output is:

```
[comment]
   Written by MOSEK version 8.1.0.19
   Date 21-08-17
   Time 10:53:36
[/comment]

[hints]
  [hint NUMVAR] 9 [/hint]
  [hint NUMCON] 4 [/hint]
  [hint NUMANZ] 11 [/hint]
  [hint NUMQNZ] 0 [/hint]
  [hint NUMCONE] 1 [/hint]
[/hints]

[variables disallow_new_variables]
  x0000_x0 x0001_x1 x0002_x2 x0003 x0004
  x0005 x0006 x0007 x0008
[/variables]

[objective minimize]
   - 2.2e+01 x0000_x0 - 1.45e+01 x0001_x1 + 1.2e+01 x0002_x2 + x0003
   + 1e+00
```

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```
[/objective]

[constraints]
  [con c0000]  3.605551275463989e+00 x0000_x0 - 5.547001962252291e-01 x0002_x2 + 3.
↪328201177351375e+00 x0001_x1 - x0006 = 0e+00 [/con]
  [con c0001]  3.419401657060442e+00 x0002_x2 + 2.294598480395823e+00 x0001_x1 - x0007 = 0e+00␣
↪[/con]
  [con c0002]  8.111071056538127e-01 x0001_x1 - x0008 = 0e+00 [/con]
  [con c0003]  - x0003 + x0004 = 0e+00 [/con]
[/constraints]

[bounds]
  [b] -1e+00     <= x0000_x0,x0001_x1,x0002_x2 <= 1e+00 [/b]
  [b]               x0003,x0004 free [/b]
  [b]               x0005 =  1e+00 [/b]
  [b]               x0006,x0007,x0008 free [/b]
  [cone rquad k0000] x0004, x0005, x0006, x0007, x0008 [/cone]
[/bounds]
```

We can clearly see that constraints c0000, c0001 and c0002 represent the original linear constraints as in (9.4), while c0003 corresponds to (9.3). The cone roots are x0005 and x0004.

9.2 Advanced hot-start

In practice it frequently occurs that when an optimization problem has been solved, then the same problem slightly modi ed should be reoptimized. Moreover, if it is just a small the modi cation, it can be expected that the optimal solution to the original problem is a good approximation to the modi ed problem. Therefore, it should be e cient to start the optimization of the modi ed problem from the previous optimal solution.

Currently, the interior-point optimizer in **MOSEK** cannot take advantage of a previous optimal solution, however, the simplex optimizer can exploit any basic solution.

We work with the simple linear problem:

$$\begin{array}{rl} \text{minimize} & x_1 + 2x_2 \\ \text{subject to} & 4 \leq x_1 + x_3 \leq 6, \\ & 1 \leq x_1 + x_2, \\ & 0 \leq x_1, x_2, x_3. \end{array}$$

9.2.1 Initial hot-start

A quick inspection of the problem indicates that $(x_1, x_3) = (1, 3)$ is an optimal solution. Hence, it seems to be a good idea to let the initial basis consist of x_1 and x_3 and all the other variables be at their lower bounds. This idea is used in the example code:

Listing 9.1: Passing the full basic solution.

```
% Specify an initial basic solution.
bas.skc      = ['LL';'LL'];
bas.skx      = ['BS';'LL';'BS'];
bas.xc       = [4 1]';
bas.xx       = [1 3 0]';

prob.sol.bas = bas;

% Specify the problem data.
prob.c       = [ 1 2 0]';
subi         = [1 2 2 1];
subj         = [1 1 2 3];
valij        = [1.0 1.0 1.0 1.0];
```

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```
prob.a       = sparse(subi,subj,valij);
prob.blc     = [4.0 1.0]';
prob.buc     = [6.0 inf]';
prob.blx     = sparse(3,1);
prob.bux     = [];

% Use the primal simplex optimizer.
param.MSK_IPAR_OPTIMIZER = 'MSK_OPTIMIZER_PRIMAL_SIMPLEX';
[r,res] = mosekopt('minimize',prob,param)
```

Comments:

- In the example the dual solution is not de ned. This is acceptable because the primal simplex optimizer is used for the reoptimization and it does not exploit a dual solution. Otherwise it will be important that a good dual solution is speci ed.
- The status keys bas.skc and bas.skx must contain only the entries BS, EQ LL, UL, SB Moreover, e.g. EQmust be speci ed only for a xed constraint or variable. LL and UL can be used only for a variable that has a nite lower or upper bound respectively. For an explanation of status keys see *stakey*.
- The number of constraints and variables de ned to be basic must correspond exactly to the number of constraints.

9.2.2 Adding a new variable

Next, assume we modify the problem by adding a new variable:

$$\begin{array}{rl} \text{minimize} & x_1 + 2x_2 - x_4 \\ \text{subject to} & 4 \leq x_1 + x_3 + x_4 \leq 6, \\ & 1 \leq x_1 + x_2, \\ & 0 \leq x_1, x_2, x_3, x_4. \end{array}$$

In continuation of the previous example this problem can be solved as follows, using the full previous basic solution in hot-start:

Listing 9.2: Hot-start when adding a new variable.

```
prob.c       = [prob.c;-1.0];
prob.a       = [prob.a,sparse([1.0 0.0]')];
prob.blx     = sparse(4,1);

% Reuse the old optimal basic solution.
bas          = res.sol.bas;

% Add to the status key.
bas.skx      = [res.sol.bas.skx;'LL'];

% The new variable is at it lower bound.
bas.xx       = [res.sol.bas.xx;0.0];
bas.slx      = [res.sol.bas.slx;0.0];
bas.sux      = [res.sol.bas.sux;0.0];

prob.sol.bas = bas;

[rcode,res]  = mosekopt('minimize',prob,param);

% The new primal optimal solution
res.sol.bas.xx'
```

9.2.3 Fixing a variable

In e.g. branch-and-bound methods for integer programming problems it is necessary to reoptimize the problem after a variable has been xed to a value. This can easily be achieved as follows:

Listing 9.3: Hot-start with a xed variable.

```
prob.blx(4)  = 1;
prob.bux     = [inf inf inf 1]    ';

% Reuse the basis.
prob.sol.bas = res.sol.bas;

[rcode,res]  = mosekopt(  'minimize',prob,param);

% Display the optimal solution.
res.sol.bas.xx   '
```

9.2.4 Adding a new constraint

Now assume that the constraint

$$x_1 + x_2 \quad 2$$

should be added to the problem and the problem should be reoptimized. The following example demonstrates how to do this.

Listing 9.4: Hot-start when adding a new constraint.

```
% Modify the problem.
prob.a       = [prob.a;sparse([1.0 1.0 0.0 0.0])];
prob.blc     = [prob.blc;2.0];
prob.buc     = [prob.buc;inf];

% Obtain the previous optimal basis.
bas          = res.sol.bas;

% Set the solution to the modified problem.
bas.skc      = [bas.skc;  'BS'];
bas.xc       = [bas.xc;bas.xx(1)+bas.xx(2)];
bas.y        = [bas.y;0.0];
bas.slc      = [bas.slc;0.0];
bas.suc      = [bas.suc;0.0];

% Reuse the basis.
prob.sol.bas = bas;

% Reoptimize.
[rcode,res]  = mosekopt(  'minimize',prob,param);

res.sol.bas.xx   '
```

Please note that the slack variable corresponding to the new constraint is declared basic. This implies that the new basis is nonsingular and can be reused.

9.2.5 Removing a constraint

We can remove a constraint in two ways:

- Set the bounds for the constraint to 1 as appropriate.
- Remove the corresponding row from prob.a and other parts of the data and update the basis.

In the following example we use the latter approach to again remove the constraint $x_1 + x_2 \quad 2$.

excludes the possibility of short-selling. This constraint can of course be excluded if short-selling is allowed.

The covariance matrix Σ is positive semide nite by de nition and therefore there exist a matrix G such that

$$\Sigma = GG^T. \tag{11.2}$$

In general the choice of G is **not** unique and one possible choice of G is the Cholesky factorization of Σ. However, in many cases another choice is better for e ciency reasons as discussed in Sec. 11.1.3. For a given G we have that

$$\begin{aligned} x^T\Sigma x &= x^T G G^T x \\ &= \left\|G^T x\right\|^2. \end{aligned}$$

Hence, we may write the risk constraint as

$$\gamma \geq \left\|G^T x\right\|$$

or equivalently

$$(\gamma, G^T x) \in \mathcal{Q}^{n+1},$$

where $\mathcal{Q}^{n+1}$ is the $(n+1)$-dimensional quadratic cone. Therefore, problem (11.1) can be written as

$$\begin{array}{lrcl} \text{maximize} & \mu^T x & & \\ \text{subject to} & e^T x & = & w + e^T x^0, \\ & (\gamma, G^T x) & \in & \mathcal{Q}^{n+1}, \\ & x & \geq & 0, \end{array} \tag{11.3}$$

which is a conic quadratic optimization problem that can easily be formulated and solved with Optimization Toolbox for MATLAB. Subsequently we will use the example data

$$\mu = \begin{bmatrix} 0.1073 \\ 0.0737 \\ 0.0627 \end{bmatrix}$$

and

$$\Sigma = 0.1 \cdot \begin{bmatrix} 0.2778 & 0.0387 & 0.0021 \\ 0.0387 & 0.1112 & -0.0020 \\ 0.0021 & -0.0020 & 0.0115 \end{bmatrix}.$$

This implies

$$G^T = \sqrt{0.1} \begin{bmatrix} 0.5271 & 0.0734 & 0.0040 \\ 0 & 0.3253 & -0.0070 \\ 0 & 0 & 0.1069 \end{bmatrix}$$

Why a Conic Formulation?

Problem (11.1) is a convex quadratically constrained optimization problem that can be solved directly using **MOSEK**. Why then reformulate it as a conic quadratic optimization problem (11.3)? The main reason for choosing a conic model is that it is more robust and usually solves faster and more reliably. For instance it is not always easy to numerically validate that the matrix Σ in (11.1) is positive semide nite due to the presence of rounding errors. It is also very easy to make a mistake so Σ becomes inde nite. These problems are completely eliminated in the conic formulation.

Moreover, observe the constraint

$$\left\|G^T x\right\| \leq \gamma$$

more numerically robust than

$$x^T\Sigma x \leq \gamma^2$$

for very small and very large values of γ. Indeed, if say $\gamma \approx 10^4$ then $\gamma^2 \approx 10^8$, which introduces a scaling issue in the model. Hence, using conic formulation we work with the standard deviation instead of variance, which usually gives rise to a better scaled model.

Example code

Listing 11.1 demonstrates how the basic Markowitz model (11.3) is implemented.

Listing 11.1: Code implementing problem (11.3).

```
function er = BasicMarkowitz(n,mu,GT,x0,w,gamma)

[rcode, res] = mosekopt('symbcon');
prob = [];

% Objective vector - expected return
prob.c = mu;

% The budget constraint  - e'x = w + sum(x0)
prob.a = ones(1,n);
prob.blc = w + sum(x0);
prob.buc = w + sum(x0);

% Bounds exclude shortselling
prob.blx = zeros(n,1);
prob.bux = inf*ones(n,1);

% An affine conic constraint: [gamma, GT*x] in quadratic cone
prob.f = sparse([ zeros(1,n); GT ]);
prob.g = [gamma; zeros(n,1)];
prob.cones = [ res.symbcon.MSK_CT_QUAD n+1 ];

% Maximize problem and return the objective value
[rcode,res] = mosekopt('maximize echo(0)', prob, []);
x = res.sol.itr.xx;
er = mu'*x;
```

The source code should be self-explanatory except perhaps for

```
prob.f = sparse([ zeros(1,n); GT ]);
prob.g = [gamma; zeros(n,1)];
prob.cones = [ res.symbcon.MSK_CT_QUAD n+1 ];
```

where the constraint

$$\left(\gamma, G^T x\right) \in \mathcal{Q}^{n+1}$$

is created as an *affine conic constraint format* of the form $Fx + g \in \mathcal{K}$, in this speci c case:

$$\begin{bmatrix} 0 \\ G^T \end{bmatrix} x + \begin{bmatrix} \gamma \\ 0 \end{bmatrix} \in \mathcal{Q}^{n+1}.$$

11.1.2 The Efficient Frontier

The portfolio computed by the Markowitz model is e cient in the sense that there is no other portfolio giving a strictly higher return for the same amount of risk. An e cient portfolio is also sometimes called a Pareto optimal portfolio. Clearly, an investor should only invest in e cient portfolios and therefore it may be relevant to present the investor with all e cient portfolios so the investor can choose the portfolio that has the desired tradeo between return and risk.

Given a nonnegative α the problem

$$\begin{array}{ll} \text{maximize} & \mu^T x - \alpha x^T \Sigma x \\ \text{subject to} & e^T x = w + e^T x^0, \\ & x \geq 0. \end{array} \tag{11.4}$$

is one standard way to trade the expected return against penalizing variance. Note that, in contrast to the previous example, we explicitly use the variance ($\|G^T x\|_2^2$) rather than standard deviation ($\|G^T x\|_2$),

therefore the conic model includes a rotated quadratic cone:

$$\begin{array}{lrcll} \text{maximize} & {}^{T}x & s & & \\ \text{subject to} & e^{T}x & = & w + e^{T}x^{0}; & \\ & (s; 0{:}5; G^{T}x) & 2 & Q_{r}^{n+2} & \text{(equiv. to } s \quad k\ G^{T}xk_{2}^{2} = x^{T} \quad x); \\ & x & & 0{:} & \end{array} \tag{11.5}$$

The parameter speci es the tradeo between expected return and variance. Ideally the problem (11.4) should be solved for all values 0 but in practice it is impossible. Using the example data from Sec. 11.1.1, the optimal values of return and variance for several values of are shown in the gure.

Fig. 11.1: The e cient frontier for the sample data.

Example code

Listing 11.2 demonstrates how to compute the e cient portfolios for several values of .

Listing 11.2: Code for the computation of the e cient frontier based on problem (11.4).

```
function frontier = EfficientFrontier(n,mu,GT,x0,w,alphas)

frontier = [];
[rcode, res] = mosekopt('symbcon');
prob = [];

% The budget constraint in terms of variables [x; s]
prob.a = [ones(1,n), 0.0];
prob.blc = w + sum(x0);
prob.buc = w + sum(x0);

% No shortselling
prob.blx = [zeros(n,1); -inf];
prob.bux = inf*ones(n+1,1);

% An affine conic constraint: [s, 0.5, GT*x] in rotated quadratic cone
% In matrix form
% [ 0   1]   [ x ]      [ 0   ]
% [ 0   0]   [   ]  +   [ 0.5 ]  \in Q_r
% [ GT 0]   [ s ]      [ 0   ]
prob.f = sparse([ [zeros(1,n), 1.0]; zeros(1, n+1); [GT, zeros(n,1)] ]);
prob.g = [ 0; 0.5; zeros(n, 1) ]
prob.cones = [ res.symbcon.MSK_CT_RQUAD n+2 ];

for alpha = alphas
    % Objective mu'*x - alpha*s
    prob.c = [mu; -alpha];

    [rcode,res] = mosekopt('maximize echo(0)',prob,[]);
    x = res.sol.itr.xx(1:n);
    s = res.sol.itr.xx(n+1);

    frontier = [frontier; [alpha, mu'*x, s] ];
end
```

11.1.3 Factor model and efficiency

In practice it is often important to solve the portfolio problem very quickly. Therefore, in this section we discuss how to improve computational e ciency at the modeling stage.

The computational cost is of course to some extent dependent on the number of constraints and variables in the optimization problem. However, in practice a more important factor is the sparsity: the number of nonzeros used to represent the problem. Indeed it is often better to focus on the number of nonzeros in G see (11.2) and try to reduce that number by for instance changing the choice of G.

In other words if the computational e ciency should be improved then it is always good idea to start with focusing at the covariance matrix. As an example assume that

$$\Sigma = D + VV^T$$

where D is a positive de nite diagonal matrix. Moreover, V is a matrix with n rows and p columns. Such a model for the covariance matrix is called a factor model and usually p is much smaller than n. In practice p tends to be a small number independent of n, say less than 100.

One possible choice for G is the Cholesky factorization of Σ which requires storage proportional to $n(n+1)/2$. However, another choice is

$$G^T = \begin{bmatrix} D^{1/2} \\ V^T \end{bmatrix}$$

because then

$$GG^T = D + VV^T.$$

This choice requires storage proportional to $n + pn$ which is much less than for the Cholesky choice of G. Indeed assuming p is a constant storage requirements are reduced by a factor of n.

The example above exploits the so-called factor structure and demonstrates that an alternative choice of G may lead to a signi cant reduction in the amount of storage used to represent the problem. This will in most cases also lead to a signi cant reduction in the solution time.

The lesson to be learned is that it is important to investigate how the covariance matrix is formed. Given this knowledge it might be possible to make a special choice for G that helps reducing the storage requirements and enhance the computational e ciency. More details about this process can be found in *[And13]*.

11.1.4 Slippage Cost

The basic Markowitz model assumes that there are no costs associated with trading the assets and that the returns of the assets are independent of the amount traded. Neither of those assumptions is usually valid in practice. Therefore, a more realistic model is

$$\begin{array}{lrcl} \text{maximize} & \mu^T x & & \\ \text{subject to} & e^T x + \sum_{j=1}^n T_j(\Delta x_j) & = & w + e^T x^0, \\ & x^T \Sigma x & \leq & \gamma^2, \\ & x & \geq & 0. \end{array} \tag{11.6}$$

Here Δx_j is the change in the holding of asset j i.e.

$$\Delta x_j = x_j - x_j^0$$

and $T_j(\Delta x_j)$ speci es the transaction costs when the holding of asset j is changed from its initial value. In the next two sections we show two di erent variants of this problem with two nonlinear cost functions T.

11.1.5 Market Impact Costs

If the initial wealth is fairly small and no short selling is allowed, then the holdings will be small and the traded amount of each asset must also be small. Therefore, it is reasonable to assume that the prices of the assets are independent of the amount traded. However, if a large volume of an asset is sold or purchased, the price, and hence return, can be expected to change. This e ect is called market impact costs. It is common to assume that the market impact cost for asset j can be modeled by

$$T_j(\Delta x_j) = m_j |\Delta x_j|^{3/2}$$

where m_j is a constant that is estimated in some way by the trader. See *[GK00]* [p. 452] for details. From the Modeling Cookbook we know that $t \geq |z|^{3/2}$ can be modeled directly using the power cone $\mathcal{P}_3^{2/3,1/3}$:

$$\{(t,z) : t \geq |z|^{3/2}\} = \{(t,z) : (t,1,z) \in \mathcal{P}_3^{2/3,1/3}\}$$

Hence, it follows that $\sum_{j=1}^n T_j(\Delta x_j) = \sum_{j=1}^n m_j |x_j - x_j^0|^{3/2}$ can be modeled by $\sum_{j=1}^n m_j t_j$ under the constraints

$$\begin{array}{rl} z_j & = |x_j - x_j^0|, \\ (t_j, 1, z_j) & \in \mathcal{P}_3^{2/3,1/3}. \end{array}$$

Unfortunately this set of constraints is nonconvex due to the constraint

$$z_j = |x_j - x_j^0| \tag{11.7}$$

but in many cases the constraint may be replaced by the relaxed constraint

$$z_j \geq |x_j - x_j^0|, \tag{11.8}$$

For instance if the universe of assets contains a risk free asset then

$$z_j > |x_j - x_j^0| \tag{11.9}$$

cannot hold for an optimal solution.

If the optimal solution has the property (11.9) then the market impact cost within the model is larger than the true market impact cost and hence money are essentially considered garbage and removed by generating transaction costs. This may happen if a portfolio with very small risk is requested because the only way to obtain a small risk is to get rid of some of the assets by generating transaction costs. We generally assume that this is not the case and hence the models (11.7) and (11.8) are equivalent.

The above observations lead to

$$\begin{array}{lrcll} \text{maximize} & \mu^T x & & & \\ \text{subject to} & e^T x + m^T t & = & w + e^T x^0, & \\ & (\gamma, G^T x) & \in & \mathcal{Q}^{n+1}, & \\ & (t_j, 1, x_j - x_j^0) & \in & \mathcal{P}_3^{2/3,1/3}, & j = 1, \ldots, n, \\ & x & \geq & 0. & \end{array} \tag{11.10}$$

The revised budget constraint

$$e^T x + m^T t = w + e^T x^0$$

speci es that the initial wealth covers the investment and the transaction costs. It should be mentioned that transaction costs of the form

$$t_j \geq |z_j|^p$$

where $p > 1$ is a real number can be modeled with the power cone as

$$(t_j, 1, z_j) \in \mathcal{P}_3^{1/p,1-1/p}.$$

See the Modeling Cookbook for details.

Example code

Listing 11.3 demonstrates how to compute an optimal portfolio when market impact cost are included.

Listing 11.3: Implementation of model (11.10).

```
function [x, t] = MarkowitzWithMarketImpact(n,mu,GT,x0,w,gamma,m)

[rcode, res] = mosekopt('symbcon');

% unrolled variable ordered as (x, t)
prob = [];
prob.c = [mu; zeros(n,1)];

In = speye(n);
On = sparse([],[],[],n,n);

% Linear part
% [ e' m' ]  * [ x; t ]  =   w + e'*x0
prob.a   = [ ones(1,n), m' ];
prob.blc = [ w + sum(x0) ];
prob.buc = [ w + sum(x0) ];

% No shortselling and no other bounds
prob.blx = [ zeros(n,1); -inf*ones(n,1) ];
prob.bux = inf*ones(2*n,1);

% Affine conic constraints representing [ gamma, GT*x ] in quadratic cone
```

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```
prob.f = sparse([ zeros(1,2*n); [GT On] ]);
prob.g = [gamma; zeros(n,1)];
prob.cones = [ res.symbcon.MSK_CT_QUAD n+1 ];

% Extend the affine conic constraints
% with power cones representing t(i) >= |x(i)-x0(i)|^1.5
fi = [];
fj = [];
g  = [];
fv = repmat([1; 1], n, 1);
for k=1:n
    fi = [fi; 3*k-2; 3*k];
    fj = [fj; n+k; k];
    g  = [g; 0; 1; -x0(k)];
end
prob.f = [prob.f; sparse(fi, fj, fv)];
prob.g = [prob.g; g];
prob.cones = [prob.cones repmat([res.symbcon.MSK_CT_PPOW, 3, 2, 2.0, 1.0], 1, n) ];

[rcode,res] = mosekopt('maximize echo(0)',prob,[]);

x = res.sol.itr.xx(1:n);
t = res.sol.itr.xx(n+(1:n));
```

In the last part of the code we extend the a ne conic constraint with triples of the form $(t_k, 1, x_k - x_k^0)$. Such a triple is constructed as an a ne conic constraint with:

$$\begin{bmatrix} e_{n+k}^T \\ 0 \\ e_k^T \end{bmatrix} \cdot \begin{bmatrix} x \\ t \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ -x_k^0 \end{bmatrix}$$

where e_j denotes the vector of length $2n$ with 1 at position j and 0 otherwise. Membership of a sequence of triples in power cones $\mathcal{P}_3^{2/3,1/3}$ is speci ed with the syntax:

```
prob.cones = [prob.cones repmat([res.symbcon.MSK_CT_PPOW, 3, 2, 2.0, 1.0], 1, n) ];
```

Note that the construction [res.symbcon.MSK_CT_PPOW, d, 2, a, b] creates a power done of dimension d with exponents

$$\frac{a}{a+b}, \frac{b}{a+b}.$$

11.1.6 Transaction Costs

Now assume there is a cost associated with trading asset j given by

$$T_j(\Delta x_j) = \begin{cases} 0, & \Delta x_j = 0, \\ f_j + g_j|\Delta x_j|, & \text{otherwise.} \end{cases}$$

Hence, whenever asset j is traded we pay a xed setup cost f_j and a variable cost of g_j per unit traded. Given the assumptions about transaction costs in this section problem (11.6) may be formulated as

$$\begin{array}{lrcll} \text{maximize} & \mu^T x & & & \\ \text{subject to} & e^T x + f^T y + g^T z & = & w + e^T x^0, & \\ & (\gamma, G^T x) & \in & \mathcal{Q}^{n+1}, & \\ & z_j & \geq & x_j - x_j^0, & j = 1, \ldots, n, \\ & z_j & \geq & x_j^0 - x_j, & j = 1, \ldots, n, \\ & z_j & \leq & U_j y_j, & j = 1, \ldots, n, \\ & y_j & \in & \{0, 1\}, & j = 1, \ldots, n, \\ & x & \geq & 0. & \end{array} \tag{11.11}$$

First observe that

$$z_j \geq |x_j - x_j^0| = |\Delta x_j|.$$

We choose U_j as some a priori upper bound on the amount of trading in asset j and therefore if $z_j > 0$ then $y_j = 1$ has to be the case. This implies that the transaction cost for asset j is given by

$$f_j y_j + g_j z_j.$$

Example code

The following example code demonstrates how to compute an optimal portfolio when transaction costs are included.

Listing 11.4: Code solving problem (11.11).

```
function [x, z, y] = MarkowitzWithTransactionsCost(n,mu,GT,x0,w,gamma,f,g)

[rcode, res] = mosekopt('symbcon');

% Upper bound on the traded amount
u = w+sum(x0);

% unrolled variable ordered as (x, z, y)
prob = [];
prob.c = [mu; zeros(2*n,1)];
In = speye(n);
On = sparse([],[],[],n,n);

% Linear constraints
% [ e'  g'  f' ]   [ x ]  =   w + e'*x0
% [ I  -I   0  ] * [ z ]  <=  x0
% [ I   I   0  ]   [ y ]  >=  x0
% [ 0   I  -U  ]          <=  0
prob.a   = [ [ones(1,n), g', f']; In -In On; In In On; On In -u*In ];
prob.blc = [ w + sum(x0); -inf*ones(n,1); x0; -inf*ones(n,1) ];
prob.buc = [ w + sum(x0); x0; inf*ones(n,1); zeros(n,1) ];

% No shortselling and the linear bound 0 <= y <= 1
prob.blx = [ zeros(n,1); -inf*ones(n,1); zeros(n,1) ];
prob.bux = [ inf*ones(2*n,1); ones(n,1) ];

% Affine conic constraints representing [ gamma, GT*x ] in quadratic cone
prob.f = sparse([ zeros(1,3*n); [GT On On];  ]);
prob.g = [gamma; zeros(n,1)];
prob.cones = [ res.symbcon.MSK_CT_QUAD n+1 ];

% Demand y to be integer (hence binary)
prob.ints.sub = 2*n+(1:n);

[rcode,res] = mosekopt('maximize echo(0)',prob,[]);

x = res.sol.int.xx(1:n);
z = res.sol.int.xx(n+(1:n));
y = res.sol.int.xx(2*n+(1:n));
```

11.1.7 Cardinality constraints

Another method to reduce costs involved with processing transactions is to only change positions in a small number of assets. In other words, at most k of the differences $|\Delta x_j| = |x_j - x_j^0|$ are allowed to be non-zero, where k is (much) smaller than the total number of assets n.

This type of constraint can be again modeled by introducing a binary variable y_j which indicates if $\Delta x_j \neq 0$ and bounding the sum of y_j. The basic Markowitz model then gets updated as follows:

$$
\begin{array}{lrcll}
\text{maximize} & \mu^T x & & & \\
\text{subject to} & e^T x & = & w + e^T x^0, & \\
& (\gamma, G^T x) & \in & \mathcal{Q}^{n+1}, & \\
& z_j & \geq & x_j - x_j^0, & j = 1, \ldots, n, \\
& z_j & \geq & x_j^0 - x_j, & j = 1, \ldots, n, \\
& z_j & \leq & U_j y_j, & j = 1, \ldots, n, \\
& y_j & \in & \{0, 1\}, & j = 1, \ldots, n, \\
& e^T y & \leq & k, & \\
& x & \geq & 0, &
\end{array}
\tag{11.12}
$$

were U_j is some a priori chosen upper bound on the amount of trading in asset j.

Example code

The following example code demonstrates how to compute an optimal portfolio with cardinality bounds.

Listing 11.5: Code solving problem (11.12).

```
function x = MarkowitzWithCardinality(n,mu,GT,x0,w,gamma,k)

[rcode, res] = mosekopt('symbcon');

% Upper bound on the traded amount
u = w+sum(x0);

% unrolled variable ordered as (x, z, y)
prob = [];
prob.c = [mu; zeros(2*n,1)];
In = speye(n);
On = sparse([],[],[],n,n);

% Linear constraints
% [ e'  0   0  ]            =   w + e'*x0
% [ I  -I   0  ]   [ x ]  <=  x0
% [ I   I   0  ] * [ z ]  >=  x0
% [ 0   I  -U  ]   [ y ]  <=  0
% [ 0   0   e' ]           <=  k
prob.a   = [ [ones(1,n), zeros(1,2*n)]; In -In On; In In On; On In -u*In; zeros(1,2*n) ones(1,
↪n) ];
prob.blc = [ w + sum(x0); -inf*ones(n,1); x0; -inf*ones(n,1); 0 ];
prob.buc = [ w + sum(x0); x0; inf*ones(n,1); zeros(n,1); k ];

% No shortselling and the linear bound 0 <= y <= 1
prob.blx = [ zeros(n,1); -inf*ones(n,1); zeros(n,1) ];
prob.bux = [ inf*ones(2*n,1); ones(n,1) ];

% Affine conic constraints representing [ gamma, GT*x ] in quadratic cone
prob.f = sparse([ zeros(1,3*n); [GT On On];  ]);
prob.g = [gamma; zeros(n,1)];
prob.cones = [ res.symbcon.MSK_CT_QUAD n+1 ];

% Demand y to be integer (hence binary)
prob.ints.sub = 2*n+(1:n);

[rcode,res] = mosekopt('maximize echo(0)',prob,[]);

x = res.sol.int.xx(1:n);
```

If we solve our running example with $k = 1, 2, 3$ then we get the following solutions, with increasing expected returns:

```
Bound:  1  Expected return: 0,0627   Solution: 0,0000 0,0000 1,0000
Bound:  2  Expected return: 0,0669   Solution: 0,0939 0,0000 0,9061
Bound:  3  Expected return: 0,0685   Solution: 0,1010 0,1156 0,7834
```

11.2 Least Squares and Other Norm Minimization Problems

A frequently occurring problem in statistics and in many other areas of science is a norm minimization problem

$$\begin{array}{ll} \text{minimize} & \|Fx - g\|, \\ \text{subject to} & Ax = b, \end{array} \tag{11.13}$$

where $x \in \mathbb{R}^n$ and of course we can allow other types of constraints. The objective can involve various norms: in nity norm, 1-norm, 2-norm, p-norms and so on. For instance the most popular case of the 2-norm corresponds to the least squares linear regression, since it is equivalent to minimization of $\|Fx - g\|_2^2$.

11.2.1 Least squares, 2-norm

In the case of the 2-norm we specify the problem directly in conic quadratic form

$$\begin{array}{ll} \text{minimize} & t, \\ \text{subject to} & (t, Fx - g) \in \mathcal{Q}^{k+1}, \\ & Ax = b. \end{array} \tag{11.14}$$

The rst constraint of the problem can be represented as an a ne conic constraint. This leads to the following model.

Listing 11.6: Script solving problem (11.14)

```
% Least squares regression
% minimize \|Fx-g\|_2
function x = norm_lse(F,g,A,b)
clear prob;
[r, res] = mosekopt('symbcon');
n = size(F,2);
k = size(g,1);
m = size(A,1);

% Linear constraints in [x; t]
prob.a   = [A, zeros(m,1)];
prob.buc = b;
prob.blc = b;
prob.blx = -inf*ones(n+1,1);
prob.bux = inf*ones(n+1,1);
prob.c   = [zeros(n,1); 1];

% Affine conic constraint
prob.f = sparse([zeros(1,n), 1; F, zeros(k,1)]);
prob.g = [0; -g];
prob.cones = [ res.symbcon.MSK_CT_QUAD k+1 ];

% Solve
[r, res] = mosekopt('minimize echo(0)', prob);
x = res.sol.itr.xx(1:n);
end
```

11.2.2 Ridge regularisation

Regularisation is classically applied to reduce the impact of outliers and to control over tting. In the conic version of *ridge (Tychonov) regression* we consider the problem

$$\begin{array}{ll} \text{minimize} & \|Fx - g\|_2 + \gamma\|x\|_2, \\ \text{subject to} & Ax = b, \end{array} \tag{11.15}$$

which can be written explicitly as

$$\begin{array}{ll} \text{minimize} & t_1 + \gamma t_2, \\ \text{subject to} & (t_1, Fx - g) \in \mathcal{Q}^{k+1}, \\ & (t_2, x) \in \mathcal{Q}^{n+1}, \\ & Ax = b. \end{array} \tag{11.16}$$

The implementation is a small extension of that from the previous section.

Listing 11.7: Script solving problem (11.16)

```
% Least squares regression with regularization
% minimize \|Fx-g\|_2 + gamma*\|x\|_2
function x = norm_lse_reg(F,g,A,b,gamma)
clear prob;
[r, res] = mosekopt('symbcon');
n = size(F,2);
k = size(g,1);
m = size(A,1);

% Linear constraints in [x; t1; t2]
prob.a   = [A, zeros(m,2)];
prob.buc = b;
prob.blc = b;
prob.blx = -inf*ones(n+2,1);
prob.bux = inf*ones(n+2,1);
prob.c   = [zeros(n,1); 1; gamma];

% Affine conic constraint
prob.f = sparse([zeros(1,n),        1, 0; ...
                 F,           zeros(k,2); ...
                 zeros(1,n),        0, 1; ...
                 eye(n),      zeros(n,2) ]);
prob.g = [0; -g; zeros(n+1,1)];
prob.cones = [ res.symbcon.MSK_CT_QUAD k+1 res.symbcon.MSK_CT_QUAD n+1 ];

% Solve
[r, res] = mosekopt('minimize echo(0)', prob);
x = res.sol.itr.xx(1:n);
end
```

Note that classically least squares problems are formulated as quadratic problems and then the objective function would be written as

$$\|Fx - g\|_2^2 + \gamma\|x\|_2^2.$$

This version can easily be obtained by replacing the quadratic cone with an appropriate rotated quadratic cone in (11.16). Then they core of the implementation would change as follows:

Listing 11.8: Script solving classical quadratic ridge regression

```
prob.f = sparse([zeros(1,n),        1, 0; ...
                 zeros(1,n+2)           ; ...
                 F,           zeros(k,2); ...
                 zeros(1,n),        0, 1; ...
```

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```
                zeros(1,n+2)          ; ...
                eye(n),       zeros(n,2) ]);
prob.g = [0; 0.5; -g; 0; 0.5; zeros(n,1)];
prob.cones = [ res.symbcon.MSK_CT_RQUAD k+2 res.symbcon.MSK_CT_RQUAD n+2 ];
```

Fig. 11.2 shows the solution to a polynomial tting problem for a few variants of least squares regression with and without ridge regularization.

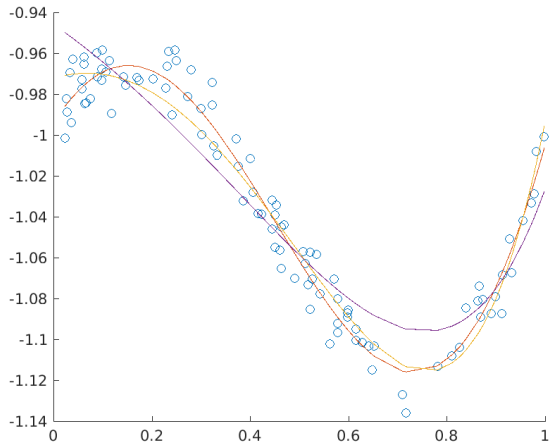

Fig. 11.2: Three ts to a dataset at various levels of regularization.

11.2.3 Lasso regularization

In *lasso* or *least absolute shrinkage and selection operator* the regularization term is the 1-norm of the solution

$$\begin{array}{ll} \text{minimize} & \|Fx-g\|_2+\gamma\|x\|_1, \\ \text{subject to} & Ax=b. \end{array} \tag{11.17}$$

This variant typically tends to give preference to sparser solutions, i.e. solutions where only a few elements of x are nonzero, and therefore it is used as an e cient approximation to the cardinality constrained problem with an upper bound on the 0-norm of x. To see how it works we rst implement (11.17) adding the constraint $t \geq \|x\|_1$ as a series of linear constraints

$$u_i \geq -x_i,\ u_i \geq x_i,\ t \geq \sum u_i,$$

so that eventually the problem becomes

$$\begin{array}{ll} \text{minimize} & t_1+\gamma t_2, \\ \text{subject to} & u+x \geq 0, \\ & u-x \geq 0, \\ & t_2-e^T u \geq 0, \\ & Ax=b, \\ & (t_1, Fx-g) \in \mathcal{Q}^{k+1}. \end{array}$$

Listing 11.9: Script solving problem (11.17)

```
% Least squares regression with lasso regularization
% minimize \|Fx-g\|_2 + gamma*\|x\|_1
function x = norm_lse_lasso(F,g,A,b,gamma)
clear prob;
```

(continues on next page)

all data from the uncertainty set, that $Ax \leq u_c$, $c^T x \leq t$, and that the entries in x satisfy the required lower and upper bounds, respectively.

Please note that at the optimal solution to (11.25), one clearly has $y_j = |x_j|$. It follows that when the bounds on the entries of x impose nonnegativity (nonpositivity) of an entry x_j, then there is no need to introduce the corresponding additional variable y_i from the very beginning it can be replaced with x_j, if x_j is nonnegative, or with $-x_j$, if x_j is nonpositive.

Another possible formulation of problem (11.25) is the following. Let

$$l_c^{\mathsf{n}} + dl_c = (A^{\mathsf{n}})x - (dA)y - f, f \geq 0$$

then this equation is equivalent to $(a) - (b)$ in (11.25). If $(l_c)_i = -\infty$, then equation i should be dropped from the computations. Similarly,

$$-x + y = g \geq 0$$

is equivalent to (d) in (11.25). This implies that

$$l_c^{\mathsf{n}} + dl_c - (A^{\mathsf{n}})x + f = -(dA)y$$

and that

$$y = g + x$$

Substituting these values into (11.25) gives

$$\begin{array}{lrcccl}
\text{minimize} & & & t & & \\
\text{subject to} & & & (c^{\mathsf{n}})^T x + (dc)^T (g + x) - t & \leq & 0, \\
& 0 & \leq & f, & & \\
& & & 2(A^{\mathsf{n}})x + (dA)(g + x) + f + l_c^{\mathsf{n}} + dl_c & \leq & u_c^{\mathsf{n}} - du_c, \\
& 0 & \leq & g, & & \\
& 0 & \leq & 2x + g, & & \\
& l_x^{\mathsf{n}} + dl_x & \leq & x & \leq & u_x^{\mathsf{n}} - du_x,
\end{array}$$

which after some simpli cations leads to

$$\begin{array}{lrcccll}
\text{minimize} & & & t & & & \\
\text{subject to} & & & (c^{\mathsf{n}} + dc)^T x + (dc)^T g - t & \leq & 0, & (a) \\
& 0 & \leq & f, & & & (b) \\
& & & 2(A^{\mathsf{n}} + dA)x + (dA)g + f - (l_c^{\mathsf{n}} + dl_c) & \leq & u_c^{\mathsf{n}} - du_c, & (c) \\
& 0 & \leq & g, & & & (d) \\
& 0 & \leq & 2x + g, & & & (e) \\
& l_x^{\mathsf{n}} + dl_x & \leq & x & \leq & u_x^{\mathsf{n}} - du_x, & (f)
\end{array}$$

and

$$\begin{array}{lrcccll}
\text{minimize} & & & t & & & \\
\text{subject to} & & & (c^{\mathsf{n}} + dc)^T x + (dc)^T g - t & \leq & 0, & (a) \\
& & & 2(A^{\mathsf{n}} + dA)x + (dA)g + f & \leq & u_c^{\mathsf{n}} - du_c + l_c^{\mathsf{n}} + dl_c, & (b) \\
& 0 & \leq & 2x + g, & & & (c) \\
& 0 & \leq & f, & & & (d) \\
& 0 & \leq & g, & & & (e) \\
& l_x^{\mathsf{n}} + dl_x & \leq & x & \leq & u_x^{\mathsf{n}} - du_x. & (f)
\end{array} \tag{11.26}$$

Please note that this problem has more variables but much fewer constraints than (11.25). Therefore, (11.26) is likely to be solved faster than (11.25). Note too that (11.26)b is trivially redundant if $l_x^{\mathsf{n}} + dl_x \geq 0$.

Introductory Example (continued)

Let us apply the Robust Optimization methodology to our drug production example presented in Sec. 11.3.1, assuming that the only uncertain data is the contents of the active agent in the raw materials,

and that these contents vary in 0.5% and 2% neighborhoods of the respective nominal values 0.01 and 0.02. With this assumption, the problem becomes an uncertain LP a ected by interval uncertainty; the robust counterpart (11.25) of this uncertain LP is the linear program

$$
\begin{array}{lcl}
\text{(Drug_RC)} & : & \\
\text{maximize} & & \\
t & & \\
\text{subject to} & & \\
t \leq -100 \cdot \texttt{RawI} - 199.9 \cdot \texttt{RawII} + 5500 \cdot \texttt{DrugI} + 6100 \cdot \texttt{DrugII} & & \\
0.01 \cdot 0.995 \cdot \texttt{RawI} + 0.02 \cdot 0.98 \cdot \texttt{RawII} - 0.500 \cdot \texttt{DrugI} - 0.600 \cdot \texttt{DrugII} & \geq & 0 \\
\texttt{RawI} + \texttt{RawII} & \leq & 1000 \\
90.0 \cdot \texttt{DrugI} + 100.0 \cdot \texttt{DrugII} & \leq & 2000 \\
40.0 \cdot \texttt{DrugI} + 50.0 \cdot \texttt{DrugII} & \leq & 800 \\
100.0 \cdot \texttt{RawI} + 199.90 \cdot \texttt{RawII} + 700 \cdot \texttt{DrugI} + 800 \cdot \texttt{DrugII} & \leq & 100000 \\
\texttt{RawI}, \texttt{RawII}, \texttt{DrugI}, \texttt{DrugII} & \geq & 0
\end{array}
\tag{11.27}
$$

Solving this problem with $\mathbf{MOSEK}$ we get the following output:

Listing 11.13: Output solving problem (11.27).

```
*** Optimal value: 8294.567
*** Optimal solution:
RawI:    877.732
RawII:     0.000
DrugI:    17.467
DrugII:    0.000
```

We see that the robust optimal solution we have built $costs\ money$ it promises a pro t of just $8,295$ (cf. with the pro t of $8,820$ promised by the nominal optimal solution). Please note, however, that the robust optimal solution remains feasible whatever are the realizations of the uncertain data from the uncertainty set in question, while the nominal optimal solution requires adjustment to this data and, with this adjustment, results in the average pro t of $7,843$, which is by 5.4% $less$ than the pro t of ` 8,295 $guaranteed$ by the robust optimal solution. Note too that the robust optimal solution is signi cantly di erent from the nominal one: both solutions prescribe to produce the same drug DrugI (in the amounts $17,467$ and $17,552$ packs, respectively) but from di erent raw materials, RawI in the case of the robust solution and RawII in the case of the nominal solution. The reason is that although the price per unit of the active agent for RawII is sligthly less than for RawI, the content of the agent in RawI is more stable, so when possible uctuations of the contents are taken into account, RawI turns out to be more pro table than RawII.

11.3.4 Random Uncertainty and Ellipsoidal Robust Counterpart

In some cases, it is natural to assume that the perturbations a ecting di erent uncertain data entries are random and independent of each other. In these cases, the robust counterpart based on the interval model of uncertainty seems to be too conservative: Why should we expect that all the data will be simultaneously driven to its most unfavorable values and immune the solution against this highly unlikely situation? A less conservative approach is o ered by the $ellipsoidal$ model of uncertainty. To motivate this model, let us seeee what happens with a particular linear constraint

$$a^T x \leq b \tag{11.28}$$

at a given candidate solution x in the case when the vector a of coe cients of the constraint is a ected by random perturbations:

$$a = a^{\mathsf{n}} + \zeta, \tag{11.29}$$

where a^{n} is the vector of nominal coe cients and ζ is a random perturbation vector with zero mean and covariance matrix V_a. In this case the value of the left-hand side of (11.28), evaluated at a given x, becomes a random variable with the expected value $(a^{\mathsf{n}})^T x$ and the standard deviation $\sqrt{x^T V_a x}$. Now let us act as an engineer who believes that the value of a random variable never exceeds its mean plus 3 times the standard deviation; we do not intend to be that speci c and replace 3 in the above rule by

a safety parameter Ω which will be in our control. Believing that the value of a random variable *never* exceeds its mean plus Ω times the standard deviation, we conclude that a *safe* version of (11.28) is the inequality

$$(a^{\mathsf{n}})^T x + \Omega\sqrt{x^T V_a x} \leq b. \tag{11.30}$$

The word *safe* above admits a quantitative interpretation: If x satis es (11.30), one can bound from above the probability of the event that random perturbations (11.29) result in violating the constraint (11.28) evaluated at x. The bound in question depends on what we know about the distribution of ζ, e.g.

- We always have the bound given by the Tschebyshev inequality: x satis es (11.30) $\Rightarrow$

$$\text{Prob}\left\{a^T x > b\right\} \leq \frac{1}{\Omega^2}.$$

- When ζ is Gaussian, then the Tschebyshev bound can be improved to: x satis es (11.30) $\Rightarrow$

$$\text{Prob}\left\{a^T x > b\right\} \leq \frac{1}{\sqrt{2\pi}}\int_{\Omega}^{\infty} \exp\{-t^2/2\}dt \leq 0.5\exp\{-\Omega^2/2\}. \tag{11.31}$$

- Assume that $\zeta = D\xi$, where Δ is certain $n \times m$ matrix, and $\xi = (\xi_1, \ldots, \xi_m)^T$ is a random vector with independent coordinates $\xi_1, \ldots, \xi_m$ symmetrically distributed in the segment $[-1, 1]$. Setting $V = DD^T$ (V is a natural *upper bound* on the covariance matrix of ζ), one has: x satis es (11.30) implies

$$\text{Prob}\left\{a^T x > b\right\} \leq 0.5\exp\{-\Omega^2/2\}. \tag{11.32}$$

Please note that in order to ensure the bounds in (11.31) and (11.32)) to be $\leq 10^{-6}$, it su ces to set $\Omega = 5.13$.

Now, assume that we are given a linear program a ected by random perturbations:

$$\begin{array}{lrcccl} \text{minimize} & & & [c^{\mathsf{n}} + dc]^T x & & \\ \text{subject to} & (l_c)_i & \leq & [a_i^{\mathsf{n}} + da_i]^T x & \leq & (u_c)_i, i = 1, \ldots, m, \\ & l_x & \leq & x & \leq & u_x, \end{array} \tag{11.33}$$

where $(c^{\mathsf{n}}, \{a_i^{\mathsf{n}}\}_{i=1}^m, l_c, u_c, l_x, u_x)$ are the nominal data, and dc, da_i are random perturbations with zero means[3]. Assume, for the sake of de niteness, that every one of the random perturbations $dc, da_1, \ldots, da_m$ satis es either the assumption of item 2 or the assumption of item 3, and let $V_c, V_1, \ldots, V_m$ be the corresponding (upper bounds on the) covariance matrices of the perturbations. Choosing a safety parameter Ω and replacing the objective and the bodies of all the constraints by their safe bounds as explained above, we arrive at the following optimization problem:

$$\begin{array}{lrcccl} \text{minimize} & & & t & & \\ \text{subject to} & & & [c^{\mathsf{n}}]^T x + \Omega\sqrt{x^T V_c x} & \leq & t, \\ & (l_c)_i & \leq & [a_i^{\mathsf{n}}]^T x - \Omega\sqrt{x^T V_{a_i} x}, & & \\ & & & [a_i^{\mathsf{n}}]^T x + \Omega\sqrt{x^T V_{a_i} x} & \leq & (u_c)_i, i = 1, \ldots, m, \\ & l_x & \leq & x & \leq & u_x. \end{array} \tag{11.34}$$

The relation between problems (11.34) and (11.33) is as follows:

- If (x, t) is a feasible solution of (11.34), then with probability at least

$$p = 1 - (m+1)\exp\{-\Omega^2/2\}$$

x is feasible for randomly perturbed problem (11.33), and t is an upper bound on the objective of (11.33) evaluated at x.

- We see that if Ω is not too small (11.34) can be treated as a safe version of (11.33).

[3] For the sake of simplicity, we assume that the bounds l_c, u_c, l_x, u_x are not affected by uncertainty; extensions to the case when it is not so are evident.

On the other hand, it is easily seen that (11.34) is nothing but the robust counterpart of the uncertain linear optimization problem with the nominal data $(c^{\mathsf{n}}, \{a_i^{\mathsf{n}}\}_{i=1}^m, l_c, u_c, l_x, u_x)$ and the row-wise ellipsoidal uncertainty given by the matrices $V_c, V_{a_1}, \ldots, V_{a_m}$. In the corresponding uncertainty set, the uncertainty a ects the coe cients of the objective and the constraint matrix only, and the perturbation vectors a ecting the objective and the vectors of coe cients of the linear constraints run, independently of each other, through the respective ellipsoids

$$\begin{array}{rcl} E_c & = & \\ E_{a_i} & = & \left\{ dc = \Omega V_c^{1/2} u : u^T u \leq 1 \right\} \\ & & \left\{ da_i = \Omega V_{a_i}^{1/2} u : u^T u \leq 1 \right\}, i = 1, \ldots, m. \end{array}$$

It turns out that in many cases the ellipsoidal model of uncertainty is signi cantly less conservative and thus better suited for practice, than the interval model of uncertainty.

Last but not least, it should be mentioned that problem (11.34) is equivalent to a conic quadratic program, speci cally to the program

$$\begin{array}{lrcl} \text{minimize} & & t & \\ \text{subject to} & & [c^{\mathsf{n}}]^T x + \Omega z & \leq t, \\ & (l_c)_i \leq & [a_i^{\mathsf{n}}]^T x - \Omega z_i, & \\ & & [a_i^{\mathsf{n}}]^T x + \Omega z_i & \leq (u_c)_i, i = 1, \ldots, m, \\ & 0 = & w - D_c x & \\ & 0 = & w^i - D_{a_i} x, & i = 1, \ldots, m, \\ & 0 \leq & z - \sqrt{w^T w}, & \\ & 0 \leq & z_i - \sqrt{(w^i)^T w^i}, & i = 1, \ldots, m, \\ & l_x \leq & x & \leq u_x. \end{array}$$

where D_c and D_{a_i} are matrices satisfying the relations

$$V_c = D_c^T D_c, V_{a_i} = D_{a_i}^T D_{a_i}, i = 1, \ldots, m.$$

Example: Interval and Ellipsoidal Robust Counterparts of Uncertain Linear Constraint with Independent Random Perturbations of Coefficients

Consider a linear constraint

$$l \leq \sum_{j=1}^n a_j x_j \leq u \tag{11.35}$$

and assume that the a_j coe cients of the body of the constraint are uncertain and vary in intervals $a_j^{\mathsf{n}} \pm \sigma_j$. The worst-case_oriented model of uncertainty here is the interval one, and the corresponding robust counterpart of the constraint is given by the system of linear inequalities

$$\begin{array}{rcl} l \leq & \sum_{j=1}^n a_j^{\mathsf{n}} x_j - \sum_{j=1}^n \sigma_j y_j, & \\ & \sum_{j=1}^n a_j^{\mathsf{n}} x_j + \sum_{j=1}^n \sigma_j y_j & \leq u, \\ 0 \leq & x_j + y_j, & \\ 0 \leq & -x_j + y_j, & j = 1, \ldots, n. \end{array} \tag{11.36}$$

Now, assume that we have reasons to believe that the true values of the coe cients a_j are obtained from their nominal values a_j^{n} by random perturbations, independent for di erent j and symmetrically distributed in the segments *[-sigma_j,sigma_j]*. With this assumption, we are in the situation of item 3 and can replace the uncertain constraint (11.35) with its ellipsoidal robust counterpart

$$\begin{array}{rcl} l \leq & \sum_{j=1}^n a_j^{\mathsf{n}} x_j - \Omega z, & \\ & \sum_{j=1}^n a_j^{\mathsf{n}} x_j + \Omega z & \leq u, \\ 0 \leq & z - \sqrt{\sum_{j=1}^n \sigma_j^2 x_j^2}. & \end{array} \tag{11.37}$$

Please note that with the model of random perturbations, a vector x satisfying (11.37) satis es a realization of (11.35) with probability at least $1 - \exp\{\Omega^2/2\}$; for $\Omega = 6$. This probability is $\geq 1 - 1.5 \cdot 10^{-8}$,

which for all practical purposes is the same as sayiong that x satis es all realizations of (11.35). On the other hand, the uncertainty set associated with (11.36) is the box

$$B = \left\{a = (a_1, \ldots, a_n)^T : a_j^{\mathsf{n}} - \sigma_j \leq a_j \leq a_j^{\mathsf{n}} + \sigma_j, j = 1, \ldots, n\right\},$$

while the uncertainty set associated with (11.37) is the ellipsoid

$$E(\Omega) = \left\{a = (a_1, \ldots, a_n)^T : \sum_{j=1}^{n} (a_j - a_j^{\mathsf{n}})^{\frac{2}{\sigma_j^2}} \leq \Omega^2\right\}.$$

For a moderate value of Ω, say $\Omega = 6$, and $n \geq 40$, the ellipsoid $E(\Omega)$ in its diameter, typical linear sizes, volume, etc. is incomparably less than the box B, the di erence becoming more dramatic the larger the dimension n of the box and the ellipsoid. It follows that the ellipsoidal robust counterpart (11.37) of the randomly perturbed uncertain constraint (11.35) is much less conservative than the interval robust counterpart (11.36), while ensuring basically the same robustness guarantees . To illustrate this important point, consider the following numerical examples:

There are n di erent assets on the market. The return on 1 invested in asset j is a random variable distributed symmetrically in the segment $[\delta_j - \sigma_j, \delta_j + \sigma_j]$, and the returns on di erent assets are independent of each other. The problem is to distribute ` 1 among the assets in order to get the largest possible total return on the resulting portfolio.

A natural model of the problem is an uncertain linear optimization problem

$$\begin{array}{lrcll} \text{maximize} & & & \sum_{j=1}^{n} a_j x_j & \\ \text{subject to} & & & \sum_{j=1}^{n} x_j & = 1, \\ & 0 & \leq & x_j, & j = 1, \ldots, n. \end{array}$$

where a_j are the uncertain returns of the assets. Both the nominal optimal solution (set all returns a_j equal to their nominal values δ_j) and the risk-neutral Stochastic Programming approach (maximize the expected total return) result in the same solution: Our money should be invested in the most promising asset(s) the one(s) with the maximal nominal return. This solution, however, can be very unreliable if, as is typically the case in reality, the most promising asset has the largest volatility σ and is in this sense the most risky. To reduce the risk, one can use the Robust Counterpart approach which results in the following optimization problems.

The Interval Model of Uncertainty:

$$\begin{array}{lrcll} \text{maximize} & & & t & \\ \text{subject to} & 0 & \leq & -t + \sum_{j=1}^{n} (\delta_j - \sigma_j) x_j, & \\ & & & \sum_{j=1}^{n} x_j & = 1, \\ & 0 & \leq & x_j, & j = 1, \ldots, n \end{array} \tag{11.38}$$

and

The ellipsoidal Model of Uncertainty:}

$$\begin{array}{lrcll} \text{maximize} & & & t & \\ \text{subject to} & 0 & \leq & -t + \sum_{j=1}^{n} (\delta_j) x_j - \Omega z, & \\ & 0 & \leq & z - \sqrt{\sum_{j=1}^{n} \sigma_j^2 x_j^2}, & \\ & & & \sum_{j=1}^{n} x_j & = 1, \\ & 0 & \leq & x_j, & j = 1, \ldots, n. \end{array} \tag{11.39}$$

Note that the problem (11.39) is essentially the risk-averted portfolio model proposed in mid-50's by Markowitz.

The solution of (11.38) is evident our `1 should be invested in the asset(s) with the largest possible $guaranteed$ return $\delta_j - \sigma_j$. In contrast to this very conservative policy (which in reality prescribes to keep

the initial capital in a bank or in the most reliable, and thus low pro t, assets), the optimal solution to (11.39) prescribes a quite reasonable diversi cation of investments which allows to get much better total return than (11.38) with basically zero risk[2]. To illustrate this, assume that there are $n = 300$ assets with the nominal returns (per year) varying from 1.04 (bank savings) to 2.00:

$$\delta_j = 1.04 + 0.96\frac{j-1}{n-1}, \quad j = 1, 2, \ldots, n = 300$$

and volatilities varying from 0 for the bank savings to 1.2 for the most promising asset:

$$\sigma_j = 1.152\frac{j-1}{n-1}, \quad j = 1, \ldots, n = 300.$$

In Listing 11.14 a MATLAB script which builds the associated problem (11.39), solves it via the **MOSEK** optimization toolbox, displays the resulting robust optimal value of the total return and the distribution of investments, and nally runs 10,000 simulations to get the distribution of the total return on the resulting portfolio (in these simulations, the returns on all assets are uniformly distributed in the corresponding intervals) is presented.

Listing 11.14: Script that implements problem (11.39).

```
function rlo2(n, Omega, draw)

n = str2num(n)
Omega = str2num(Omega)
draw

[r, res] = mosekopt('symbcon echo(0)');
sym = res.symbcon;

% Set nominal returns and volatilities
delta = (0.96/(n-1))*[0:1:n-1]+1.04;
sigma = (1.152/(n-1))*[0:1:n-1];

% Set mosekopt description of the problem
prob.c              = [1;zeros(n+1,1)];
A                   = [-1, delta,     -Omega; ...
                         0, ones(1,n), 0];
prob.a              = sparse(A);
prob.blc            = [0;1];
prob.buc            = [inf;1];
prob.blx            = [-inf;zeros(n,1);0];
prob.bux            = inf*ones(n+2,1);
F                   = [zeros(1,n+1), 1; ...
                       zeros(n,1), diag(sigma), zeros(n,1)];
prob.f              = sparse(F);
prob.cones          = [ sym.MSK_CT_QUAD n+1 ];

% Run mosekopt
[r,res]=mosekopt('maximize echo(3)',prob);

xx = res.sol.itr.xx;
t  = xx(1);

disp(sprintf('Robust optimal value: %5.4f',t));
x = max(xx(2:1+n),zeros(n,1));

if draw == true
    % Display the solution
    plot([1:1:n],x,'-m');
```

(continues on next page)

[2] Recall that in our discussion we have assumed the returns on different assets to be independent of each other. In reality, this is not so and this is why diversification of investments, although reducing the risk, never eliminates it completely

(continued from previous page)

```
    grid on;

    disp('Press <Enter> to run simulations');
    pause

    % Run simulations

    Nsim = 10000;
    out  = zeros(Nsim,1);
    for i=1:Nsim,
        returns  = delta+(2*rand(1,n)-1).*sigma;
        out(i)   = returns*x;
    end;
    disp(sprintf('Actual returns over %d simulations:',Nsim));
    disp(sprintf('Min=%5.4f Mean=%5.4f Max=%5.4f StD=%5.2f',...
                 min(out),mean(out),max(out),std(out)));
    hist(out);
end
```

Here are the results displayed by the script:

Listing 11.15: Output of script *rlo2.m*.

```
Robust optimal value: 1.3428
Actual returns over 10000 simulations:
Min=1.5724 Mean=1.6965 Max=1.8245 StD= 0.03
```

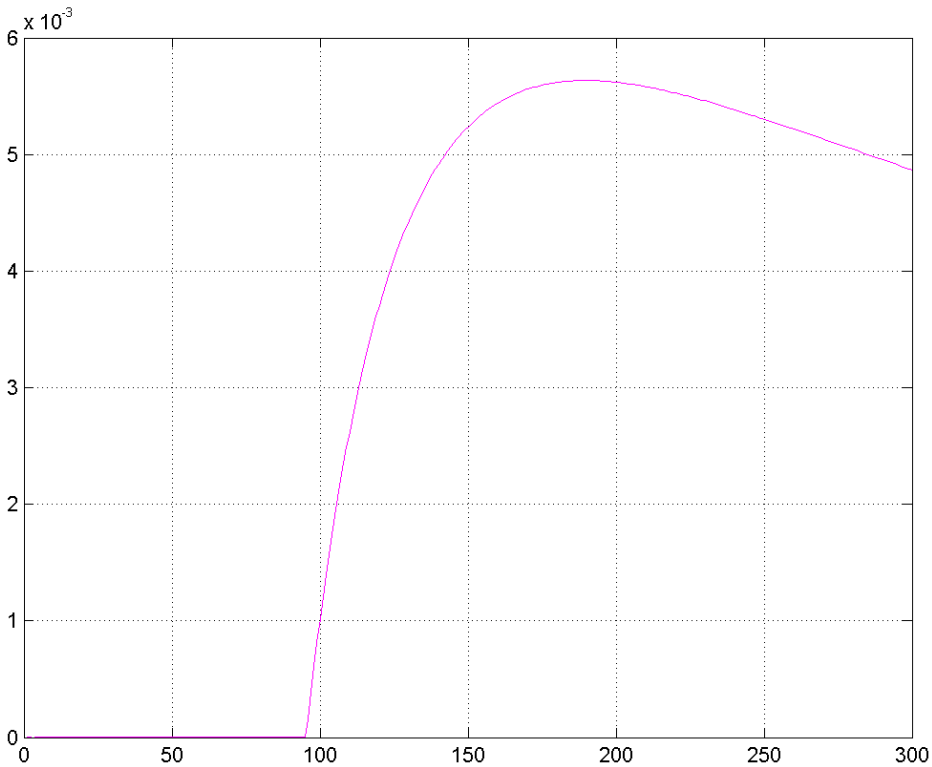

Fig. 11.4: Distribution of investments among the assets in the optimal solution of.

Please note that with our set-up there is exactly one asset with guaranteed return greater than 1 asset # 1 (bank savings, return 1.04, zero volatility). Consequently, the interval robust counterpart

(11.38) prescribes to put our ` #1 in the bank, thus getting a 4% pro t. In contrast to this, the diversi ed portfolio given by the optimal solution of (11.39) never yields pro t less than 57.2%, and yields at average a 69.67% pro t with pretty low (0.03) standard deviation. We see that in favorable circumstances the ellipsoidal robust counterpart of an uncertain linear program indeed is less conservative than, although basically as reliable as, the interval robust counterpart.

Finally, let us compare our results with those given by the nominal optimal solution. The latter prescribes to invest everything we have in the most promising asset (in our example this is the asset # 300 with a nominal return of 2.00 and volatility of 1.152). Assuming that the actual return is uniformly distributed in the corresponding interval and running 10,000 simulations, we get the following results:

```
Nominal optimal value: 2.0000
Actual returns over 10000 simulations:
Min=0.8483 Mean=1.9918 Max=3.1519 StD= 0.66
```

We see that the nominal solution results in a portfolio which is much more risky, although better at average, than the portfolio given by the robust solution.

Combined Interval-Ellipsoidal Robust Counterpart

We have considered the case when the coe cients a_j of uncertain linear constraint (11.35) are a ected by uncorrelated random perturbations symmetrically distributed in given intervals $[-\sigma_j, \sigma_j]$, and we have discussed two ways to model the uncertainty:

- The interval uncertainty model (the uncertainty set $\mathcal{U}$ is the box B), where we ignore the stochastic nature of the perturbations and their independence. This model yields the Interval Robust Counterpart (11.36);
- The ellipsoidal uncertainty model ($\mathcal{U}$ is the ellipsoid $E(\Omega)$), which takes into account the stochastic nature of data perturbations and yields the Ellipsoidal Robust Counterpart (11.37).

Please note that although for large n the ellipsoid $E(\Omega)$ in its diameter, volume and average linear sizes is incomparably smaller than the box B, in the case of $\Omega > 1$ the ellipsoid $E(\Omega)$ in certain directions goes beyond the box. E.g. the ellipsoid $E(6)$, although much more narrow than B in most of the directions, is 6 times wider than B in the directions of the coordinate axes. Intuition says that it hardly makes sense to keep in the uncertainty set realizations of the data which are outside of B and thus forbidden by our model of perturbations, so in the situation under consideration the intersection of $E(\Omega)$ and B is a better model of the uncertainty set than the ellipsoid $E(\Omega)$ itself. What happens when the model of the uncertainty set is the *combined interval-ellipsoidal* uncertainty $\mathcal{U}(\Omega) = E(\Omega) \cap B$?

First, it turns out that the RC of (11.35) corresponding to the uncertainty set $\mathcal{U}(\Omega)$ is still given by a system of linear and conic quadratic inequalities, speci cally the system

$$\begin{array}{rcl} l & \leq & \sum_{j=1}^n a_j^{\mathsf{n}} x_j - \sum_{j=1}^n \sigma_j y_j - \Omega\sqrt{\sum_{j=1}^n \sigma_j^2 u_j^2}, \\ & & \sum_{j=1}^n a_j^{\mathsf{n}} x_j + \sum_{j=1}^n \sigma_j z_j + \Omega\sqrt{\sum_{j=1}^n \sigma_j^2 v_j^2} \leq u, \\ -y_j & \leq & x_j - u_j \leq y_j, j = 1, \ldots, n, \\ -z_j & \leq & x_j - v_j \leq z_j, j = 1, \ldots, n. \end{array} \tag{11.40}$$

Second, it turns out that our intuition is correct: As a model of uncertainty, $U(\Omega)$ is as reliable as the ellipsoid $E(\Omega)$. Speci cally, if x can be extended to a feasible solution of (11.40), then the probability for x to satisfy a realization of (11.35) is $\geq 1 - \exp\{-\Omega^2/2\}$.

The conclusion is that if we have reasons to assume that the perturbations of uncertain coe cients in a constraint of an uncertain linear optimization problem are (a) random, (b) independent of each other, and (c) symmetrically distributed in given intervals, then it makes sense to associate with this constraint an interval-ellipsoidal model of uncertainty and use a system of linear and conic quadratic inequalities (11.40). Please note that when building the robust counterpart of an uncertain linear optimization problem, one can use di erent models of the uncertainty (e.g., interval, ellipsoidal, combined interval-ellipsoidal) for di erent uncertain constraints within the same problem.

Chapter 12

Problem Formulation and Solutions

In this chapter we will discuss the following issues:

- The formal, mathematical formulations of the problem types that **MOSEK** can solve and their duals.
- The solution information produced by **MOSEK**.
- The infeasibility certi cate produced by **MOSEK** if the problem is infeasible.

For the underlying mathematical concepts, derivations and proofs see the Modeling Cookbook or any book on convex optimization. This chapter explains how the related data is organized speci cally within the **MOSEK** API.

12.1 Linear Optimization

MOSEK accepts linear optimization problems of the form

$$\begin{array}{lccccc} \text{minimize} & & & c^T x + c^f & & \\ \text{subject to} & l^c & \leq & Ax & \leq & u^c, \\ & l^x & \leq & x & \leq & u^x, \end{array} \tag{12.1}$$

where

- m is the number of constraints.
- n is the number of decision variables.
- $x \in \mathbb{R}^n$ is a vector of decision variables.
- $c \in \mathbb{R}^n$ is the linear part of the objective function.
- $c^f \in \mathbb{R}$ is a constant term in the objective
- $A \in \mathbb{R}^{m \times n}$ is the constraint matrix.
- $l^c \in \mathbb{R}^m$ is the lower limit on the activity for the constraints.
- $u^c \in \mathbb{R}^m$ is the upper limit on the activity for the constraints.
- $l^x \in \mathbb{R}^n$ is the lower limit on the activity for the variables.
- $u^x \in \mathbb{R}^n$ is the upper limit on the activity for the variables.

Lower and upper bounds can be in nite, or in other words the corresponding bound may be omitted.

A primal solution (x) is *(primal) feasible* if it satis es all constraints in (12.1). If (12.1) has at least one primal feasible solution, then (12.1) is said to be (primal) feasible. In case (12.1) does not have a feasible solution, the problem is said to be *(primal) infeasible*

12.1.1 Duality for Linear Optimization

Corresponding to the primal problem (12.1), there is a dual problem

$$\begin{array}{lrcl} \text{maximize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x + c^f & & \\ & A^T y + s_l^x - s_u^x & = & c, \\ \text{subject to} & -y + s_l^c - s_u^c & = & 0, \\ & s_l^c, s_u^c, s_l^x, s_u^x & \geq & 0. \end{array} \tag{12.2}$$

If a bound in the primal problem is plus or minus in nity, the corresponding dual variable is xed at 0, and we use the convention that the product of the bound value and the corresponding dual variable is 0. This is equivalent to removing variable $(s_l^x)_j$ from the dual problem. In other words:

$$l_j^x = -\infty \quad \Rightarrow \quad (s_l^x)_j = 0 \text{ and } l_j^x \cdot (s_l^x)_j = 0.$$

A solution

$$(y, s_l^c, s_u^c, s_l^x, s_u^x)$$

to the dual problem is feasible if it satis es all the constraints in (12.2). If (12.2) has at least one feasible solution, then (12.2) is *(dual) feasible*, otherwise the problem is *(dual) infeasible*.

A solution

$$(x^*, y^*, (s_l^c)^*, (s_u^c)^*, (s_l^x)^*, (s_u^x)^*)$$

is denoted a *primal-dual feasible solution*, if (x^*) is a solution to the primal problem (12.1) and $(y^*, (s_l^c)^*, (s_u^c)^*, (s_l^x)^*, (s_u^x)^*)$ is a solution to the corresponding dual problem (12.2). We also de ne an auxiliary vector

$$(x^c)^* := Ax^*$$

containing the activities of linear constraints.

For a primal-dual feasible solution we de ne the *duality gap* as the di erence between the primal and the dual objective value,

$$\begin{array}{l} c^T x^* + c^f - \left\{(l^c)^T (s_l^c)^* - (u^c)^T (s_u^c)^* + (l^x)^T (s_l^x)^* - (u^x)^T (s_u^x)^* + c^f\right\} \\ = \sum_{i=0}^{m-1} \left[(s_l^c)_i^* ((x_i^c)^* - l_i^c) + (s_u^c)_i^* (u_i^c - (x_i^c)^*)\right] \\ + \sum_{j=0}^{n-1} \left[(s_l^x)_j^* (x_j - l_j^x) + (s_u^x)_j^* (u_j^x - x_j^*)\right] \geq 0 \end{array} \tag{12.3}$$

where the rst relation can be obtained by transposing and multiplying the dual constraints (12.2) by x^* and $(x^c)^*$ respectively, and the second relation comes from the fact that each term in each sum is nonnegative. It follows that the primal objective will always be greater than or equal to the dual objective.

It is well-known that a linear optimization problem has an optimal solution if and only if there exist feasible primal-dual solution so that the duality gap is zero, or, equivalently, that the *complementarity conditions*

$$\begin{array}{rcll} (s_l^c)_i^* ((x_i^c)^* - l_i^c) & = & 0, & i = 0, \ldots, m-1, \\ (s_u^c)_i^* (u_i^c - (x_i^c)^*) & = & 0, & i = 0, \ldots, m-1, \\ (s_l^x)_j^* (x_j^* - l_j^x) & = & 0, & j = 0, \ldots, n-1, \\ (s_u^x)_j^* (u_j^x - x_j^*) & = & 0, & j = 0, \ldots, n-1, \end{array}$$

are satis ed.

If (12.1) has an optimal solution and **MOSEK** solves the problem successfully, both the primal and dual solution are reported, including a status indicating the exact state of the solution.

12.1.2 Infeasibility for Linear Optimization

Primal Infeasible Problems

If the problem (12.1) is infeasible (has no feasible solution)**MOSEK** will report a certi cate of primal infeasibility: The dual solution reported is the certi cate of infeasibility, and the primal solution is unde ned.

A certi cate of primal infeasibility is a feasible solution to the modi ed dual problem

$$\begin{array}{ll} \text{maximize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x \\ \text{subject to} & \\ & A^T y + s_l^x - s_u^x = 0, \\ & -y + s_l^c - s_u^c = 0, \\ & s_l^c, s_u^c, s_l^x, s_u^x \geq 0, \end{array} \tag{12.4}$$

such that the objective value is strictly positive, i.e. a solution

$$(y^*, (s_l^c)^*, (s_u^c)^*, (s_l^x)^*, (s_u^x)^*)$$

to (12.4) so that

$$(l^c)^T (s_l^c)^* - (u^c)^T (s_u^c)^* + (l^x)^T (s_l^x)^* - (u^x)^T (s_u^x)^* > 0.$$

Such a solution implies that (12.4) is unbounded, and that (12.1) is infeasible.

Dual Infeasible Problems

If the problem (12.2) is infeasible (has no feasible solution), **MOSEK** will report a certi cate of dual infeasibility: The primal solution reported is the certi cate of infeasibility, and the dual solution is unde ned.

A certi cate of dual infeasibility is a feasible solution to the modi ed primal problem

$$\begin{array}{lccccc} \text{minimize} & & & c^T x & & \\ \text{subject to} & \hat{l}^c & \leq & Ax & \leq & \hat{u}^c, \\ & \hat{l}^x & \leq & x & \leq & \hat{u}^x, \end{array} \tag{12.5}$$

where

$$\hat{l}_i^c = \left\{ \begin{array}{ll} 0 & \text{if } l_i^c > -\infty, \\ -\infty & \text{otherwise,} \end{array} \right\} \quad \text{and} \quad \hat{u}_i^c := \left\{ \begin{array}{ll} 0 & \text{if } u_i^c < \infty, \\ \infty & \text{otherwise,} \end{array} \right\}$$

and

$$\hat{l}_j^x = \left\{ \begin{array}{ll} 0 & \text{if } l_j^x > -\infty, \\ -\infty & \text{otherwise,} \end{array} \right\} \quad \text{and} \quad \hat{u}_j^x := \left\{ \begin{array}{ll} 0 & \text{if } u_j^x < \infty, \\ \infty & \text{otherwise,} \end{array} \right\}$$

such that

$$c^T x < 0.$$

Such a solution implies that (12.5) is unbounded, and that (12.2) is infeasible.

In case that both the primal problem (12.1) and the dual problem (12.2) are infeasible, **MOSEK** will report only one of the two possible certi cates which one is not de ned (**MOSEK** returns the rst certi cate found).

12.1.3 Minimalization vs. Maximalization

When the objective sense of problem (12.1) is maximization, i.e.

$$\begin{array}{lccccc} \text{maximize} & & & c^T x + c^f & & \\ \text{subject to} & l^c & \leq & Ax & \leq & u^c, \\ & l^x & \leq & x & \leq & u^x, \end{array}$$

the objective sense of the dual problem changes to minimization, and the domain of all dual variables changes sign in comparison to (12.2). The dual problem thus takes the form

$$\begin{array}{ll} \text{minimize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x + c^f \\ \text{subject to} & \\ & A^T y + s_l^x - s_u^x = c, \\ & -y + s_l^c - s_u^c = 0, \\ & s_l^c, s_u^c, s_l^x, s_u^x \leq 0. \end{array}$$

$$\mathcal{Q}^n = \left\{ x \in \mathbb{R}^n : x_1 \geq \sqrt{\sum_{j=2}^{n} x_j^2} \right\}.$$

- Rotated quadratic cone

$$\mathcal{Q}_r^n = \left\{ x \in \mathbb{R}^n : 2x_1x_2 \geq \sum_{j=3}^{n} x_j^2, \quad x_1 \geq 0, \quad x_2 \geq 0 \right\}.$$

- Primal exponential cone

$$K_{\exp} = \left\{ x \in \mathbb{R}^3 : x_1 \geq x_2 \exp(x_3/x_2), \quad x_1, x_2 \geq 0 \right\}$$

  as well as its dual

$$K_{\exp}^* = \left\{ x \in \mathbb{R}^3 : x_1 \geq -x_3 e^{-1} \exp(x_2/x_3), \quad x_3 \leq 0, x_1 \geq 0 \right\}.$$

- Primal power cone (with parameter $0 < \alpha < 1$)

$$\mathcal{P}_n^{\alpha,1-\alpha} = \left\{ x \in \mathbb{R}^n : x_1^\alpha x_2^{1-\alpha} \geq \sqrt{\sum_{j=3}^{n} x_j^2}, \quad x_1, x_2 \geq 0 \right\}$$

  as well as its dual

$$(\mathcal{P}_n^{\alpha,1-\alpha})^* = \left\{ x \in \mathbb{R}^n : \left(\frac{x_1}{\alpha}\right)^\alpha \left(\frac{x_2}{1-\alpha}\right)^{1-\alpha} \geq \sqrt{\sum_{j=3}^{n} x_j^2}, \quad x_1, x_2 \geq 0 \right\}.$$

MOSEK supports also the cone of positive semide nite matrices. Since that is handled through a separate interface, we discuss it in Sec. 12.3.

12.2.1 Duality for Conic Optimization

Corresponding to the primal problem (12.7), there is a dual problem

$$\begin{array}{ll} \text{maximize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x + c^f \\ \text{subject to} & \\ & \begin{array}{c} A^T y + s_l^x - s_u^x + s_n^x = c \\ -y + s_l^c - s_u^c = 0, \\ s_l^c, s_u^c, s_l^x, s_u^x \geq 0, \\ s_n^x \in \mathcal{K}^*, \end{array} \end{array} \tag{12.8}$$

where the dual cone $\mathcal{K}^*$ is a Cartesian product of the cones dual to $\mathcal{K}_t$. In practice this means that s_n^x has one entry for each entry in x. Please note that the dual problem of the dual problem is identical to the original primal problem.

If a bound in the primal problem is plus or minus in nity, the corresponding dual variable is xed at 0, and we use the convention that the product of the bound value and the corresponding dual variable is 0. This is equivalent to removing variable $(s_l^x)_j$ from the dual problem. In other words:

$$l_j^x = -\infty \quad \Rightarrow \quad (s_l^x)_j = 0 \text{ and } l_j^x \cdot (s_l^x)_j = 0.$$

A solution

$$(y, s_l^c, s_u^c, s_l^x, s_u^x, s_n^x)$$

to the dual problem is feasible if it satis es all the constraints in (12.8). If (12.8) has at least one feasible solution, then (12.8) is *(dual) feasible*, otherwise the problem is *(dual) infeasible*.

A solution

$$(x^*, y^*, (s_l^c)^*, (s_u^c)^*, (s_l^x)^*, (s_u^x)^*, (s_n^x)^*)$$

is denoted a *primal-dual feasible solution*, if (x^*) is a solution to the primal problem (12.7) and $(y^*, (s_l^c)^*, (s_u^c)^*, (s_l^x)^*, (s_u^x)^*, (s_n^x)^*)$ is a solution to the corresponding dual problem (12.8). We also de ne an auxiliary vector

$$(x^c)^* := Ax^*$$

containing the activities of linear constraints.

For a primal-dual feasible solution we de ne the *duality gap* as the di erence between the primal and the dual objective value,

$$\begin{array}{l} c^T x^* + c^f - \left\{(l^c)^T (s_l^c)^* - (u^c)^T (s_u^c)^* + (l^x)^T (s_l^x)^* - (u^x)^T (s_u^x)^* + c^f\right\} \\ = \sum_{i=0}^{m-1} \left[(s_l^c)_i^* ((x_i^c)^* - l_i^c) + (s_u^c)_i^* (u_i^c - (x_i^c)^*)\right] \\ + \sum_{j=0}^{n-1} \left[(s_l^x)_j^* (x_j - l_j^x) + (s_u^x)_j^* (u_j^x - x_j^*)\right] + \sum_{j=0}^{n-1} (s_n^x)_j^* x_j^* \geq 0 \end{array} \tag{12.9}$$

where the rst relation can be obtained by transposing and multiplying the dual constraints (12.2) by x^* and $(x^c)^*$ respectively, and the second relation comes from the fact that each term in each sum is nonnegative. It follows that the primal objective will always be greater than or equal to the dual objective.

It is well-known that, under some non-degeneracy assumptions that exclude ill-posed cases, a conic optimization problem has an optimal solution if and only if there exist feasible primal-dual solution so that the duality gap is zero, or, equivalently, that the *complementarity conditions*

$$\begin{array}{rcll} (s_l^c)_i^* ((x_i^c)^* - l_i^c) & = & 0, & i = 0, \ldots, m-1, \\ (s_u^c)_i^* (u_i^c - (x_i^c)^*) & = & 0, & i = 0, \ldots, m-1, \\ (s_l^x)_j^* (x_j^* - l_j^x) & = & 0, & j = 0, \ldots, n-1, \\ (s_u^x)_j^* (u_j^x - x_j^*) & = & 0, & j = 0, \ldots, n-1, \\ \sum_{j=0}^{n-1} (s_n^x)_j^* x_j^* & = & 0. & \end{array} \tag{12.10}$$

are satis ed.

If (12.7) has an optimal solution and **MOSEK** solves the problem successfully, both the primal and dual solution are reported, including a status indicating the exact state of the solution.

12.2.2 Infeasibility for Conic Optimization

Primal Infeasible Problems

If the problem (12.7) is infeasible (has no feasible solution)**MOSEK** will report a certi cate of primal infeasibility: The dual solution reported is the certi cate of infeasibility, and the primal solution is unde ned.

A certi cate of primal infeasibility is a feasible solution to the modi ed dual problem

$$\begin{array}{ll} \text{maximize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x \\ \text{subject to} & \\ & \begin{array}{c} A^T y + s_l^x - s_u^x + s_n^x = 0, \\ -y + s_l^c - s_u^c = 0, \\ s_l^c, s_u^c, s_l^x, s_u^x \geq 0, \\ s_n^x \in \mathcal{K}^*, \end{array} \end{array} \tag{12.11}$$

such that the objective value is strictly positive, i.e. a solution

$$(y^*, (s_l^c)^*, (s_u^c)^*, (s_l^x)^*, (s_u^x)^*, (s_n^x)^*)$$

to (12.11) so that

$$(l^c)^T (s_l^c)^* - (u^c)^T (s_u^c)^* + (l^x)^T (s_l^x)^* - (u^x)^T (s_u^x)^* > 0.$$

Such a solution implies that (12.11) is unbounded, and that (12.7) is infeasible.

Dual Infeasible Problems

If the problem (12.8) is infeasible (has no feasible solution), **MOSEK** will report a certificate of dual infeasibility: The primal solution reported is the certificate of infeasibility, and the dual solution is undefined.

A certificate of dual infeasibility is a feasible solution to the modified primal problem

$$\begin{array}{lccccc} \text{minimize} & & & c^T x & & \\ \text{subject to} & \hat{l}^c & \leq & Ax & \leq & \hat{u}^c, \\ & \hat{l}^x & \leq & x & \leq & \hat{u}^x, \\ & & & x \in K, & & \end{array} \tag{12.12}$$

where

$$\hat{l}_i^c = \left\{ \begin{array}{ll} 0 & \text{if } l_i^c > -\infty, \\ -\infty & \text{otherwise,} \end{array} \right\} \quad \text{and} \quad \hat{u}_i^c := \left\{ \begin{array}{ll} 0 & \text{if } u_i^c < \infty, \\ \infty & \text{otherwise,} \end{array} \right\} \tag{12.13}$$

and

$$\hat{l}_j^x = \left\{ \begin{array}{ll} 0 & \text{if } l_j^x > -\infty, \\ -\infty & \text{otherwise,} \end{array} \right\} \quad \text{and} \quad \hat{u}_j^x := \left\{ \begin{array}{ll} 0 & \text{if } u_j^x < \infty, \\ \infty & \text{otherwise,} \end{array} \right\} \tag{12.14}$$

such that

$$c^T x < 0.$$

Such a solution implies that (12.12) is unbounded, and that (12.8) is infeasible.

In case that both the primal problem (12.7) and the dual problem (12.8) are infeasible, **MOSEK** will report only one of the two possible certificates which one is not defined (**MOSEK** returns the first certificate found).

12.2.3 Minimalization vs. Maximalization

When the objective sense of problem (12.7) is maximization, i.e.

$$\begin{array}{lccccc} \text{maximize} & & & c^T x + c^f & & \\ \text{subject to} & l^c & \leq & Ax & \leq & u^c, \\ & l^x & \leq & x & \leq & u^x, \\ & & & x \in \mathcal{K}, & & \end{array}$$

the objective sense of the dual problem changes to minimization, and the domain of all dual variables changes sign in comparison to (12.2). The dual problem thus takes the form

$$\begin{array}{ll} \text{minimize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x + c^f \\ \text{subject to} & A^T y + s_l^x - s_u^x + s_n^x = c, \\ & -y + s_l^c - s_u^c = 0, \\ & s_l^c, s_u^c, s_l^x, s_u^x \leq 0, \\ & -s_n^x \in \mathcal{K}^* \end{array}$$

This means that the duality gap, defined in (12.9) as the primal minus the dual objective value, becomes nonpositive. It follows that the dual objective will always be greater than or equal to the primal objective. The primal infeasibility certificate will be reported by **MOSEK** as a solution to the system

$$\begin{array}{c} A^T y + s_l^x - s_u^x + s_n^x = 0, \\ -y + s_l^c - s_u^c = 0, \\ s_l^c, s_u^c, s_l^x, s_u^x \leq 0, \\ -s_n^x \in \mathcal{K}^* \end{array} \tag{12.15}$$

such that the objective value is strictly negative

$$(l^c)^T (s_l^c)^* - (u^c)^T (s_u^c)^* + (l^x)^T (s_l^x)^* - (u^x)^T (s_u^x)^* < 0.$$

Similarly, the certificate of dual infeasibility is an x satisfying the requirements of (12.12) such that $c^T x > 0$.

12.3 Semidefinite Optimization

Semidefinite optimization is an extension of conic optimization (see Sec. 12.2) allowing positive semide - nite matrix variables to be used in addition to the usual scalar variables. All the other parts of the input are de ned exactly as in Sec. 12.2, and the discussion from that section applies verbatim to all properties of problems with semide nite variables. We only brie y indicate how the corresponding formulae should be modi ed with semide nite terms.

A semide nite optimization problem can be written as

$$\begin{array}{lrcccl} \text{minimize} & & & \sum_{j=0}^{n-1} c_j x_j + \sum_{j=0}^{p-1} \langle \overline{C}_j, \overline{X}_j \rangle + c^f & & \\ \text{subject to} & l_i^c & \leq & \sum_{j=0}^{n-1} a_{ij} x_j + \sum_{j=0}^{p-1} \langle \overline{A}_{ij}, \overline{X}_j \rangle & \leq & u_i^c, \quad i = 0, \ldots, m-1 \\ & l_j^x & \leq & x_j & \leq & u_j^x, \quad j = 0, \ldots, n-1 \\ & & & x \in \mathcal{K}, & & \\ & & & \overline{X}_j \in \mathcal{S}_+^{r_j}, & & \quad j = 0, \ldots, p-1 \end{array} \tag{12.16}$$

where the problem has p symmetric positive semide nite variables $\overline{X}_j \in \mathcal{S}_+^{r_j}$ of dimension r_j with symmetric coe cient matrices $\overline{C}_j \in \mathcal{S}^{r_j}$ and $\overline{A}_{i,j} \in \mathcal{S}^{r_j}$. We use standard notation for the matrix inner product, i.e., for $U, V \in \mathbb{R}^{m \times n}$ we have

$$\langle U, V \rangle := \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} U_{ij} V_{ij}.$$

As always we write $A = (a_{i,j})$ for the linear coe cient matrix.

Duality

The de nition of the dual problem (12.8) becomes:

$$\begin{array}{ll} \text{maximize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x + c^f \\ \text{subject to} & \\ & A^T y + s_l^x - s_u^x + s_n^x = c \\ & -y + s_l^c - s_u^c = 0, \\ & \overline{C}_j - \sum_{i=0}^{m-1} y_i \overline{A}_{ij} = \overline{S}_j, \qquad j = 0, \ldots, p-1 \\ & s_l^c, s_u^c, s_l^x, s_u^x \geq 0, \\ & s_n^x \in \mathcal{K}^*, \\ & \overline{S}_j \in \mathcal{S}_+^{r_j}, \qquad j = 0, \ldots, p-1. \end{array} \tag{12.17}$$

The duality gap (12.9) is computed as:

$$\begin{array}{l} c^T x^* + c^f - \left\{ (l^c)^T (s_l^c)^* - (u^c)^T (s_u^c)^* + (l^x)^T (s_l^x)^* - (u^x)^T (s_u^x)^* + c^f \right\} \\ = \sum_{i=0}^{m-1} \left[(s_l^c)_i^* ((x_i^c)^* - l_i^c) + (s_u^c)_i^* (u_i^c - (x_i^c)^*) \right] \\ + \sum_{j=0}^{n-1} \left[(s_l^x)_j^* (x_j - l_j^x) + (s_u^x)_j^* (u_j^x - x_j^*) \right] + \sum_{j=0}^{n-1} (s_n^x)_j^* x_j^* + \sum_{j=0}^{p-1} \langle \overline{X}_j, \overline{S}_j \rangle \geq 0. \end{array} \tag{12.18}$$

Complementarity conditions (12.10) include the additional relation:

$$\langle \overline{X}_j, \overline{S}_j \rangle = 0 \quad j = 0, \ldots, p-1. \tag{12.19}$$

Infeasibility

A certi cate of primal infeasibility (12.11) is now a feasible solution to:

$$\begin{array}{ll} \text{maximize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x \\ \text{subject to} & \\ & A^T y + s_l^x - s_u^x + s_n^x = 0, \\ & -y + s_l^c - s_u^c = 0, \\ & \sum_{i=0}^{m-1} y_i \overline{A}_{ij} + \overline{S}_j = 0, \qquad j = 0, \ldots, p-1 \\ & s_l^c, s_u^c, s_l^x, s_u^x \geq 0, \\ & s_n^x \in \mathcal{K}^*, \\ & \overline{S}_j \in \mathcal{S}_+^{r_j}, \qquad j = 0, \ldots, p-1. \end{array} \tag{12.20}$$

such that the objective value is strictly positive.

Similarly, a dual infeasibility certi cate (12.12) is a feasible solution to

$$\begin{array}{lrcccl} \text{minimize} & & & \sum_{j=0}^{n-1} c_j x_j + \sum_{j=0}^{p-1} \langle \overline{C}_j, \overline{X}_j \rangle & & \\ \text{subject to} & \hat{l}_i^c & \leq & \sum_{j=0}^{n-1} a_{ij} x_j + \sum_{j=0}^{p-1} \langle \overline{A}_{ij}, \overline{X}_j \rangle & \leq & \hat{u}_i^c, \quad i = 0, \ldots, m-1 \\ & \hat{l}_j^x & \leq & x_j & \leq & \hat{u}_j^x, \quad j = 0, \ldots, n-1 \\ & & & x \in \mathcal{K}, & & \\ & & & \overline{X}_j \in \mathcal{S}_+^{r_j}, & & \quad j = 0, \ldots, p-1 \end{array} \tag{12.21}$$

where the modi ed bounds are as in (12.13) and (12.14) and the objective value is strictly negative.

12.4 Quadratic and Quadratically Constrained Optimization

A convex quadratic and quadratically constrained optimization problem has the form

$$\begin{array}{lrcccl} \text{minimize} & & & \frac{1}{2} x^T Q^o x + c^T x + c^f & & \\ \text{subject to} & l_k^c & \leq & \frac{1}{2} x^T Q^k x + \sum_{j=0}^{n-1} a_{kj} x_j & \leq & u_k^c, \quad k = 0, \ldots, m-1, \\ & l_j^x & \leq & x_j & \leq & u_j^x, \quad j = 0, \ldots, n-1, \end{array} \tag{12.22}$$

where all variables and bounds have the same meaning as for linear problems (see Sec. 12.1) and Q^o and all Q^k are symmetric matrices. Moreover, for convexity, Q^o must be a positive semide nite matrix and Q^k must satisfy

$$\begin{array}{rcl} -\infty < l_k^c & \Rightarrow & Q^k \text{ is negative semide nite,} \\ u_k^c < \infty & \Rightarrow & Q^k \text{ is positive semide nite,} \\ -\infty < l_k^c \leq u_k^c < \infty & \Rightarrow & Q^k = 0. \end{array}$$

The convexity requirement is very important and **MOSEK** checks whether it is ful lled.

12.4.1 A Recommendation

Any convex quadratic optimization problem can be reformulated as a conic quadratic optimization problem, see Modeling Cookbook and [And13]. In fact **MOSEK** does such conversion internally as a part of the solution process for the following reasons:

- the conic optimizer is numerically more robust than the one for quadratic problems.
- the conic optimizer is usually faster because quadratic cones are simpler than quadratic functions, even though the conic reformulation usually has more constraints and variables than the original quadratic formulation.
- it is easy to dualize the conic formulation if deemed worthwhile potentially leading to (huge) computational savings.

However, instead of relying on the automatic reformulation we recommend to formulate the problem as a conic problem from scratch because:

- it saves the computational overhead of the reformulation including the convexity check. A conic problem is convex by construction and hence no convexity check is needed for conic problems.
- usually the modeler can do a better reformulation than the automatic method because the modeler can exploit the knowledge of the problem at hand.

To summarize we recommend to formulate quadratic problems and in particular quadratically constrained problems directly in conic form.

12.4.2 Duality for Quadratic and Quadratically Constrained Optimization

The dual problem corresponding to the quadratic and quadratically constrained optimization problem (12.22) is given by

$$\begin{array}{ll} \text{maximize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x + \frac{1}{2} x^T \left\{ \sum_{k=0}^{m-1} y_k Q^k - Q^o \right\} x + c^f \\ \text{subject to} & A^T y + s_l^x - s_u^x + \left\{ \sum_{k=0}^{m-1} y_k Q^k - Q^o \right\} x = c, \\ & -y + s_l^c - s_u^c = 0, \\ & s_l^c, s_u^c, s_l^x, s_u^x \geq 0. \end{array} \tag{12.23}$$

The dual problem is related to the dual problem for linear optimization (see Sec. 12.1.1), but depends on the variable x which in general can not be eliminated. In the solutions reported by **MOSEK**, the value of x is the same for the primal problem (12.22) and the dual problem (12.23).

12.4.3 Infeasibility for Quadratic Optimization

In case **MOSEK** nds a problem to be infeasible it reports a certi cate of infeasibility. We write them out explicitly for quadratic problems, that is when $Q^k = 0$ for all k and quadratic terms appear only in the objective Q^o. In this case the constraints both in the primal and dual problem are linear, and **MOSEK** produces for them the same infeasibility certi cate as for linear problems.

The certi cate of primal infeasibility is a solution to the problem (12.4) such that the objective value is strictly positive.

The certi cate of dual infeasibility is a solution to the problem (12.5) together with an additional constraint

$$Q^o x = 0$$

such that the objective value is strictly negative.

12.5 A□ne Conic Constraints

Optimization Toolbox for MATLAB allows conic problems to be speci ed in another format, namely with *affine conic constraints*. A conic problem can thus be speci ed as:

$$\begin{array}{lrcccll} \text{minimize} & & & \sum_{j=1}^n c_j x_j + \sum_{j=1}^p \langle \overline{C}_j, \overline{X}_j \rangle + c^f & & & \\ \text{subject to} & l_i^c & \leq & \sum_{j=1}^n a_{ij} x_j + \sum_{j=1}^p \langle \overline{A}_{ij}, \overline{X}_j \rangle & \leq & u_i^c, & i = 1, \ldots, m, \\ & l_j^x & \leq & x_j & \leq & u_j^x, & j = 1, \ldots, n, \\ & & & Fx + g \in \mathcal{K}, & & & \\ & & & \overline{X}_j \in \mathcal{S}_+^{r_j}, & & & j = 1, \ldots, p \end{array} \tag{12.24}$$

where all the data has the same meaning as in Sec. 12.2 and Sec. 12.3 and $F \in \mathbb{R}^{k \times n}$, $g \in \mathbb{R}^k$ speci y the a ne conic constraint.

Duality

The dual of problem (12.24) is

$$\begin{array}{ll} \text{maximize} & (l^c)^T s_l^c - (u^c)^T s_u^c + (l^x)^T s_l^x - (u^x)^T s_u^x - \dot{y}^T g + c^f \\ \text{subject to} & \\ & A^T y + s_l^x - s_u^x + F^T \dot{y} = c, \\ & -y + s_l^c - s_u^c = 0, \\ & \overline{C}_j - \sum_{i=0}^{m-1} y_i \overline{A}_{ij} = \overline{S}_j, \qquad j = 0, \ldots, p-1 \\ & s_l^c, s_u^c, s_l^x, s_u^x \geq 0, \\ & \dot{y} \in \mathcal{K}^*, \\ & \overline{S}_j \in \mathcal{S}_+^{r_j}, \qquad j = 0, \ldots, p-1. \end{array} \tag{12.25}$$

Duality and infeasibility cer cates behave analogously as in Sec. 12.2.

Remark

A problem of this form is internally converted into the problem:

$$
\begin{array}{llcccll}
\text{minimize} & & & \sum_{j=1}^{n} c_j x_j + \sum_{j=1}^{p} \left\langle \overline{C}_j, \overline{X}_j \right\rangle + c^f & & & \\
\text{subject to} & l_i^c & \leq & \sum_{j=1}^{n} a_{ij} x_j + \sum_{j=1}^{p} \left\langle \overline{A}_{ij}, \overline{X}_j \right\rangle & \leq & u_i^c, & i = 1, \ldots, m, \\
 & g_i & \leq & z_i - \sum_{j=1}^{n} f_{ij} x_j & \leq & g_i & i = 1, \ldots, k, \\
 & l_j^x & \leq & x_j & \leq & u_j^x, & j = 1, \ldots, n, \\
 & & & z \in \mathcal{K}, & & & \\
 & & & \overline{X}_j \in \mathcal{S}_+^{r_j}, & & & j = 1, \ldots, p
\end{array}
\tag{12.26}
$$

which conforms with the format in Sec. 12.2 and Sec. 12.3. The reformulated problem has $n+k$ variables, $m+k$ linear constraints and in total k variables in cones. The new columns and rows are appended at the end of the original ones. If a problem with a ne conic constraints is saved to a le then this reformulation will be written.

Chapter 13

Optimizers

The most essential part of **MOSEK** are the optimizers:

- *primal simplex* (linear problems),
- *dual simplex* (linear problems),
- *interior-point* (linear, quadratic and conic problems),
- *mixed-integer* (problems with integer variables).

The structure of a successful optimization process is roughly:

- **Presolve**
  1. *Elimination*: Reduce the size of the problem.
  2. *Dualizer*: Choose whether to solve the primal or the dual form of the problem.
  3. *Scaling*: Scale the problem for better numerical stability.
- **Optimization**
  1. *Optimize*: Solve the problem using selected method.
  2. *Terminate*: Stop the optimization when speci c termination criteria have been met.
  3. *Report*: Return the solution or an infeasibility certi cate.

The preprocessing stage is transparent to the user, but useful to know about for tuning purposes. The purpose of the preprocessing steps is to make the actual optimization more e cient and robust. We discuss the details of the above steps in the following sections.

13.1 Presolve

Before an optimizer actually performs the optimization the problem is preprocessed using the so-called presolve. The purpose of the presolve is to

1. remove redundant constraints,
2. eliminate xed variables,
3. remove linear dependencies,
4. substitute out (implied) free variables, and
5. reduce the size of the optimization problem in general.

After the presolved problem has been optimized the solution is automatically postsolved so that the returned solution is valid for the original problem. Hence, the presolve is completely transparent. For further details about the presolve phase, please see *[AA95]* and *[AGMX96]*.

It is possible to ne-tune the behavior of the presolve or to turn it o entirely. If presolve consumes too much time or memory compared to the reduction in problem size gained it may be disabled. This is done by setting the parameter `MSK_IPAR_PRESOLVE_USE` to `"MSK_PRESOLVE_MODE_OFF"`. The two most time-consuming steps of the presolve are

Scaling

Problems containing data with large and/or small coe cients, say $1.0e+9$ or $1.0e-7$, are often hard to solve. Signi cant digits may be truncated in calculations with nite precision, which can result in the optimizer relying on inaccurate data. Since computers work in nite precision, extreme coe cients should be avoided. In general, data around the same *order of magnitude* is preferred, and we will refer to a problem, satisfying this loose property, as being *well-scaled*. If the problem is not well scaled, **MOSEK** will try to scale (multiply) constraints and variables by suitable constants. **MOSEK** solves the scaled problem to improve the numerical properties.

The scaling process is transparent, i.e. the solution to the original problem is reported. It is important to be aware that the optimizer terminates when the termination criterion is met on the scaled problem, therefore signi cant primal or dual infeasibilities may occur after unscaling for badly scaled problems. The best solution of this issue is to reformulate the problem, making it better scaled.

By default **MOSEK** heuristically chooses a suitable scaling. The scaling for interior-point and simplex optimizers can be controlled with the parameters `MSK_IPAR_INTPNT_SCALING` and `MSK_IPAR_SIM_SCALING` respectively.

13.2 Linear Optimization

13.2.1 Optimizer Selection

Two di erent types of optimizers are available for linear problems: The default is an interior-point method, and the alternative is the simplex method (primal or dual). The optimizer can be selected using the parameter `MSK_IPAR_OPTIMIZER`.

The Interior-point or the Simplex Optimizer?

Given a linear optimization problem, which optimizer is the best: the simplex or the interior-point optimizer? It is impossible to provide a general answer to this question. However, the interior-point optimizer behaves more predictably: it tends to use between 20 and 100 iterations, almost independently of problem size, but cannot perform warm-start. On the other hand the simplex method can take advantage of an initial solution, but is less predictable from cold-start. The interior-point optimizer is used by default.

The Primal or the Dual Simplex Variant?

MOSEK provides both a primal and a dual simplex optimizer. Predicting which simplex optimizer is faster is impossible, however, in recent years the dual optimizer has seen several algorithmic and computational improvements, which, in our experience, make it faster on average than the primal version. Still, it depends much on the problem structure and size. Setting the `MSK_IPAR_OPTIMIZER` parameter to `"MSK_OPTIMIZER_FREE_SIMPLEX"` instructs **MOSEK** to choose one of the simplex variants automatically.

To summarize, if you want to know which optimizer is faster for a given problem type, it is best to try all the options.

13.2.2 The Interior-point Optimizer

The purpose of this section is to provide information about the algorithm employed in the **MOSEK** interior-point optimizer for linear problems and about its termination criteria.

The homogeneous primal-dual problem

In order to keep the discussion simple it is assumed that **MOSEK** solves linear optimization problems of standard form

$$\begin{array}{lll} \text{minimize} & c^T x & \\ \text{subject to} & Ax & = \quad b, \\ & x \geq 0. & \end{array} \tag{13.1}$$

This is in fact what happens inside $\mathbf{MOSEK}$; for e ciency reasons $\mathbf{MOSEK}$ converts the problem to standard form before solving, then converts it back to the input form when reporting the solution.

Since it is not known beforehand whether problem (13.1) has an optimal solution, is primal infeasible or is dual infeasible, the optimization algorithm must deal with all three situations. This is the reason why $\mathbf{MOSEK}$ solves the so-called homogeneous model

$$\begin{array}{rcl} Ax - b\tau & = & 0, \\ A^T y + s - c\tau & = & 0, \\ -c^T x + b^T y - \kappa & = & 0, \\ x, s, \tau, \kappa & \geq & 0, \end{array} \tag{13.2}$$

where y and s correspond to the dual variables in (13.1), and τ and κ are two additional scalar variables. Note that the homogeneous model (13.2) always has solution since

$$(x, y, s, \tau, \kappa) = (0, 0, 0, 0, 0)$$

is a solution, although not a very interesting one. Any solution

$$(x^*, y^*, s^*, \tau^*, \kappa^*)$$

to the homogeneous model (13.2) satis es

$$x_j^* s_j^* = 0 \text{ and } \tau^* \kappa^* = 0.$$

Moreover, there is always a solution that has the property $\tau^* + \kappa^* > 0$.

First, assume that $\tau^* > 0$. It follows that

$$\begin{array}{rcl} A\frac{x^*}{\tau^*} & = & b, \\ A^T \frac{y^*}{\tau^*} + \frac{s^*}{\tau^*} & = & c, \\ -c^T \frac{x^*}{\tau^*} + b^T \frac{y^*}{\tau^*} & = & 0, \\ x^*, s^*, \tau^*, \kappa^* & \geq & 0. \end{array}$$

This shows that $\frac{x^*}{\tau^*}$ is a primal optimal solution and $(\frac{y^*}{\tau^*}, \frac{s^*}{\tau*})$ is a dual optimal solution; this is reported as the optimal interior-point solution since

$$(x, y, s) = \left\{ \frac{x^*}{\tau^*}, \frac{y^*}{\tau^*}, \frac{s^*}{\tau^*} \right\}$$

is a primal-dual optimal solution (see Sec. 12.1 for the mathematical background on duality and optimality).

On other hand, if $\kappa^* > 0$ then

$$\begin{array}{rcl} Ax^* & = & 0, \\ A^T y^* + s^* & = & 0, \\ -c^T x^* + b^T y^* & = & \kappa^*, \\ x^*, s^*, \tau^*, \kappa^* & \geq & 0. \end{array}$$

This implies that at least one of

$$c^T x^* < 0 \tag{13.3}$$

or

$$b^T y^* > 0 \tag{13.4}$$

is satis ed. If (13.3) is satis ed then x^* is a certi cate of dual infeasibility, whereas if (13.4) is satis ed then y^* is a certi cate of primal infeasibility.

In summary, by computing an appropriate solution to the homogeneous model, all information required for a solution to the original problem is obtained. A solution to the homogeneous model can be computed using a primal-dual interior-point algorithm *[And09]*.

Interior-point Termination Criterion

For e ciency reasons it is not practical to solve the homogeneous model exactly. Hence, an exact optimal solution or an exact infeasibility certi cate cannot be computed and a reasonable termination criterion has to be employed.

In the k-th iteration of the interior-point algorithm a trial solution

$$(x^k, y^k, s^k, \tau^k, \kappa^k)$$

to homogeneous model is generated, where

$$x^k, s^k, \tau^k, \kappa^k > 0.$$

Optimal case

Whenever the trial solution satis es the criterion

$$\begin{aligned} \left\| A\frac{x^k}{\tau^k} - b \right\|_\infty &\leq \epsilon_p(1 + \|b\|_\infty), \\ \left\| A^T \frac{y^k}{\tau^k} + \frac{s^k}{\tau^k} - c \right\|_\infty &\leq \epsilon_d(1 + \|c\|_\infty), \text{ and} \\ \min\left(\frac{(x^k)^T s^k}{(\tau^k)^2}, |\frac{c^T x^k}{\tau^k} - \frac{b^T y^k}{\tau^k}|\right) &\leq \epsilon_g \max\left(1, \frac{\min(|c^T x^k|, |b^T y^k|)}{\tau^k}\right), \end{aligned} \tag{13.5}$$

the interior-point optimizer is terminated and

$$\frac{(x^k, y^k, s^k)}{\tau^k}$$

is reported as the primal-dual optimal solution. The interpretation of (13.5) is that the optimizer is terminated if

- $\frac{x^k}{\tau^k}$ is approximately primal feasible,
- $\left\{\frac{y^k}{\tau^k}, \frac{s^k}{\tau^k}\right\}$ is approximately dual feasible, and
- the duality gap is almost zero.

Dual infeasibility certificate

On the other hand, if the trial solution satis es

$$-\epsilon_i c^T x^k > \frac{\|c\|_\infty}{\max(1, \|b\|_\infty)} \left\| Ax^k \right\|_\infty$$

then the problem is declared dual infeasible and x^k is reported as a certi cate of dual infeasibility. The motivation for this stopping criterion is as follows: First assume that $\left\| Ax^k \right\|_\infty = 0$; then x^k is an exact certi cate of dual infeasibility. Next assume that this is not the case, i.e.

$$\left\| Ax^k \right\|_\infty > 0,$$

and de ne

$$\bar{x} := \epsilon_i \frac{\max(1, \|b\|_\infty)}{\|Ax^k\|_\infty \|c\|_\infty} x^k.$$

It is easy to verify that

$$\|A\bar{x}\|_\infty = \epsilon_i \frac{\max(1, \|b\|_\infty)}{\|c\|_\infty} \text{ and } -c^T \bar{x} > 1,$$

which shows $\bar{x}$ is an approximate certi cate of dual infeasibility, where ε_i controls the quality of the approximation. A smaller value means a better approximation.

Primal infeasibility certificate

Finally, if

$$\epsilon_i b^T y^k > \frac{\|b\|_\infty}{\max(1, \|c\|_\infty)} \left\|A^T y^k + s^k\right\|_\infty$$

then y^k is reported as a certi cate of primal infeasibility.

Adjusting optimality criteria

It is possible to adjust the tolerancesε_p, ε_d, ε_g and ε_i using parameters; see table for details.

Table 13.1: Parameters employed in termination criterion

ToleranceParameter	name
ε_p	*MSK_DPAR_INTPNT_TOL_PFEAS*
ε_d	*MSK_DPAR_INTPNT_TOL_DFEAS*
ε_g	*MSK_DPAR_INTPNT_TOL_REL_GAP*
ε_i	*MSK_DPAR_INTPNT_TOL_INFEAS*

The default values of the termination tolerances are chosen such that for a majority of problems appearing in practice it is not possible to achieve much better accuracy. Therefore, tightening the tolerances usually is not worthwhile. However, an inspection of (13.5) reveals that the quality of the solution depends on$\|b\|_\infty$ and $\|c\|_\infty$; the smaller the norms are, the better the solution accuracy.

The interior-point method as implemented by **MOSEK** will converge toward optimality and primal and dual feasibility at the same rate *[And09]*. This means that if the optimizer is stopped prematurely then it is very unlikely that either the primal or dual solution is feasible. Another consequence is that in most cases all the tolerancesε_p, ε_d, ε_g and ε_i, have to be relaxed together to achieve an e ect.

If the optimizer terminates without locating a solution that satis es the termination criteria, for example because of a stall or other numerical issues, then it will check if the solution found up to that point satis es the same criteria with all tolerances multiplied by the value of *MSK_DPAR_INTPNT_CO_TOL_NEAR_REL*. If this is the case, the solution is still declared as optimal.

The basis identi cation discussed in Sec. 13.2.2 requires an optimal solution to work well; hence basis identi cation should be turned o if the termination criterion is relaxed.

To conclude the discussion in this section, relaxing the termination criterion is usually not worthwhile.

Basis Identification

An interior-point optimizer does not return an optimal basic solution unless the problem has a unique primal and dual optimal solution. Therefore, the interior-point optimizer has an optional post-processing step that computes an optimal basic solution starting from the optimal interior-point solution. More information about the basis identi cation procedure may be found in *[AY96]*. In the following we provide an overall idea of the procedure.

There are some cases in which a basic solution could be more valuable:

- a basic solution is often more accurate than an interior-point solution,
- a basic solution can be used to warm-start the simplex algorithm in case of reoptimization,
- a basic solution is in general more sparse, i.e. more variables are xed to zero. This is particularly appealing when solving continuous relaxations of mixed integer problems, as well as in all applications in which sparser solutions are preferred.

To illustrate how the basis identi cation routine works, we use the following trivial example:

$$\begin{array}{lll} \text{minimize} & x+y & \\ \text{subject to} & x+y & = \quad 1, \\ & x, y \geq 0. & \end{array}$$

It is easy to see that all feasible solutions are also optimal. In particular, there are two basic solutions, namely

$$\begin{array}{rcl} (x_1^*, y_1^*) & = & (1, 0), \\ (x_2^*, y_2^*) & = & (0, 1). \end{array}$$

The interior point algorithm will actually converge to the center of the optimal set, i.e. to $(x^*, y^*) = (1/2, 1/2)$ (to see this in **MOSEK** deactivate *Presolve*).

In practice, when the algorithm gets close to the optimal solution, it is possible to construct in polynomial time an initial basis for the simplex algorithm from the current interior point solution. This basis is used to warm-start the simplex algorithm that will provide the optimal basic solution. In most cases the constructed basis is optimal, or very few iterations are required by the simplex algorithm to make it optimal and hence the nal *clean-up* phase be short. However, for some cases of ill-conditioned problems the additional simplex clean up phase may take of lot a time.

By default **MOSEK** performs a basis identi cation. However, if a basic solution is not needed, the basis identi cation procedure can be turned o . The parameters

- *MSK_IPAR_INTPNT_BASIS*,
- *MSK_IPAR_BI_IGNORE_MAX_ITER*, and
- *MSK_IPAR_BI_IGNORE_NUM_ERROR*

control when basis identi cation is performed.

The type of simplex algorithm to be used (primal/dual) can be tuned with the parameter *MSK_IPAR_BI_CLEAN_OPTIMIZER*, and the maximum number of iterations can be set with *MSK_IPAR_BI_MAX_ITERATIONS*.

Finally, it should be mentioned that there is no guarantee on which basic solution will be returned.

The Interior-point Log

Below is a typical log output from the interior-point optimizer:

```
Optimizer  - threads                : 1
Optimizer  - solved problem         : the dual
Optimizer  - Constraints            : 2
Optimizer  - Cones                  : 0
Optimizer  - Scalar variables       : 6                 conic                  : 0
Optimizer  - Semi-definite variables: 0                 scalarized             : 0
Factor     - setup time             : 0.00              dense det. time        : 0.00
Factor     - ML order time          : 0.00              GP order time          : 0.00
Factor     - nonzeros before factor : 3                 after factor           : 3
Factor     - dense dim.             : 0                 flops                  : 7.00e+001
ITE PFEAS    DFEAS    GFEAS    PRSTATUS   POBJ              DOBJ              MU       TIME
0   1.0e+000 8.6e+000 6.1e+000 1.00e+000  0.000000000e+000  -2.208000000e+003 1.0e+000 0.00
1   1.1e+000 2.5e+000 1.6e-001 0.00e+000  -7.901380925e+003 -7.394611417e+003 2.5e+000 0.00
2   1.4e-001 3.4e-001 2.1e-002 8.36e-001  -8.113031650e+003 -8.055866001e+003 3.3e-001 0.00
3   2.4e-002 5.8e-002 3.6e-003 1.27e+000  -7.777530698e+003 -7.766471080e+003 5.7e-002 0.01
4   1.3e-004 3.2e-004 2.0e-005 1.08e+000  -7.668323435e+003 -7.668207177e+003 3.2e-004 0.01
5   1.3e-008 3.2e-008 2.0e-009 1.00e+000  -7.668000027e+003 -7.668000015e+003 3.2e-008 0.01
6   1.3e-012 3.2e-012 2.0e-013 1.00e+000  -7.667999994e+003 -7.667999994e+003 3.2e-012 0.01
```

The rst line displays the number of threads used by the optimizer and the second line indicates if the optimizer chose to solve the primal or dual problem (see *MSK_IPAR_INTPNT_SOLVE_FORM*). The next lines display the problem dimensions as seen by the optimizer, and the Factor... lines show various statistics. This is followed by the iteration log.

Using the same notation as in Sec. 13.2.2 the columns of the iteration log have the following meaning:

- ITE: Iteration index k.
- PFEAS $\left\|Ax^k - b\tau^k\right\|_\infty$. The numbers in this column should converge monotonically towards zero but may stall at low level due to rounding errors.
- DFEAS $\left\|A^T y^k + s^k - c\tau^k\right\|_\infty$. The numbers in this column should converge monotonically towards zero but may stall at low level due to rounding errors.
- GFEAS $|-c^T x^k + b^T y^k - \kappa^k|$. The numbers in this column should converge monotonically towards zero but may stall at low level due to rounding errors.
- PRSTATUS: This number converges to 1 if the problem has an optimal solution whereas it converges to -1 if that is not the case.

- POBJ $c^T x^k/\tau^k$. An estimate for the primal objective value.
- DOBJ $b^T y^k/\tau^k$. An estimate for the dual objective value.
- MU $\frac{(x^k)^T s^k + \tau^k \kappa^k}{n+1}$. The numbers in this column should always converge to zero.
- TIME Time spent since the optimization started.

13.2.3 The Simplex Optimizer

An alternative to the interior-point optimizer is the simplex optimizer. The simplex optimizer uses a di erent method that allows exploiting an initial guess for the optimal solution to reduce the solution time. Depending on the problem it may be faster or slower to use an initial guess; see Sec. 13.2.1 for a discussion. **MOSEK** provides both a primal and a dual variant of the simplex optimizer.

Simplex Termination Criterion

The simplex optimizer terminates when it nds an optimal basic solution or an infeasibility certi cate. A basic solution is optimal when it is primal and dual feasible; see Sec. 12.1 for a de nition of the primal and dual problem. Due to the fact that computations are performed in nite precision **MOSEK** allows violations of primal and dual feasibility within certain tolerances. The user can control the allowed primal and dual tolerances with the parameters *MSK_DPAR_BASIS_TOL_X* and *MSK_DPAR_BASIS_TOL_S*.

Setting the parameter *MSK_IPAR_OPTIMIZER* to *"MSK_OPTIMIZER_FREE_SIMPLEX"* instructs **MOSEK** to select automatically between the primal and the dual simplex optimizers. Hence **MOSEK** tries to choose the best optimizer for the given problem and the available solution. The same parameter can also be used to force one of the variants.

Starting From an Existing Solution

When using the simplex optimizer it may be possible to reuse an existing solution and thereby reduce the solution time signi cantly. When a simplex optimizer starts from an existing solution it is said to perform a *warm-start*. If the user is solving a sequence of optimization problems by solving the problem, making modi cations, and solving again, **MOSEK** will warm-start automatically.

By default **MOSEK** uses presolve when performing a warm-start. If the optimizer only needs very few iterations to nd the optimal solution it may be better to turn o the presolve.

Numerical Difficulties in the Simplex Optimizers

Though **MOSEK** is designed to minimize numerical instability, completely avoiding it is impossible when working in nite precision. **MOSEK** treats a numerically unexpected behavior event inside the optimizer as a *set-back*. The user can de ne how many set-backs the optimizer accepts; if that number is exceeded, the optimization will be aborted. Set-backs are a way to escape long sequences where the optimizer tries to recover from an unstable situation.

Examples of set-backs are: repeated singularities when factorizing the basis matrix, repeated loss of feasibility, degeneracy problems (no progress in objective) and other events indicating numerical di culties. If the simplex optimizer encounters a lot of set-backs the problem is usually badly scaled; in such a situation try to reformulate it into a better scaled problem. Then, if a lot of set-backs still occur, trying one or more of the following suggestions may be worthwhile:

- Raise tolerances for allowed primal or dual feasibility: increase the value of
  - *MSK_DPAR_BASIS_TOL_X*, and
  - *MSK_DPAR_BASIS_TOL_S*.
- Raise or lower pivot tolerance: Change the *MSK_DPAR_SIMPLEX_ABS_TOL_PIV* parameter.
- Switch optimizer: Try another optimizer.
- Switch o crash: Set both *MSK_IPAR_SIM_PRIMAL_CRASH* and *MSK_IPAR_SIM_DUAL_CRASH* to 0.
- Experiment with other pricing strategies: Try di erent values for the parameters

- *MSK_IPAR_SIM_PRIMAL_SELECTION* and
- *MSK_IPAR_SIM_DUAL_SELECTION*.

- If you are using warm-starts, in rare cases switching o this feature may improve stability. This is controlled by the *MSK_IPAR_SIM_HOTSTART* parameter.
- Increase maximum number of set-backs allowed controlled by *MSK_IPAR_SIM_MAX_NUM_SETBACKS*.
- If the problem repeatedly becomes infeasible try switching o the special degeneracy handling. See the parameter *MSK_IPAR_SIM_DEGEN* for details.

The Simplex Log

Below is a typical log output from the simplex optimizer:

```
Optimizer  - solved problem         : the primal
Optimizer  - Constraints            : 667
Optimizer  - Scalar variables       : 1424              conic                  : 0
Optimizer  - hotstart               : no
ITER       DEGITER(%)  PFEAS       DFEAS       POBJ                  DOBJ                  TIME␣
↪     TOTTIME
0          0.00        1.43e+05    NA          6.5584140832e+03      NA                    0.00␣
↪     0.02
1000       1.10        0.00e+00    NA          1.4588289726e+04      NA                    0.13␣
↪     0.14
2000       0.75        0.00e+00    NA          7.3705564855e+03      NA                    0.21␣
↪     0.22
3000       0.67        0.00e+00    NA          6.0509727712e+03      NA                    0.29␣
↪     0.31
4000       0.52        0.00e+00    NA          5.5771203906e+03      NA                    0.38␣
↪     0.39
4533       0.49        0.00e+00    NA          5.5018458883e+03      NA                    0.42␣
↪     0.44
```

The rst lines summarize the problem the optimizer is solving. This is followed by the iteration log, with the following meaning:

- ITER: Number of iterations.
- DEGITER(%): Ratio of degenerate iterations.
- PFEAS: Primal feasibility measure reported by the simplex optimizer. The numbers should be 0 if the problem is primal feasible (when the primal variant is used).
- DFEAS: Dual feasibility measure reported by the simplex optimizer. The number should be 0 if the problem is dual feasible (when the dual variant is used).
- POBJ: An estimate for the primal objective value (when the primal variant is used).
- DOBJ: An estimate for the dual objective value (when the dual variant is used).
- TIME: Time spent since this instance of the simplex optimizer was invoked (in seconds).
- TOTTIME: Time spent since optimization started (in seconds).

13.3 Conic Optimization - Interior-point optimizer

For conic optimization problems only an interior-point type optimizer is available.

13.3.1 The homogeneous primal-dual problem

The interior-point optimizer is an implementation of the so-called homogeneous and self-dual algorithm. For a detailed description of the algorithm, please see [ART03]. In order to keep our discussion simple we will assume that **MOSEK** solves a conic optimization problem of the form:

$$\begin{array}{lll} \text{minimize} & c^T x & \\ \text{subject to} & Ax & = & b, \\ & x \in \mathcal{K} & \end{array} \tag{13.6}$$

where K is a convex cone. The corresponding dual problem is

$$\begin{array}{lll} \text{maximize} & b^T y & \\ \text{subject to} & A^T y + s & = & c, \\ & s \in \mathcal{K}^* & \end{array} \tag{13.7}$$

where $\mathcal{K}^*$ is the dual cone of $\mathcal{K}$. See Sec. 12.2 for de nitions.

Since it is not known beforehand whether problem (13.6) has an optimal solution, is primal infeasible or is dual infeasible, the optimization algorithm must deal with all three situations. This is the reason that **MOSEK** solves the so-called homogeneous model

$$\begin{array}{rcl} Ax - b\tau & = & 0, \\ A^T y + s - c\tau & = & 0, \\ -c^T x + b^T y - \kappa & = & 0, \\ x & \in & \mathcal{K}, \\ s & \in & \mathcal{K}^*, \\ \tau, \kappa & \geq & 0, \end{array} \tag{13.8}$$

where y and s correspond to the dual variables in (13.6), and τ and κ are two additional scalar variables. Note that the homogeneous model (13.8) always has a solution since

$$(x, y, s, \tau, \kappa) = (0, 0, 0, 0, 0)$$

is a solution, although not a very interesting one. Any solution

$$(x^*, y^*, s^*, \tau^*, \kappa^*)$$

to the homogeneous model (13.8) satis es

$$(x^*)^T s^* + \tau^* \kappa^* = 0$$

i.e. complementarity. Observe that $x^* \in \mathcal{K}$ and $s^* \in \mathcal{K}^*$ implies

$$(x^*)^T s^* \geq 0$$

and therefore

$$\tau^* \kappa^* = 0.$$

since $\tau^*, \kappa^* \geq 0$. Hence, at least one of τ^* and κ^* is zero.

First, assume that $\tau^* > 0$ and hence $\kappa^* = 0$. It follows that

$$\begin{array}{rcl} A\frac{x^*}{\tau^*} & = & b, \\ A^T \frac{y^*}{\tau^*} + \frac{s^*}{\tau^*} & = & c, \\ -c^T \frac{x^*}{\tau^*} + b^T \frac{y^*}{\tau^*} & = & 0, \\ x^*/\tau^* & \in & \mathcal{K}, \\ s^*/\tau^* & \in & \mathcal{K}^*. \end{array}$$

This shows that $\frac{x^*}{\tau^*}$ is a primal optimal solution and $(\frac{y^*}{\tau^*}, \frac{s^*}{\tau^*})$ is a dual optimal solution; this is reported as the optimal interior-point solution since

$$(x, y, s) = \left(\frac{x^*}{\tau^*}, \frac{y^*}{\tau^*}, \frac{s^*}{\tau^*}\right)$$

is a primal-dual optimal solution.

On other hand, if $\kappa^* > 0$ then

$$\begin{array}{rcl} Ax^* & = & 0, \\ A^T y^* + s^* & = & 0, \\ -c^T x^* + b^T y^* & = & \kappa^*, \\ x^* & \in & \mathcal{K}, \\ s^* & \in & \mathcal{K}^*. \end{array}$$

This implies that at least one of

$$c^T x^* < 0 \tag{13.9}$$

or

$$b^T y^* > 0 \tag{13.10}$$

holds. If (13.9) is satis ed, then x^* is a certi cate of dual infeasibility, whereas if (13.10) holds then y^* is a certi cate of primal infeasibility.

In summary, by computing an appropriate solution to the homogeneous model, all information required for a solution to the original problem is obtained. A solution to the homogeneous model can be computed using a primal-dual interior-point algorithm *[And09]*.

13.3.2 Interior-point Termination Criterion

Since computations are performed in nite precision, and for e ciency reasons, it is not possible to solve the homogeneous model exactly in general. Hence, an exact optimal solution or an exact infeasibility certi cate cannot be computed and a reasonable termination criterion has to be employed.

In every iteration k of the interior-point algorithm a trial solution

$$(x^k, y^k, s^k, \tau^k, \kappa^k)$$

to the homogeneous model is generated, where

$$x^k \in \mathcal{K}, s^k \in \mathcal{K}^*, \tau^k, \kappa^k > 0.$$

Therefore, it is possible to compute the values:

$$\begin{array}{rcl} \rho_p^k & = & \text{arg min}_\rho \left\{ \rho \mid \left\| A\frac{x^k}{\tau^k} - b \right\|_\infty \le \rho\varepsilon_p(1 + \|b\|_\infty) \right\}, \\ \rho_d^k & = & \text{arg min}_\rho \left\{ \rho \mid \left\| A^T\frac{y^k}{\tau^k} + \frac{s^k}{\tau^k} - c \right\|_\infty \le \rho\varepsilon_d(1 + \|c\|_\infty) \right\}, \\ \rho_g^k & = & \text{arg min}_\rho \left\{ \rho \mid \left(\frac{(x^k)^T s^k}{(\tau^k)^2}, \left|\frac{c^T x^k}{\tau^k} - \frac{b^T y^k}{\tau^k}\right| \right) \le \rho\varepsilon_g \max\left(1, \frac{\min(|c^T x^k|, |b^T y^k|)}{\tau^k}\right) \right\}, \\ \rho_{pi}^k & = & \text{arg min}_\rho \left\{ \rho \mid \left\| A^T y^k + s^k \right\|_\infty \le \rho\varepsilon_i b^T y^k,\ b^T y^k > 0 \right\} \text{ and} \\ \rho_{di}^k & = & \text{arg min}_\rho \left\{ \rho \mid \left\| Ax^k \right\|_\infty \le -\rho\varepsilon_i c^T x^k,\ c^T x^k < 0 \right\}. \end{array}$$

Note $\varepsilon_p, \varepsilon_d, \varepsilon_g$ and ε_i are nonnegative user speci ed tolerances.

Optimal Case

Observe ρ_p^k measures how far x^k/τ^k is from being a good approximate primal feasible solution. Indeed if $\rho_p^k \le 1$, then

$$\left\| A\frac{x^k}{\tau^k} - b \right\|_\infty \le \varepsilon_p(1 + \|b\|_\infty). \tag{13.11}$$

This shows the violations in the primal equality constraints for the solution x^k/τ^k is small compared to the size of b given ε_p is small.

Similarly, if $\rho_d^k \le 1$, then $(y^k, s^k)/\tau^k$ is an approximate dual feasible solution. If in addition $\rho_g \le 1$, then the solution $(x^k, y^k, s^k)/\tau^k$ is approximate optimal because the associated primal and dual objective values are almost identical.

The interior-point method as implemented by MOSEK will converge toward optimality and primal and dual feasibility at the same rate [And09]. This means that if the optimizer is stopped prematurely then it is very unlikely that either the primal or dual solution is feasible. Another consequence is that in most cases all the tolerances ε_p, ε_d, ε_g and ε_i, have to be relaxed together to achieve an effect.

If the optimizer terminates without locating a solution that satisfies the termination criteria, for example because of a stall or other numerical issues, then it will check if the solution found up to that point satisfies the same criteria with all tolerances multiplied by the value of MSK_DPAR_INTPNT_CO_TOL_NEAR_REL. If this is the case, the solution is still declared as optimal.

To conclude the discussion in this section, relaxing the termination criterion is usually not worthwhile.

13.3.4 The Interior-point Log

Below is a typical log output from the interior-point optimizer:

```
Optimizer  - threads                : 20
Optimizer  - solved problem         : the primal
Optimizer  - Constraints            : 1
Optimizer  - Cones                  : 2
Optimizer  - Scalar variables       : 6         conic                  : 6
Optimizer  - Semi-definite variables: 0         scalarized             : 0
Factor     - setup time             : 0.00      dense det. time        : 0.00
Factor     - ML order time          : 0.00      GP order time          : 0.00
Factor     - nonzeros before factor : 1         after factor           : 1
Factor     - dense dim.             : 0         flops                  : 1.70e+01
ITE PFEAS    DFEAS    GFEAS    PRSTATUS   POBJ              DOBJ              MU       TIME
0   1.0e+00  2.9e-01  3.4e+00  0.00e+00   2.414213562e+00   0.000000000e+00   1.0e+00  0.01
1   2.7e-01  7.9e-02  2.2e+00  8.83e-01   6.969257574e-01  -9.685901771e-03   2.7e-01  0.01
2   6.5e-02  1.9e-02  1.2e+00  1.16e+00   7.606090061e-01   6.046141322e-01   6.5e-02  0.01
3   1.7e-03  5.0e-04  2.2e-01  1.12e+00   7.084385672e-01   7.045122560e-01   1.7e-03  0.01
4   1.4e-08  4.2e-09  4.9e-08  1.00e+00   7.071067941e-01   7.071067599e-01   1.4e-08  0.01
```

The first line displays the number of threads used by the optimizer and the second line indicates if the optimizer chose to solve the primal or dual problem (see MSK_IPAR_INTPNT_SOLVE_FORM). The next lines display the problem dimensions as seen by the optimizer, and the Factor... lines show various statistics. This is followed by the iteration log.

Using the same notation as in Sec. 13.3.1 the columns of the iteration log have the following meaning:

- ITE: Iteration index k.
- PFEAS: $\|Ax^k - b\tau^k\|_1$. The numbers in this column should converge monotonically towards zero but may stall at low level due to rounding errors.
- DFEAS: $\|A^T y^k + s^k - c\tau^k\|_1$. The numbers in this column should converge monotonically towards zero but may stall at low level due to rounding errors.
- GFEAS: $|c^T x^k + b^T y^k - \kappa^k|$. The numbers in this column should converge monotonically towards zero but may stall at low level due to rounding errors.
- PRSTATUS: This number converges to 1 if the problem has an optimal solution whereas it converges to -1 if that is not the case.
- POBJ: $c^T x^k / \tau^k$. An estimate for the primal objective value.
- DOBJ: $b^T y^k / \tau^k$. An estimate for the dual objective value.
- MU: $\frac{(x^k)^T s^k + \tau^k \kappa^k}{n+1}$. The numbers in this column should always converge to zero.
- TIME: Time spent since the optimization started (in seconds).

13.4 The Optimizer for Mixed-integer Problems

A problem is a mixed-integer optimization problem when one or more of the variables are constrained to be integer valued. Readers unfamiliar with integer optimization are recommended to consult some relevant literature, e.g. the book [Wol98] by Wolsey.

13.4.1 The Mixed-integer Optimizer Overview

MOSEK can solve mixed-integer

- linear,
- quadratic and quadratically constrained, and
- conic

problems, except for mixed-integer semide nite problems. The mixed-integer optimizer is specialized for solving linear and conic optimization problems. Pure quadratic and quadratically constrained problems are automatically converted to conic form.

By default the mixed-integer optimizer is run-to-run deterministic. This means that if a problem is solved twice on the same computer with identical parameter settings and no time limit then the obtained solutions will be identical. If a time limit is set then this may not be case since the time taken to solve a problem is not deterministic. The mixed-integer optimizer is parallelized i.e. it can exploit multiple cores during the optimization.

The solution process can be split into these phases:

1. **Presolve:** See Sec. 13.1.
2. **Cut generation:** Valid inequalities (cuts) are added to improve the lower bound.
3. **Heuristic:** Using heuristics the optimizer tries to guess a good feasible solution. Heuristics can be controlled by the parameter *MSK_IPAR_MIO_HEURISTIC_LEVEL*.
4. **Search:** The optimal solution is located by branching on integer variables.

13.4.2 Relaxations and bounds

It is important to understand that, in a worst-case scenario, the time required to solve integer optimization problems grows exponentially with the size of the problem (solving mixed-integer problems is NP-hard). For instance, a problem with n binary variables, may require time proportional to 2^n . The value of 2^n is huge even for moderate values of n.

In practice this implies that the focus should be on computing a near-optimal solution quickly rather than on locating an optimal solution. Even if the problem is only solved approximately, it is important to know how far the approximate solution is from an optimal one. In order to say something about the quality of an approximate solution the concept of *relaxation* is important.

Consider for example a mixed-integer optimization problem

$$\begin{array}{rcll} z^* & = & \text{minimize} & c^T x \\ & & \text{subject to} & Ax = b, \\ & & & x \geq 0 \\ & & & x_j \in \mathbb{Z}, \quad \forall j \in \mathcal{J}. \end{array} \tag{13.12}$$

It has the continuous relaxation

$$\begin{array}{rcll} \underline{z} & = & \text{minimize} & c^T x \\ & & \text{subject to} & Ax = b, \\ & & & x \geq 0 \end{array} \tag{13.13}$$

obtained simply by ignoring the integrality restrictions. The relaxation is a continuous problem, and therefore much faster to solve to optimality with a linear (or, in the general case, conic) optimizer. We call the optimal value $\underline{z}$ the *objective bound*. The objective bound $\underline{z}$ normally increases during the solution search process when the continuous relaxation is gradually re ned.

Moreover, if $\hat{x}$ is any feasible solution to (13.12) and

$$\bar{z} := c^T \hat{x}$$

then

$$\underline{z} \leq z^* \leq \bar{z}.$$

These two inequalities allow us to estimate the quality of the integer solution: it is no further away from the optimum than $\bar{z} - \underline{z}$ in terms of the objective value. Whenever a mixed-integer problem is solved **MOSEK** reports this lower bound so that the quality of the reported solution can be evaluated.

13.4.3 Outer approximation for mixed-integer conic problems

The relaxations of mixed integer conic problems can be solved either as a nonlinear problem with the interior point algorithm (default) or with a linear outer approximation algorithm. The type of relaxation used can be set with *MSK_IPAR_MIO_CONIC_OUTER_APPROXIMATION*. The best value for this option is highly problem dependent.

13.4.4 Randomization

A number of internal algorithms of the mixed-integer solver are dependend on random tie-breaking. The random tie-breaking can have a signi cant impact on the path taken by the algorithm and the optimal solution returned. The random seed can be set with the parameter *MSK_IPAR_MIO_SEED*.

13.4.5 Termination Criterion

In general, it is time consuming to nd an exact feasible and optimal solution to an integer optimization problem, though in many practical cases it may be possible to nd a su ciently good solution. The issue of terminating the mixed-integer optimizer is rather delicate and the user has numerous possibilities of in uencing it with various parameters. The mixed-integer optimizer employs a relaxed feasibility and optimality criterion to determine when a satisfactory solution is located.

A candidate solution that is feasible for the continuous relaxation is said to be an *integer feasible solution* if the criterion

$$\min(x_j - \lfloor x_j \rfloor, \lceil x_j \rceil - x_j) \leq \delta_1 \quad \forall j \in \mathcal{J}$$

is satis ed, meaning that x_j is at most δ_1 from the nearest integer.

Whenever the integer optimizer locates an integer feasible solution it will check if the criterion

$$\bar{z} - \underline{z} \leq \max(\delta_2, \delta_3 \max(\delta_4, |\bar{z}|))$$

is satis ed. If this is the case, the integer optimizer terminates and reports the integer feasible solution as an optimal solution.

All the δ tolerances discussed above can be adjusted using suitable parameters see Table 13.3.

Table 13.3: Tolerances for the mixed-integer optimizer.

Tolerance	Parameter name
δ_1	*MSK_DPAR_MIO_TOL_ABS_RELAX_INT*
δ_2	*MSK_DPAR_MIO_TOL_ABS_GAP*
δ_3	*MSK_DPAR_MIO_TOL_REL_GAP*
δ_4	*MSK_DPAR_MIO_REL_GAP_CONST*

In Table 13.4 some other common parameters a ecting the integer optimizer termination criterion are shown.

Table 13.4: Other parameters a ecting the integer optimizer termination criterion.

Parameter name	Explanation
MSK_IPAR_MIO_MAX_NUM_BRANCHES	Maximum number of branches allowed.
MSK_IPAR_MIO_MAX_NUM_RELAXS	Maximum number of relaxations allowed.
MSK_IPAR_MIO_MAX_NUM_SOLUTIONS	Maximum number of feasible integer solutions allowed.

13.4.6 Speeding Up the Solution Process

As mentioned previously, in many cases it is not possible to nd an optimal solution to an integer optimization problem in a reasonable amount of time. Some suggestions to reduce the solution time are:

- Relax the termination criterion: In case the run time is not acceptable, the rst thing to do is to relax the termination criterion see Sec. 13.4.5 for details.

- Specify a good initial solution: In many cases a good feasible solution is either known or easily computed using problem-speci c knowledge. If a good feasible solution is known, it is usually worthwhile to use this as a starting point for the integer optimizer. See Sec. 6.9.2.
- Improve the formulation: A mixed-integer optimization problem may be impossible to solve in one form and quite easy in another form. However, it is beyond the scope of this manual to discuss good formulations for mixed-integer problems. For discussions on this topic see for example [Wol98].

13.4.7 Understanding Solution Quality

To determine the quality of the solution one should check the following:

- The problem status and solution status returned by **MOSEK**, as well as constraint violations in case of suboptimal solutions.
- The *optimality gap* de ned as

$$\epsilon = |(\text{objective value of feasible solution}) - (\text{objective bound})| = |\bar{z} - \underline{z}|.$$

  which measures how much the located solution can deviate from the optimal solution to the problem. The optimality gap can be retrieved through the information item *"MSK_DINF_MIO_OBJ_ABS_GAP"*. Often it is more meaningful to look at the relative optimality gap normalized against the magnitude of the solution.

$$\epsilon_{\text{rel}} = \frac{|\bar{z} - \underline{z}|}{\max(\delta_4, |\bar{z}|)}.$$

  The relative optimality gap is available in the information item *"MSK_DINF_MIO_OBJ_REL_GAP"*.

13.4.8 The Mixed-integer Log

Below is a typical log output from the mixed-integer optimizer:

```
Presolved problem: 6573 variables, 35728 constraints, 101258 non-zeros
Presolved problem: 0 general integer, 4294 binary, 2279 continuous
Clique table size: 1636
BRANCHES RELAXS   ACT_NDS  DEPTH    BEST_INT_OBJ         BEST_RELAX_OBJ       REL_GAP(%)  TIME
0        1        0        0        NA                   1.8218819866e+07     NA          1.6
0        1        0        0        1.8331557950e+07     1.8218819866e+07     0.61        3.5
0        1        0        0        1.8300507546e+07     1.8218819866e+07     0.45        4.3
Cut generation started.
0        2        0        0        1.8300507546e+07     1.8218819866e+07     0.45        5.3
Cut generation terminated. Time = 1.43
0        3        0        0        1.8286893047e+07     1.8231580587e+07     0.30        7.5
15       18       1        0        1.8286893047e+07     1.8231580587e+07     0.30        10.5
31       34       1        0        1.8286893047e+07     1.8231580587e+07     0.30        11.1
51       54       1        0        1.8286893047e+07     1.8231580587e+07     0.30        11.6
91       94       1        0        1.8286893047e+07     1.8231580587e+07     0.30        12.4
171      174      1        0        1.8286893047e+07     1.8231580587e+07     0.30        14.3
331      334      1        0        1.8286893047e+07     1.8231580587e+07     0.30        17.9

[ ... ]

Objective of best integer solution : 1.825846762609e+07
Best objective bound               : 1.823311032986e+07
Construct solution objective       : Not employed
Construct solution # roundings     : 0
User objective cut value           : 0
Number of cuts generated           : 117
  Number of Gomory cuts            : 108
  Number of CMIR cuts              : 9
```

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```
Number of branches                 : 4425
Number of relaxations solved       : 4410
Number of interior point iterations: 25
Number of simplex iterations       : 221131
```

The first lines contain a summary of the problem as seen by the optimizer. This is followed by the iteration log. The columns have the following meaning:

- BRANCHES: Number of branches generated.
- RELAXS: Number of relaxations solved.
- ACT_NDS: Number of active branch bound nodes.
- DEPTH: Depth of the recently solved node.
- BEST_INT_OBJ: The best integer objective value, $\bar{z}$.
- BEST_RELAX_OBJ: The best objective bound, $\underline{z}$.
- REL_GAP(%): Relative optimality gap, $100\% \cdot \epsilon_{\mathrm{rel}}$
- TIME: Time (in seconds) from the start of optimization.

Following that a summary of the optimization process is printed.

Chapter 14

Additional features

In this section we describe additional features and tools which enable more detailed analysis of optimization problems with **MOSEK**.

14.1 Problem Analyzer

The problem analyzer prints a survey of the structure of the problem, with information about linear constraints and objective, quadratic constraints, conic constraints and variables.

In the initial stages of model formulation the problem analyzer may be used as a quick way of verifying that the model has been built or imported correctly. In later stages it can help revealing special structures within the model that may be used to tune the optimizer's performance or to identify the causes of numerical di culties.

The problem analyzer is run using the *mosekopt* ('anapro') command and produces output similar to the following (this is the problem analyzer's survey of the aflow30a problem from the MIPLIB 2003 collection).

```
                    Analyzing the problem

*** Structural report
               Dimensions
               Constraints   Variables     Matrix var.   Cones
               479           842           0             0

               Constraint and bound types
               Free          Lower         Upper         Ranged        Fixed
 Constraints:  0             0             421           0             58
   Variables:  0             0             0             842           0

               Integer constraint types
               Binary        General
               421           0

*** Data report
               Nonzeros      Min           Max
        |cj|:  421           1.1e+01       5.0e+02
       |Aij|:  2091          1.0e+00       1.0e+02

               # finite      Min           Max
      |blci|:  58            1.0e+00       1.0e+01
      |buci|:  479           0.0e+00       1.0e+01
      |blxj|:  842           0.0e+00       0.0e+00
      |buxj|:  842           1.0e+00       1.0e+02

*** Done analyzing the problem
```

The survey is divided into a structural and numerical report. The content should be self-explanatory.

Caveats

Observe if the infeasible problem

$$\begin{array}{lrcl} \text{minimize} & x+z & & \\ \text{subject to} & x & = & -1, \\ & x & \geq & 0 \end{array}$$

is repaired then it will become unbounded. Hence, a repaired problem may not have an optimal solution.

Another and more important caveat is that only a minimal repair is performed i.e. the repair that barely makes the problem feasible. Hence, the repaired problem is barely feasible and that sometimes makes the repaired problem hard to solve.

Using the automatic repair tool

In this subsection we consider an infeasible linear optimization example:

$$\begin{array}{lrcrcl} \text{minimize} & -10x_1 & & -9x_2, & & \\ \text{subject to} & 7/10x_1 & + & 1x_2 & \leq & 630, \\ & 1/2x_1 & + & 5/6x_2 & \leq & 600, \\ & 1x_1 & + & 2/3x_2 & \leq & 708, \\ & 1/10x_1 & + & 1/4x_2 & \leq & 135, \\ & x_1, & & x_2 & \geq & 0, \\ & & & x_2 & \geq & 650. \end{array} \tag{14.2}$$

The code following code will form the repaired problem and solve it.

Listing 14.1: An example of feasibility repair applied to problem (14.2).

```
function feasrepairex1(inputfile)

cmd = sprintf('read(%s)', inputfile);
[r,res]=mosekopt(cmd);

res.prob.primalrepair = [];
res.prob.primalrepair.wux = [1,1];
res.prob.primalrepair.wlx = [1,1];
res.prob.primalrepair.wuc = [1,1,1,1];
res.prob.primalrepair.wlc = [1,1,1,1];

param.MSK_IPAR_LOG_FEAS_REPAIR = 3;
[r,res]=mosekopt('minimize primalrepair',res.prob,param);
fprintf('Return code: %d\n',r);

end
```

The parameter *MSK_IPAR_LOG_FEAS_REPAIR* controls the amount of log output from the repair. A value of 2 causes the optimal repair to printed out. If the elds wlx, wux, wlc or wuc are not speci ed, they are all assumed to be 1-vectors of appropriate dimensions.

The above code will produce the following log report:

```
MOSEK Version 9.0.0.25(ALPHA) (Build date: 2017-11-7 16:11:50)
Copyright (c) MOSEK ApS, Denmark. WWW: mosek.com
Platform: Linux/64-X86

Open file 'feasrepair.lp'
Reading started.
Reading terminated. Time: 0.00

Read summary
  Type             : LO (linear optimization problem)
```

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```
  Objective sense  : min
  Scalar variables : 2
  Matrix variables : 0
  Constraints      : 4
  Cones            : 0
  Time             : 0.0

Problem
  Name                   :
  Objective sense        : min
  Type                   : LO (linear optimization problem)
  Constraints            : 4
  Cones                  : 0
  Scalar variables       : 2
  Matrix variables       : 0
  Integer variables      : 0

Primal feasibility repair started.
Optimizer started.
Presolve started.
Linear dependency checker started.
Linear dependency checker terminated.
Eliminator started.
Freed constraints in eliminator : 2
Eliminator terminated.
Eliminator - tries                  : 1                 time                   : 0.00
Lin. dep.  - tries                  : 1                 time                   : 0.00
Lin. dep.  - number                 : 0
Presolve terminated. Time: 0.00
Problem
  Name                   :
  Objective sense        : min
  Type                   : LO (linear optimization problem)
  Constraints            : 8
  Cones                  : 0
  Scalar variables       : 14
  Matrix variables       : 0
  Integer variables      : 0

Optimizer  - threads                : 20
Optimizer  - solved problem         : the primal
Optimizer  - Constraints            : 2
Optimizer  - Cones                  : 0
Optimizer  - Scalar variables       : 5                 conic                  : 0
Optimizer  - Semi-definite variables: 0                 scalarized             : 0
Factor     - setup time             : 0.00              dense det. time        : 0.00
Factor     - ML order time          : 0.00              GP order time          : 0.00
Factor     - nonzeros before factor : 3                 after factor           : 3
Factor     - dense dim.             : 0                 flops                  : 5.00e+01
ITE PFEAS    DFEAS    GFEAS    PRSTATUS   POBJ              DOBJ              MU       TIME
0   2.7e+01  1.0e+00  4.0e+00  1.00e+00   3.000000000e+00   0.000000000e+00   1.0e+00  0.00
1   2.5e+01  9.1e-01  1.4e+00  0.00e+00   8.711262850e+00   1.115287830e+01   2.4e+00  0.00
2   2.4e+00  8.8e-02  1.4e-01  -7.33e-01  4.062505701e+01   4.422203730e+01   2.3e-01  0.00
3   9.4e-02  3.4e-03  5.5e-03  1.33e+00   4.250700434e+01   4.258548510e+01   9.1e-03  0.00
4   2.0e-05  7.2e-07  1.1e-06  1.02e+00   4.249996599e+01   4.249998669e+01   1.9e-06  0.00
5   2.0e-09  7.2e-11  1.1e-10  1.00e+00   4.250000000e+01   4.250000000e+01   1.9e-10  0.00
Basis identification started.
Basis identification terminated. Time: 0.00
Optimizer terminated. Time: 0.01

Basic solution summary
```

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(continued from previous page)

```
  Problem status  : PRIMAL_AND_DUAL_FEASIBLE
  Solution status : OPTIMAL
  Primal.  obj: 4.2500000000e+01    nrm: 6e+02    Viol.  con: 1e-13    var: 0e+00
  Dual.    obj: 4.2499999999e+01    nrm: 2e+00    Viol.  con: 0e+00    var: 9e-11
Optimal objective value of the penalty problem: 4.250000000000e+01

Repairing bounds.
Increasing the upper bound 1.35e+02 on constraint 'c4' (3) with 2.25e+01.
Decreasing the lower bound 6.50e+02 on variable 'x2' (4) with 2.00e+01.
Primal feasibility repair terminated.
Optimizer started.
Optimizer terminated. Time: 0.00


Interior-point solution summary
  Problem status  : PRIMAL_AND_DUAL_FEASIBLE
  Solution status : OPTIMAL
  Primal.  obj: -5.6700000000e+03   nrm: 6e+02    Viol.  con: 0e+00    var: 0e+00
  Dual.    obj: -5.6700000000e+03   nrm: 1e+01    Viol.  con: 0e+00    var: 0e+00

Basic solution summary
  Problem status  : PRIMAL_AND_DUAL_FEASIBLE
  Solution status : OPTIMAL
  Primal.  obj: -5.6700000000e+03   nrm: 6e+02    Viol.  con: 0e+00    var: 0e+00
  Dual.    obj: -5.6700000000e+03   nrm: 1e+01    Viol.  con: 0e+00    var: 0e+00

Optimizer summary
  Optimizer                 -                        time: 0.00
    Interior-point          - iterations : 0         time: 0.00
      Basis identification  -                        time: 0.00
        Primal              - iterations : 0         time: 0.00
        Dual                - iterations : 0         time: 0.00
        Clean primal        - iterations : 0         time: 0.00
        Clean dual          - iterations : 0         time: 0.00
    Simplex                 -                        time: 0.00
      Primal simplex        - iterations : 0         time: 0.00
      Dual simplex          - iterations : 0         time: 0.00
    Mixed integer           - relaxations: 0         time: 0.00
```

It will also modify the task according to the optimal elasticity variables found. In this case the optimal repair it is to increase the upper bound on constraint c4 by 22.5 and decrease the lower bound on variable x2 by 20.

14.3 Sensitivity Analysis

Given an optimization problem it is often useful to obtain information about how the optimal objective value changes when the problem parameters are perturbed. E.g, assume that a bound represents the capacity of a machine. Now, it may be possible to expand the capacity for a certain cost and hence it is worthwhile knowing what the value of additional capacity is. This is precisely the type of questions the sensitivity analysis deals with.

Analyzing how the optimal objective value changes when the problem data is changed is called *sensitivity analysis*.

References

The book *[Chv83]* discusses the classical sensitivity analysis in Chapter 10 whereas the book *[RTV97]* presents a modern introduction to sensitivity analysis. Finally, it is recommended to read the short paper *[Wal00]* to avoid some of the pitfalls associated with sensitivity analysis.

Warning: Currently, sensitivity analysis is only available for continuous linear optimization problems. Moreover, **MOSEK** can only deal with perturbations of bounds and objective function coe cients.

14.3.1 Sensitivity Analysis for Linear Problems

The Optimal Objective Value Function

Assume that we are given the problem

$$\begin{array}{rcl} z(l^c, u^c, l^x, u^x, c) & = & \text{minimize} \quad c^T x \\ & & \text{subject to} \quad \begin{array}{ccccc} l^c & \leq & Ax & \leq & u^c, \\ l^x & \leq & x & \leq & u^x, \end{array} \end{array} \tag{14.3}$$

and we want to know how the optimal objective value changes as l_i^c is perturbed. To answer this question we de ne the perturbed problem for l_i^c as follows

$$\begin{array}{rcl} f_{l_i^c}(\beta) & = & \text{minimize} \quad c^T x \\ & & \text{subject to} \quad \begin{array}{ccccc} l^c + \beta e_i & \leq & Ax & \leq u^c, \\ l^x & \leq & x \leq & u^x, \end{array} \end{array}$$

where e_i is the i-th column of the identity matrix. The function

$$f_{l_i^c}(\beta) \tag{14.4}$$

shows the optimal objective value as a function of β. Please note that a change in β corresponds to a perturbation in l_i^c and hence (14.4) shows the optimal objective value as a function of varying l_i^c with the other bounds xed.

It is possible to prove that the function (14.4) is a piecewise linear and convex function, i.e. its graph may look like in Fig. 14.1 and Fig. 14.2.

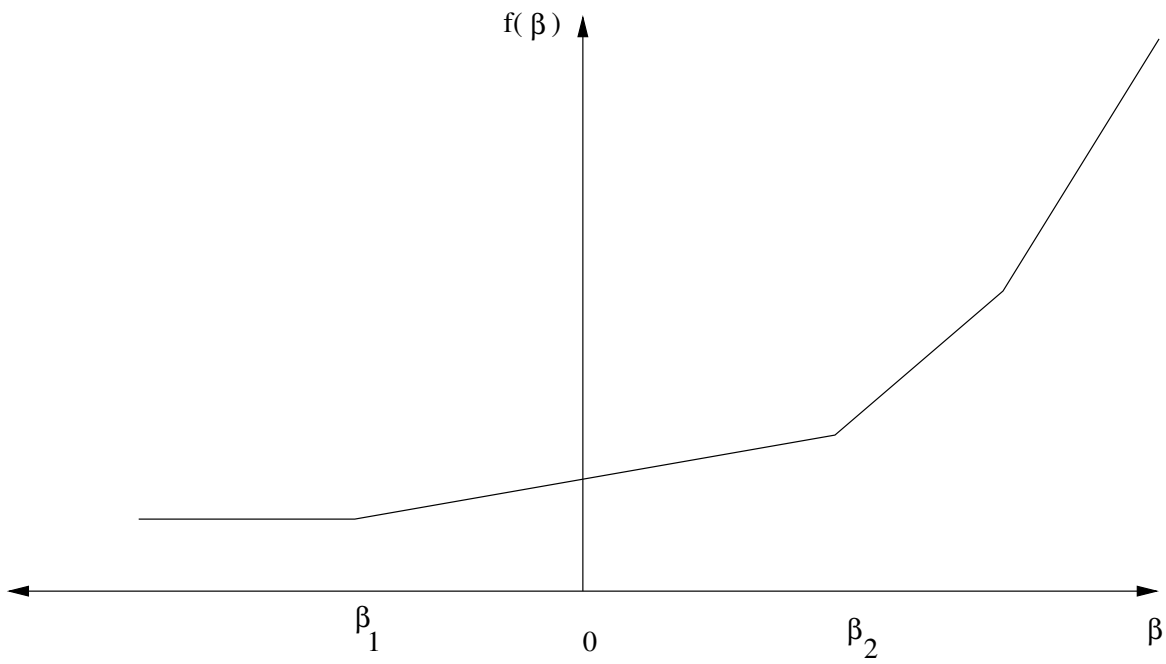

Fig. 14.1: $\beta = 0$ is in the interior of linearity interval.

Clearly, if the function $f_{l_i^c}(\beta)$ does not change much when β is changed, then we can conclude that the optimal objective value is insensitive to changes in l_i^c. Therefore, we are interested in the rate of change in $f_{l_i^c}(\beta)$ for small changes in β speci cally the gradient

$$f'_{l_i^c}(0),$$

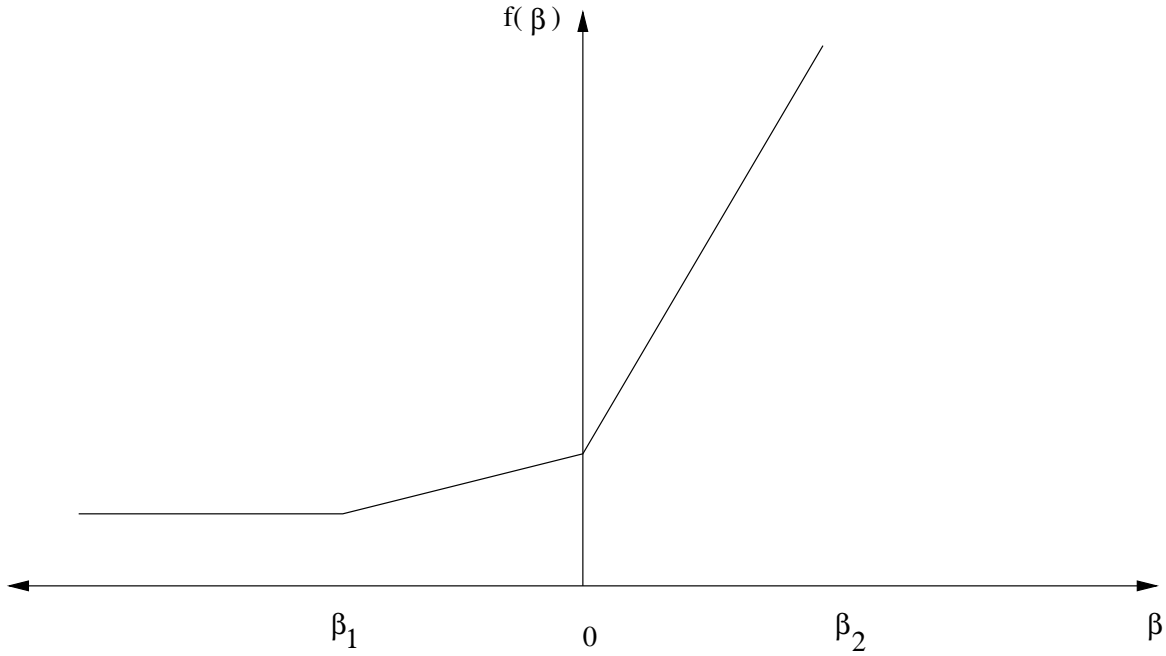

Fig. 14.2: $\beta = 0$ is a breakpoint.

which is called the *shadow price* related to l_i^c. The shadow price speci es how the objective value changes for small changes of β around zero. Moreover, we are interested in the *linearity interval*

$$\beta \in [\beta_1, \beta_2]$$

for which

$$f'_{l_i^c}(\beta) = f'_{l_i^c}(0).$$

Since $f_{l_i^c}$ is not a smooth function $f'_{l_i^c}$ may not be de ned at 0, as illustrated in Fig. 14.2. In this case we can de ne a left and a right shadow price and a left and a right linearity interval.

The function $f_{l_i^c}$ considered only changes in l_i^c. We can de ne similar functions for the remaining parameters of the z de ned in (14.3) as well:

$$\begin{array}{rcll} f_{l_i^c}(\beta) & = & z(l^c + \beta e_i, u^c, l^x, u^x, c), & i = 1, \ldots, m, \\ f_{u_i^c}(\beta) & = & z(l^c, u^c + \beta e_i, l^x, u^x, c), & i = 1, \ldots, m, \\ f_{l_j^x}(\beta) & = & z(l^c, u^c, l^x + \beta e_j, u^x, c), & j = 1, \ldots, n, \\ f_{u_j^x}(\beta) & = & z(l^c, u^c, l^x, u^x + \beta e_j, c), & j = 1, \ldots, n, \\ f_{c_j}(\beta) & = & z(l^c, u^c, l^x, u^x, c + \beta e_j), & j = 1, \ldots, n. \end{array}$$

Given these de nitions it should be clear how linearity intervals and shadow prices are de ned for the parameters u_i^c etc.

Equality Constraints

In $\mathbf{MOSEK}$ a constraint can be speci ed as either an equality constraint or a ranged constraint. If some constraint e_i^c is an equality constraint, we de ne the optimal value function for this constraint as

$$f_{e_i^c}(\beta) = z(l^c + \beta e_i, u^c + \beta e_i, l^x, u^x, c)$$

Thus for an equality constraint the upper and the lower bounds (which are equal) are perturbed simultaneously. Therefore, $\mathbf{MOSEK}$ will handle sensitivity analysis di erently for a ranged constraint with $l_i^c = u_i^c$ and for an equality constraint.

The Basis Type Sensitivity Analysis

The classical sensitivity analysis discussed in most textbooks about linear optimization, e.g. [Chv83], is based on an optimal basis. This method may produce misleading results [RTV97] but is computationally cheap. This is the type of sensitivity analysis implemented in **MOSEK**.

We will now brie y discuss the basis type sensitivity analysis. Given an optimal basic solution which provides a partition of variables into basic and non-basic variables, the basis type sensitivity analysis computes the linearity interval $[\beta_1, \beta_2]$ so that the basis remains optimal for the perturbed problem. A shadow price associated with the linearity interval is also computed. However, it is well-known that an optimal basic solution may not be unique and therefore the result depends on the optimal basic solution employed in the sensitivity analysis. If the optimal objective value function has a breakpoint for $\beta = 0$ then the basis type sensitivity method will only provide a subset of either the left or the right linearity interval.

In summary, the basis type sensitivity analysis is computationally cheap but does not provide complete information. Hence, the results of the basis type sensitivity analysis should be used with care.

Example: Sensitivity Analysis

As an example we will use the following transportation problem. Consider the problem of minimizing the transportation cost between a number of production plants and stores. Each plant supplies a number of goods and each store has a given demand that must be met. Supply, demand and cost of transportation per unit are shown in Fig. 14.3.

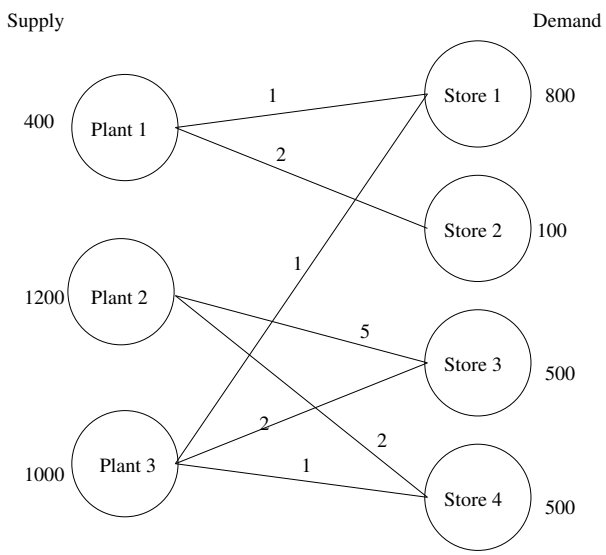

Fig. 14.3: Supply, demand and cost of transportation.

If we denote the number of transported goods from location i to location j by x_{ij}, problem can be formulated as the linear optimization problem of minimizing

$$1x_{11} + 2x_{12} + 5x_{23} + 2x_{24} + 1x_{31} + 2x_{33} + 1x_{34}$$

subject to

$$\begin{array}{lllllllllllll}
x_{11} & + & x_{12} & & & & & & & & & \leq & 400, \\
 & & & x_{23} & + & x_{24} & & & & & & \leq & 1200, \\
 & & & & & & & x_{31} & + & x_{33} & + \; x_{34} & \leq & 1000, \\
x_{11} & & & & & & + & x_{31} & & & & = & 800, \\
 & & x_{12} & & & & & & & & & = & 100, \\
 & & & x_{23} & + & & & & & x_{33} & & = & 500, \\
 & & & & & x_{24} & + & & & & x_{34} & = & 500, \\
x_{11}, & & x_{12}, & x_{23}, & & x_{24}, & & x_{31}, & & x_{33}, & x_{34} & \geq & 0.
\end{array} \tag{14.5}$$

The sensitivity parameters are shown in Table 14.1 and Table 14.2.

Table 14.1: Ranges and shadow prices related to bounds on constraints and variables.

Con.	$_1$	$_2$	$_1$	$_2$
1	300.00	0.00	3.00	3.00
2	700.00	+ 1	0.00	0.00
3	500.00	0.00	3.00	3.00
4	0.00	500.00	4.00	4.00
5	0.00	300.00	5.00	5.00
6	0.00	700.00	5.00	5.00
7	500.00	700.00	2.00	2.00
Var.	$_1$	$_2$	$_1$	$_2$
x_{11}	1	300.00	0.00	0.00
x_{12}	1	100.00	0.00	0.00
x_{23}	1	0.00	0.00	0.00
x_{24}	1	500.00	0.00	0.00
x_{31}	1	500.00	0.00	0.00
x_{33}	1	500.00	0.00	0.00
x_{34}	0.000000	500.00	2.00	2.00

Table 14.2: Ranges and shadow prices related to the objective coe cients.

Var.	$_1$	$_2$	$_1$	$_2$
c_1	1	3.00	300.00	300.00
c_2	1	1	100.00	100.00
c_3	2.00	1	0.00	0.00
c_4	1	2.00	500.00	500.00
c_5	3.00	1	500.00	500.00
c_6	1	2.00	500.00	500.00
c_7	2.00	1	0.00	0.00

Examining the results from the sensitivity analysis we see that for constraint number 1 we have $_1 = 3$ and $_1 = 300$; $_2 = 0$.

If the upper bound on constraint 1 is decreased by

$$2 \quad [0; 300]$$

then the optimal objective value will increase by the value

$$_1 \quad = 3 \ :$$

14.3.2 Sensitivity Analysis with MOSEK

The following describe sensitivity analysis from the MATLAB toolbox.

On bounds

The index of bounds/variables to analyzed for sensitivity are speci ed in the following sub elds of the MATLAB structure prob:

- ˆ .prisen.cons.subu Indexes of constraints, where upper bounds are analyzed for sensitivity.
- ˆ .prisen.cons.subl Indexes of constraints, where lower bounds are analyzed for sensitivity.

- .prisen.vars.subu Indexes of variables, where upper bounds are analyzed for sensitivity.
- .prisen.vars.subl Indexes of variables, where lower bounds are analyzed for sensitivity.
- .duasen.sub Index of variables where coe cients are analyzed for sensitivity.

For an equality constraint, the index can be speci ed in either subu or subl . After calling *mosekopt* the results are returned in the sub elds prisen and duasen of res .

prisen

The eld prisen is structured as follows:

- .cons : a MATLAB structure with sub elds:
  - .lr_bl Left value β_1 in the linearity interval for a lower bound.
  - .rr_bl Right value β_2 in the linearity interval for a lower bound.
  - .ls_bl Left shadow price s_l for a lower bound.
  - .rs_bl Right shadow price s_r for a lower bound.
  - .lr_bu Left value β_1 in the linearity interval for an upper bound.
  - .rr_bu Right value β_2 in the linearity interval for an upper bound.
  - .ls_bu Left shadow price s_l for an upper bound.
  - .rs_bu Right shadow price s_r for an upper bound.
- .var : MATLAB structure with sub elds:
  - .lr_bl Left value β_1 in the linearity interval for a lower bound on a varable.
  - .rr_bl Right value β_2 in the linearity interval for a lower bound on a varable.
  - .ls_bl Left shadow price s_l for a lower bound on a varable.
  - .rs_bl Right shadow price s_r for lower bound on a varable.
  - .lr_bu Left value β_1 in the linearity interval for an upper bound on a varable.
  - .rr_bu Right value β_2 in the linearity interval for an upper bound on a varable.
  - .ls_bu Left shadow price s_l for an upper bound on a varables.
  - .rs_bu Right shadow price s_r for an upper bound on a varables.

duasen

The eld duasen is structured as follows:

- .lr_c Left value β_1 of linearity interval for an objective coe cient.
- .rr_c Right value β_2 of linearity interval for an objective coe cient.
- .ls_c Left shadow price s_l for an objective coe cients .
- .rs_c Right shadow price s_r for an objective coe cients.

Example

Consider the problem de ned in (14.5). Suppose we wish to perform sensitivity analysis on all bounds and coe cients. The following example demonstrates this as well as the method for changing between basic and full sensitivity analysis.

Listing 14.2: A script to perform sensitivity analysis on problem (14.5).

```
function sensitivity()

clear prob;

% Obtain all symbolic constants
% defined by MOSEK.
[r,res] = mosekopt( ' symbcon' );
sc = res.symbcon;

prob.blc = [-Inf, -Inf, -Inf, 800,100,500,500];
prob.buc = [ 400, 1200, 1000, 800,100,500,500];
prob.c = [1.0,2.0,5.0,2.0,1.0,2.0,1.0] ' ;
prob.blx = [0.0,0.0,0.0,0.0,0.0,0.0,0.0];
prob.bux = [Inf,Inf,Inf,Inf, Inf,Inf,Inf];

subi = [ 1, 1, 2, 2, 3, 3, 3, 4, 4, 5, 6, 6, 7, 7];
subj = [ 1, 2, 3, 4, 5, 6, 7, 1, 5, 6, 3, 6, 4, 7];
val = [1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0];

prob.a = sparse(subi,subj,val);

% analyse upper bound 1:7
prob.prisen.cons.subl = [];
prob.prisen.cons.subu = [1:7];
% analyse lower bound on variables 1:7
prob.prisen.vars.subl = [1:7];
prob.prisen.vars.subu = [];
% analyse coeficient 1:7
prob.duasen.sub = [1:7];
[r,res] = mosekopt( ' minimize echo(0) ' ,prob);

%Print results

fprintf( ' \nBasis sensitivity results:\n ' )
fprintf( ' \nSensitivity for bounds on constraints:\n ' )
for i = 1:length(prob.prisen.cons.subl)
  fprintf ( ...
  ' con = %d, beta_1 = %.1f, beta_2 = %.1f, delta_1 = %.1f,delta_2 = %.1f\n ' , ...
  prob.prisen.cons.subl(i),res.prisen.cons.lr_bl(i), ...
  res.prisen.cons.rr_bl(i), ...
  res.prisen.cons.ls_bl(i), ...
  res.prisen.cons.rs_bl(i));
end

for i = 1:length(prob.prisen.cons.subu)
  fprintf ( ...
  ' con = %d, beta_1 = %.1f, beta_2 = %.1f, delta_1 = %.1f,delta_2 = %.1f\n ' , ...
  prob.prisen.cons.subu(i),res.prisen.cons.lr_bu(i), ...
  res.prisen.cons.rr_bu(i), ...
  res.prisen.cons.ls_bu(i), ...
  res.prisen.cons.rs_bu(i));
end
fprintf( ' Sensitivity for bounds on variables:\n ' )
for i = 1:length(prob.prisen.vars.subl)
fprintf ( ...
' var = %d, beta_1 = %.1f, beta_2 = %.1f, delta_1 = %.1f,delta_2 = %.1f\n ' , ...
 prob.prisen.vars.subl(i),res.prisen.vars.lr_bl(i), ...
 res.prisen.vars.rr_bl(i), ...
 res.prisen.vars.ls_bl(i), ...
```

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```
 res.prisen.vars.rs_bl(i));
end

for i = 1:length(prob.prisen.vars.subu)
  fprintf (...
  'var = %d, beta_1 = %.1f, beta_2 = %.1f, delta_1 = %.1f,delta_2 = %.1f\n', ...
  prob.prisen.vars.subu(i),res.prisen.vars.lr_bu(i), ...
  res.prisen.vars.rr_bu(i),...
  res.prisen.vars.ls_bu(i),...
  res.prisen.vars.rs_bu(i));
end

fprintf('Sensitivity for coefficients in objective:\n')
for i = 1:length(prob.duasen.sub)
  fprintf (...
  'var = %d, beta_1 = %.1f, beta_2 = %.1f, delta_1 = %.1f,delta_2 = %.1f\n', ...
  prob.duasen.sub(i),res.duasen.lr_c(i), ...
  res.duasen.rr_c(i),...
  res.duasen.ls_c(i),...
  res.duasen.rs_c(i));
end
```

The output from running the example in Listing 14.2 is shown below.

```
Sensitivity for bounds on constraints:
con = 1, beta_1 = -300.0, beta_2 = 0.0, delta_1 = 3.0,delta_2 = 3.0
con = 2, beta_1 = -700.0, beta_2 = Inf, delta_1 = 0.0,delta_2 = 0.0
con = 3, beta_1 = -500.0, beta_2 = 0.0, delta_1 = 3.0,delta_2 = 3.0
con = 4, beta_1 = -0.0, beta_2 = 500.0, delta_1 = 4.0,delta_2 = 4.0
con = 5, beta_1 = -0.0, beta_2 = 300.0, delta_1 = 5.0,delta_2 = 5.0
con = 6, beta_1 = -0.0, beta_2 = 700.0, delta_1 = 5.0,delta_2 = 5.0
con = 7, beta_1 = -500.0, beta_2 = 700.0, delta_1 = 2.0,delta_2 = 2.0
Sensitivity for bounds on variables:
var = 1, beta_1 = Inf, beta_2 = 300.0, delta_1 = 0.0,delta_2 = 0.0
var = 2, beta_1 = Inf, beta_2 = 100.0, delta_1 = 0.0,delta_2 = 0.0
var = 3, beta_1 = Inf, beta_2 = 0.0, delta_1 = 0.0,delta_2 = 0.0
var = 4, beta_1 = Inf, beta_2 = 500.0, delta_1 = 0.0,delta_2 = 0.0
var = 5, beta_1 = Inf, beta_2 = 500.0, delta_1 = 0.0,delta_2 = 0.0
var = 6, beta_1 = Inf, beta_2 = 500.0, delta_1 = 0.0,delta_2 = 0.0
var = 7, beta_1 = -0.0, beta_2 = 500.0, delta_1 = 2.0,delta_2 = 2.0
Sensitivity for coefficients in objective:
var = 1, beta_1 = Inf, beta_2 = 3.0, delta_1 = 300.0,delta_2 = 300.0
var = 2, beta_1 = Inf, beta_2 = Inf, delta_1 = 100.0,delta_2 = 100.0
var = 3, beta_1 = -2.0, beta_2 = Inf, delta_1 = 0.0,delta_2 = 0.0
var = 4, beta_1 = Inf, beta_2 = 2.0, delta_1 = 500.0,delta_2 = 500.0
var = 5, beta_1 = -3.0, beta_2 = Inf, delta_1 = 500.0,delta_2 = 500.0
var = 6, beta_1 = Inf, beta_2 = 2.0, delta_1 = 500.0,delta_2 = 500.0
var = 7, beta_1 = -2.0, beta_2 = Inf, delta_1 = 0.0,delta_2 = 0.0
```

Chapter 15

Toolbox API Reference

- *General API conventions.*
- **Command reference:**
  - *Complete list of functions*
  - `mosekopt` - the main interface
  - *Data structures*
- **Optimizer parameters:**
  - *Double*, *Integer*, *String*
  - *Full list*
  - *Browse by topic*
- **Optimizer information items:**
  - `Double`, `Integer`, `Long`
- *Optimizer response codes*
- *Constants*
- *Functions compatible with the MATLAB Optimization Toolbox*
- *Nonlinear API (mskenopt, mskscopt, mskgpopt)*

15.1 API conventions

Problem setup

An optimization problem in Optimization Toolbox for MATLAB is speci ed using the `prob` structure. The speci cation of numerical part of the data can be found in Sec. 15.3.1.

Constants

Constants mentioned in Sec. 15.7 and Sec. 15.5 can be used as strings or as symbolic constants. To get the structure with all symbolic constants available execute:

```
[r, res] = mosekopt('symbcon');
```

They can later be used simply as, for example:

```
res.symbcon.MSK_IPAR_OPTIMIZER
```

15.2 Command Reference

The **MOSEK** toolbox provides a set of functions to interface to the**MOSEK** solver.

Main interface

mosekopt is the main interface to MOSEK.

Helper functions

These functions provide an easy-to-use but less flexible interface than the *mosekopt* function. They are just wrappers around the *mosekopt* interface written in MATLAB.

- *msklpopt* : Solves linear optimization problems.
- *mskqpopt* : Solves quadratic optimization problems.

Options

Functions for manipulating parameter values.

- *mskoptimget* : Get the solver parameters.
- *mskoptimset* : Set the solver parameters.

MATLAB Optimization Toolbox compatible functions.

Functions that override standard functions from the MATLAB Optimization Toolbox (the user may choose not to install those).

- *linprog* : Solves linear optimization problems.
- *quadprog* : Solves quadratic optimization problems.
- *intlinprog* : Solves linear optimization problems with integer variables.
- *lsqlin* : Solves least-squares with linear constraints.
- *lsqnonneg* : Solves least-squares with non-negativity constraints.

15.2.1 Main Interface

rcode, res = mosekopt(cmd, prob, param, callback, optserver)

Solves an optimization problem. Data specifying the optimization problem can either be read from a file or be inputted directly from MATLAB. It also makes it possible to write a file and provides other functionalities.

The behavior is specified by the cmd parameter which recognizes the following commands:

- anapro: Runs the problem analyzer.
- echo(n) : Controls how much log information is printed to the screen. n must be a nonnegative integer, where 0 means silent. See Sec. 7.3.1.
- info : Return the complete task information database in res.info . See Sec. 7.5.
- param: Return the complete parameter database in res.param . See Sec. 7.4.
- primalrepair : Performs a primal feasibility repair. See Sec. 14.2.
- maximize: Maximize the objective.
- max: Sets the objective sense (similar to maximize), without performing an optimization.
- minimize : Minimize the objective.
- min: Sets the objective sense (similar to minimize), without performing an optimization.
- nokeepenv: Delete the MOSEK environment after running the optimizer. This can increase the license checkout overhead significantly and is therefore only intended as a debug feature. Can also be used to delete the environment and release all licenses. See Sec. 10.4.
- read(name): Request that data is read from a file name. See Sec. 7.3.4.

res = mskqpopt(q, c, a, blc , buc, blx , bux, param, cmd)

Solves the optimization problem

$$\begin{array}{ll} \text{minimize} & \frac{1}{2}x^T Q x + c^T x \\ \text{subject to} & l^c \leq Ax \leq u^c, \\ & l^x \leq x \leq u^x. \end{array}$$

blc=[] and buc=[] mean that the lower and upper bounds are $-\infty$ and $+\infty$, respectively. The same interpretation is used for blx and bux. The value -inf is allowed in blc and blx . Similarly, inf is allowed in buc and bux.

Parameters

- q (double[]) The matrix Q, which must be symmetric positive semide nite.
- c [in] (double[]) The objective function vector.
- a (double[][]) A (preferably) sparse matrix.
- blc [in] (double[]) Constraints lower bounds.
- buc [in] (double[]) Constraints upper bounds
- blx [in] (double[]) Variables lower bounds
- bux [in] (double[]) Variables upper bounds
- param [in] (struct) **MOSEK** parameters. (optional)
- cmd [in] (string) The command list. See *mosekopt* for a list of available commands. (optional)

Return res (*res*) Solution information.

15.2.3 Options

val = mskoptimget(options , param, default)

Obtains the value of an optimization parameter. See the *mskoptimset* function for which parameters that can be set.

Parameters

- options [in] (struct) The optimization options structure.
- param [in] (string) Name of the optimization parameter for which the value should be obtained.
- default [in] (string) If param is not de ned, the value of default is returned instead. (optional)

Return val (list) Value of the required option. If the option does not exist, then [] is returned unless the value default is de ned in which case the default value is returned.

options = mskoptimset(arg1 , arg2 , param1, value1 , param2, value2 , ...)

Obtains and modi es the optimization options structure. Only a subset of the elds in the optimization structure recognized by the MATLAB Optimization Toolbox is recognized by **MOSEK**. In addition the optimization options structure can be used to modify all the **MOSEK** speci c parameters de ned in Sec. 15.5.

- .Diagnostics Used to control how much diagnostic information is printed. Following values are accepted:

off	No diagnostic information is printed.
on	Diagnostic information is printed.

- .Display De nes what information is displayed. The following values are accepted:

off	No output is displayed.
iter	Some output is displayed for each iteration.
final	Only the nal output is displayed.

- .MaxIter Maximum number of iterations allowed.

- .Write A le name to write the problem to. If equal to the empty string no le is written. E.g the option Write(myfile.opf) writes the le myfile.opf in the opf format.

Parameters

- arg1 [in] (None) Is allowed to be any of the following two things (optional):
  - Any string The same as using no argument.
  - A structure The argument is assumed to be a structure containing options, which are copied to the return options.
- param1 [in] (string) A string containing the name of a parameter that should be modi ed. (optional)
- value1 [in] (None) The new value assigned to the parameter with the name param1 (optional)
- param2 [in] (None) See param1 (optional)
- value2 [in] (None) See value1 . (optional)

Return options (struct) The updated optimization options structure.

15.2.4 MATLAB Optimization Toolbox Compatible Functions.

x, fval , exitflag , output = intlinprog(f , intcon , A, b, B, c, l , u, options)
x, fval , exitflag , output = intlinprog(problem)

Solves the mixed-integer linear optimization problem:

$$\begin{aligned} \text{minimize} \quad & f^T x \\ \text{subject to} \quad & Ax \quad b; \\ & Bx = c; \\ & l \quad x \quad u; \\ & x(\text{intcon}) \ 2 \ Z: \end{aligned}$$

Parameters

- f [in] (double[]) The objective function.
- intcon [in] (int[]) The list of variables constrained to the set Z.
- A [in] (double[][]) Constraint matrix for the inequalities. Use A=[] if there are no inequalities.
- b [in] (double[]) Right-hand side for the inequalities. Use b=[] if there are no inequalities.
- B [in] (double[][]) Constraint matrix for the equalities. (optional)
- c [in] (double[]) Right-hand side for the equalities. (optional)
- l [in] (double[]) Lower bounds for variables. Use -inf to represent in nite lower bounds. (optional)
- u [in] (double[]) Upper bounds for variables. Use inf to represent in nite upper bounds. (optional)
- options [in] (struct) An optimization options structure. See the mskoptimset function for the de nition of the optimization options structure (optional). This function uses the options
  - .Diagnostics
  - .Display
  - .MaxTime Time limit in seconds.
  - .MaxNodes The maximum number of branch-and-bounds allowed.
  - .Write Name of le to save the problem.
- problem [in] (struct) A structure containing the elds f, intcon, A, b, B, c, l, u and options .

Return

- x (double[]) The solution x.
- fval (double) The objective $f^T x$.
- exitflag (int) A number which has the interpretation:

- 1 The function returned an integer feasible solution.
- -2 The problem is infeasible.
- -4 MaxNodes reached without converging.
- -5 MaxTime reached without converging.

x, fval , exitflag , output , lambda = linprog(f , A, b, B, c, l , u, options)
x, fval , exitflag , output , lambda = linprog(problem)

Solves the linear optimization problem:

$$\begin{array}{ll} \text{minimize} & f^T x \\ \text{subject to} & Ax \leq b, \\ & Bx = c, \\ & l \leq x \leq u. \end{array}$$

Parameters

- f [in] (double[]) The objective function.
- A [in] (double[][]) Constraint matrix for the inequalities. Use $A = []$ if there are no inequalities.
- b [in] (double[]) Right-hand side for the inequalities. Use $b = []$ if there are no inequalities.
- B [in] (double[][]) Constraint matrix for the equalities. (optional)
- c [in] (double[]) Right-hand side for the equalities. (optional)
- l [in] (double[]) Lower bounds on the variables. Use -inf to represent in nite lower bounds. (optional)
- u [in] (double[]) Upper bounds on the variables. Use inf to represent in nite upper bounds. (optional)
- options [in] (struct) An optimization options structure (optional). See the *mskoptimset* function for the de nition of the optimization options structure. This function uses the options
  - .Diagnostics
  - .Display
  - .MaxIter
  - .Simplex Choose the simplex algorithm: 'on' the optimizer chooses wither primal or dual simplex (as in *"MSK_OPTIMIZER_FREE_SIMPLEX"*), 'primal ' use primal simplex, 'dual ' use dual simplex. The 'primal ' and 'dual ' values are speci c for the **MOSEK** interface, and not present in the standard MATLAB version.
  - .Write Name of le to save the problem.
- problem [in] (struct) structure containing the elds f , A, b, B, c, l , u and options .
- output [in] (struct) A structure with the following elds
  - .iterations Number of interior-point iterations spent to reach the optimum.
  - .algorithm Always de ned as 'MOSEK'.
- lambda [in] (struct) A struct with the following elds
  - .lower Lagrange multipliers for lower bounds l.
  - .upper Lagrange multipliers for upper bounds u.
  - .ineqlin Lagrange multipliers for the inequalities.
  - .eqlin Lagrange multipliers for the equalities.

Return

- x (double[]) The optimal x solution.
- fval (double) The optimal objective value, i.e. $f^T x$.
- exitflag (int) A number which has the interpretation [in]:
  - < 0 The problem is likely to be either primal or dual infeasible.
  - $= 0$ The maximum number of iterations was reached.

- > 0 x is an optimal solution.

x, resnorm, residual , exitflag , output , lambda = lsqlin(C , d, A, b, B, c, l , u, x0, options)

Solves the linear least squares problem:

$$\begin{array}{ll} \text{minimize} & \frac{1}{2}\|Cx-d\|_2^2 \\ \text{subject to} & Ax \leq b, \\ & Bx = c, \\ & l \leq x \leq u. \end{array}$$

Parameters

- C [in] (double[][]) The matrix in the objective.
- d [in] (double[]) The vector in the objective.
- A [in] (double[][]) Constraint matrix for the inequalities. Use $A = []$ if there are no inequalities.
- b [in] (double[]) Right-hand side for the inequalities. Use $b = []$ if there are no inequalities.
- B [in] (double[][]) Constraint matrix for the equalities. (optional)
- c [in] (double[]) Right-hand side for the equalities. (optional)
- l [in] (double[]) Lower bounds on the variables. Use -inf to represent in nite lower bounds. (optional)
- u [in] (double[]) Upper bounds on the variables. Use inf to represent in nite upper bounds. (optional)
- x0 [in] (double[]) Ignored by **MOSEK**. (optional)
- options [in] (struct) An optimization options structure (optional). See the function *mskoptimset* function for the de nition of the optimization options structure. This function uses the options
  - .Diagnostics
  - .Display
  - .MaxIter
  - .Write

Return

- x (double[]) The optimal x solution.
- resnorm (double) The squared norm of the optimal residuals, i.e. $\|Cx-d\|_2^2$ evaluated at the optimal solution.
- residual (double) The residual $Cx-d$.
- exitflag (int) A scalar which has the interpretation:
  - < 0 The problem is likely to be either primal or dual infeasible.
  - $= 0$ The maximum number of iterations was reached.
  - > 0 x is the optimal solution.
- output (struct)
  - .iterations Number of iterations spent to reach the optimum.
  - .algorithm Always de ned as 'MOSEK'.
- lambda (struct)
  - .lower Lagrange multipliers for lower bounds l.
  - .upper Lagrange multipliers for upper bounds u.
  - .ineqlin Lagrange multipliers for inequalities.
  - .eqlin Lagrange multipliers for equalities.

x, resnorm, residual , exitflag , output , lambda = lsqnonneg(C, d, x0, options)

Solves the linear least squares problem:

$$\begin{array}{ll} \text{minimize} & \frac{1}{2}\|Cx-d\|_2^2 \\ \text{subject to} & x \geq 0. \end{array}$$

Parameters

- C [in] (double[][]) The matrix in the objective.
- d [in] (double[]) The vector in the objective.
- x0 [in] (double[]) Ignored by **MOSEK**. (optional)
- options [in] (struct) An optimization options structure (optional). See the *mskoptimset* function for the definition of the optimization options structure. This function uses the options
  - .Diagnostics
  - .Display
  - .MaxIter
  - .Write

Return

- x (double[]) The x solution.
- resnorm (double) The squared norm of the optimal residuals, i.e. $\|Cx - d\|_2^2$ evaluated at the optimal solution.
- exitflag (int) A number which has the interpretation:
  - < 0 The problem is likely to be either primal or dual infeasible.
  - $= 0$ The maximum number of iterations was reached.
  - > 0 x is optimal solution.
- output (struct)
  - .iterations Number of iterations spend to reach the optimum.
  - .algorithm Always defined to be 'MOSEK'.
- lambda (struct)
  - .lower Lagrange multipliers for lower bounds l.
  - .upper Lagrange multipliers for upper bounds u.
  - .ineqlin Lagrange multipliers for inequalities.
  - .eqlin Lagrange multipliers for equalities.

x, fval , exitflag , output , lambda = quadprog(H, f , A, b, B, c, l , u, x0, options)

Solves the quadratic optimization problem:

$$\begin{array}{ll} \text{minimize} & \frac{1}{2}x^T H x + f^T x \\ \text{subject to} & Ax \leq b, \\ & Bx = c, \\ & l \leq x \leq u. \end{array}$$

Parameters

- H [in] (double[][]) Hessian of the objective function. The matrix H must be symmetric positive semidefinite. Contrary to the MATLAB optimization toolbox, **MOSEK** handles only the cases where H is positive semidefinite. On the other hand **MOSEK** always computes a global optimum.
- f [in] (double[]) The linear term of the objective.
- A [in] (double[][]) Constraint matrix for the inequalities. Use $A = []$ if there are no inequalities.
- b [in] (double[]) Right-hand side for the inequalities. Use $b = []$ if there are no inequalities.
- B [in] (double[][]) Constraint matrix for the equalities. (optional)
- c [in] (double[]) Right-hand side for the equalities. (optional)
- l [in] (double[]) Lower bounds on the variables. Use -inf to represent infinite lower bounds. (optional)
- u [in] (double[]) Upper bounds on the variables. Use inf to represent infinite upper bounds. (optional)
- x0 [in] (double[]) Ignored by **MOSEK**. (optional)

- options [in] (struct) An optimization options structure (optional). See the *mskoptimset* function for the de nition of the optimizations options structure. This function uses the options
  - .Diagnostics
  - .Display
  - .MaxIter
  - .Write

Return

- x (double[]) The x solution.
- fval (double) The optimal objective value i.e. $\frac{1}{2}x^T Hx + f^T x$.
- exitflag (int) A scalar which has the interpretation:
  - < 0 The problem is likely to be either primal or dual infeasible.
  - $= 0$ The maximum number of iterations was reached.
  - > 0 x is an optimal solution.
- output (struct) A structure with the following elds
  - .iterations Number of iterations spent to reach the optimum.
  - .algorithm Always de ned as 'MOSEK'.
- lambda (struct) A structure with the following elds
  - .lower Lagrange multipliers for lower bounds l.
  - .upper Lagrange multipliers for upper bounds u.
  - .ineqlin Lagrange multipliers for inequalities.
  - .eqlin Lagrange multipliers for equalities.

15.3 Data Structures and Notation

We specify the notation and data structures used in the interface.

Problem definition

- *prob* describes an optimization problem.
- *cones* description of cones.
- *names* names of objects in the optimization problem.
- *barc*, *bara* description of the semide nite part.

Solutions

- *res* result returned by *mosekopt*.
- *solver_solutions* solutions.
- *solution* one solution.

Other

- *primal_repair* used in feasibility repair.
- *prisen*, *prisen_data*, *duasen* used in sensitivity analysis.
- *callback* used to set up a callback function.
- *optserver* used to set up remote optimization.

15.3.1 Notation

Linear problem

A linear problem has the form:

$$\begin{array}{lccccl} \text{minimize} & & \sum_{j=1}^n c_j x_j + c^f & & & \\ \text{subject to} & l_i^c & \leq & \sum_{j=1}^n a_{ij} x_j & \leq & u_i^c, \quad i = 1, \ldots, m, \\ & l_j^x & \leq & x_j & \leq & u_j^x, \quad j = 1, \ldots, n. \end{array} \tag{15.1}$$

It has n variables and m linear constraints. See Sec. 12.1.

Conic problem

A conic problem is an extension of a linear problem and has the form:

$$\begin{array}{lccccl} \text{minimize} & & \sum_{j=1}^n c_j x_j + \sum_{j=1}^p \langle \overline{C}_j, \overline{X}_j \rangle + c^f & & & \\ \text{subject to} & l_i^c & \leq & \sum_{j=1}^n a_{ij} x_j + \sum_{j=1}^p \langle \overline{A}_{ij}, \overline{X}_j \rangle & \leq & u_i^c, \quad i = 1, \ldots, m, \\ & l_j^x & \leq & x_j & \leq & u_j^x, \quad j = 1, \ldots, n, \\ & & & x \in \mathcal{K}, & & \\ & & & \overline{X}_j \in \mathcal{S}_+^{r_j}, & & \quad j = 1, \ldots, p \end{array} \tag{15.2}$$

It has n variables, m linear constraints, a cone $\mathcal{K}$ (see below) and $p \geq 0$ semide nite variables. See also Sec. 12.2 (or Sec. 12.3 for SDP). The conic constraint

$$x \in \mathcal{K}$$

means that a partitioning of x belongs to a set of cones $\mathcal{K} = \mathcal{K}_1 \times \ldots \times \mathcal{K}_s$, which can be one of:

- Quadratic cone

$$\mathcal{Q}^n = \left\{ x \in \mathbb{R}^n : x_1 \geq \sqrt{\sum_{j=2}^n x_j^2} \right\}.$$

- Rotated quadratic cone

$$\mathcal{Q}_r^n = \left\{ x \in \mathbb{R}^n : 2x_1 x_2 \geq \sum_{j=3}^n x_j^2, \quad x_1 \geq 0, \quad x_2 \geq 0 \right\}.$$

- Primal exponential cone

$$K_{\exp} = \left\{ x \in \mathbb{R}^3 : x_1 \geq x_2 \exp(x_3/x_2), \quad x_1, x_2 \geq 0 \right\}$$

  as well as its dual

$$K_{\exp}^* = \left\{ x \in \mathbb{R}^3 : x_1 \geq -x_3 e^{-1} \exp(x_2/x_3), \quad x_3 \leq 0, x_1 \geq 0 \right\}.$$

- Primal power cone (with parameter $0 < \alpha < 1$)

$$\mathcal{P}_n^{\alpha,1-\alpha} = \left\{ x \in \mathbb{R}^n : x_1^\alpha x_2^{1-\alpha} \geq \sqrt{\sum_{j=3}^n x_j^2}, \quad x_1, x_2 \geq 0 \right\}$$

  as well as its dual

$$(\mathcal{P}_n^{\alpha,1-\alpha})^* = \left\{ x \in \mathbb{R}^n : \left(\frac{x_1}{\alpha}\right)^\alpha \left(\frac{x_2}{1-\alpha}\right)^{1-\alpha} \geq \sqrt{\sum_{j=3}^n x_j^2}, \quad x_1, x_2 \geq 0 \right\}.$$

- The set $\mathbb{R}^n$.
- The zero cone $\{(0, \ldots, 0)\}$.

Membership in the trivial cones does not have to be speci ed.

Conic problem with affine conic constraints

A conic problem with a ne conic constraints is an extension of a linear problem and has the form:

$$\begin{array}{lrcccll} \text{minimize} & & & \sum_{j=1}^n c_j x_j + \sum_{j=1}^p \langle \overline{C}_j, \overline{X}_j \rangle + c^f & & & \\ \text{subject to} & l_i^c & \leq & \sum_{j=1}^n a_{ij} x_j + \sum_{j=1}^p \langle \overline{A}_{ij}, \overline{X}_j \rangle & \leq & u_i^c, & i = 1, \ldots, m, \\ & l_j^x & \leq & x_j & \leq & u_j^x, & j = 1, \ldots, n, \\ & & & Fx + g \in \mathcal{K}, & & & \\ & & & \overline{X}_j \in \mathcal{S}_+^{r_j}, & & & j = 1, \ldots, p \end{array} \tag{15.3}$$

It has n variables, m linear constraints, a cone $\mathcal{K}$ (see below) and $p \geq 0$ semide nite variables. See also Sec. 12.5.

The conic constraint

$$Fx + g \in \mathcal{K}$$

where $F \in \mathbb{R}^{k \times n}$ and $g \in \mathbb{R}^k$ means that an a ne combination of x belongs to a product of cones $\mathcal{K} = \mathcal{K}_1 \times \ldots \times \mathcal{K}_s$ of total length (dimension) k. The available cone types are the same as above.

Quadratic and quadratically constrained problems

A problem with quadratic objective or constraints has the form:

$$\begin{array}{lrcccll} \text{minimize} & & & \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n q_{ij}^o x_i x_j + \sum_{j=1}^n c_j x_j + c^f & & & \\ \text{subject to} & l_i^c & \leq & \frac{1}{2} \sum_{j=1}^n \sum_{k=1}^n q_{jk}^i x_j x_k + \sum_{j=1}^n a_{ij} x_j & \leq & u_i^c, & i = 1, \ldots, m, \\ & l_j^x & \leq & x & \leq & u_j^x, & j = 1, \ldots, n. \end{array} \tag{15.4}$$

It has n variables, and m constraints. The matrix $Q^o = (q_{ij}^o)_{i=1,\ldots,n, j=1,\ldots,n}$ must be symmetric positive semide nite. See also Sec. 12.4. Each of the matrices $Q^i = (q_{jk}^i)_{j=1,\ldots,n, k=1,\ldots,n}$ for $j = 1 \ldots, m$ must be

- negative semide nite if $-\infty < l_i^c$, $u_i^c = +\infty$,
- positive semide nite if $-\infty = l_i^c$, $u_i^c < +\infty$,
- zero otherwise.

Mixed-integer problems

All problems without semide nite variables may be integer-constrained, i.e., for some set $\mathcal{J} \subseteq \{1, \ldots, n\}$ we require

$$x_j \in \mathbb{Z} \text{ for all } j \in \mathcal{J} \tag{15.5}$$

Minimization vs. Maximization

The objective of every problem can be maximized rather than minimized without any change. In case of quadratic problems the matrix Q^o must be negative semide nite.

Data specification in MATLAB

- The linear constraint matrix $A = (a_{ij})_{i=1\ldots,m, j=1,\ldots,n}$ must be a sparse matrix. The dimensions of A are used to determine the number of constraints m and the number of variables n in the problem.
- The symmetric matrices Q^o, Q^i, $\overline{C}_j$ and $\overline{A}_{ij}$ are speci ed in sparse triplet format discarding zero elements, and since they are symmetric, only the lower triangular parts should be speci ed. A generic matrix M speci ed in sparse triplet format is given by three arrays subi , subj and val of the same length such that

$$M_{\texttt{subi[t]},\texttt{subj[t]}} = \texttt{val[t]}, \qquad t = 1, \ldots, \texttt{len(val)}$$

- For a speci cation of the cones $\mathcal{K}$ see *cones*.

- For a speci cation of the semide nite part see *bara* and *barc*.

The parameters of the optimization problem are stored using one or more sub elds of the *prob* structure using the naming convention in Table 15.1. Only a is obligatory. All other elds are optional depending on what problem type is de ned.

Table 15.1: The relation between elds and problem parameters

Field name	Type	Dimension	Problem parameters
a	sparse matrix	$m \times n$	a_{ij}
c	double[]	n	c_j
cfix	double	1	c^f
blc	double[]	m	l_i^c
buc	double[]	m	u_i^c
blx	double[]	n	l_j^x
bux	double[]	n	u_j^x
ints.subs	int[]	$\lvert\mathcal{J}\rvert$	$\mathcal{J}$
cones	*cones*		$\mathcal{K}$
f	sparse matrix	$k \times n$	F
g	double[]	k	g
bardim	int[]	p	r_j
barc	*barc*		$\overline{C}_j$
bara	*bara*		$\overline{A}_{ij}$
qosubi	int[]	len(qoval)	q_{ij}^o, sparse rep.
qosubj	int[]	len(qoval)	q_{ij}^o, sparse rep.
qoval	double[]	len(qoval)	q_{ij}^o, sparse rep.
qcsubk	int[]	len(qcval)	q_{ij}^k, sparse rep.
qcsubi	int[]	len(qcval)	q_{ij}^k, sparse rep.
qcsubj	int[]	len(qcval)	q_{ij}^k, sparse rep.
qcval	double[]	len(qcval)	q_{ij}^k, sparse rep.

The int type indicates that the eld must contain an integer value, double indicates any real number. This distinction is only a convenience for the reader all actual data structures in MATLAB are ordinary matrices/arrays of oating-point numbers.

The sparse representation of quadratic terms is:

$$\begin{aligned} q^{o}_{\mathtt{qosubi(t)},\mathtt{qoval(t)}} &= \mathtt{qoval(t)}, \quad t = 1,2,\ldots,\mathtt{length(qoval)}, \\ q^{\mathtt{qcsubk(t)}}_{\mathtt{qcsubi(t)},\mathtt{qcsubj(t)}} &= \mathtt{qcval(t)}, \quad t = 1,2,\ldots,\mathtt{length(qcval)}. \end{aligned} \tag{15.6}$$

Since Q^o, Q^i are by assumption symmetric, all elements are assumed to belong to the lower triangular part. If an element is speci ed multiple times, the di erent elements are added together.

15.3.2 Data Types and Structures

prob

The prob data structure is used to communicate an optimization problem to **MOSEK** or for **MOSEK** to return an optimization problem to the user. It de nes an optimization problem using a number of sub elds. Most of the elds are optional, depending on what problem type is being solved.

Fields

- names(*names*) A structure which contains the names of the problem, variables, constraints and so on.
- a (double[][]) The linear constraint matrix. It is obligatory, and its dimensions de ne the number of variables and constraints. It must be a **sparse matrix**. This eld should always be de ned, even if the problem does not have any constraints. In that case a sparse matrix having zero rows and the correct number of columns is the appropriate de nition of the eld.
- c (double[]) Linear term in the objective.

- cfix (double) Fixed term in the objective.
- blc (double[]) Lower bounds of the constraints. $-\infty$ denotes an in nite lower bound. If the eld is not de ned or blc==[] , then all the lower bounds are assumed to be equal to $-\infty$.
- buc (double[]) Upper bounds of the constraints. ∞ denotes an in nite upper bound. If the eld is not de ned or buc==[] , then all the upper bounds are assumed to be equal to ∞.
- blx (double[]) Lower bounds on the variables. $-\infty$ denotes an in nite lower bound. If the eld is not de ned or blx==[] , then all the lower bounds are assumed to be equal to $-\infty$.
- bux (double[]) Upper bounds on the variables. ∞ denotes an in nite upper bound. If the eld is not de ned or bux==[] , then all the upper bounds are assumed to be equal to ∞.
- bardim (int[]) A list with the dimensions of the semide nite variables.
- barc (*barc*) A structure for specifying $\overline{C}_j$.
- bara (*bara*) A structure for specifying $\overline{A}_{ij}$.
- qosubi (int[]) i subscripts in the sparse speci cation of q^o_{ij} in Q^o. See (15.6).
- qosubj (int[]) j subscripts in the sparse speci cation of q^o_{ij} in Q^o. See (15.6).
- qoval (double[]) Numerical values in the sparse speci cation of q^o_{ij} in Q^o. See (15.6).
- qcsubk (int[]) k subscripts in the sparse speci cation of q^k_{ij} in Q^k. See (15.6)
- qcsubi (int[]) i subscripts in the sparse speci cation of q^k_{ij} in Q^k. See (15.6)
- qcsubj (double[]) j subscripts in the sparse speci cation of q^k_{ij} in Q^k. See (15.6)
- qcval (double[]) Numerical values in the sparse speci cation of q^k_{ij} in Q^k. See (15.6)
- f (double[][]) The matrix of a ne conic constraints. It must be a sparse matrix.
- g (double[]) The constant term of a ne conic constraints. If not present or g==[] it is assumed $g = 0$.
- ints.sub (int[]) A list of indexes of integer-constrained variables. ints.sub is identical to the set $|$ in (15.5).
- cones (*cones*) A structure de ning either the conic constraints in (15.2) or the a ne conic constraints in (15.3).
- sol (*solver_solutions*) A structure containing a guess on the optimal solution which some of the optimizers in **MOSEK** may exploit.
- primlarepair (*primal_repair*) Speci cation of primal feasibility repair. See Sec. 14.2.1.
- prisen (*prisen*) Request sensitivity analysis. See Sec. 14.3.
- duasen (*duasen*) Request sensitivity analysis. See Sec. 14.3.

res

Contains a response from *mosekopt*.

Fields

- sol (*solver_solutions*) A structure containing solutions (if any).
- rcode (int) The numerical response code from the solver. See Sec. 7.2.
- rcodestr (string) The response code from the solver as a symbolic string. See Sec. 7.2.
- rmsg (string) A message explaining the error (if any). See Sec. 7.2.
- info (struct) A structure containing information items (if requested by the command info in *mosekopt*). See Sec. 7.5.
- prob (*prob*) Contains the problem data, if the command read was used to read a problem from a le. See Sec. 7.3.4.
- param (struct) A structure which contains the complete **MOSEK** parameter database (if requested by the command param in *mosekopt*). See Sec. 7.4.

- symbcon (struct) A structure which contains symbolic constants and their numerical values (if requested by the command symbcon in *mosekopt*). See Sec. 15.7 and Sec. 15.6.
- version (struct) A structure which contains the **MOSEK** version numbers (if requested by the command version in *mosekopt*).
- prisen (*prisen*) A structure with results of sensitivity analysis (if requested by passing prisen data in prob). See Sec. 14.3.
- duasen (*duasen*) A structure with results of sensitivity analysis (if requested by passing duasen data in prob). See Sec. 14.3.

solver_solutions

It contains informations about initial/ nal solutions. Availability of solutions depends on the problem/algorithm type, see Sec. 7.1.2.

Fields

- itr (*solution*) Interior solution.
- bas (*solution*) Basic solution.
- int (*solution*) Integer solution.

solution

Stores information about one solution. See Sec. 7.1.2.

Fields

- prosta (string) Problem status (*prosta*).
- solsta (string) Solution status (*solsta*).
- skc (string[]) Linear constraint status keys (*stakey*).
- skx (string[]) Variable status keys (*stakey*).
- skn (string[]) Conic constraint status keys (*stakey*, not in basic solution).
- xc (double[]) Constraint activities, i.e., $x_c = Ax$ where x is the optimal solution.
- xx (double[]) The optimal x solution.
- barx (list) Semide nite variable solution (not in basic solution).
- y (double[]) Identical to sol.slc-sol.suc (not in integer solution).
- slc (double[]) Dual variable for constraint lower bounds (not in integer solution).
- suc (double[]) Dual variable for constraint upper bounds (not in integer solution).
- slx (double[]) Dual variable for variable lower bounds (not in integer solution).
- sux (double[]) Dual variable for variable upper bounds (not in integer solution).
- snx (double[]) Dual variable of conic constraints (not in basic or integer solution).
- doty (double[]) Dual variables of a ne conic constraints (not in basic or integer solution).
- bars (list) Dual variable of semide nite domains (not in basic or integer solution).
- pobjval (double) The primal objective value.
- dobjval (double) The dual objective value (not in integer solution).

names

This structure is used to store all the names of individual items in the optimization problem such as the constraints and the variables.

Fields

- name(string) contains the problem name.
- obj (string) contains the name of the objective.
- con (cell) a cell array where names.con{i} contains the name of the i-th constraint.

- var (cell) a cell array where names.var{j} contains the name of the j-th variable.
- cone (cell) a cell array where names.cone{t} contains the name of the t-th conic constraint.
- barvar (cell) a cell array where names.barvar{j} contains the name of the j-th semide nite variable.

cones

Represents either conic constraints or a ne conic constraints.

Conic constraints. For conic constraints $x \in \mathcal{K}$, where $\mathcal{K} = \mathcal{K}_1 \times \cdots \times \mathcal{K}_s$, cones is a structure containing three or four elds:

- type (list) An array with the cone type for each cone; see *conetype*.
- sub (int[]) A concatenation of index lists of all the cones.
- subptr (int[]) An array of pointers indicating the beginning of consecutive cones in sub.
- conepar (double[]) An array of cone parameters; for a power cone this is the exponent α, for other cone types the value is irrelevant. If the problem contains no power cones this eld is not required.

The arrays type and subptr (and conepar if present) must have the same length s. For every $j = 1, \ldots, s$ the vector $x_{\mathtt{sub[subptr[j]:(subptr[j+1]-1)]}}$ belongs to a cone of type $\mathtt{type[j]}$ with parameter $\mathtt{conepar[j]}$. For example for the two cones

$$x_5 \geq \sqrt{x_3^2 + x_1^2}, \quad x_6^{0.3} x_4^{0.7} \geq \sqrt{x_2^2 + x_7^2}$$

the description could be:

```
cones.type   = [res.symbcon.MSK_CT_QUAD, res.symbcon.MSK_CT_PPOW];
cones.sub    = [5, 3, 1, 6, 4, 2, 7];
cones.subptr = [1, 4];
cones.conepar= [0.0, 0.3];
```

Affine conic constraints. For a ne conic constraints $Fx + g \in \mathcal{K}$, where $\mathcal{K} = \mathcal{K}_1 \times \cdots \times \mathcal{K}_s$, cones is a list consisting of s concatenated cone descriptions. If a cone requires no additional parameters (quadratic, rotated quadratic, exponential, zero) then its description is

$$[\mathrm{type}, \mathrm{len}]$$

where type is the type (*conetype*) and len is the length (dimension). The length must be present. If a cone requires additional parameters (power cones) then its description has the form

$$[\mathrm{type}, \mathrm{len}, k, a_1, \ldots, a_k]$$

where $k \geq 1$ is an integer and $a_1, \ldots, a_k \in \mathbb{R}$ are the additional parameters. For the power cone it is required that $k = 2$ and then a power cone with parameter $\alpha = a_1/(a_1 + a_2)$ is constructed. For example $\mathcal{Q}^5 \times \mathcal{P}_4^{0.4}$ could be de ned as

```
cones = [res.symbcon.MSK_CT_QUAD 5 res.symbcon.MSK_CT_PPOW, 4, 2, 40.0, 60.0 ];
```

barc

Together with eld bardim this structure speci es the symmetric matrices $\overline{C}_j$ in the objective for semide nite problems.

The symmetric matrices are speci ed in block-triplet format as

$$[\overline{C}_{\mathtt{barc.subj(t)}}]_{\mathtt{barc.subk(t),barc.subl(t)}} = \mathtt{barc.val(t)}, \quad t = 1, 2, \ldots, \mathtt{length(barc.subj)}.$$

Only the lower triangular parts of $\overline{C}_j$ are speci ed, i.e., it is required that

$$\mathtt{barc.subk(t)} \geq \mathtt{barc.subl(t)}, \quad t = 1, 2, \ldots, \mathtt{length(barc.subk)},$$

and that

$$1 \leq \texttt{barc.subk(t)} \leq \texttt{bardim(barc.subj(t))}, \quad t = 1, 2, \ldots, \texttt{length(barc.subj)}.,$$

All the structure elds must be arrays of the same length.

Fields

- subj (int[]) Semide nite variable indices j.
- subk (int[]) k subscripts of nonzeros elements.
- subl (int[]) l subscripts of nonzeros elements.
- val (double) Numerical values.

bara

Together with the eld bardim this structure speci es the symmetric matrices $\overline{A}_{ij}$ in the constraints of semide nite problems.

The symmetric matrices are speci ed in block-triplet format as

$$[\overline{A}_{\texttt{bara.subi(t)},\texttt{bara.subj(t)}}]_{\texttt{bara.subk(t)},\texttt{bara.subl(t)}} = \texttt{bara.val(t)}, \quad t = 1, 2, \ldots, \texttt{length(bara.subi)}.$$

Only the lower triangular parts of $\overline{A}_{ij}$ are speci ed, i.e., it is required that

$$\texttt{bara.subk(t)} \geq \texttt{bara.subl(t)}, \quad t = 1, 2, \ldots, \texttt{length(bara.subk)},$$

and that

$$1 \leq \texttt{bara.subk(t)} \leq \texttt{bardim(bara.subj(t))}, \quad t = 1, 2, \ldots, \texttt{length(bara.subj)},$$

All the structure elds must be arrays of the same length.

Fields

- subi (int[]) Constraint indices i.
- subj (int[]) Semide nite variable indices j.
- subk (int[]) k subscripts of nonzeros elements.
- subl (int[]) l subscripts of nonzeros elements.
- val (double[]) Numerical values.

primal_repair

A structure holding data for primal feasibility repair. If either of the sub elds is missing, it assumed to be a vector with value 1 of appropriate dimension. See Sec. 14.2.1.

Fields

- wlc (double[]) Weights for lower bounds on constraints.
- wuc (double[]) Weights for upper bounds on constraints.
- wlx (double[]) Weights for lower bounds on variables.
- wux (double[]) Weights for upper bounds on variables.

prisen

A structure holding information about primal sensitivity analysis. See Sec. 14.3.

Fields

- cons (*prisen_data*) Constraints shadow prices.
- vars (*prisen_data*) Variables shadow prices.

prisen_data

A structure holding information about shadow prices of constraints or variables.

Fields

- subl (int[]) Indices of variables/constraints to be analyzed for lower bounds.
- subu (int[]) Indices of variables/constraints to be analyzed for upper bounds.

- lr_bl (double[]) Left value β_1 in the linearity interval for a lower bound.
- rr_bl (double[]) Right value β_2 in the linearity interval for a lower bound.
- ls_bl (double[]) Left shadow price s_l for a lower bound.
- rs_bl (double[]) Right shadow price s_r for a lower bound.
- lr_bu (double[]) Left value β_1 in the linearity interval for an upper bound.
- rr_bu (double[]) Right value β_2 in the linearity interval for an upper bound.
- ls_bu (double[]) Left shadow price s_l for an upper bound.
- rs_bu (double[]) Right shadow price s_r for an upper bound.

duasen

A structure holding information about dual sensitivity analysis. See Sec. 14.3.

Fields

- sub (int[]) Indices of variables to be analyzed.
- lr_c (double) Left value β_1 in linearity interval for an objective coe cient
- rr_c (double) Right value β_2 in linearity interval for an objective coe cient
- ls_c (double) Left shadow price s_l for an objective coe cient
- rs_c (double) Right shadow price s_r for an objective coe cient

callback

A structure containing callback information (all sub elds are optional).

Fields

- loghandle (struct) A data structure or just [] .
- log (string) Log handler. The name of a user-de ned function which must accept two input arguments, e.g.,

```
function myprint(handle,str)
```

  where handle will be identical to callback.handle when myfunc is called, and str is a string of text from the log.
- iterhandle (struct) A data structure or just [] .
- iter (string) Progress callback handler. The name of a user-de ned function which must accept three input arguments,

```
function [r] = callback_handler(handle,where,info)
```

  where handle will be identical to callback.iterhandle when the handler is called, where indicates the current progress of the solver (*callback*) and info is the current information items list. See Sec. 7.6 for further details.

optserver

A structure containing information about the OptServer which should be used for remote optimization.

Fields host (string) URL of the OptServer in the form http://server:port .

15.4 Parameters grouped by topic

Analysis

- *MSK_DPAR_ANA_SOL_INFEAS_TOL*
- *MSK_IPAR_ANA_SOL_BASIS*
- *MSK_IPAR_ANA_SOL_PRINT_VIOLATED*
- *MSK_IPAR_LOG_ANA_PRO*

Basis identi cation

- MSK_DPAR_SIM_LU_TOL_REL_PIV
- MSK_IPAR_BI_CLEAN_OPTIMIZER
- MSK_IPAR_BI_IGNORE_MAX_ITER
- MSK_IPAR_BI_IGNORE_NUM_ERROR
- MSK_IPAR_BI_MAX_ITERATIONS
- MSK_IPAR_INTPNT_BASIS
- MSK_IPAR_LOG_BI
- MSK_IPAR_LOG_BI_FREQ

Conic interior-point method

- MSK_DPAR_INTPNT_CO_TOL_DFEAS
- MSK_DPAR_INTPNT_CO_TOL_INFEAS
- MSK_DPAR_INTPNT_CO_TOL_MU_RED
- MSK_DPAR_INTPNT_CO_TOL_NEAR_REL
- MSK_DPAR_INTPNT_CO_TOL_PFEAS
- MSK_DPAR_INTPNT_CO_TOL_REL_GAP

Data check

- MSK_DPAR_DATA_SYM_MAT_TOL
- MSK_DPAR_DATA_SYM_MAT_TOL_HUGE
- MSK_DPAR_DATA_SYM_MAT_TOL_LARGE
- MSK_DPAR_DATA_TOL_AIJ_HUGE
- MSK_DPAR_DATA_TOL_AIJ_LARGE
- MSK_DPAR_DATA_TOL_BOUND_INF
- MSK_DPAR_DATA_TOL_BOUND_WRN
- MSK_DPAR_DATA_TOL_C_HUGE
- MSK_DPAR_DATA_TOL_CJ_LARGE
- MSK_DPAR_DATA_TOL_QIJ
- MSK_DPAR_DATA_TOL_X
- MSK_DPAR_SEMIDEFINITE_TOL_APPROX
- MSK_IPAR_CHECK_CONVEXITY
- MSK_IPAR_LOG_CHECK_CONVEXITY

Data input/output

- *MSK_IPAR_INFEAS_REPORT_AUTO*
- *MSK_IPAR_LOG_FILE*
- *MSK_IPAR_OPF_WRITE_HEADER*
- *MSK_IPAR_OPF_WRITE_HINTS*
- *MSK_IPAR_OPF_WRITE_LINE_LENGTH*
- *MSK_IPAR_OPF_WRITE_PARAMETERS*
- *MSK_IPAR_OPF_WRITE_PROBLEM*
- *MSK_IPAR_OPF_WRITE_SOL_BAS*
- *MSK_IPAR_OPF_WRITE_SOL_ITG*
- *MSK_IPAR_OPF_WRITE_SOL_ITR*
- *MSK_IPAR_OPF_WRITE_SOLUTIONS*
- *MSK_IPAR_PARAM_READ_CASE_NAME*
- *MSK_IPAR_PARAM_READ_IGN_ERROR*
- *MSK_IPAR_PTF_WRITE_TRANSFORM*
- *MSK_IPAR_READ_DEBUG*
- *MSK_IPAR_READ_KEEP_FREE_CON*
- *MSK_IPAR_READ_LP_DROP_NEW_VARS_IN_BOU*
- *MSK_IPAR_READ_LP_QUOTED_NAMES*
- *MSK_IPAR_READ_MPS_FORMAT*
- *MSK_IPAR_READ_MPS_WIDTH*
- *MSK_IPAR_READ_TASK_IGNORE_PARAM*
- *MSK_IPAR_SOL_READ_NAME_WIDTH*
- *MSK_IPAR_SOL_READ_WIDTH*
- *MSK_IPAR_WRITE_BAS_CONSTRAINTS*
- *MSK_IPAR_WRITE_BAS_HEAD*
- *MSK_IPAR_WRITE_BAS_VARIABLES*
- *MSK_IPAR_WRITE_COMPRESSION*
- *MSK_IPAR_WRITE_DATA_PARAM*
- *MSK_IPAR_WRITE_FREE_CON*
- *MSK_IPAR_WRITE_GENERIC_NAMES*
- *MSK_IPAR_WRITE_GENERIC_NAMES_IO*
- *MSK_IPAR_WRITE_IGNORE_INCOMPATIBLE_ITEMS*
- *MSK_IPAR_WRITE_INT_CONSTRAINTS*
- *MSK_IPAR_WRITE_INT_HEAD*
- *MSK_IPAR_WRITE_INT_VARIABLES*

- *MSK_IPAR_WRITE_LP_FULL_OBJ*
- *MSK_IPAR_WRITE_LP_LINE_WIDTH*
- *MSK_IPAR_WRITE_LP_QUOTED_NAMES*
- *MSK_IPAR_WRITE_LP_STRICT_FORMAT*
- *MSK_IPAR_WRITE_LP_TERMS_PER_LINE*
- *MSK_IPAR_WRITE_MPS_FORMAT*
- *MSK_IPAR_WRITE_MPS_INT*
- *MSK_IPAR_WRITE_PRECISION*
- *MSK_IPAR_WRITE_SOL_BARVARIABLES*
- *MSK_IPAR_WRITE_SOL_CONSTRAINTS*
- *MSK_IPAR_WRITE_SOL_HEAD*
- *MSK_IPAR_WRITE_SOL_IGNORE_INVALID_NAMES*
- *MSK_IPAR_WRITE_SOL_VARIABLES*
- *MSK_IPAR_WRITE_TASK_INC_SOL*
- *MSK_IPAR_WRITE_XML_MODE*
- *MSK_SPAR_BAS_SOL_FILE_NAME*
- *MSK_SPAR_DATA_FILE_NAME*
- *MSK_SPAR_DEBUG_FILE_NAME*
- *MSK_SPAR_INT_SOL_FILE_NAME*
- *MSK_SPAR_ITR_SOL_FILE_NAME*
- *MSK_SPAR_MIO_DEBUG_STRING*
- *MSK_SPAR_PARAM_COMMENT_SIGN*
- *MSK_SPAR_PARAM_READ_FILE_NAME*
- *MSK_SPAR_PARAM_WRITE_FILE_NAME*
- *MSK_SPAR_READ_MPS_BOU_NAME*
- *MSK_SPAR_READ_MPS_OBJ_NAME*
- *MSK_SPAR_READ_MPS_RAN_NAME*
- *MSK_SPAR_READ_MPS_RHS_NAME*
- *MSK_SPAR_SENSITIVITY_FILE_NAME*
- *MSK_SPAR_SENSITIVITY_RES_FILE_NAME*
- *MSK_SPAR_SOL_FILTER_XC_LOW*
- *MSK_SPAR_SOL_FILTER_XC_UPR*
- *MSK_SPAR_SOL_FILTER_XX_LOW*
- *MSK_SPAR_SOL_FILTER_XX_UPR*
- *MSK_SPAR_STAT_FILE_NAME*
- *MSK_SPAR_STAT_KEY*
- *MSK_SPAR_STAT_NAME*
- *MSK_SPAR_WRITE_LP_GEN_VAR_NAME*

Debugging

- *MSK_IPAR_AUTO_SORT_A_BEFORE_OPT*

Dual simplex

- *MSK_IPAR_SIM_DUAL_CRASH*
- *MSK_IPAR_SIM_DUAL_RESTRICT_SELECTION*
- *MSK_IPAR_SIM_DUAL_SELECTION*

Infeasibility report

- *MSK_IPAR_INFEAS_GENERIC_NAMES*
- *MSK_IPAR_INFEAS_REPORT_LEVEL*
- *MSK_IPAR_LOG_INFEAS_ANA*

Interior-point method

- *MSK_DPAR_CHECK_CONVEXITY_REL_TOL*
- *MSK_DPAR_INTPNT_CO_TOL_DFEAS*
- *MSK_DPAR_INTPNT_CO_TOL_INFEAS*
- *MSK_DPAR_INTPNT_CO_TOL_MU_RED*
- *MSK_DPAR_INTPNT_CO_TOL_NEAR_REL*
- *MSK_DPAR_INTPNT_CO_TOL_PFEAS*
- *MSK_DPAR_INTPNT_CO_TOL_REL_GAP*
- *MSK_DPAR_INTPNT_QO_TOL_DFEAS*
- *MSK_DPAR_INTPNT_QO_TOL_INFEAS*
- *MSK_DPAR_INTPNT_QO_TOL_MU_RED*
- *MSK_DPAR_INTPNT_QO_TOL_NEAR_REL*
- *MSK_DPAR_INTPNT_QO_TOL_PFEAS*
- *MSK_DPAR_INTPNT_QO_TOL_REL_GAP*
- *MSK_DPAR_INTPNT_TOL_DFEAS*
- *MSK_DPAR_INTPNT_TOL_DSAFE*
- *MSK_DPAR_INTPNT_TOL_INFEAS*
- *MSK_DPAR_INTPNT_TOL_MU_RED*
- *MSK_DPAR_INTPNT_TOL_PATH*
- *MSK_DPAR_INTPNT_TOL_PFEAS*
- *MSK_DPAR_INTPNT_TOL_PSAFE*
- *MSK_DPAR_INTPNT_TOL_REL_GAP*
- *MSK_DPAR_INTPNT_TOL_REL_STEP*

- *MSK_DPAR_INTPNT_TOL_STEP_SIZE*
- *MSK_DPAR_QCQO_REFORMULATE_REL_DROP_TOL*
- *MSK_IPAR_BI_IGNORE_MAX_ITER*
- *MSK_IPAR_BI_IGNORE_NUM_ERROR*
- *MSK_IPAR_INTPNT_BASIS*
- *MSK_IPAR_INTPNT_DIFF_STEP*
- *MSK_IPAR_INTPNT_HOTSTART*
- *MSK_IPAR_INTPNT_MAX_ITERATIONS*
- *MSK_IPAR_INTPNT_MAX_NUM_COR*
- *MSK_IPAR_INTPNT_MAX_NUM_REFINEMENT_STEPS*
- *MSK_IPAR_INTPNT_OFF_COL_TRH*
- *MSK_IPAR_INTPNT_ORDER_GP_NUM_SEEDS*
- *MSK_IPAR_INTPNT_ORDER_METHOD*
- *MSK_IPAR_INTPNT_PURIFY*
- *MSK_IPAR_INTPNT_REGULARIZATION_USE*
- *MSK_IPAR_INTPNT_SCALING*
- *MSK_IPAR_INTPNT_SOLVE_FORM*
- *MSK_IPAR_INTPNT_STARTING_POINT*
- *MSK_IPAR_LOG_INTPNT*

License manager

- *MSK_IPAR_CACHE_LICENSE*
- *MSK_IPAR_LICENSE_DEBUG*
- *MSK_IPAR_LICENSE_PAUSE_TIME*
- *MSK_IPAR_LICENSE_SUPPRESS_EXPIRE_WRNS*
- *MSK_IPAR_LICENSE_TRH_EXPIRY_WRN*
- *MSK_IPAR_LICENSE_WAIT*

Logging

- *MSK_IPAR_LOG*
- *MSK_IPAR_LOG_ANA_PRO*
- *MSK_IPAR_LOG_BI*
- *MSK_IPAR_LOG_BI_FREQ*
- *MSK_IPAR_LOG_CUT_SECOND_OPT*
- *MSK_IPAR_LOG_EXPAND*
- *MSK_IPAR_LOG_FEAS_REPAIR*

- *MSK_IPAR_LOG_FILE*
- *MSK_IPAR_LOG_INCLUDE_SUMMARY*
- *MSK_IPAR_LOG_INFEAS_ANA*
- *MSK_IPAR_LOG_INTPNT*
- *MSK_IPAR_LOG_LOCAL_INFO*
- *MSK_IPAR_LOG_MIO*
- *MSK_IPAR_LOG_MIO_FREQ*
- *MSK_IPAR_LOG_ORDER*
- *MSK_IPAR_LOG_PRESOLVE*
- *MSK_IPAR_LOG_RESPONSE*
- *MSK_IPAR_LOG_SENSITIVITY*
- *MSK_IPAR_LOG_SENSITIVITY_OPT*
- *MSK_IPAR_LOG_SIM*
- *MSK_IPAR_LOG_SIM_FREQ*
- *MSK_IPAR_LOG_STORAGE*

Mixed-integer optimization

- *MSK_DPAR_MIO_MAX_TIME*
- *MSK_DPAR_MIO_REL_GAP_CONST*
- *MSK_DPAR_MIO_TOL_ABS_GAP*
- *MSK_DPAR_MIO_TOL_ABS_RELAX_INT*
- *MSK_DPAR_MIO_TOL_FEAS*
- *MSK_DPAR_MIO_TOL_REL_DUAL_BOUND_IMPROVEMENT*
- *MSK_DPAR_MIO_TOL_REL_GAP*
- *MSK_IPAR_LOG_MIO*
- *MSK_IPAR_LOG_MIO_FREQ*
- *MSK_IPAR_MIO_BRANCH_DIR*
- *MSK_IPAR_MIO_CONIC_OUTER_APPROXIMATION*
- *MSK_IPAR_MIO_CUT_CLIQUE*
- *MSK_IPAR_MIO_CUT_CMIR*
- *MSK_IPAR_MIO_CUT_GMI*
- *MSK_IPAR_MIO_CUT_IMPLIED_BOUND*
- *MSK_IPAR_MIO_CUT_KNAPSACK_COVER*
- *MSK_IPAR_MIO_CUT_SELECTION_LEVEL*
- *MSK_IPAR_MIO_FEASPUMP_LEVEL*
- *MSK_IPAR_MIO_HEURISTIC_LEVEL*

- *MSK_IPAR_MIO_MAX_NUM_BRANCHES*
- *MSK_IPAR_MIO_MAX_NUM_RELAXS*
- *MSK_IPAR_MIO_MAX_NUM_ROOT_CUT_ROUNDS*
- *MSK_IPAR_MIO_MAX_NUM_SOLUTIONS*
- *MSK_IPAR_MIO_NODE_OPTIMIZER*
- *MSK_IPAR_MIO_NODE_SELECTION*
- *MSK_IPAR_MIO_PERSPECTIVE_REFORMULATE*
- *MSK_IPAR_MIO_PROBING_LEVEL*
- *MSK_IPAR_MIO_PROPAGATE_OBJECTIVE_CONSTRAINT*
- *MSK_IPAR_MIO_RINS_MAX_NODES*
- *MSK_IPAR_MIO_ROOT_OPTIMIZER*
- *MSK_IPAR_MIO_ROOT_REPEAT_PRESOLVE_LEVEL*
- *MSK_IPAR_MIO_SEED*
- *MSK_IPAR_MIO_VB_DETECTION_LEVEL*

Output information

- *MSK_IPAR_INFEAS_REPORT_LEVEL*
- *MSK_IPAR_LICENSE_SUPPRESS_EXPIRE_WRNS*
- *MSK_IPAR_LICENSE_TRH_EXPIRY_WRN*
- *MSK_IPAR_LOG*
- *MSK_IPAR_LOG_BI*
- *MSK_IPAR_LOG_BI_FREQ*
- *MSK_IPAR_LOG_CUT_SECOND_OPT*
- *MSK_IPAR_LOG_EXPAND*
- *MSK_IPAR_LOG_FEAS_REPAIR*
- *MSK_IPAR_LOG_FILE*
- *MSK_IPAR_LOG_INCLUDE_SUMMARY*
- *MSK_IPAR_LOG_INFEAS_ANA*
- *MSK_IPAR_LOG_INTPNT*
- *MSK_IPAR_LOG_LOCAL_INFO*
- *MSK_IPAR_LOG_MIO*
- *MSK_IPAR_LOG_MIO_FREQ*
- *MSK_IPAR_LOG_ORDER*
- *MSK_IPAR_LOG_RESPONSE*
- *MSK_IPAR_LOG_SENSITIVITY*
- *MSK_IPAR_LOG_SENSITIVITY_OPT*

- *MSK_IPAR_LOG_SIM*
- *MSK_IPAR_LOG_SIM_FREQ*
- *MSK_IPAR_LOG_SIM_MINOR*
- *MSK_IPAR_LOG_STORAGE*
- *MSK_IPAR_MAX_NUM_WARNINGS*

Overall solver

- *MSK_IPAR_BI_CLEAN_OPTIMIZER*
- *MSK_IPAR_INFEAS_PREFER_PRIMAL*
- *MSK_IPAR_LICENSE_WAIT*
- *MSK_IPAR_MIO_MODE*
- *MSK_IPAR_OPTIMIZER*
- *MSK_IPAR_PRESOLVE_LEVEL*
- *MSK_IPAR_PRESOLVE_MAX_NUM_REDUCTIONS*
- *MSK_IPAR_PRESOLVE_USE*
- *MSK_IPAR_PRIMAL_REPAIR_OPTIMIZER*
- *MSK_IPAR_SENSITIVITY_ALL*
- *MSK_IPAR_SENSITIVITY_OPTIMIZER*
- *MSK_IPAR_SENSITIVITY_TYPE*
- *MSK_IPAR_SOLUTION_CALLBACK*

Overall system

- *MSK_IPAR_AUTO_UPDATE_SOL_INFO*
- *MSK_IPAR_INTPNT_MULTI_THREAD*
- *MSK_IPAR_LICENSE_WAIT*
- *MSK_IPAR_LOG_STORAGE*
- *MSK_IPAR_MT_SPINCOUNT*
- *MSK_IPAR_NUM_THREADS*
- *MSK_IPAR_REMOVE_UNUSED_SOLUTIONS*
- *MSK_IPAR_TIMING_LEVEL*
- *MSK_SPAR_REMOTE_ACCESS_TOKEN*

Presolve

- *MSK_DPAR_PRESOLVE_TOL_ABS_LINDEP*
- *MSK_DPAR_PRESOLVE_TOL_AIJ*
- *MSK_DPAR_PRESOLVE_TOL_REL_LINDEP*
- *MSK_DPAR_PRESOLVE_TOL_S*
- *MSK_DPAR_PRESOLVE_TOL_X*
- *MSK_IPAR_PRESOLVE_ELIMINATOR_MAX_FILL*
- *MSK_IPAR_PRESOLVE_ELIMINATOR_MAX_NUM_TRIES*
- *MSK_IPAR_PRESOLVE_LEVEL*
- *MSK_IPAR_PRESOLVE_LINDEP_ABS_WORK_TRH*
- *MSK_IPAR_PRESOLVE_LINDEP_REL_WORK_TRH*
- *MSK_IPAR_PRESOLVE_LINDEP_USE*
- *MSK_IPAR_PRESOLVE_MAX_NUM_PASS*
- *MSK_IPAR_PRESOLVE_MAX_NUM_REDUCTIONS*
- *MSK_IPAR_PRESOLVE_USE*

Primal simplex

- *MSK_IPAR_SIM_PRIMAL_CRASH*
- *MSK_IPAR_SIM_PRIMAL_RESTRICT_SELECTION*
- *MSK_IPAR_SIM_PRIMAL_SELECTION*

Progress callback

- *MSK_IPAR_SOLUTION_CALLBACK*

Simplex optimizer

- *MSK_DPAR_BASIS_REL_TOL_S*
- *MSK_DPAR_BASIS_TOL_S*
- *MSK_DPAR_BASIS_TOL_X*
- *MSK_DPAR_SIM_LU_TOL_REL_PIV*
- *MSK_DPAR_SIMPLEX_ABS_TOL_PIV*
- *MSK_IPAR_BASIS_SOLVE_USE_PLUS_ONE*
- *MSK_IPAR_LOG_SIM*
- *MSK_IPAR_LOG_SIM_FREQ*
- *MSK_IPAR_LOG_SIM_MINOR*
- *MSK_IPAR_SENSITIVITY_OPTIMIZER*
- *MSK_IPAR_SIM_BASIS_FACTOR_USE*

- *MSK_IPAR_SIM_DEGEN*
- *MSK_IPAR_SIM_DUAL_PHASEONE_METHOD*
- *MSK_IPAR_SIM_EXPLOIT_DUPVEC*
- *MSK_IPAR_SIM_HOTSTART*
- *MSK_IPAR_SIM_HOTSTART_LU*
- *MSK_IPAR_SIM_MAX_ITERATIONS*
- *MSK_IPAR_SIM_MAX_NUM_SETBACKS*
- *MSK_IPAR_SIM_NON_SINGULAR*
- *MSK_IPAR_SIM_PRIMAL_PHASEONE_METHOD*
- *MSK_IPAR_SIM_REFACTOR_FREQ*
- *MSK_IPAR_SIM_REFORMULATION*
- *MSK_IPAR_SIM_SAVE_LU*
- *MSK_IPAR_SIM_SCALING*
- *MSK_IPAR_SIM_SCALING_METHOD*
- *MSK_IPAR_SIM_SEED*
- *MSK_IPAR_SIM_SOLVE_FORM*
- *MSK_IPAR_SIM_STABILITY_PRIORITY*
- *MSK_IPAR_SIM_SWITCH_OPTIMIZER*

Solution input/output

- *MSK_IPAR_INFEAS_REPORT_AUTO*
- *MSK_IPAR_SOL_FILTER_KEEP_BASIC*
- *MSK_IPAR_SOL_FILTER_KEEP_RANGED*
- *MSK_IPAR_SOL_READ_NAME_WIDTH*
- *MSK_IPAR_SOL_READ_WIDTH*
- *MSK_IPAR_WRITE_BAS_CONSTRAINTS*
- *MSK_IPAR_WRITE_BAS_HEAD*
- *MSK_IPAR_WRITE_BAS_VARIABLES*
- *MSK_IPAR_WRITE_INT_CONSTRAINTS*
- *MSK_IPAR_WRITE_INT_HEAD*
- *MSK_IPAR_WRITE_INT_VARIABLES*
- *MSK_IPAR_WRITE_SOL_BARVARIABLES*
- *MSK_IPAR_WRITE_SOL_CONSTRAINTS*
- *MSK_IPAR_WRITE_SOL_HEAD*
- *MSK_IPAR_WRITE_SOL_IGNORE_INVALID_NAMES*
- *MSK_IPAR_WRITE_SOL_VARIABLES*

- *MSK_SPAR_BAS_SOL_FILE_NAME*
- *MSK_SPAR_INT_SOL_FILE_NAME*
- *MSK_SPAR_ITR_SOL_FILE_NAME*
- *MSK_SPAR_SOL_FILTER_XC_LOW*
- *MSK_SPAR_SOL_FILTER_XC_UPR*
- *MSK_SPAR_SOL_FILTER_XX_LOW*
- *MSK_SPAR_SOL_FILTER_XX_UPR*

Termination criteria

- *MSK_DPAR_BASIS_REL_TOL_S*
- *MSK_DPAR_BASIS_TOL_S*
- *MSK_DPAR_BASIS_TOL_X*
- *MSK_DPAR_INTPNT_CO_TOL_DFEAS*
- *MSK_DPAR_INTPNT_CO_TOL_INFEAS*
- *MSK_DPAR_INTPNT_CO_TOL_MU_RED*
- *MSK_DPAR_INTPNT_CO_TOL_NEAR_REL*
- *MSK_DPAR_INTPNT_CO_TOL_PFEAS*
- *MSK_DPAR_INTPNT_CO_TOL_REL_GAP*
- *MSK_DPAR_INTPNT_QO_TOL_DFEAS*
- *MSK_DPAR_INTPNT_QO_TOL_INFEAS*
- *MSK_DPAR_INTPNT_QO_TOL_MU_RED*
- *MSK_DPAR_INTPNT_QO_TOL_NEAR_REL*
- *MSK_DPAR_INTPNT_QO_TOL_PFEAS*
- *MSK_DPAR_INTPNT_QO_TOL_REL_GAP*
- *MSK_DPAR_INTPNT_TOL_DFEAS*
- *MSK_DPAR_INTPNT_TOL_INFEAS*
- *MSK_DPAR_INTPNT_TOL_MU_RED*
- *MSK_DPAR_INTPNT_TOL_PFEAS*
- *MSK_DPAR_INTPNT_TOL_REL_GAP*
- *MSK_DPAR_LOWER_OBJ_CUT*
- *MSK_DPAR_LOWER_OBJ_CUT_FINITE_TRH*
- *MSK_DPAR_MIO_MAX_TIME*
- *MSK_DPAR_MIO_REL_GAP_CONST*
- *MSK_DPAR_MIO_TOL_REL_GAP*
- *MSK_DPAR_OPTIMIZER_MAX_TIME*
- *MSK_DPAR_UPPER_OBJ_CUT*

Groups *Simplex optimizer*, *Termination criteria*

MSK_DPAR_CHECK_CONVEXITY_REL_TOL

This parameter controls when the full convexity check declares a problem to be non-convex. Increasing this tolerance relaxes the criteria for declaring the problem non-convex.

A problem is declared non-convex if negative (positive) pivot elements are detected in the Cholesky factor of a matrix which is required to be PSD (NSD). This parameter controls how much this non-negativity requirement may be violated.

If d_i is the pivot element for column i, then the matrix Q is considered to not be PSD if:

$$d_i \leq -|Q_{ii}|\texttt{check_convexity_rel_tol}$$

Default 1e-10

Accepted [0; +inf]

Example param.MSK_DPAR_CHECK_CONVEXITY_REL_TOL = 1e-10

Groups *Interior-point method*

MSK_DPAR_DATA_SYM_MAT_TOL

Absolute zero tolerance for elements in in symmetric matrices. If any value in a symmetric matrix is smaller than this parameter in absolute terms**MOSEK** will treat the values as zero and generate a warning.

Default 1.0e-12

Accepted [1.0e-16; 1.0e-6]

Example param.MSK_DPAR_DATA_SYM_MAT_TOL = 1.0e-12

Groups *Data check*

MSK_DPAR_DATA_SYM_MAT_TOL_HUGE

An element in a symmetric matrix which is larger than this value in absolute size causes an error.

Default 1.0e20

Accepted [0.0; +inf]

Example param.MSK_DPAR_DATA_SYM_MAT_TOL_HUGE = 1.0e20

Groups *Data check*

MSK_DPAR_DATA_SYM_MAT_TOL_LARGE

An element in a symmetric matrix which is larger than this value in absolute size causes a warning message to be printed.

Default 1.0e10

Accepted [0.0; +inf]

Example param.MSK_DPAR_DATA_SYM_MAT_TOL_LARGE = 1.0e10

Groups *Data check*

MSK_DPAR_DATA_TOL_AIJ_HUGE

An element in A which is larger than this value in absolute size causes an error.

Default 1.0e20

Accepted [0.0; +inf]

Example param.MSK_DPAR_DATA_TOL_AIJ_HUGE = 1.0e20

Groups *Data check*

MSK_DPAR_DATA_TOL_AIJ_LARGE

An element in A which is larger than this value in absolute size causes a warning message to be printed.

Default 1.0e10

Accepted [0.0; +inf]

Example param.MSK_DPAR_DATA_TOL_AIJ_LARGE = 1.0e10

Default *"FREE"*
Accepted *"FREE"*, *"PRIMAL"*, *"DUAL"*
Example param.MSK_IPAR_INTPNT_SOLVE_FORM = MSK_SOLVE_FREE
Groups *Interior-point method*

MSK_IPAR_INTPNT_STARTING_POINT
Starting point used by the interior-point optimizer.

Default *"FREE"*
Accepted *"FREE"*, *"GUESS"*, *"CONSTANT"*, *"SATISFY_BOUNDS"*
Example param.MSK_IPAR_INTPNT_STARTING_POINT = MSK_STARTING_POINT_FREE
Groups *Interior-point method*

MSK_IPAR_LICENSE_DEBUG
This option is used to turn on debugging of the license manager.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_LICENSE_DEBUG = MSK_OFF
Groups *License manager*

MSK_IPAR_LICENSE_PAUSE_TIME
If *MSK_IPAR_LICENSE_WAIT* is *"MSK_ON"* and no license is available, then **MOSEK** sleeps a number of milliseconds between each check of whether a license has become free.

Default 100
Accepted [0; 1000000]
Example param.MSK_IPAR_LICENSE_PAUSE_TIME = 100
Groups *License manager*

MSK_IPAR_LICENSE_SUPPRESS_EXPIRE_WRNS
Controls whether license features expire warnings are suppressed.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_LICENSE_SUPPRESS_EXPIRE_WRNS = MSK_OFF
Groups *License manager*, *Output information*

MSK_IPAR_LICENSE_TRH_EXPIRY_WRN
If a license feature expires in a numbers of days less than the value of this parameter then a warning will be issued.

Default 7
Accepted [0; +inf]
Example param.MSK_IPAR_LICENSE_TRH_EXPIRY_WRN = 7
Groups *License manager*, *Output information*

MSK_IPAR_LICENSE_WAIT
If all licenses are in use **MOSEK** returns with an error code. However, by turning on this parameter **MOSEK** will wait for an available license.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_LICENSE_WAIT = MSK_OFF
Groups *Overall solver*, *Overall system*, *License manager*

MSK_IPAR_LOG

Controls the amount of log information. The value 0 implies that all log information is suppressed. A higher level implies that more information is logged.

Please note that if a task is employed to solve a sequence of optimization problems the value of this parameter is reduced by the value of *MSK_IPAR_LOG_CUT_SECOND_OPT* for the second and any subsequent optimizations.

Default 10
Accepted [0; +inf]
Example param.MSK_IPAR_LOG = 10
See also *MSK_IPAR_LOG_CUT_SECOND_OPT*
Groups *Output information*, *Logging*

MSK_IPAR_LOG_ANA_PRO

Controls amount of output from the problem analyzer.

Default 1
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_ANA_PRO = 1
Groups *Analysis*, *Logging*

MSK_IPAR_LOG_BI

Controls the amount of output printed by the basis identi cation procedure. A higher level implies that more information is logged.

Default 1
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_BI = 1
Groups *Basis identification*, *Output information*, *Logging*

MSK_IPAR_LOG_BI_FREQ

Controls how frequently the optimizer outputs information about the basis identi cation and how frequent the user-de ned callback function is called.

Default 2500
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_BI_FREQ = 2500
Groups *Basis identification*, *Output information*, *Logging*

MSK_IPAR_LOG_CHECK_CONVEXITY

Controls logging in convexity check on quadratic problems. Set to a positive value to turn logging on. If a quadratic coe cient matrix is found to violate the requirement of PSD (NSD) then a list of negative (positive) pivot elements is printed. The absolute value of the pivot elements is also shown.

Default 0
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_CHECK_CONVEXITY = 0
Groups *Data check*

MSK_IPAR_LOG_CUT_SECOND_OPT

If a task is employed to solve a sequence of optimization problems, then the value of the log levels is reduced by the value of this parameter. E.g *MSK_IPAR_LOG* and *MSK_IPAR_LOG_SIM* are reduced by the value of this parameter for the second and any subsequent optimizations.

Default 1
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_CUT_SECOND_OPT = 1

See also *MSK_IPAR_LOG*, *MSK_IPAR_LOG_INTPNT*, *MSK_IPAR_LOG_MIO*, *MSK_IPAR_LOG_SIM*

Groups *Output information*, *Logging*

MSK_IPAR_LOG_EXPAND

Controls the amount of logging when a data item such as the maximum number constrains is expanded.

Default 0

Accepted [0; +inf]

Example param.MSK_IPAR_LOG_EXPAND = 0

Groups *Output information*, *Logging*

MSK_IPAR_LOG_FEAS_REPAIR

Controls the amount of output printed when performing feasibility repair. A value higher than one means extensive logging.

Default 1

Accepted [0; +inf]

Example param.MSK_IPAR_LOG_FEAS_REPAIR = 1

Groups *Output information*, *Logging*

MSK_IPAR_LOG_FILE

If turned on, then some log info is printed when a le is written or read.

Default 1

Accepted [0; +inf]

Example param.MSK_IPAR_LOG_FILE = 1

Groups *Data input/output*, *Output information*, *Logging*

MSK_IPAR_LOG_INCLUDE_SUMMARY

Not relevant for this API.

Default *"OFF"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_LOG_INCLUDE_SUMMARY = OFF

Groups *Output information*, *Logging*

MSK_IPAR_LOG_INFEAS_ANA

Controls amount of output printed by the infeasibility analyzer procedures. A higher level implies that more information is logged.

Default 1

Accepted [0; +inf]

Example param.MSK_IPAR_LOG_INFEAS_ANA = 1

Groups *Infeasibility report*, *Output information*, *Logging*

MSK_IPAR_LOG_INTPNT

Controls amount of output printed by the interior-point optimizer. A higher level implies that more information is logged.

Default 1

Accepted [0; +inf]

Example param.MSK_IPAR_LOG_INTPNT = 1

Groups *Interior-point method*, *Output information*, *Logging*

MSK_IPAR_LOG_LOCAL_INFO

Controls whether local identifying information like environment variables, lenames, IP addresses etc. are printed to the log.

Note that this will only a ect some functions. Some functions that speci cally emit system information will not be a ected.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_LOG_LOCAL_INFO MSK_ON
Groups *Output information*, *Logging*

MSK_IPAR_LOG_MIO
Controls the log level for the mixed-integer optimizer. A higher level implies that more information is logged.

Default 4
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_MIO = 4
Groups *Mixed-integer optimization*, *Output information*, *Logging*

MSK_IPAR_LOG_MIO_FREQ
Controls how frequent the mixed-integer optimizer prints the log line. It will print line every time *MSK_IPAR_LOG_MIO_FREQ* relaxations have been solved.

Default 10
Accepted [-inf; +inf]
Example param.MSK_IPAR_LOG_MIO_FREQ = 10
Groups *Mixed-integer optimization*, *Output information*, *Logging*

MSK_IPAR_LOG_ORDER
If turned on, then factor lines are added to the log.

Default 1
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_ORDER = 1
Groups *Output information*, *Logging*

MSK_IPAR_LOG_PRESOLVE
Controls amount of output printed by the presolve procedure. A higher level implies that more information is logged.

Default 1
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_PRESOLVE = 1
Groups *Logging*

MSK_IPAR_LOG_RESPONSE
Controls amount of output printed when response codes are reported. A higher level implies that more information is logged.

Default 0
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_RESPONSE = 0
Groups *Output information*, *Logging*

MSK_IPAR_LOG_SENSITIVITY
Controls the amount of logging during the sensitivity analysis.

- 0. Means no logging information is produced.
- 1. Timing information is printed.
- 2. Sensitivity results are printed.

Default 1
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_SENSITIVITY = 1

Groups *Output information*, *Logging*

MSK_IPAR_LOG_SENSITIVITY_OPT
Controls the amount of logging from the optimizers employed during the sensitivity analysis. 0 means no logging information is produced.

Default 0
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_SENSITIVITY_OPT = 0
Groups *Output information*, *Logging*

MSK_IPAR_LOG_SIM
Controls amount of output printed by the simplex optimizer. A higher level implies that more information is logged.

Default 4
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_SIM = 4
Groups *Simplex optimizer*, *Output information*, *Logging*

MSK_IPAR_LOG_SIM_FREQ
Controls how frequent the simplex optimizer outputs information about the optimization and how frequent the user-de ned callback function is called.

Default 1000
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_SIM_FREQ = 1000
Groups *Simplex optimizer*, *Output information*, *Logging*

MSK_IPAR_LOG_SIM_MINOR
Currently not in use.

Default 1
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_SIM_MINOR = 1
Groups *Simplex optimizer*, *Output information*

MSK_IPAR_LOG_STORAGE
When turned on, **MOSEK** prints messages regarding the storage usage and allocation.

Default 0
Accepted [0; +inf]
Example param.MSK_IPAR_LOG_STORAGE = 0
Groups *Output information*, *Overall system*, *Logging*

MSK_IPAR_MAX_NUM_WARNINGS
Each warning is shown a limited number of times controlled by this parameter. A negative value is identical to in nite number of times.

Default 10
Accepted [-inf; +inf]
Example param.MSK_IPAR_MAX_NUM_WARNINGS = 10
Groups *Output information*

MSK_IPAR_MIO_BRANCH_DIR
Controls whether the mixed-integer optimizer is branching up or down by default.

Default *"FREE"*
Accepted *"FREE"*, *"UP"*, *"DOWN"*, *"NEAR"*, *"FAR"*, *"ROOT_LP"*, *"GUIDED"*, *"PSEUDOCOST"*

Example param.MSK_IPAR_MIO_BRANCH_DIR=MSK_BRANCH_DIR_FREE
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_CONIC_OUTER_APPROXIMATION
If this option is turned on outer approximation is used when solving relaxations of conic problems; otherwise interior point is used.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_MIO_CONIC_OUTER_APPROXIMATION=MSK_OFF
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_CUT_CLIQUE
Controls whether clique cuts should be generated.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_MIO_CUT_CLIQUE=MSK_ON
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_CUT_CMIR
Controls whether mixed integer rounding cuts should be generated.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_MIO_CUT_CMIR=MSK_ON
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_CUT_GMI
Controls whether GMI cuts should be generated.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_MIO_CUT_GMI=MSK_ON
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_CUT_IMPLIED_BOUND
Controls whether implied bound cuts should be generated.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_MIO_CUT_IMPLIED_BOUND=MSK_OFF
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_CUT_KNAPSACK_COVER
Controls whether knapsack cover cuts should be generated.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_MIO_CUT_KNAPSACK_COVER=MSK_OFF
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_CUT_SELECTION_LEVEL
Controls how aggressively generated cuts are selected to be included in the relaxation.

- -1. The optimizer chooses the level of cut selection
- 0. Generated cuts less likely to be added to the relaxation
- 1. Cuts are more aggressively selected to be included in the relaxation

Default -1

Accepted [-1; +1]
Example param.MSK_IPAR_MIO_CUT_SELECTION_LEVEL = -1
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_FEASPUMP_LEVEL
Controls the way the Feasibility Pump heuristic is employed by the mixed-integer optimizer.

- -1. The optimizer chooses how the Feasibility Pump is used
- 0. The Feasibility Pump is disabled
- 1. The Feasibility Pump is enabled with an e ort to improve solution quality
- 2. The Feasibility Pump is enabled with an e ort to reach feasibility early

Default -1
Accepted [-1; 2]
Example param.MSK_IPAR_MIO_FEASPUMP_LEVEL = -1
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_HEURISTIC_LEVEL
Controls the heuristic employed by the mixed-integer optimizer to locate an initial good integer feasible solution. A value of zero means the heuristic is not used at all. A larger value than 0 means that a gradually more sophisticated heuristic is used which is computationally more expensive. A negative value implies that the optimizer chooses the heuristic. Normally a value around 3 to 5 should be optimal.

Default -1
Accepted [-inf; +inf]
Example param.MSK_IPAR_MIO_HEURISTIC_LEVEL = -1
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_MAX_NUM_BRANCHES
Maximum number of branches allowed during the branch and bound search. A negative value means in nite.

Default -1
Accepted [-inf; +inf]
Example param.MSK_IPAR_MIO_MAX_NUM_BRANCHES = -1
Groups *Mixed-integer optimization*, *Termination criteria*

MSK_IPAR_MIO_MAX_NUM_RELAXS
Maximum number of relaxations allowed during the branch and bound search. A negative value means in nite.

Default -1
Accepted [-inf; +inf]
Example param.MSK_IPAR_MIO_MAX_NUM_RELAXS = -1
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_MAX_NUM_ROOT_CUT_ROUNDS
Maximum number of cut separation rounds at the root node.

Default 100
Accepted [0; +inf]
Example param.MSK_IPAR_MIO_MAX_NUM_ROOT_CUT_ROUNDS = 100
Groups *Mixed-integer optimization*, *Termination criteria*

MSK_IPAR_MIO_MAX_NUM_SOLUTIONS
The mixed-integer optimizer can be terminated after a certain number of di erent feasible solutions has been located. If this parameter has the value $n > 0$, then the mixed-integer optimizer will be terminated when n feasible solutions have been located.

Example param.MSK_IPAR_MIO_PROPAGATE_OBJECTIVE_CONSTRAINT = MSK_OFF
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_RINS_MAX_NODES
Controls the maximum number of nodes allowed in each call to the RINS heuristic. The default value of -1 means that the value is determined automatically. A value of zero turns o the heuristic.

Default -1
Accepted [-1; +inf]
Example param.MSK_IPAR_MIO_RINS_MAX_NODES = -1
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_ROOT_OPTIMIZER
Controls which optimizer is employed at the root node in the mixed-integer optimizer.

Default *"FREE"*
Accepted *"FREE"*, *"INTPNT"*, *"CONIC"*, *"PRIMAL_SIMPLEX"*, *"DUAL_SIMPLEX"*, *"FREE_SIMPLEX"*, *"MIXED_INT"*
Example param.MSK_IPAR_MIO_ROOT_OPTIMIZER = MSK_OPTIMIZER_FREE
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_ROOT_REPEAT_PRESOLVE_LEVEL
Controls whether presolve can be repeated at root node.

- -1. The optimizer chooses whether presolve is repeated
- 0. Never repeat presolve
- 1. Always repeat presolve

Default -1
Accepted [-1; 1]
Example param.MSK_IPAR_MIO_ROOT_REPEAT_PRESOLVE_LEVEL = -1
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_SEED
Sets the random seed used for randomization in the mixed integer optimizer. Selecting a di erent seed can change the path the optimizer takes to the optimal solution.

Default 42
Accepted [0; +inf]
Example param.MSK_IPAR_MIO_SEED = 42
Groups *Mixed-integer optimization*

MSK_IPAR_MIO_VB_DETECTION_LEVEL
Controls how much e ort is put into detecting variable bounds.

- -1. The optimizer chooses
- 0. No variable bounds are detected
- 1. Only detect variable bounds that are directly represented in the problem
- 2. Detect variable bounds in probing

Default -1
Accepted [-1; +2]
Example param.MSK_IPAR_MIO_VB_DETECTION_LEVEL = -1
Groups *Mixed-integer optimization*

MSK_IPAR_MT_SPINCOUNT
Set the number of iterations to spin before sleeping.

Default 0

Accepted [0; 1000000000]

Example param.MSK_IPAR_MT_SPINCOUNT = 0

Groups *Overall system*

MSK_IPAR_NUM_THREADS

Controls the number of threads employed by the optimizer. If set to 0 the number of threads used will be equal to the number of cores detected on the machine.

If using the conic optimizer, the value of this parameter set at first optimization remains constant through the lifetime of the process. **MOSEK** will allocate a thread pool of given size, and changing the parameter value later will have no effect. It will, however, remain possible to demand single-threaded execution by setting *MSK_IPAR_INTPNT_MULTI_THREAD*.

For the mixed-integer optimizer and interior-point linear optimizer there is no such restriction.

Default 0

Accepted [0; +inf]

Example param.MSK_IPAR_NUM_THREADS = 0

Groups *Overall system*

MSK_IPAR_OPF_WRITE_HEADER

Write a text header with date and **MOSEK** version in an OPF file.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_OPF_WRITE_HEADER = MSK_ON

Groups *Data input/output*

MSK_IPAR_OPF_WRITE_HINTS

Write a hint section with problem dimensions in the beginning of an OPF file.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_OPF_WRITE_HINTS = MSK_ON

Groups *Data input/output*

MSK_IPAR_OPF_WRITE_LINE_LENGTH

Aim to keep lines in OPF files not much longer than this.

Default 80

Accepted [0; +inf]

Example param.MSK_IPAR_OPF_WRITE_LINE_LENGTH = 80

Groups *Data input/output*

MSK_IPAR_OPF_WRITE_PARAMETERS

Write a parameter section in an OPF file.

Default *"OFF"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_OPF_WRITE_PARAMETERS = MSK_OFF

Groups *Data input/output*

MSK_IPAR_OPF_WRITE_PROBLEM

Write objective, constraints, bounds etc. to an OPF file.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_OPF_WRITE_PROBLEM = MSK_ON

Groups *Data input/output*

MSK_IPAR_PRESOLVE_ELIMINATOR_MAX_FILL

Controls the maximum amount of fill-in that can be created by one pivot in the elimination phase of the presolve. A negative value means the parameter value is selected automatically.

Default -1
Accepted [-inf; +inf]
Example param.MSK_IPAR_PRESOLVE_ELIMINATOR_MAX_FILL = -1
Groups *Presolve*

MSK_IPAR_PRESOLVE_ELIMINATOR_MAX_NUM_TRIES

Control the maximum number of times the eliminator is tried. A negative value implies **MOSEK** decides.

Default -1
Accepted [-inf; +inf]
Example param.MSK_IPAR_PRESOLVE_ELIMINATOR_MAX_NUM_TRIES = -1
Groups *Presolve*

MSK_IPAR_PRESOLVE_LEVEL

Currently not used.

Default -1
Accepted [-inf; +inf]
Example param.MSK_IPAR_PRESOLVE_LEVEL = -1
Groups *Overall solver*, *Presolve*

MSK_IPAR_PRESOLVE_LINDEP_ABS_WORK_TRH

Controls linear dependency check in presolve. The linear dependency check is potentially computationally expensive.

Default 100
Accepted [-inf; +inf]
Example param.MSK_IPAR_PRESOLVE_LINDEP_ABS_WORK_TRH = 100
Groups *Presolve*

MSK_IPAR_PRESOLVE_LINDEP_REL_WORK_TRH

Controls linear dependency check in presolve. The linear dependency check is potentially computationally expensive.

Default 100
Accepted [-inf; +inf]
Example param.MSK_IPAR_PRESOLVE_LINDEP_REL_WORK_TRH = 100
Groups *Presolve*

MSK_IPAR_PRESOLVE_LINDEP_USE

Controls whether the linear constraints are checked for linear dependencies.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_PRESOLVE_LINDEP_USE = MSK_ON
Groups *Presolve*

MSK_IPAR_PRESOLVE_MAX_NUM_PASS

Control the maximum number of times presolve passes over the problem. A negative value implies **MOSEK** decides.

Default -1
Accepted [-inf; +inf]
Example param.MSK_IPAR_PRESOLVE_MAX_NUM_PASS = -1
Groups *Presolve*

MSK_IPAR_PRESOLVE_MAX_NUM_REDUCTIONS

Controls the maximum number of reductions performed by the presolve. The value of the parameter is normally only changed in connection with debugging. A negative value implies that an in nite number of reductions are allowed.

Default -1

Accepted [-inf; +inf]

Example param.MSK_IPAR_PRESOLVE_MAX_NUM_REDUCTIONS = -1

Groups *Overall solver*, *Presolve*

MSK_IPAR_PRESOLVE_USE

Controls whether the presolve is applied to a problem before it is optimized.

Default *"FREE"*

Accepted *"OFF"*, *"ON"*, *"FREE"*

Example param.MSK_IPAR_PRESOLVE_USE = 'MSK_PRESOLVE_MODE_FREE'

Groups *Overall solver*, *Presolve*

MSK_IPAR_PRIMAL_REPAIR_OPTIMIZER

Controls which optimizer that is used to nd the optimal repair.

Default *"FREE"*

Accepted *"FREE"*, *"INTPNT"*, *"CONIC"*, *"PRIMAL_SIMPLEX"*, *"DUAL_SIMPLEX"*, *"FREE_SIMPLEX"*, *"MIXED_INT"*

Example param.MSK_IPAR_PRIMAL_REPAIR_OPTIMIZER = 'MSK_OPTIMIZER_FREE'

Groups *Overall solver*

MSK_IPAR_PTF_WRITE_TRANSFORM

If *MSK_IPAR_PTF_WRITE_TRANSFORM* is *"MSK_ON"*, constraint blocks with identi able conic slacks are transformed into conic constraints and the slacks are eliminated.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_PTF_WRITE_TRANSFORM = 'MSK_ON'

Groups *Data input/output*

MSK_IPAR_READ_DEBUG

Turns on additional debugging information when reading les.

Default *"OFF"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_READ_DEBUG = 'MSK_OFF'

Groups *Data input/output*

MSK_IPAR_READ_KEEP_FREE_CON

Controls whether the free constraints are included in the problem.

Default *"OFF"*

Accepted

- *"ON"*: The free constraints are kept.
- *"OFF"*: The free constraints are discarded.

Example param.MSK_IPAR_READ_KEEP_FREE_CON = 'MSK_OFF'

Groups *Data input/output*

MSK_IPAR_READ_LP_DROP_NEW_VARS_IN_BOU

If this option is turned on, **MOSEK** will drop variables that are de ned for the rst time in the bounds section.

Default *"OFF"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_READ_LP_DROP_NEW_VARS_IN_BOUNDS = MSK_OFF
Groups *Data input/output*

MSK_IPAR_READ_LP_QUOTED_NAMES
If a name is in quotes when reading an LP file, the quotes will be removed.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_READ_LP_QUOTED_NAMES = MSK_ON
Groups *Data input/output*

MSK_IPAR_READ_MPS_FORMAT
Controls how strictly the MPS file reader interprets the MPS format.

Default *"FREE"*
Accepted *"STRICT"*, *"RELAXED"*, *"FREE"*, *"CPLEX"*
Example param.MSK_IPAR_READ_MPS_FORMAT = MSK_MPS_FORMAT_FREE
Groups *Data input/output*

MSK_IPAR_READ_MPS_WIDTH
Controls the maximal number of characters allowed in one line of the MPS file.

Default 1024
Accepted [80; +inf]
Example param.MSK_IPAR_READ_MPS_WIDTH = 1024
Groups *Data input/output*

MSK_IPAR_READ_TASK_IGNORE_PARAM
Controls whether **MOSEK** should ignore the parameter setting defined in the task file and use the default parameter setting instead.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_READ_TASK_IGNORE_PARAM = MSK_OFF
Groups *Data input/output*

MSK_IPAR_REMOVE_UNUSED_SOLUTIONS
Removes unused solutions before the optimization is performed.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_REMOVE_UNUSED_SOLUTIONS = MSK_OFF
Groups *Overall system*

MSK_IPAR_SENSITIVITY_ALL
Not applicable.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_SENSITIVITY_ALL = MSK_OFF
Groups *Overall solver*

MSK_IPAR_SENSITIVITY_OPTIMIZER
Controls which optimizer is used for optimal partition sensitivity analysis.

Default *"FREE_SIMPLEX"*
Accepted *"FREE"*, *"INTPNT"*, *"CONIC"*, *"PRIMAL_SIMPLEX"*, *"DUAL_SIMPLEX"*, *"FREE_SIMPLEX"*, *"MIXED_INT"*
Example param.MSK_IPAR_SENSITIVITY_OPTIMIZER = MSK_OPTIMIZER_FREE_SIMPLEX
Groups *Overall solver*, *Simplex optimizer*

MSK_IPAR_SENSITIVITY_TYPE

Controls which type of sensitivity analysis is to be performed.

Default *"BASIS"*

Accepted *"BASIS"*

Example param.MSK_IPAR_SENSITIVITY_TYPE = MSK_SENSITIVITY_TYPE_BASIS

Groups *Overall solver*

MSK_IPAR_SIM_BASIS_FACTOR_USE

Controls whether an LU factorization of the basis is used in a hot-start. Forcing a refactorization sometimes improves the stability of the simplex optimizers, but in most cases there is a performance penalty.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_SIM_BASIS_FACTOR_USE = MSK_ON

Groups *Simplex optimizer*

MSK_IPAR_SIM_DEGEN

Controls how aggressively degeneration is handled.

Default *"FREE"*

Accepted *"NONE"*, *"FREE"*, *"AGGRESSIVE"*, *"MODERATE"*, *"MINIMUM"*

Example param.MSK_IPAR_SIM_DEGEN = MSK_SIM_DEGEN_FREE

Groups *Simplex optimizer*

MSK_IPAR_SIM_DUAL_CRASH

Controls whether crashing is performed in the dual simplex optimizer. If this parameter is set to x, then a crash will be performed if a basis consists of more than $(100 - x) \mod f_v$ entries, where f_v is the number of fixed variables.

Default 90

Accepted [0; +inf]

Example param.MSK_IPAR_SIM_DUAL_CRASH = 90

Groups *Dual simplex*

MSK_IPAR_SIM_DUAL_PHASEONE_METHOD

An experimental feature.

Default 0

Accepted [0; 10]

Example param.MSK_IPAR_SIM_DUAL_PHASEONE_METHOD = 0

Groups *Simplex optimizer*

MSK_IPAR_SIM_DUAL_RESTRICT_SELECTION

The dual simplex optimizer can use a so-called restricted selection/pricing strategy to choose the outgoing variable. Hence, if restricted selection is applied, then the dual simplex optimizer first choose a subset of all the potential outgoing variables. Next, for some time it will choose the outgoing variable only among the subset. From time to time the subset is redefined. A larger value of this parameter implies that the optimizer will be more aggressive in its restriction strategy, i.e. a value of 0 implies that the restriction strategy is not applied at all.

Default 50

Accepted [0; 100]

Example param.MSK_IPAR_SIM_DUAL_RESTRICT_SELECTION = 50

Groups *Dual simplex*

MSK_IPAR_SIM_DUAL_SELECTION

Controls the choice of the incoming variable, known as the selection strategy, in the dual simplex optimizer.

Default "FREE"
Accepted "FREE", "FULL", "ASE", "DEVEX", "SE", "PARTIAL"
Example param.MSK_IPAR_SIM_DUAL_SELECTION = MSK_SIM_SELECTION_FREE
Groups Dual simplex

MSK_IPAR_SIM_EXPLOIT_DUPVEC
Controls if the simplex optimizers are allowed to exploit duplicated columns.

Default "OFF"
Accepted "ON", "OFF", "FREE"
Example param.MSK_IPAR_SIM_EXPLOIT_DUPVEC = MSK_SIM_EXPLOIT_DUPVEC_OFF
Groups Simplex optimizer

MSK_IPAR_SIM_HOTSTART
Controls the type of hot-start that the simplex optimizer perform.

Default "FREE"
Accepted "NONE", "FREE", "STATUS_KEYS"
Example param.MSK_IPAR_SIM_HOTSTART = MSK_SIM_HOTSTART_FREE
Groups Simplex optimizer

MSK_IPAR_SIM_HOTSTART_LU
Determines if the simplex optimizer should exploit the initial factorization.

Default "ON"
Accepted
- "ON": Factorization is reused if possible.
- "OFF": Factorization is recomputed.

Example param.MSK_IPAR_SIM_HOTSTART_LU = MSK_ON
Groups Simplex optimizer

MSK_IPAR_SIM_MAX_ITERATIONS
Maximum number of iterations that can be used by a simplex optimizer.

Default 10000000
Accepted [0; +inf]
Example param.MSK_IPAR_SIM_MAX_ITERATIONS = 10000000
Groups Simplex optimizer, Termination criteria

MSK_IPAR_SIM_MAX_NUM_SETBACKS
Controls how many set-backs are allowed within a simplex optimizer. A set-back is an event where the optimizer moves in the wrong direction. This is impossible in theory but may happen due to numerical problems.

Default 250
Accepted [0; +inf]
Example param.MSK_IPAR_SIM_MAX_NUM_SETBACKS = 250
Groups Simplex optimizer

MSK_IPAR_SIM_NON_SINGULAR
Controls if the simplex optimizer ensures a non-singular basis, if possible.

Default "ON"
Accepted "ON", "OFF"
Example param.MSK_IPAR_SIM_NON_SINGULAR = MSK_ON
Groups Simplex optimizer

MSK_IPAR_SIM_PRIMAL_CRASH
Controls whether crashing is performed in the primal simplex optimizer. In general, if a basis consists of more than (100-this parameter value)% xed variables, then a crash will be performed.

Default 90
Accepted [0; +inf]
Example param.MSK_IPAR_SIM_PRIMAL_CRASH = 90
Groups *Primal simplex*

MSK_IPAR_SIM_PRIMAL_PHASEONE_METHOD
An experimental feature.

Default 0
Accepted [0; 10]
Example param.MSK_IPAR_SIM_PRIMAL_PHASEONE_METHOD = 0
Groups *Simplex optimizer*

MSK_IPAR_SIM_PRIMAL_RESTRICT_SELECTION
The primal simplex optimizer can use a so-called restricted selection/pricing strategy to choose the outgoing variable. Hence, if restricted selection is applied, then the primal simplex optimizer rst choose a subset of all the potential incoming variables. Next, for some time it will choose the incoming variable only among the subset. From time to time the subset is rede ned. A larger value of this parameter implies that the optimizer will be more aggressive in its restriction strategy, i.e. a value of 0 implies that the restriction strategy is not applied at all.

Default 50
Accepted [0; 100]
Example param.MSK_IPAR_SIM_PRIMAL_RESTRICT_SELECTION = 50
Groups *Primal simplex*

MSK_IPAR_SIM_PRIMAL_SELECTION
Controls the choice of the incoming variable, known as the selection strategy, in the primal simplex optimizer.

Default *"FREE"*
Accepted *"FREE"*, *"FULL"*, *"ASE"*, *"DEVEX"*, *"SE"*, *"PARTIAL"*
Example param.MSK_IPAR_SIM_PRIMAL_SELECTION = MSK_SIM_SELECTION_FREE
Groups *Primal simplex*

MSK_IPAR_SIM_REFACTOR_FREQ
Controls how frequent the basis is refactorized. The value 0 means that the optimizer determines the best point of refactorization. It is strongly recommended NOT to change this parameter.

Default 0
Accepted [0; +inf]
Example param.MSK_IPAR_SIM_REFACTOR_FREQ = 0
Groups *Simplex optimizer*

MSK_IPAR_SIM_REFORMULATION
Controls if the simplex optimizers are allowed to reformulate the problem.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*, *"FREE"*, *"AGGRESSIVE"*
Example param.MSK_IPAR_SIM_REFORMULATION = MSK_SIM_REFORMULATION_OFF
Groups *Simplex optimizer*

MSK_IPAR_SIM_SAVE_LU
Controls if the LU factorization stored should be replaced with the LU factorization corresponding to the initial basis.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_SIM_SAVE_LU = MSK_OFF

Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_BAS_VARIABLES
Controls whether the variables section is written to the basic solution file.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_BAS_VARIABLES = MSK_ON
Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_COMPRESSION
Controls whether the data file is compressed while it is written. 0 means no compression while higher values mean more compression.

Default 9
Accepted [0; +inf]
Example param.MSK_IPAR_WRITE_COMPRESSION = 9
Groups *Data input/output*

MSK_IPAR_WRITE_DATA_PARAM
If this option is turned on the parameter settings are written to the data file as parameters.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_DATA_PARAM = MSK_OFF
Groups *Data input/output*

MSK_IPAR_WRITE_FREE_CON
Controls whether the free constraints are written to the data file.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_FREE_CON = MSK_ON
Groups *Data input/output*

MSK_IPAR_WRITE_GENERIC_NAMES
Controls whether generic names should be used instead of user-defined names when writing to the data file.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_GENERIC_NAMES = MSK_OFF
Groups *Data input/output*

MSK_IPAR_WRITE_GENERIC_NAMES_IO
Index origin used in generic names.

Default 1
Accepted [0; +inf]
Example param.MSK_IPAR_WRITE_GENERIC_NAMES_IO = 1
Groups *Data input/output*

MSK_IPAR_WRITE_IGNORE_INCOMPATIBLE_ITEMS
Controls if the writer ignores incompatible problem items when writing files.

Default *"OFF"*
Accepted

- *"ON"*: Ignore items that cannot be written to the current output file format.
- *"OFF"*: Produce an error if the problem contains items that cannot the written to the current output file format.

Example param.MSK_IPAR_WRITE_IGNORE_INCOMPATIBLE_ITEMS = MSK_OFF
Groups *Data input/output*

MSK_IPAR_WRITE_INT_CONSTRAINTS
Controls whether the constraint section is written to the integer solution file.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_INT_CONSTRAINTS = MSK_ON
Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_INT_HEAD
Controls whether the header section is written to the integer solution file.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_INT_HEAD = MSK_ON
Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_INT_VARIABLES
Controls whether the variables section is written to the integer solution file.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_INT_VARIABLES = MSK_ON
Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_LP_FULL_OBJ
Write all variables, including the ones with 0-coefficients, in the objective.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_LP_FULL_OBJ = MSK_ON
Groups *Data input/output*

MSK_IPAR_WRITE_LP_LINE_WIDTH
Maximum width of line in an LP file written by **MOSEK**.

Default 80
Accepted [40; +inf]
Example param.MSK_IPAR_WRITE_LP_LINE_WIDTH = 80
Groups *Data input/output*

MSK_IPAR_WRITE_LP_QUOTED_NAMES
If this option is turned on, then **MOSEK** will quote invalid LP names when writing an LP file.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_LP_QUOTED_NAMES = MSK_ON
Groups *Data input/output*

MSK_IPAR_WRITE_LP_STRICT_FORMAT
Controls whether LP output files satisfy the LP format strictly.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_LP_STRICT_FORMAT = MSK_OFF
Groups *Data input/output*

MSK_IPAR_WRITE_LP_TERMS_PER_LINE

Maximum number of terms on a single line in an LP file written by **MOSEK**. 0 means unlimited.

Default 10

Accepted [0; +inf]

Example param.MSK_IPAR_WRITE_LP_TERMS_PER_LINE = 10

Groups *Data input/output*

MSK_IPAR_WRITE_MPS_FORMAT

Controls in which format the MPS is written.

Default *"FREE"*

Accepted *"STRICT"*, *"RELAXED"*, *"FREE"*, *"CPLEX"*

Example param.MSK_IPAR_WRITE_MPS_FORMAT = MSK_MPS_FORMAT_FREE

Groups *Data input/output*

MSK_IPAR_WRITE_MPS_INT

Controls if marker records are written to the MPS file to indicate whether variables are integer restricted.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_WRITE_MPS_INT = MSK_ON

Groups *Data input/output*

MSK_IPAR_WRITE_PRECISION

Controls the precision with which double numbers are printed in the MPS data file. In general it is not worthwhile to use a value higher than 15.

Default 15

Accepted [0; +inf]

Example param.MSK_IPAR_WRITE_PRECISION = 15

Groups *Data input/output*

MSK_IPAR_WRITE_SOL_BARVARIABLES

Controls whether the symmetric matrix variables section is written to the solution file.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_WRITE_SOL_BARVARIABLES = MSK_ON

Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_SOL_CONSTRAINTS

Controls whether the constraint section is written to the solution file.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_WRITE_SOL_CONSTRAINTS = MSK_ON

Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_SOL_HEAD

Controls whether the header section is written to the solution file.

Default *"ON"*

Accepted *"ON"*, *"OFF"*

Example param.MSK_IPAR_WRITE_SOL_HEAD = MSK_ON

Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_SOL_IGNORE_INVALID_NAMES

Even if the names are invalid MPS names, then they are employed when writing the solution file.

Default *"OFF"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_SOL_IGNORE_INVALID_NAMES MSK_OFF
Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_SOL_VARIABLES
Controls whether the variables section is written to the solution file.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_SOL_VARIABLES MSK_ON
Groups *Data input/output*, *Solution input/output*

MSK_IPAR_WRITE_TASK_INC_SOL
Controls whether the solutions are stored in the task file too.

Default *"ON"*
Accepted *"ON"*, *"OFF"*
Example param.MSK_IPAR_WRITE_TASK_INC_SOL MSK_ON
Groups *Data input/output*

MSK_IPAR_WRITE_XML_MODE
Controls if linear coefficients should be written by row or column when writing in the XML file format.

Default *"ROW"*
Accepted *"ROW"*, *"COL"*
Example param.MSK_IPAR_WRITE_XML_MODE MSK_WRITE_XML_MODE_ROW
Groups *Data input/output*

15.5.3 String parameters

sparam
The enumeration type containing all string parameters.

MSK_SPAR_BAS_SOL_FILE_NAME
Name of the bas solution file.

Accepted Any valid file name.
Example param.MSK_SPAR_BAS_SOL_FILE_NAME 'somevalue'
Groups *Data input/output*, *Solution input/output*

MSK_SPAR_DATA_FILE_NAME
Data are read and written to this file.

Accepted Any valid file name.
Example param.MSK_SPAR_DATA_FILE_NAME 'somevalue'
Groups *Data input/output*

MSK_SPAR_DEBUG_FILE_NAME
MOSEK debug file.

Accepted Any valid file name.
Example param.MSK_SPAR_DEBUG_FILE_NAME 'somevalue'
Groups *Data input/output*

MSK_SPAR_INT_SOL_FILE_NAME
Name of the int solution file.

Accepted Any valid file name.
Example param.MSK_SPAR_INT_SOL_FILE_NAME 'somevalue'

Groups *Data input/output*, *Solution input/output*

MSK_SPAR_ITR_SOL_FILE_NAME
Name of the itr solution le.

Accepted Any valid le name.
Example param.MSK_SPAR_ITR_SOL_FILE_NAME = 'Some value'
Groups *Data input/output*, *Solution input/output*

MSK_SPAR_MIO_DEBUG_STRING
For internal debugging purposes.

Accepted Any valid string.
Example param.MSK_SPAR_MIO_DEBUG_STRING = 'Some value'
Groups *Data input/output*

MSK_SPAR_PARAM_COMMENT_SIGN
Only the rst character in this string is used. It is considered as a start of comment sign in the **MOSEK** parameter le. Spaces are ignored in the string.

Default
%%
Accepted Any valid string.
Example param.MSK_SPAR_PARAM_COMMENT_SIGN = '%%'
Groups *Data input/output*

MSK_SPAR_PARAM_READ_FILE_NAME
Modi cations to the parameter database is read from this le.

Accepted Any valid le name.
Example param.MSK_SPAR_PARAM_READ_FILE_NAME = 'Some value'
Groups *Data input/output*

MSK_SPAR_PARAM_WRITE_FILE_NAME
The parameter database is written to this le.

Accepted Any valid le name.
Example param.MSK_SPAR_PARAM_WRITE_FILE_NAME = 'Some value'
Groups *Data input/output*

MSK_SPAR_READ_MPS_BOU_NAME
Name of the BOUNDS vector used. An empty name means that the rst BOUNDS vector is used.

Accepted Any valid MPS name.
Example param.MSK_SPAR_READ_MPS_BOU_NAME = 'Some value'
Groups *Data input/output*

MSK_SPAR_READ_MPS_OBJ_NAME
Name of the free constraint used as objective function. An empty name means that the rst constraint is used as objective function.

Accepted Any valid MPS name.
Example param.MSK_SPAR_READ_MPS_OBJ_NAME = 'Some value'
Groups *Data input/output*

MSK_SPAR_READ_MPS_RAN_NAME
Name of the RANGE vector used. An empty name means that the rst RANGE vector is used.

Accepted Any valid MPS name.
Example param.MSK_SPAR_READ_MPS_RAN_NAME = 'Some value'
Groups *Data input/output*

MSK_SPAR_READ_MPS_RHS_NAME

Name of the RHS used. An empty name means that the first RHS vector is used.

Accepted Any valid MPS name.

Example param.MSK_SPAR_READ_MPS_RHS_NAME='MYRHS'

Groups *Data input/output*

MSK_SPAR_REMOTE_ACCESS_TOKEN

An access token used to submit tasks to a remote **MOSEK** server. An access token is a random 32-byte string encoded in base64, i.e. it is a 44 character ASCII string.

Accepted Any valid string.

Example param.MSK_SPAR_REMOTE_ACCESS_TOKEN='Some value'

Groups *Overall system*

MSK_SPAR_SENSITIVITY_FILE_NAME

If defined, **MOSEK** reads this file as a sensitivity analysis data file specifying the type of analysis to be done.

Accepted Any valid string.

Example param.MSK_SPAR_SENSITIVITY_FILE_NAME='Some value'

Groups *Data input/output*

MSK_SPAR_SENSITIVITY_RES_FILE_NAME

Accepted Any valid string.

Example param.MSK_SPAR_SENSITIVITY_RES_FILE_NAME='Some value'

Groups *Data input/output*

MSK_SPAR_SOL_FILTER_XC_LOW

A filter used to determine which constraints should be listed in the solution file. A value of 0.5 means that all constraints having xc[i]>0.5 should be listed, whereas +0.5 means that all constraints having xc[i]>=blc[i]+0.5 should be listed. An empty filter means that no filter is applied.

Accepted Any valid filter.

Example param.MSK_SPAR_SOL_FILTER_XC_LOW='Some value'

Groups *Data input/output*, *Solution input/output*

MSK_SPAR_SOL_FILTER_XC_UPR

A filter used to determine which constraints should be listed in the solution file. A value of 0.5 means that all constraints having xc[i]<0.5 should be listed, whereas -0.5 means all constraints having xc[i]<=buc[i]-0.5 should be listed. An empty filter means that no filter is applied.

Accepted Any valid filter.

Example param.MSK_SPAR_SOL_FILTER_XC_UPR='Some value'

Groups *Data input/output*, *Solution input/output*

MSK_SPAR_SOL_FILTER_XX_LOW

A filter used to determine which variables should be listed in the solution file. A value of 0.5 means that all constraints having xx[j]>=0.5 should be listed, whereas +0.5 means that all constraints having xx[j]>=blx[j]+0.5 should be listed. An empty filter means no filter is applied.

Accepted Any valid filter.

Example param.MSK_SPAR_SOL_FILTER_XX_LOW='Some value'

Groups *Data input/output*, *Solution input/output*

MSK_SPAR_SOL_FILTER_XX_UPR

A filter used to determine which variables should be listed in the solution file. A value of 0.5 means that all constraints having xx[j]<0.5 should be printed, whereas -0.5 means all constraints having xx[j]<=bux[j]-0.5 should be listed. An empty filter means no filter is applied.

Accepted Any valid file name.
Example param.MSK_SPAR_SOL_FILTER_XX_UPPER='somevalue'
Groups *Data input/output*, *Solution input/output*

MSK_SPAR_STAT_FILE_NAME
Statistics file name.

Accepted Any valid file name.
Example param.MSK_SPAR_STAT_FILE_NAME='somevalue'
Groups *Data input/output*

MSK_SPAR_STAT_KEY
Key used when writing the summary file.

Accepted Any valid string.
Example param.MSK_SPAR_STAT_KEY='somevalue'
Groups *Data input/output*

MSK_SPAR_STAT_NAME
Name used when writing the statistics file.

Accepted Any valid XML string.
Example param.MSK_SPAR_STAT_NAME='somevalue'
Groups *Data input/output*

MSK_SPAR_WRITE_LP_GEN_VAR_NAME
Sometimes when an LP file is written additional variables must be inserted. They will have the prefix denoted by this parameter.

Default xmskgen
Accepted Any valid string.
Example param.MSK_SPAR_WRITE_LP_GEN_VAR_NAME='xmskgen'
Groups *Data input/output*

15.6 Response codes

Response codes include:

- *Termination codes*
- *Warnings*
- *Errors*

The numerical code (in brackets) identifies the response in error messages and in the log output.
rescode
The enumeration type containing all response codes.

15.6.1 Termination

"MSK_RES_OK" (0)
No error occurred.
"MSK_RES_TRM_MAX_ITERATIONS" (10000)
The optimizer terminated at the maximum number of iterations.
"MSK_RES_TRM_MAX_TIME" (10001)
The optimizer terminated at the maximum amount of time.
"MSK_RES_TRM_OBJECTIVE_RANGE" (10002)
The optimizer terminated with an objective value outside the objective range.
"MSK_RES_TRM_MIO_NUM_RELAXS" (10008)
The mixed-integer optimizer terminated as the maximum number of relaxations was reached.

"MSK_RES_TRM_MIO_NUM_BRANCHES" (10009)
The mixed-integer optimizer terminated as the maximum number of branches was reached.

"MSK_RES_TRM_NUM_MAX_NUM_INT_SOLUTIONS" (10015)
The mixed-integer optimizer terminated as the maximum number of feasible solutions was reached.

"MSK_RES_TRM_STALL" (10006)
The optimizer is terminated due to slow progress.

Stalling means that numerical problems prevent the optimizer from making reasonable progress and that it makes no sense to continue. In many cases this happens if the problem is badly scaled or otherwise ill-conditioned. There is no guarantee that the solution will be feasible or optimal. However, often stalling happens near the optimum, and the returned solution may be of good quality. Therefore, it is recommended to check the status of the solution. If the solution status is optimal the solution is most likely good enough for most practical purposes.

Please note that if a linear optimization problem is solved using the interior-point optimizer with basis identi cation turned on, the returned basic solution likely to have high accuracy, even though the optimizer stalled.

Some common causes of stalling are a) badly scaled models, b) near feasible or near infeasible problems.

"MSK_RES_TRM_USER_CALLBACK" (10007)
The optimizer terminated due to the return of the user-de ned callback function.

"MSK_RES_TRM_MAX_NUM_SETBACKS" (10020)
The optimizer terminated as the maximum number of set-backs was reached. This indicates serious numerical problems and a possibly badly formulated problem.

"MSK_RES_TRM_NUMERICAL_PROBLEM" (10025)
The optimizer terminated due to numerical problems.

"MSK_RES_TRM_INTERNAL" (10030)
The optimizer terminated due to some internal reason. Please contact **MOSEK** support.

"MSK_RES_TRM_INTERNAL_STOP" (10031)
The optimizer terminated for internal reasons. Please contact **MOSEK** support.

15.6.2 Warnings

"MSK_RES_WRN_OPEN_PARAM_FILE" (50)
The parameter le could not be opened.

"MSK_RES_WRN_LARGE_BOUND" (51)
A numerically large bound value is speci ed.

"MSK_RES_WRN_LARGE_LO_BOUND" (52)
A numerically large lower bound value is speci ed.

"MSK_RES_WRN_LARGE_UP_BOUND" (53)
A numerically large upper bound value is speci ed.

"MSK_RES_WRN_LARGE_CON_FX" (54)
An equality constraint is xed to a numerically large value. This can cause numerical problems.

"MSK_RES_WRN_LARGE_CJ" (57)
A numerically large value is speci ed for one c_j.

"MSK_RES_WRN_LARGE_AIJ" (62)
A numerically large value is speci ed for an $a_{i,j}$ element in A. The parameter *MSK_DPAR_DATA_TOL_AIJ_LARGE* controls when an $a_{i,j}$ is considered large.

"MSK_RES_WRN_ZERO_AIJ" (63)
One or more zero elements are speci ed in A.

"MSK_RES_WRN_NAME_MAX_LEN" (65)
A name is longer than the bu er that is supposed to hold it.

"MSK_RES_WRN_SPAR_MAX_LEN" (66)
A value for a string parameter is longer than the bu er that is supposed to hold it.

"MSK_RES_WRN_MPS_SPLIT_RHS_VECTOR" (70)
An RHS vector is split into several nonadjacent parts in an MPS le.

"MSK_RES_WRN_MPS_SPLIT_RAN_VECTOR" (71)
A RANGE vector is split into several nonadjacent parts in an MPS le.

"MSK_RES_WRN_MPS_SPLIT_BOU_VECTOR" (72)
A BOUNDS vector is split into several nonadjacent parts in an MPS le.
"MSK_RES_WRN_LP_OLD_QUAD_FORMAT" (80)
Missing `/2' after quadratic expressions in bound or objective.
"MSK_RES_WRN_LP_DROP_VARIABLE" (85)
Ignored a variable because the variable was not previously de ned. Usually this implies that a variable appears in the bound section but not in the objective or the constraints.
"MSK_RES_WRN_NZ_IN_UPR_TRI" (200)
Non-zero elements speci ed in the upper triangle of a matrix were ignored.
"MSK_RES_WRN_DROPPED_NZ_QOBJ" (201)
One or more non-zero elements were dropped in the Q matrix in the objective.
"MSK_RES_WRN_IGNORE_INTEGER" (250)
Ignored integer constraints.
"MSK_RES_WRN_NO_GLOBAL_OPTIMIZER" (251)
No global optimizer is available.
"MSK_RES_WRN_MIO_INFEASIBLE_FINAL" (270)
The nal mixed-integer problem with all the integer variables xed at their optimal values is infeasible.
"MSK_RES_WRN_SOL_FILTER" (300)
Invalid solution lter is speci ed.
"MSK_RES_WRN_UNDEF_SOL_FILE_NAME" (350)
Unde ned name occurred in a solution.
"MSK_RES_WRN_SOL_FILE_IGNORED_CON" (351)
One or more lines in the constraint section were ignored when reading a solution le.
"MSK_RES_WRN_SOL_FILE_IGNORED_VAR" (352)
One or more lines in the variable section were ignored when reading a solution le.
"MSK_RES_WRN_TOO_FEW_BASIS_VARS" (400)
An incomplete basis has been speci ed. Too few basis variables are speci ed.
"MSK_RES_WRN_TOO_MANY_BASIS_VARS" (405)
A basis with too many variables has been speci ed.
"MSK_RES_WRN_LICENSE_EXPIRE" (500)
The license expires.
"MSK_RES_WRN_LICENSE_SERVER" (501)
The license server is not responding.
"MSK_RES_WRN_EMPTY_NAME" (502)
A variable or constraint name is empty. The output le may be invalid.
"MSK_RES_WRN_USING_GENERIC_NAMES" (503)
Generic names are used because a name is not valid. For instance when writing an LP le the names must not contain blanks or start with a digit.
"MSK_RES_WRN_LICENSE_FEATURE_EXPIRE" (505)
The license expires.
"MSK_RES_WRN_PARAM_NAME_DOU" (510)
The parameter name is not recognized as a double parameter.
"MSK_RES_WRN_PARAM_NAME_INT" (511)
The parameter name is not recognized as a integer parameter.
"MSK_RES_WRN_PARAM_NAME_STR" (512)
The parameter name is not recognized as a string parameter.
"MSK_RES_WRN_PARAM_STR_VALUE" (515)
The string is not recognized as a symbolic value for the parameter.
"MSK_RES_WRN_PARAM_IGNORED_CMIO" (516)
A parameter was ignored by the conic mixed integer optimizer.
"MSK_RES_WRN_ZEROS_IN_SPARSE_ROW" (705)
One or more (near) zero elements are speci ed in a sparse row of a matrix. Since, it is redundant to specify zero elements then it may indicate an error.
"MSK_RES_WRN_ZEROS_IN_SPARSE_COL" (710)
One or more (near) zero elements are speci ed in a sparse column of a matrix. It is redundant to specify zero elements. Hence, it may indicate an error.

"MSK_RES_WRN_INCOMPLETE_LINEAR_DEPENDENCY_CHECK" (800)
The linear dependency check(s) is incomplete. Normally this is not an important warning unless the optimization problem has been formulated with linear dependencies. Linear dependencies may prevent **MOSEK** from solving the problem.

"MSK_RES_WRN_ELIMINATOR_SPACE" (801)
The eliminator is skipped at least once due to lack of space.

"MSK_RES_WRN_PRESOLVE_OUTOFSPACE" (802)
The presolve is incomplete due to lack of space.

"MSK_RES_WRN_WRITE_CHANGED_NAMES" (803)
Some names were changed because they were invalid for the output le format.

"MSK_RES_WRN_WRITE_DISCARDED_CFIX" (804)
The xed objective term could not be converted to a variable and was discarded in the output le.

"MSK_RES_WRN_DUPLICATE_CONSTRAINT_NAMES" (850)
Two constraint names are identical.

"MSK_RES_WRN_DUPLICATE_VARIABLE_NAMES" (851)
Two variable names are identical.

"MSK_RES_WRN_DUPLICATE_BARVARIABLE_NAMES" (852)
Two barvariable names are identical.

"MSK_RES_WRN_DUPLICATE_CONE_NAMES" (853)
Two cone names are identical.

"MSK_RES_WRN_ANA_LARGE_BOUNDS" (900)
This warning is issued by the problem analyzer, if one or more constraint or variable bounds are very large. One should consider omitting these bounds entirely by setting them to +inf or -inf.

"MSK_RES_WRN_ANA_C_ZERO" (901)
This warning is issued by the problem analyzer, if the coe cients in the linear part of the objective are all zero.

"MSK_RES_WRN_ANA_EMPTY_COLS" (902)
This warning is issued by the problem analyzer, if columns, in which all coe cients are zero, are found.

"MSK_RES_WRN_ANA_CLOSE_BOUNDS" (903)
This warning is issued by problem analyzer, if ranged constraints or variables with very close upper and lower bounds are detected. One should consider treating such constraints as equalities and such variables as constants.

"MSK_RES_WRN_ANA_ALMOST_INT_BOUNDS" (904)
This warning is issued by the problem analyzer if a constraint is bound nearly integral.

"MSK_RES_WRN_QUAD_CONES_WITH_ROOT_FIXED_AT_ZERO" (930)
For at least one quadratic cone the root is xed at (nearly) zero. This may cause problems such as a very large dual solution. Therefore, it is recommended to remove such cones before optimizing the problem, or to x all the variables in the cone to 0.

"MSK_RES_WRN_RQUAD_CONES_WITH_ROOT_FIXED_AT_ZERO" (931)
For at least one rotated quadratic cone at least one of the root variables are xed at (nearly) zero. This may cause problems such as a very large dual solution. Therefore, it is recommended to remove such cones before optimizing the problem, or to x all the variables in the cone to 0.

"MSK_RES_WRN_EXP_CONES_WITH_VARIABLES_FIXED_AT_ZERO" (932)
For at least one exponential cone $x \geq y \exp(z/y)$ either the variable x or y is xed at (nearly) zero. This may cause problems such as a very large dual solution. Therefore, it is recommended to remove such cones before optimizing the problem, or to x all the variables in the cone to 0.

"MSK_RES_WRN_POW_CONES_WITH_ROOT_FIXED_AT_ZERO" (933)
For at least one power cone at least one of the root variables are xed at (nearly) zero. This may cause problems such as a very large dual solution. Therefore, it is recommended to remove such cones before optimizing the problem, or to x all the variables in the cone to 0.

"MSK_RES_WRN_NO_DUALIZER" (950)
No automatic dualizer is available for the speci ed problem. The primal problem is solved.

"MSK_RES_WRN_SYM_MAT_LARGE" (960)
A numerically large value is speci ed for an $e_{i,j}$ element in E. The parameter *MSK_DPAR_DATA_SYM_MAT_TOL_LARGE* controls when an $e_{i,j}$ is considered large.

15.6.3 Errors

"MSK_RES_ERR_LICENSE" (1000)
Invalid license.

"MSK_RES_ERR_LICENSE_EXPIRED" (1001)
The license has expired.

"MSK_RES_ERR_LICENSE_VERSION" (1002)
The license is valid for another version of MOSEK.

"MSK_RES_ERR_SIZE_LICENSE" (1005)
The problem is bigger than the license.

"MSK_RES_ERR_PROB_LICENSE" (1006)
The software is not licensed to solve the problem.

"MSK_RES_ERR_FILE_LICENSE" (1007)
Invalid license file.

"MSK_RES_ERR_MISSING_LICENSE_FILE" (1008)
MOSEK cannot find license file or a token server. See the MOSEK licensing manual for details.

"MSK_RES_ERR_SIZE_LICENSE_CON" (1010)
The problem has too many constraints to be solved with the available license.

"MSK_RES_ERR_SIZE_LICENSE_VAR" (1011)
The problem has too many variables to be solved with the available license.

"MSK_RES_ERR_SIZE_LICENSE_INTVAR" (1012)
The problem contains too many integer variables to be solved with the available license.

"MSK_RES_ERR_OPTIMIZER_LICENSE" (1013)
The optimizer required is not licensed.

"MSK_RES_ERR_FLEXLM" (1014)
The FLEXlm license manager reported an error.

"MSK_RES_ERR_LICENSE_SERVER" (1015)
The license server is not responding.

"MSK_RES_ERR_LICENSE_MAX" (1016)
Maximum number of licenses is reached.

"MSK_RES_ERR_LICENSE_MOSEKLM_DAEMON" (1017)
The MOSEKLM license manager daemon is not up and running.

"MSK_RES_ERR_LICENSE_FEATURE" (1018)
A requested feature is not available in the license file(s). Most likely due to an incorrect license system setup.

"MSK_RES_ERR_PLATFORM_NOT_LICENSED" (1019)
A requested license feature is not available for the required platform.

"MSK_RES_ERR_LICENSE_CANNOT_ALLOCATE" (1020)
The license system cannot allocate the memory required.

"MSK_RES_ERR_LICENSE_CANNOT_CONNECT" (1021)
MOSEK cannot connect to the license server. Most likely the license server is not up and running.

"MSK_RES_ERR_LICENSE_INVALID_HOSTID" (1025)
The host ID specified in the license file does not match the host ID of the computer.

"MSK_RES_ERR_LICENSE_SERVER_VERSION" (1026)
The version specified in the checkout request is greater than the highest version number the daemon supports.

"MSK_RES_ERR_LICENSE_NO_SERVER_SUPPORT" (1027)
The license server does not support the requested feature. Possible reasons for this error include:

- The feature has expired.
- The feature's start date is later than today's date.
- The version requested is higher than feature's the highest supported version.
- A corrupted license file.

Try restarting the license and inspect the license server debug file, usually called lmgrd.log .

"MSK_RES_ERR_LICENSE_NO_SERVER_LINE" (1028)
There is no SERVER line in the license file. All non-zero license count features need at least one SERVER line.

"MSK_RES_ERR_OLDER_DLL" (1035)
The dynamic link library is older than the speci ed version.
"MSK_RES_ERR_NEWER_DLL" (1036)
The dynamic link library is newer than the speci ed version.
"MSK_RES_ERR_LINK_FILE_DLL" (1040)
A le cannot be linked to a stream in the DLL version.
"MSK_RES_ERR_THREAD_MUTEX_INIT" (1045)
Could not initialize a mutex.
"MSK_RES_ERR_THREAD_MUTEX_LOCK" (1046)
Could not lock a mutex.
"MSK_RES_ERR_THREAD_MUTEX_UNLOCK" (1047)
Could not unlock a mutex.
"MSK_RES_ERR_THREAD_CREATE" (1048)
Could not create a thread. This error may occur if a large number of environments are created and not deleted again. In any case it is a good practice to minimize the number of environments created.
"MSK_RES_ERR_THREAD_COND_INIT" (1049)
Could not initialize a condition.
"MSK_RES_ERR_UNKNOWN" (1050)
Unknown error.
"MSK_RES_ERR_SPACE" (1051)
Out of space.
"MSK_RES_ERR_FILE_OPEN" (1052)
Error while opening a le.
"MSK_RES_ERR_FILE_READ" (1053)
File read error.
"MSK_RES_ERR_FILE_WRITE" (1054)
File write error.
"MSK_RES_ERR_DATA_FILE_EXT" (1055)
The data le format cannot be determined from the le name.
"MSK_RES_ERR_INVALID_FILE_NAME" (1056)
An invalid le name has been speci ed.
"MSK_RES_ERR_INVALID_SOL_FILE_NAME" (1057)
An invalid le name has been speci ed.
"MSK_RES_ERR_END_OF_FILE" (1059)
End of le reached.
"MSK_RES_ERR_NULL_ENV" (1060)
env is a NULL pointer.
"MSK_RES_ERR_NULL_TASK" (1061)
task is a NULL pointer.
"MSK_RES_ERR_INVALID_STREAM" (1062)
An invalid stream is referenced.
"MSK_RES_ERR_NO_INIT_ENV" (1063)
env is not initialized.
"MSK_RES_ERR_INVALID_TASK" (1064)
The task is invalid.
"MSK_RES_ERR_NULL_POINTER" (1065)
An argument to a function is unexpectedly a NULL pointer.
"MSK_RES_ERR_LIVING_TASKS" (1066)
All tasks associated with an enviroment must be deleted before the environment is deleted. There are still some undeleted tasks.
"MSK_RES_ERR_BLANK_NAME" (1070)
An all blank name has been speci ed.
"MSK_RES_ERR_DUP_NAME" (1071)
The same name was used multiple times for the same problem item type.
"MSK_RES_ERR_FORMAT_STRING" (1072)
The name format string is invalid.

"MSK_RES_ERR_OPF_PREMATURE_EOF" (1172)
Premature end of le in an OPF le.
"MSK_RES_ERR_JSON_SYNTAX" (1175)
Syntax error in an JSON data
"MSK_RES_ERR_JSON_STRING" (1176)
Error in JSON string.
"MSK_RES_ERR_JSON_NUMBER_OVERFLOW" (1177)
Invalid number entry - wrong type or value over ow.
"MSK_RES_ERR_JSON_FORMAT" (1178)
Error in an JSON Task le
"MSK_RES_ERR_JSON_DATA" (1179)
Inconsistent data in JSON Task le
"MSK_RES_ERR_JSON_MISSING_DATA" (1180)
Missing data section in JSON task le.
"MSK_RES_ERR_ARGUMENT_LENNEQ" (1197)
Incorrect length of arguments.
"MSK_RES_ERR_ARGUMENT_TYPE" (1198)
Incorrect argument type.
"MSK_RES_ERR_NUM_ARGUMENTS" (1199)
Incorrect number of function arguments.
"MSK_RES_ERR_IN_ARGUMENT" (1200)
A function argument is incorrect.
"MSK_RES_ERR_ARGUMENT_DIMENSION" (1201)
A function argument is of incorrect dimension.
"MSK_RES_ERR_SHAPE_IS_TOO_LARGE" (1202)
The size of the n-dimensional shape is too large.
"MSK_RES_ERR_INDEX_IS_TOO_SMALL" (1203)
An index in an argument is too small.
"MSK_RES_ERR_INDEX_IS_TOO_LARGE" (1204)
An index in an argument is too large.
"MSK_RES_ERR_PARAM_NAME" (1205)
The parameter name is not correct.
"MSK_RES_ERR_PARAM_NAME_DOU" (1206)
The parameter name is not correct for a double parameter.
"MSK_RES_ERR_PARAM_NAME_INT" (1207)
The parameter name is not correct for an integer parameter.
"MSK_RES_ERR_PARAM_NAME_STR" (1208)
The parameter name is not correct for a string parameter.
"MSK_RES_ERR_PARAM_INDEX" (1210)
Parameter index is out of range.
"MSK_RES_ERR_PARAM_IS_TOO_LARGE" (1215)
The parameter value is too large.
"MSK_RES_ERR_PARAM_IS_TOO_SMALL" (1216)
The parameter value is too small.
"MSK_RES_ERR_PARAM_VALUE_STR" (1217)
The parameter value string is incorrect.
"MSK_RES_ERR_PARAM_TYPE" (1218)
The parameter type is invalid.
"MSK_RES_ERR_INF_DOU_INDEX" (1219)
A double information index is out of range for the speci ed type.
"MSK_RES_ERR_INF_INT_INDEX" (1220)
An integer information index is out of range for the speci ed type.
"MSK_RES_ERR_INDEX_ARR_IS_TOO_SMALL" (1221)
An index in an array argument is too small.
"MSK_RES_ERR_INDEX_ARR_IS_TOO_LARGE" (1222)
An index in an array argument is too large.
"MSK_RES_ERR_INF_LINT_INDEX" (1225)
A long integer information index is out of range for the speci ed type.

"MSK_RES_ERR_ARG_IS_TOO_SMALL" (1226)
The value of a argument is too small.
"MSK_RES_ERR_ARG_IS_TOO_LARGE" (1227)
The value of a argument is too large.
"MSK_RES_ERR_INVALID_WHICHSOL" (1228)
whichsol is invalid.
"MSK_RES_ERR_INF_DOU_NAME" (1230)
A double information name is invalid.
"MSK_RES_ERR_INF_INT_NAME" (1231)
An integer information name is invalid.
"MSK_RES_ERR_INF_TYPE" (1232)
The information type is invalid.
"MSK_RES_ERR_INF_LINT_NAME" (1234)
A long integer information name is invalid.
"MSK_RES_ERR_INDEX" (1235)
An index is out of range.
"MSK_RES_ERR_WHICHSOL" (1236)
The solution de ned by whichsol does not exists.
"MSK_RES_ERR_SOLITEM" (1237)
The solution item number solitem is invalid. Please note that *"MSK_SOL_ITEM_SNX"* is invalid for the basic solution.
"MSK_RES_ERR_WHICHITEM_NOT_ALLOWED" (1238)
whichitem is unacceptable.
"MSK_RES_ERR_MAXNUMCON" (1240)
The maximum number of constraints speci ed is smaller than the number of constraints in the task.
"MSK_RES_ERR_MAXNUMVAR" (1241)
The maximum number of variables speci ed is smaller than the number of variables in the task.
"MSK_RES_ERR_MAXNUMBARVAR" (1242)
The maximum number of semide nite variables speci ed is smaller than the number of semide nite variables in the task.
"MSK_RES_ERR_MAXNUMQNZ" (1243)
The maximum number of non-zeros speci ed for the Q matrices is smaller than the number of non-zeros in the current Q matrices.
"MSK_RES_ERR_TOO_SMALL_MAX_NUM_NZ" (1245)
The maximum number of non-zeros speci ed is too small.
"MSK_RES_ERR_INVALID_IDX" (1246)
A speci ed index is invalid.
"MSK_RES_ERR_INVALID_MAX_NUM" (1247)
A speci ed index is invalid.
"MSK_RES_ERR_NUMCONLIM" (1250)
Maximum number of constraints limit is exceeded.
"MSK_RES_ERR_NUMVARLIM" (1251)
Maximum number of variables limit is exceeded.
"MSK_RES_ERR_TOO_SMALL_MAXNUMANZ" (1252)
The maximum number of non-zeros speci ed for A is smaller than the number of non-zeros in the current A.
"MSK_RES_ERR_INV_APTRE" (1253)
aptre[j] is strictly smaller than aptrb[j] for some j .
"MSK_RES_ERR_MUL_A_ELEMENT" (1254)
An element in A is de ned multiple times.
"MSK_RES_ERR_INV_BK" (1255)
Invalid bound key.
"MSK_RES_ERR_INV_BKC" (1256)
Invalid bound key is speci ed for a constraint.
"MSK_RES_ERR_INV_BKX" (1257)
An invalid bound key is speci ed for a variable.

"MSK_RES_ERR_INV_VAR_TYPE" (1258)
An invalid variable type is speci ed for a variable.
"MSK_RES_ERR_SOLVER_PROBTYPE" (1259)
Problem type does not match the chosen optimizer.
"MSK_RES_ERR_OBJECTIVE_RANGE" (1260)
Empty objective range.
"MSK_RES_ERR_UNDEF_SOLUTION" (1265)
MOSEK has the following solution types:

- an interior-point solution,
- a basic solution,
- and an integer solution.

Each optimizer may set one or more of these solutions; e.g by default a successful optimization with the interior-point optimizer de nes the interior-point solution and, for linear problems, also the basic solution. This error occurs when asking for a solution or for information about a solution that is not de ned.
"MSK_RES_ERR_BASIS" (1266)
An invalid basis is speci ed. Either too many or too few basis variables are speci ed.
"MSK_RES_ERR_INV_SKC" (1267)
Invalid value in skc.
"MSK_RES_ERR_INV_SKX" (1268)
Invalid value in skx.
"MSK_RES_ERR_INV_SKN" (1274)
Invalid value in skn.
"MSK_RES_ERR_INV_SK_STR" (1269)
Invalid status key string encountered.
"MSK_RES_ERR_INV_SK" (1270)
Invalid status key code.
"MSK_RES_ERR_INV_CONE_TYPE_STR" (1271)
Invalid cone type string encountered.
"MSK_RES_ERR_INV_CONE_TYPE" (1272)
Invalid cone type code is encountered.
"MSK_RES_ERR_INVALID_SURPLUS" (1275)
Invalid surplus.
"MSK_RES_ERR_INV_NAME_ITEM" (1280)
An invalid name item code is used.
"MSK_RES_ERR_PRO_ITEM" (1281)
An invalid problem is used.
"MSK_RES_ERR_INVALID_FORMAT_TYPE" (1283)
Invalid format type.
"MSK_RES_ERR_FIRSTI" (1285)
Invalid firsti .
"MSK_RES_ERR_LASTI" (1286)
Invalid lasti .
"MSK_RES_ERR_FIRSTJ" (1287)
Invalid firstj .
"MSK_RES_ERR_LASTJ" (1288)
Invalid lastj .
"MSK_RES_ERR_MAX_LEN_IS_TOO_SMALL" (1289)
A maximum length that is too small has been speci ed.
"MSK_RES_ERR_NONLINEAR_EQUALITY" (1290)
The model contains a nonlinear equality which de nes a nonconvex set.
"MSK_RES_ERR_NONCONVEX" (1291)
The optimization problem is nonconvex.
"MSK_RES_ERR_NONLINEAR_RANGED" (1292)
Nonlinear constraints with nite lower and upper bound always de ne a nonconvex feasible set.

"MSK_RES_ERR_CON_Q_NOT_PSD" (1293)
The quadratic constraint matrix is not positive semide nite as expected for a constraint with nite upper bound. This results in a nonconvex problem. The parameter *MSK_DPAR_CHECK_CONVEXITY_REL_TOL* can be used to relax the convexity check.

"MSK_RES_ERR_CON_Q_NOT_NSD" (1294)
The quadratic constraint matrix is not negative semide nite as expected for a constraint with nite lower bound. This results in a nonconvex problem. The parameter *MSK_DPAR_CHECK_CONVEXITY_REL_TOL* can be used to relax the convexity check.

"MSK_RES_ERR_OBJ_Q_NOT_PSD" (1295)
The quadratic coe cient matrix in the objective is not positive semide nite as expected for a minimization problem. The parameter *MSK_DPAR_CHECK_CONVEXITY_REL_TOL* can be used to relax the convexity check.

"MSK_RES_ERR_OBJ_Q_NOT_NSD" (1296)
The quadratic coe cient matrix in the objective is not negative semide nite as expected for a maximization problem. The parameter *MSK_DPAR_CHECK_CONVEXITY_REL_TOL* can be used to relax the convexity check.

"MSK_RES_ERR_ARGUMENT_PERM_ARRAY" (1299)
An invalid permutation array is speci ed.

"MSK_RES_ERR_CONE_INDEX" (1300)
An index of a non-existing cone has been speci ed.

"MSK_RES_ERR_CONE_SIZE" (1301)
A cone with incorrect number of members is speci ed.

"MSK_RES_ERR_CONE_OVERLAP" (1302)
One or more of the variables in the cone to be added is already member of another cone. Now assume the variable is x_j then add a new variable say x_k and the constraint

$$x_j = x_k$$

and then let x_k be member of the cone to be appended.

"MSK_RES_ERR_CONE_REP_VAR" (1303)
A variable is included multiple times in the cone.

"MSK_RES_ERR_MAXNUMCONE" (1304)
The value speci ed for maxnumcone is too small.

"MSK_RES_ERR_CONE_TYPE" (1305)
Invalid cone type speci ed.

"MSK_RES_ERR_CONE_TYPE_STR" (1306)
Invalid cone type speci ed.

"MSK_RES_ERR_CONE_OVERLAP_APPEND" (1307)
The cone to be appended has one variable which is already member of another cone.

"MSK_RES_ERR_REMOVE_CONE_VARIABLE" (1310)
A variable cannot be removed because it will make a cone invalid.

"MSK_RES_ERR_APPENDING_TOO_BIG_CONE" (1311)
Trying to append a too big cone.

"MSK_RES_ERR_CONE_PARAMETER" (1320)
An invalid cone parameter.

"MSK_RES_ERR_SOL_FILE_INVALID_NUMBER" (1350)
An invalid number is speci ed in a solution le.

"MSK_RES_ERR_HUGE_C" (1375)
A huge value in absolute size is speci ed for one c_j.

"MSK_RES_ERR_HUGE_AIJ" (1380)
A numerically huge value is speci ed for an $a_{i,j}$ element in A. The parameter *MSK_DPAR_DATA_TOL_AIJ_HUGE* controls when an $a_{i,j}$ is considered huge.

"MSK_RES_ERR_DUPLICATE_AIJ" (1385)
An element in the A matrix is speci ed twice.

"MSK_RES_ERR_LOWER_BOUND_IS_A_NAN" (1390)
The lower bound speci ed is not a number (nan).

"MSK_RES_ERR_UPPER_BOUND_IS_A_NAN" (1391)
The upper bound speci ed is not a number (nan).

"MSK_RES_ERR_MIXED_CONIC_AND_NL" (1501)
The problem contains nonlinear terms conic constraints. The requested operation cannot be applied to this type of problem.
"MSK_RES_ERR_GLOBAL_INV_CONIC_PROBLEM" (1503)
The global optimizer can only be applied to problems without semide nite variables.
"MSK_RES_ERR_INV_OPTIMIZER" (1550)
An invalid optimizer has been chosen for the problem.
"MSK_RES_ERR_MIO_NO_OPTIMIZER" (1551)
No optimizer is available for the current class of integer optimization problems.
"MSK_RES_ERR_NO_OPTIMIZER_VAR_TYPE" (1552)
No optimizer is available for this class of optimization problems.
"MSK_RES_ERR_FINAL_SOLUTION" (1560)
An error occurred during the solution nalization.
"MSK_RES_ERR_FIRST" (1570)
Invalid first .
"MSK_RES_ERR_LAST" (1571)
Invalid index last . A given index was out of expected range.
"MSK_RES_ERR_SLICE_SIZE" (1572)
Invalid slice size speci ed.
"MSK_RES_ERR_NEGATIVE_SURPLUS" (1573)
Negative surplus.
"MSK_RES_ERR_NEGATIVE_APPEND" (1578)
Cannot append a negative number.
"MSK_RES_ERR_POSTSOLVE" (1580)
An error occurred during the postsolve. Please contact MOSEK support.
"MSK_RES_ERR_OVERFLOW" (1590)
A computation produced an over ow i.e. a very large number.
"MSK_RES_ERR_NO_BASIS_SOL" (1600)
No basic solution is de ned.
"MSK_RES_ERR_BASIS_FACTOR" (1610)
The factorization of the basis is invalid.
"MSK_RES_ERR_BASIS_SINGULAR" (1615)
The basis is singular and hence cannot be factored.
"MSK_RES_ERR_FACTOR" (1650)
An error occurred while factorizing a matrix.
"MSK_RES_ERR_FEASREPAIR_CANNOT_RELAX" (1700)
An optimization problem cannot be relaxed.
"MSK_RES_ERR_FEASREPAIR_SOLVING_RELAXED" (1701)
The relaxed problem could not be solved to optimality. Please consult the log le for further details.
"MSK_RES_ERR_FEASREPAIR_INCONSISTENT_BOUND" (1702)
The upper bound is less than the lower bound for a variable or a constraint. Please correct this before running the feasibility repair.
"MSK_RES_ERR_REPAIR_INVALID_PROBLEM" (1710)
The feasibility repair does not support the speci ed problem type.
"MSK_RES_ERR_REPAIR_OPTIMIZATION_FAILED" (1711)
Computation the optimal relaxation failed. The cause may have been numerical problems.
"MSK_RES_ERR_NAME_MAX_LEN" (1750)
A name is longer than the bu er that is supposed to hold it.
"MSK_RES_ERR_NAME_IS_NULL" (1760)
The name bu er is a NULL pointer.
"MSK_RES_ERR_INVALID_COMPRESSION" (1800)
Invalid compression type.
"MSK_RES_ERR_INVALID_IOMODE" (1801)
Invalid io mode.
"MSK_RES_ERR_NO_PRIMAL_INFEAS_CER" (2000)
A certi cate of primal infeasibility is not available.
"MSK_RES_ERR_NO_DUAL_INFEAS_CER" (2001)
A certi cate of infeasibility is not available.

"MSK_RES_ERR_NO_SOLUTION_IN_CALLBACK" (2500)
The required solution is not available.
"MSK_RES_ERR_INV_MARKI" (2501)
Invalid value in marki.
"MSK_RES_ERR_INV_MARKJ" (2502)
Invalid value in markj.
"MSK_RES_ERR_INV_NUMI" (2503)
Invalid numi.
"MSK_RES_ERR_INV_NUMJ" (2504)
Invalid numj.
"MSK_RES_ERR_TASK_INCOMPATIBLE" (2560)
The Task le is incompatible with this platform. This results from reading a le on a 32 bit platform generated on a 64 bit platform.
"MSK_RES_ERR_TASK_INVALID" (2561)
The Task le is invalid.
"MSK_RES_ERR_TASK_WRITE" (2562)
Failed to write the task le.
"MSK_RES_ERR_LU_MAX_NUM_TRIES" (2800)
Could not compute the LU factors of the matrix within the maximum number of allowed tries.
"MSK_RES_ERR_INVALID_UTF8" (2900)
An invalid UTF8 string is encountered.
"MSK_RES_ERR_INVALID_WCHAR" (2901)
An invalid wchar string is encountered.
"MSK_RES_ERR_NO_DUAL_FOR_ITG_SOL" (2950)
No dual information is available for the integer solution.
"MSK_RES_ERR_NO_SNX_FOR_BAS_SOL" (2953)
s_n^x is not available for the basis solution.
"MSK_RES_ERR_INTERNAL" (3000)
An internal error occurred. Please report this problem.
"MSK_RES_ERR_API_ARRAY_TOO_SMALL" (3001)
An input array was too short.
"MSK_RES_ERR_API_CB_CONNECT" (3002)
Failed to connect a callback object.
"MSK_RES_ERR_API_FATAL_ERROR" (3005)
An internal error occurred in the API. Please report this problem.
"MSK_RES_ERR_API_INTERNAL" (3999)
An internal fatal error occurred in an interface function.
"MSK_RES_ERR_SEN_FORMAT" (3050)
Syntax error in sensitivity analysis le.
"MSK_RES_ERR_SEN_UNDEF_NAME" (3051)
An unde ned name was encountered in the sensitivity analysis le.
"MSK_RES_ERR_SEN_INDEX_RANGE" (3052)
Index out of range in the sensitivity analysis le.
"MSK_RES_ERR_SEN_BOUND_INVALID_UP" (3053)
Analysis of upper bound requested for an index, where no upper bound exists.
"MSK_RES_ERR_SEN_BOUND_INVALID_LO" (3054)
Analysis of lower bound requested for an index, where no lower bound exists.
"MSK_RES_ERR_SEN_INDEX_INVALID" (3055)
Invalid range given in the sensitivity le.
"MSK_RES_ERR_SEN_INVALID_REGEXP" (3056)
Syntax error in regexp or regexp longer than 1024.
"MSK_RES_ERR_SEN_SOLUTION_STATUS" (3057)
No optimal solution found to the original problem given for sensitivity analysis.
"MSK_RES_ERR_SEN_NUMERICAL" (3058)
Numerical di culties encountered performing the sensitivity analysis.
"MSK_RES_ERR_SEN_UNHANDLED_PROBLEM_TYPE" (3080)
Sensitivity analysis cannot be performed for the speci ed problem. Sensitivity analysis is only possible for linear problems.

"MSK_RES_ERR_UNB_STEP_SIZE" (3100)
A step size in an optimizer was unexpectedly unbounded. For instance, if the step-size becomes unbounded in phase 1 of the simplex algorithm then an error occurs. Normally this will happen only if the problem is badly formulated. Please contact **MOSEK** support if this error occurs.

"MSK_RES_ERR_IDENTICAL_TASKS" (3101)
Some tasks related to this function call were identical. Unique tasks were expected.

"MSK_RES_ERR_AD_INVALID_CODELIST" (3102)
The code list data was invalid.

"MSK_RES_ERR_INTERNAL_TEST_FAILED" (3500)
An internal unit test function failed.

"MSK_RES_ERR_XML_INVALID_PROBLEM_TYPE" (3600)
The problem type is not supported by the XML format.

"MSK_RES_ERR_INVALID_AMPL_STUB" (3700)
Invalid AMPL stub.

"MSK_RES_ERR_INT64_TO_INT32_CAST" (3800)
A 64 bit integer could not be cast to a 32 bit integer.

"MSK_RES_ERR_SIZE_LICENSE_NUMCORES" (3900)
The computer contains more cpu cores than the license allows for.

"MSK_RES_ERR_INFEAS_UNDEFINED" (3910)
The requested value is not de ned for this solution type.

"MSK_RES_ERR_NO_BARX_FOR_SOLUTION" (3915)
There is no $\overline{X}$ available for the solution speci ed. In particular note there are no $\overline{X}$ de ned for the basic and integer solutions.

"MSK_RES_ERR_NO_BARS_FOR_SOLUTION" (3916)
There is no $\bar{s}$ available for the solution speci ed. In particular note there are no $\bar{s}$ de ned for the basic and integer solutions.

"MSK_RES_ERR_BAR_VAR_DIM" (3920)
The dimension of a symmetric matrix variable has to be greater than 0.

"MSK_RES_ERR_SYM_MAT_INVALID_ROW_INDEX" (3940)
A row index speci ed for sparse symmetric matrix is invalid.

"MSK_RES_ERR_SYM_MAT_INVALID_COL_INDEX" (3941)
A column index speci ed for sparse symmetric matrix is invalid.

"MSK_RES_ERR_SYM_MAT_NOT_LOWER_TRINGULAR" (3942)
Only the lower triangular part of sparse symmetric matrix should be speci ed.

"MSK_RES_ERR_SYM_MAT_INVALID_VALUE" (3943)
The numerical value speci ed in a sparse symmetric matrix is not a oating point value.

"MSK_RES_ERR_SYM_MAT_DUPLICATE" (3944)
A value in a symmetric matric as been speci ed more than once.

"MSK_RES_ERR_INVALID_SYM_MAT_DIM" (3950)
A sparse symmetric matrix of invalid dimension is speci ed.

"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_SYM_MAT" (4000)
The le format does not support a problem with symmetric matrix variables.

"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_CFIX" (4001)
The le format does not support a problem with nonzero xed term in c.

"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_RANGED_CONSTRAINTS" (4002)
The le format does not support a problem with ranged constraints.

"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_FREE_CONSTRAINTS" (4003)
The le format does not support a problem with free constraints.

"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_CONES" (4005)
The le format does not support a problem with conic constraints.

"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_NONLINEAR" (4010)
The le format does not support a problem with nonlinear terms.

"MSK_RES_ERR_DUPLICATE_CONSTRAINT_NAMES" (4500)
Two constraint names are identical.

"MSK_RES_ERR_DUPLICATE_VARIABLE_NAMES" (4501)
Two variable names are identical.

"MSK_RES_ERR_DUPLICATE_BARVARIABLE_NAMES" (4502)
Two barvariable names are identical.

"MSK_RES_ERR_DUPLICATE_CONE_NAMES" (4503)
Two cone names are identical.
"MSK_RES_ERR_NON_UNIQUE_ARRAY" (5000)
An array does not contain unique elements.
"MSK_RES_ERR_ARGUMENT_IS_TOO_LARGE" (5005)
The value of a function argument is too large.
"MSK_RES_ERR_MIO_INTERNAL" (5010)
A fatal error occurred in the mixed integer optimizer. Please contact MOSEK support.
"MSK_RES_ERR_INVALID_PROBLEM_TYPE" (6000)
An invalid problem type.
"MSK_RES_ERR_UNHANDLED_SOLUTION_STATUS" (6010)
Unhandled solution status.
"MSK_RES_ERR_UPPER_TRIANGLE" (6020)
An element in the upper triangle of a lower triangular matrix is speci ed.
"MSK_RES_ERR_LAU_SINGULAR_MATRIX" (7000)
A matrix is singular.
"MSK_RES_ERR_LAU_NOT_POSITIVE_DEFINITE" (7001)
A matrix is not positive de nite.
"MSK_RES_ERR_LAU_INVALID_LOWER_TRIANGULAR_MATRIX" (7002)
An invalid lower triangular matrix.
"MSK_RES_ERR_LAU_UNKNOWN" (7005)
An unknown error.
"MSK_RES_ERR_LAU_ARG_M" (7010)
Invalid argument m.
"MSK_RES_ERR_LAU_ARG_N" (7011)
Invalid argument n.
"MSK_RES_ERR_LAU_ARG_K" (7012)
Invalid argument k.
"MSK_RES_ERR_LAU_ARG_TRANSA" (7015)
Invalid argument transa.
"MSK_RES_ERR_LAU_ARG_TRANSB" (7016)
Invalid argument transb.
"MSK_RES_ERR_LAU_ARG_UPLO" (7017)
Invalid argument uplo.
"MSK_RES_ERR_LAU_ARG_TRANS" (7018)
Invalid argument trans.
"MSK_RES_ERR_LAU_INVALID_SPARSE_SYMMETRIC_MATRIX" (7019)
An invalid sparse symmetric matrix is spec ed. Note only the lower triangular part with no duplicates is specifed.
"MSK_RES_ERR_CBF_PARSE" (7100)
An error occurred while parsing an CBF le.
"MSK_RES_ERR_CBF_OBJ_SENSE" (7101)
An invalid objective sense is speci ed.
"MSK_RES_ERR_CBF_NO_VARIABLES" (7102)
No variables are speci ed.
"MSK_RES_ERR_CBF_TOO_MANY_CONSTRAINTS" (7103)
Too many constraints speci ed.
"MSK_RES_ERR_CBF_TOO_MANY_VARIABLES" (7104)
Too many variables speci ed.
"MSK_RES_ERR_CBF_NO_VERSION_SPECIFIED" (7105)
No version speci ed.
"MSK_RES_ERR_CBF_SYNTAX" (7106)
Invalid syntax.
"MSK_RES_ERR_CBF_DUPLICATE_OBJ" (7107)
Duplicate OBJ keyword.
"MSK_RES_ERR_CBF_DUPLICATE_CON" (7108)
Duplicate CON keyword.

"MSK_RES_ERR_CBF_DUPLICATE_VAR" (7109)
Duplicate VAR keyword.
"MSK_RES_ERR_CBF_DUPLICATE_INT" (7110)
Duplicate INT keyword.
"MSK_RES_ERR_CBF_INVALID_VAR_TYPE" (7111)
Invalid variable type.
"MSK_RES_ERR_CBF_INVALID_CON_TYPE" (7112)
Invalid constraint type.
"MSK_RES_ERR_CBF_INVALID_DOMAIN_DIMENSION" (7113)
Invalid domain dimension.
"MSK_RES_ERR_CBF_DUPLICATE_OBJACOORD" (7114)
Duplicate index in OBJCOORD.
"MSK_RES_ERR_CBF_DUPLICATE_BCOORD" (7115)
Duplicate index in BCOORD.
"MSK_RES_ERR_CBF_DUPLICATE_ACOORD" (7116)
Duplicate index in ACOORD.
"MSK_RES_ERR_CBF_TOO_FEW_VARIABLES" (7117)
Too few variables de ned.
"MSK_RES_ERR_CBF_TOO_FEW_CONSTRAINTS" (7118)
Too few constraints de ned.
"MSK_RES_ERR_CBF_TOO_FEW_INTS" (7119)
Too few ints are speci ed.
"MSK_RES_ERR_CBF_TOO_MANY_INTS" (7120)
Too many ints are speci ed.
"MSK_RES_ERR_CBF_INVALID_INT_INDEX" (7121)
Invalid INT index.
"MSK_RES_ERR_CBF_UNSUPPORTED" (7122)
Unsupported feature is present.
"MSK_RES_ERR_CBF_DUPLICATE_PSDVAR" (7123)
Duplicate PSDVAR keyword.
"MSK_RES_ERR_CBF_INVALID_PSDVAR_DIMENSION" (7124)
Invalid PSDVAR dimension.
"MSK_RES_ERR_CBF_TOO_FEW_PSDVAR" (7125)
Too few variables de ned.
"MSK_RES_ERR_CBF_INVALID_EXP_DIMENSION" (7126)
Invalid dimension of a exponential cone.
"MSK_RES_ERR_CBF_DUPLICATE_POW_CONES" (7130)
Multiple POWCONES speci ed.
"MSK_RES_ERR_CBF_DUPLICATE_POW_STAR_CONES" (7131)
Multiple POW*CONES speci ed.
"MSK_RES_ERR_CBF_INVALID_POWER" (7132)
Invalid power speci ed.
"MSK_RES_ERR_CBF_POWER_CONE_IS_TOO_LONG" (7133)
Power cone is too long.
"MSK_RES_ERR_CBF_INVALID_POWER_CONE_INDEX" (7134)
Invalid power cone index.
"MSK_RES_ERR_CBF_INVALID_POWER_STAR_CONE_INDEX" (7135)
Invalid power star cone index.
"MSK_RES_ERR_CBF_UNHANDLED_POWER_CONE_TYPE" (7136)
An unhandled power cone type.
"MSK_RES_ERR_CBF_UNHANDLED_POWER_STAR_CONE_TYPE" (7137)
An unhandled power star cone type.
"MSK_RES_ERR_CBF_POWER_CONE_MISMATCH" (7138)
The power cone does not match with it de nition.
"MSK_RES_ERR_CBF_POWER_STAR_CONE_MISMATCH" (7139)
The power star cone does not match with it de nition.
"MSK_RES_ERR_CBF_INVALID_NUMBER_OF_CONES" (7740)
Invalid number of cones.

"MSK_RES_ERR_CBF_INVALID_DIMENSION_OF_CONES" (7741)
Invalid dimension of cones.
"MSK_RES_ERR_MIO_INVALID_ROOT_OPTIMIZER" (7700)
An invalid root optimizer was selected for the problem type.
"MSK_RES_ERR_MIO_INVALID_NODE_OPTIMIZER" (7701)
An invalid node optimizer was selected for the problem type.
"MSK_RES_ERR_TOCONIC_CONSTR_Q_NOT_PSD" (7800)
The matrix de ning the quadratric part of constraint is not positive semide nite.
"MSK_RES_ERR_TOCONIC_CONSTRAINT_FX" (7801)
The quadratic constraint is an equality, thus not convex.
"MSK_RES_ERR_TOCONIC_CONSTRAINT_RA" (7802)
The quadratic constraint has nite lower and upper bound, and therefore it is not convex.
"MSK_RES_ERR_TOCONIC_CONSTR_NOT_CONIC" (7803)
The constraint is not conic representable.
"MSK_RES_ERR_TOCONIC_OBJECTIVE_NOT_PSD" (7804)
The matrix de ning the quadratric part of the objective function is not positive semide nite.
"MSK_RES_ERR_SERVER_CONNECT" (8000)
Failed to connect to remote solver server. The server string or the port string were invalid, or the server did not accept connection.
"MSK_RES_ERR_SERVER_PROTOCOL" (8001)
Unexpected message or data from solver server.
"MSK_RES_ERR_SERVER_STATUS" (8002)
Server returned non-ok HTTP status code
"MSK_RES_ERR_SERVER_TOKEN" (8003)
The job ID speci ed is incorrect or invalid
"MSK_RES_ERR_SERVER_PROBLEM_SIZE" (8008)
The size of the problem exceeds the dimensions permitted by the instance of the OptServer where it was run.

15.7 Enumerations

basindtype
Basis identi cation

"MSK_BI_NEVER"
Never do basis identi cation.

"MSK_BI_ALWAYS"
Basis identi cation is always performed even if the interior-point optimizer terminates abnormally.

"MSK_BI_NO_ERROR"
Basis identi cation is performed if the interior-point optimizer terminates without an error.

"MSK_BI_IF_FEASIBLE"
Basis identi cation is not performed if the interior-point optimizer terminates with a problem status saying that the problem is primal or dual infeasible.

"MSK_BI_RESERVERED"
Not currently in use.

boundkey
Bound keys

"MSK_BK_LO"
The constraint or variable has a nite lower bound and an in nite upper bound.

"MSK_BK_UP"
The constraint or variable has an in nite lower bound and an nite upper bound.

"MSK_BK_FX"
The constraint or variable is xed.

"MSK_BK_FR"
The constraint or variable is free.

"MSK_BK_RA"
The constraint or variable is ranged.

mark

Mark

"MSK_MARK_LO"
The lower bound is selected for sensitivity analysis.

"MSK_MARK_UP"
The upper bound is selected for sensitivity analysis.

simdegen

Degeneracy strategies

"MSK_SIM_DEGEN_NONE"
The simplex optimizer should use no degeneration strategy.

"MSK_SIM_DEGEN_FREE"
The simplex optimizer chooses the degeneration strategy.

"MSK_SIM_DEGEN_AGGRESSIVE"
The simplex optimizer should use an aggressive degeneration strategy.

"MSK_SIM_DEGEN_MODERATE"
The simplex optimizer should use a moderate degeneration strategy.

"MSK_SIM_DEGEN_MINIMUM"
The simplex optimizer should use a minimum degeneration strategy.

transpose

Transposed matrix.

"MSK_TRANSPOSE_NO"
No transpose is applied.

"MSK_TRANSPOSE_YES"
A transpose is applied.

uplo

Triangular part of a symmetric matrix.

"MSK_UPLO_LO"
Lower part.

"MSK_UPLO_UP"
Upper part.

simreform

Problem reformulation.

"MSK_SIM_REFORMULATION_ON"
Allow the simplex optimizer to reformulate the problem.

"MSK_SIM_REFORMULATION_OFF"
Disallow the simplex optimizer to reformulate the problem.

"MSK_SIM_REFORMULATION_FREE"
The simplex optimizer can choose freely.

"MSK_SIM_REFORMULATION_AGGRESSIVE"
The simplex optimizer should use an aggressive reformulation strategy.

simdupvec

Exploit duplicate columns.

"MSK_SIM_EXPLOIT_DUPVEC_ON"
Allow the simplex optimizer to exploit duplicated columns.

"MSK_SIM_EXPLOIT_DUPVEC_OFF"
Disallow the simplex optimizer to exploit duplicated columns.

"MSK_SIM_EXPLOIT_DUPVEC_FREE"
The simplex optimizer can choose freely.

simhotstart

Hot-start type employed by the simplex optimizer

"MSK_SIM_HOTSTART_NONE"
The simplex optimizer performs a coldstart.

"MSK_SIM_HOTSTART_FREE"
The simplex optimize chooses the hot-start type.

"MSK_SIM_HOTSTART_STATUS_KEYS"
Only the status keys of the constraints and variables are used to choose the type of hot-start.

intpnthotstart

Hot-start type employed by the interior-point optimizers.

"MSK_INTPNT_HOTSTART_NONE"
The interior-point optimizer performs a coldstart.

"MSK_INTPNT_HOTSTART_PRIMAL"
The interior-point optimizer exploits the primal solution only.

"MSK_INTPNT_HOTSTART_DUAL"
The interior-point optimizer exploits the dual solution only.

"MSK_INTPNT_HOTSTART_PRIMAL_DUAL"
The interior-point optimizer exploits both the primal and dual solution.

purify

Solution puri cation employed optimizer.

"MSK_PURIFY_NONE"
The optimizer performs no solution puri cation.

"MSK_PURIFY_PRIMAL"
The optimizer puri es the primal solution.

"MSK_PURIFY_DUAL"
The optimizer puri es the dual solution.

"MSK_PURIFY_PRIMAL_DUAL"
The optimizer puri es both the primal and dual solution.

"MSK_PURIFY_AUTO"
TBD

callbackcode

Progress callback codes

"MSK_CALLBACK_BEGIN_BI"
The basis identi cation procedure has been started.

"MSK_CALLBACK_BEGIN_CONIC"
The callback function is called when the conic optimizer is started.

"MSK_CALLBACK_BEGIN_DUAL_BI"
The callback function is called from within the basis identi cation procedure when the dual phase is started.

"MSK_CALLBACK_BEGIN_DUAL_SENSITIVITY"
Dual sensitivity analysis is started.

"MSK_CALLBACK_BEGIN_DUAL_SETUP_BI"
The callback function is called when the dual BI phase is started.

"MSK_CALLBACK_BEGIN_DUAL_SIMPLEX"
The callback function is called when the dual simplex optimizer started.

"MSK_CALLBACK_BEGIN_DUAL_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure when the dual simplex clean-up phase is started.

"MSK_CALLBACK_BEGIN_FULL_CONVEXITY_CHECK"
Begin full convexity check.

"MSK_CALLBACK_BEGIN_INFEAS_ANA"
The callback function is called when the infeasibility analyzer is started.

"MSK_CALLBACK_BEGIN_INTPNT"
The callback function is called when the interior-point optimizer is started.

"MSK_CALLBACK_BEGIN_LICENSE_WAIT"
Begin waiting for license.

"MSK_CALLBACK_BEGIN_MIO"
The callback function is called when the mixed-integer optimizer is started.

"MSK_CALLBACK_BEGIN_OPTIMIZER"
The callback function is called when the optimizer is started.

"MSK_CALLBACK_BEGIN_PRESOLVE"
The callback function is called when the presolve is started.

"MSK_CALLBACK_BEGIN_PRIMAL_BI"
The callback function is called from within the basis identi cation procedure when the primal phase is started.

"MSK_CALLBACK_BEGIN_PRIMAL_REPAIR"
Begin primal feasibility repair.

"MSK_CALLBACK_BEGIN_PRIMAL_SENSITIVITY"
Primal sensitivity analysis is started.

"MSK_CALLBACK_BEGIN_PRIMAL_SETUP_BI"
The callback function is called when the primal BI setup is started.

"MSK_CALLBACK_BEGIN_PRIMAL_SIMPLEX"
The callback function is called when the primal simplex optimizer is started.

"MSK_CALLBACK_BEGIN_PRIMAL_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure when the primal simplex clean-up phase is started.

"MSK_CALLBACK_BEGIN_QCQO_REFORMULATE"
Begin QCQO reformulation.

"MSK_CALLBACK_BEGIN_READ"
MOSEK has started reading a problem le.

"MSK_CALLBACK_BEGIN_ROOT_CUTGEN"
The callback function is called when root cut generation is started.

"MSK_CALLBACK_BEGIN_SIMPLEX"
The callback function is called when the simplex optimizer is started.

"MSK_CALLBACK_BEGIN_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure when the simplex clean-up phase is started.

"MSK_CALLBACK_BEGIN_TO_CONIC"
Begin conic reformulation.

"MSK_CALLBACK_BEGIN_WRITE"
MOSEK has started writing a problem le.

"MSK_CALLBACK_CONIC"
The callback function is called from within the conic optimizer after the information database has been updated.

"MSK_CALLBACK_DUAL_SIMPLEX"
The callback function is called from within the dual simplex optimizer.

"MSK_CALLBACK_END_BI"
The callback function is called when the basis identi cation procedure is terminated.

"MSK_CALLBACK_END_CONIC"
The callback function is called when the conic optimizer is terminated.

"MSK_CALLBACK_END_DUAL_BI"
The callback function is called from within the basis identi cation procedure when the dual phase is terminated.

"MSK_CALLBACK_END_DUAL_SENSITIVITY"
Dual sensitivity analysis is terminated.

"MSK_CALLBACK_END_DUAL_SETUP_BI"
The callback function is called when the dual BI phase is terminated.

"MSK_CALLBACK_END_DUAL_SIMPLEX"
The callback function is called when the dual simplex optimizer is terminated.

"MSK_CALLBACK_END_DUAL_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure when the dual clean-up phase is terminated.

"MSK_CALLBACK_END_FULL_CONVEXITY_CHECK"
End full convexity check.

"MSK_CALLBACK_END_INFEAS_ANA"
The callback function is called when the infeasibility analyzer is terminated.

"MSK_CALLBACK_END_INTPNT"
The callback function is called when the interior-point optimizer is terminated.

"MSK_CALLBACK_END_LICENSE_WAIT"
End waiting for license.

"MSK_CALLBACK_END_MIO"
The callback function is called when the mixed-integer optimizer is terminated.

"MSK_CALLBACK_END_OPTIMIZER"
The callback function is called when the optimizer is terminated.

"MSK_CALLBACK_END_PRESOLVE"
The callback function is called when the presolve is completed.

"MSK_CALLBACK_END_PRIMAL_BI"
The callback function is called from within the basis identi cation procedure when the primal phase is terminated.

"MSK_CALLBACK_END_PRIMAL_REPAIR"
End primal feasibility repair.

"MSK_CALLBACK_END_PRIMAL_SENSITIVITY"
Primal sensitivity analysis is terminated.

"MSK_CALLBACK_END_PRIMAL_SETUP_BI"
The callback function is called when the primal BI setup is terminated.

"MSK_CALLBACK_END_PRIMAL_SIMPLEX"
The callback function is called when the primal simplex optimizer is terminated.

"MSK_CALLBACK_END_PRIMAL_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure when the primal clean-up phase is terminated.

"MSK_CALLBACK_END_QCQO_REFORMULATE"
End QCQO reformulation.

"MSK_CALLBACK_END_READ"
MOSEK has nished reading a problem le.

"MSK_CALLBACK_END_ROOT_CUTGEN"
The callback function is called when root cut generation is terminated.

"MSK_CALLBACK_END_SIMPLEX"
The callback function is called when the simplex optimizer is terminated.

"MSK_CALLBACK_END_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure when the simplex clean-up phase is terminated.

"MSK_CALLBACK_END_TO_CONIC"
End conic reformulation.

"MSK_CALLBACK_END_WRITE"
MOSEK has nished writing a problem le.

"MSK_CALLBACK_IM_BI"
The callback function is called from within the basis identi cation procedure at an intermediate point.

"MSK_CALLBACK_IM_CONIC"
The callback function is called at an intermediate stage within the conic optimizer where the information database has not been updated.

"MSK_CALLBACK_IM_DUAL_BI"
The callback function is called from within the basis identi cation procedure at an intermediate point in the dual phase.

"MSK_CALLBACK_IM_DUAL_SENSIVITY"
The callback function is called at an intermediate stage of the dual sensitivity analysis.

"MSK_CALLBACK_IM_DUAL_SIMPLEX"
The callback function is called at an intermediate point in the dual simplex optimizer.

"MSK_CALLBACK_IM_FULL_CONVEXITY_CHECK"
The callback function is called at an intermediate stage of the full convexity check.

"MSK_CALLBACK_IM_INTPNT"
The callback function is called at an intermediate stage within the interior-point optimizer where the information database has not been updated.

"MSK_CALLBACK_IM_LICENSE_WAIT"
MOSEK is waiting for a license.

"MSK_CALLBACK_IM_LU"
The callback function is called from within the LU factorization procedure at an intermediate point.

"MSK_CALLBACK_IM_MIO"
The callback function is called at an intermediate point in the mixed-integer optimizer.

"MSK_CALLBACK_IM_MIO_DUAL_SIMPLEX"
The callback function is called at an intermediate point in the mixed-integer optimizer while running the dual simplex optimizer.

"MSK_CALLBACK_IM_MIO_INTPNT"
The callback function is called at an intermediate point in the mixed-integer optimizer while running the interior-point optimizer.

"MSK_CALLBACK_IM_MIO_PRIMAL_SIMPLEX"
The callback function is called at an intermediate point in the mixed-integer optimizer while running the primal simplex optimizer.

"MSK_CALLBACK_IM_ORDER"
The callback function is called from within the matrix ordering procedure at an intermediate point.

"MSK_CALLBACK_IM_PRESOLVE"
The callback function is called from within the presolve procedure at an intermediate stage.

"MSK_CALLBACK_IM_PRIMAL_BI"
The callback function is called from within the basis identi cation procedure at an intermediate point in the primal phase.

"MSK_CALLBACK_IM_PRIMAL_SENSIVITY"
The callback function is called at an intermediate stage of the primal sensitivity analysis.

"MSK_CALLBACK_IM_PRIMAL_SIMPLEX"
The callback function is called at an intermediate point in the primal simplex optimizer.

"MSK_CALLBACK_IM_QO_REFORMULATE"
The callback function is called at an intermediate stage of the conic quadratic reformulation.

"MSK_CALLBACK_IM_READ"
Intermediate stage in reading.

"MSK_CALLBACK_IM_ROOT_CUTGEN"
The callback is called from within root cut generation at an intermediate stage.

"MSK_CALLBACK_IM_SIMPLEX"
The callback function is called from within the simplex optimizer at an intermediate point.

"MSK_CALLBACK_IM_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure at an intermediate point in the simplex clean-up phase. The frequency of the callbacks is controlled by the *MSK_IPAR_LOG_SIM_FREQ* parameter.

"MSK_CALLBACK_INTPNT"
The callback function is called from within the interior-point optimizer after the information database has been updated.

"MSK_CALLBACK_NEW_INT_MIO"
The callback function is called after a new integer solution has been located by the mixed-integer optimizer.

"MSK_CALLBACK_PRIMAL_SIMPLEX"
The callback function is called from within the primal simplex optimizer.

"MSK_CALLBACK_READ_OPF"
The callback function is called from the OPF reader.

"MSK_CALLBACK_READ_OPF_SECTION"
A chunk of Q non-zeros has been read from a problem le.

"MSK_CALLBACK_SOLVING_REMOTE"
The callback function is called while the task is being solved on a remote server.

"MSK_CALLBACK_UPDATE_DUAL_BI"
The callback function is called from within the basis identi cation procedure at an intermediate point in the dual phase.

"MSK_CALLBACK_UPDATE_DUAL_SIMPLEX"
The callback function is called in the dual simplex optimizer.

"MSK_CALLBACK_UPDATE_DUAL_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure at an intermediate point in the dual simplex clean-up phase. The frequency of the callbacks is controlled by the *MSK_IPAR_LOG_SIM_FREQ* parameter.

"MSK_CALLBACK_UPDATE_PRESOLVE"
The callback function is called from within the presolve procedure.

"MSK_CALLBACK_UPDATE_PRIMAL_BI"
The callback function is called from within the basis identi cation procedure at an intermediate point in the primal phase.

"MSK_CALLBACK_UPDATE_PRIMAL_SIMPLEX"
The callback function is called in the primal simplex optimizer.

"MSK_CALLBACK_UPDATE_PRIMAL_SIMPLEX_BI"
The callback function is called from within the basis identi cation procedure at an intermediate point in the primal simplex clean-up phase. The frequency of the callbacks is controlled by the *MSK_IPAR_LOG_SIM_FREQ* parameter.

"MSK_CALLBACK_WRITE_OPF"
The callback function is called from the OPF writer.

checkconvexitytype
Types of convexity checks.

"MSK_CHECK_CONVEXITY_NONE"
No convexity check.

"MSK_CHECK_CONVEXITY_SIMPLE"
Perform simple and fast convexity check.

"MSK_CHECK_CONVEXITY_FULL"
Perform a full convexity check.

compresstype
Compression types

"MSK_COMPRESS_NONE"
No compression is used.

"MSK_COMPRESS_FREE"
The type of compression used is chosen automatically.

"MSK_COMPRESS_GZIP"
The type of compression used is gzip compatible.

"MSK_COMPRESS_ZSTD"
The type of compression used is zstd compatible.

conetype
Cone types

"MSK_CT_QUAD"
The cone is a quadratic cone.

"MSK_CT_RQUAD"
The cone is a rotated quadratic cone.

"MSK_CT_PEXP"
A primal exponential cone.

"MSK_CT_DEXP"
A dual exponential cone.

"MSK_CT_PPOW"
A primal power cone.

"MSK_CT_DPOW"
A dual power cone.

"MSK_CT_ZERO"
The zero cone.

nametype
Name types

"MSK_NAME_TYPE_GEN"
General names. However, no duplicate and blank names are allowed.

"MSK_NAME_TYPE_MPS"
MPS type names.

"MSK_NAME_TYPE_LP"
LP type names.

scopr
SCopt operator types

"MSK_OPR_ENT"
Entropy

"MSK_OPR_EXP"
Exponential

"MSK_OPR_LOG"
Logarithm

"MSK_OPR_POW"
Power

"MSK_OPR_SQRT"
Square root

symmattype
Cone types

"MSK_SYMMAT_TYPE_SPARSE"
Sparse symmetric matrix.

dataformat
Data format types

"MSK_DATA_FORMAT_EXTENSION"
The le extension is used to determine the data le format.

"MSK_DATA_FORMAT_MPS"
The data le is MPS formatted.

"MSK_DATA_FORMAT_LP"
The data le is LP formatted.

"MSK_DATA_FORMAT_OP"
The data le is an optimization problem formatted le.

"MSK_DATA_FORMAT_FREE_MPS"
The data a free MPS formatted le.

"MSK_DATA_FORMAT_TASK"
Generic task dump le.

"MSK_DATA_FORMAT_PTF"
(P)retty (T)ext (F)format.

"MSK_DATA_FORMAT_CB"
Conic benchmark format,

"MSK_DATA_FORMAT_JSON_TASK"
JSON based task format.

dinfitem

Double information items

"MSK_DINF_BI_CLEAN_DUAL_TIME"
Time spent within the dual clean-up optimizer of the basis identi cation procedure since its invocation.

"MSK_DINF_BI_CLEAN_PRIMAL_TIME"
Time spent within the primal clean-up optimizer of the basis identi cation procedure since its invocation.

"MSK_DINF_BI_CLEAN_TIME"
Time spent within the clean-up phase of the basis identi cation procedure since its invocation.

"MSK_DINF_BI_DUAL_TIME"
Time spent within the dual phase basis identi cation procedure since its invocation.

"MSK_DINF_BI_PRIMAL_TIME"
Time spent within the primal phase of the basis identi cation procedure since its invocation.

"MSK_DINF_BI_TIME"
Time spent within the basis identi cation procedure since its invocation.

"MSK_DINF_INTPNT_DUAL_FEAS"
Dual feasibility measure reported by the interior-point optimizer. (For the interior-point optimizer this measure is not directly related to the original problem because a homogeneous model is employed.)

"MSK_DINF_INTPNT_DUAL_OBJ"
Dual objective value reported by the interior-point optimizer.

"MSK_DINF_INTPNT_FACTOR_NUM_FLOPS"
An estimate of the number of ops used in the factorization.

"MSK_DINF_INTPNT_OPT_STATUS"
A measure of optimality of the solution. It should converge to +1 if the problem has a primal-dual optimal solution, and converge to 1 if the problem is (strictly) primal or dual infeasible. If the measure converges to another constant, or fails to settle, the problem is usually ill-posed.

"MSK_DINF_INTPNT_ORDER_TIME"
Order time (in seconds).

"MSK_DINF_INTPNT_PRIMAL_FEAS"
Primal feasibility measure reported by the interior-point optimizer. (For the interior-point optimizer this measure is not directly related to the original problem because a homogeneous model is employed).

"MSK_DINF_INTPNT_PRIMAL_OBJ"
Primal objective value reported by the interior-point optimizer.

"MSK_DINF_INTPNT_TIME"
Time spent within the interior-point optimizer since its invocation.

"MSK_DINF_MIO_CLIQUE_SEPARATION_TIME"
Separation time for clique cuts.

"MSK_DINF_MIO_CMIR_SEPARATION_TIME"
Separation time for CMIR cuts.

"MSK_DINF_MIO_CONSTRUCT_SOLUTION_OBJ"
If **MOSEK** has successfully constructed an integer feasible solution, then this item contains the optimal objective value corresponding to the feasible solution.

"MSK_DINF_MIO_DUAL_BOUND_AFTER_PRESOLVE"
Value of the dual bound after presolve but before cut generation.

"MSK_DINF_MIO_GMI_SEPARATION_TIME"
Separation time for GMI cuts.

"MSK_DINF_MIO_IMPLIED_BOUND_TIME"
Separation time for implied bound cuts.

"MSK_DINF_MIO_KNAPSACK_COVER_SEPARATION_TIME"
Separation time for knapsack cover.

"MSK_DINF_MIO_OBJ_ABS_GAP"
Given the mixed-integer optimizer has computed a feasible solution and a bound on the optimal objective value, then this item contains the absolute gap de ned by

$$|(\text{objective value of feasible solution}) - (\text{objective bound})|.$$

Otherwise it has the value -1.0.

"MSK_DINF_MIO_OBJ_BOUND"
The best known bound on the objective function. This value is unde ned until at least one relaxation has been solved: To see if this is the case check that *"MSK_IINF_MIO_NUM_RELAX"* is strictly positive.

"MSK_DINF_MIO_OBJ_INT"
The primal objective value corresponding to the best integer feasible solution. Please note that at least one integer feasible solution must have been located i.e. check *"MSK_IINF_MIO_NUM_INT_SOLUTIONS"*.

"MSK_DINF_MIO_OBJ_REL_GAP"
Given that the mixed-integer optimizer has computed a feasible solution and a bound on the optimal objective value, then this item contains the relative gap de ned by

$$\frac{|(\text{objective value of feasible solution}) - (\text{objective bound})|}{\max(\delta, |(\text{objective value of feasible solution})|)}.$$

where δ is given by the parameter *MSK_DPAR_MIO_REL_GAP_CONST*. Otherwise it has the value -1.0.

"MSK_DINF_MIO_PROBING_TIME"
Total time for probing.

"MSK_DINF_MIO_ROOT_CUTGEN_TIME"
Total time for cut generation.

"MSK_DINF_MIO_ROOT_OPTIMIZER_TIME"
Time spent in the optimizer while solving the root node relaxation

"MSK_DINF_MIO_ROOT_PRESOLVE_TIME"
Time spent presolving the problem at the root node.

"MSK_DINF_MIO_TIME"
Time spent in the mixed-integer optimizer.

"MSK_DINF_MIO_USER_OBJ_CUT"
If the objective cut is used, then this information item has the value of the cut.

"MSK_DINF_OPTIMIZER_TIME"
Total time spent in the optimizer since it was invoked.

"MSK_DINF_PRESOLVE_ELI_TIME"
Total time spent in the eliminator since the presolve was invoked.

"MSK_DINF_PRESOLVE_LINDEP_TIME"
Total time spent in the linear dependency checker since the presolve was invoked.

"MSK_DINF_PRESOLVE_TIME"
Total time (in seconds) spent in the presolve since it was invoked.

"MSK_DINF_PRIMAL_REPAIR_PENALTY_OBJ"
The optimal objective value of the penalty function.

"MSK_DINF_QCQO_REFORMULATE_MAX_PERTURBATION"
Maximum absolute diagonal perturbation occurring during the QCQO reformulation.

"MSK_DINF_QCQO_REFORMULATE_TIME"
Time spent with conic quadratic reformulation.

"MSK_DINF_QCQO_REFORMULATE_WORST_CHOLESKY_COLUMN_SCALING"
Worst Cholesky column scaling.

"MSK_DINF_QCQO_REFORMULATE_WORST_CHOLESKY_DIAG_SCALING"
Worst Cholesky diagonal scaling.

"MSK_DINF_RD_TIME"
Time spent reading the data le.

"MSK_DINF_SIM_DUAL_TIME"
Time spent in the dual simplex optimizer since invoking it.

"MSK_DINF_SIM_FEAS"
Feasibility measure reported by the simplex optimizer.

"MSK_DINF_SIM_OBJ"
Objective value reported by the simplex optimizer.

"MSK_DINF_SIM_PRIMAL_TIME"
Time spent in the primal simplex optimizer since invoking it.

"MSK_DINF_SIM_TIME"
Time spent in the simplex optimizer since invoking it.

"MSK_DINF_SOL_BAS_DUAL_OBJ"
Dual objective value of the basic solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_BAS_DVIOLCON"
Maximal dual bound violation for x^c in the basic solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_BAS_DVIOLVAR"
Maximal dual bound violation for x^x in the basic solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_BAS_NRM_BARX"
In nity norm of $\overline{X}$ in the basic solution.

"MSK_DINF_SOL_BAS_NRM_SLC"
In nity norm of s_l^c in the basic solution.

"MSK_DINF_SOL_BAS_NRM_SLX"
In nity norm of s_l^x in the basic solution.

"MSK_DINF_SOL_BAS_NRM_SUC"
In nity norm of s_u^c in the basic solution.

"MSK_DINF_SOL_BAS_NRM_SUX"
In nity norm of s_u^X in the basic solution.

"MSK_DINF_SOL_BAS_NRM_XC"
In nity norm of x^c in the basic solution.

"MSK_DINF_SOL_BAS_NRM_XX"
In nity norm of x^x in the basic solution.

"MSK_DINF_SOL_BAS_NRM_Y"
In nity norm of y in the basic solution.

"MSK_DINF_SOL_BAS_PRIMAL_OBJ"
Primal objective value of the basic solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_BAS_PVIOLCON"
Maximal primal bound violation for x^c in the basic solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_BAS_PVIOLVAR"
Maximal primal bound violation for x^x in the basic solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITG_NRM_BARX"
In nity norm of $\overline{X}$ in the integer solution.

"MSK_DINF_SOL_ITG_NRM_XC"
In nity norm of x^c in the integer solution.

"MSK_DINF_SOL_ITG_NRM_XX"
In nity norm of x^x in the integer solution.

"MSK_DINF_SOL_ITG_PRIMAL_OBJ"
Primal objective value of the integer solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITG_PVIOLBARVAR"
Maximal primal bound violation for $\overline{X}$ in the integer solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITG_PVIOLCON"
Maximal primal bound violation for x^c in the integer solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITG_PVIOLCONES"
Maximal primal violation for primal conic constraints in the integer solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITG_PVIOLITG"
Maximal violation for the integer constraints in the integer solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITG_PVIOLVAR"
Maximal primal bound violation for x^x in the integer solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_DUAL_OBJ"
Dual objective value of the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_DVIOLBARVAR"
Maximal dual bound violation for $\overline{X}$ in the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_DVIOLCON"
Maximal dual bound violation for x^c in the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_DVIOLCONES"
Maximal dual violation for dual conic constraints in the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_DVIOLVAR"
Maximal dual bound violation for x^x in the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_NRM_BARS"
In nity norm of $\overline{S}$ in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_BARX"
In nity norm of $\overline{X}$ in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_SLC"
In nity norm of s_l^c in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_SLX"
In nity norm of s_l^x in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_SNX"
In nity norm of s_n^x in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_SUC"
In nity norm of s_u^c in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_SUX"
In nity norm of s_u^X in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_XC"
In nity norm of x^c in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_XX"
In nity norm of x^x in the interior-point solution.

"MSK_DINF_SOL_ITR_NRM_Y"
In nity norm of y in the interior-point solution.

"MSK_DINF_SOL_ITR_PRIMAL_OBJ"
Primal objective value of the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_PVIOLBARVAR"
Maximal primal bound violation for $\overline{X}$ in the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_PVIOLCON"
Maximal primal bound violation for x^c in the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_PVIOLCONES"
Maximal primal violation for primal conic constraints in the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_SOL_ITR_PVIOLVAR"
Maximal primal bound violation for x^x in the interior-point solution. Updated if *MSK_IPAR_AUTO_UPDATE_SOL_INFO* is set .

"MSK_DINF_TO_CONIC_TIME"
Time spent in the last to conic reformulation.

feature
License feature

"MSK_FEATURE_PTS"
Base system.

"MSK_FEATURE_PTON"
Conic extension.

liinfitem
Long integer information items.

"MSK_LIINF_BI_CLEAN_DUAL_DEG_ITER"
Number of dual degenerate clean iterations performed in the basis identi cation.

"MSK_LIINF_BI_CLEAN_DUAL_ITER"
Number of dual clean iterations performed in the basis identi cation.

"MSK_LIINF_BI_CLEAN_PRIMAL_DEG_ITER"
Number of primal degenerate clean iterations performed in the basis identi cation.

"MSK_LIINF_BI_CLEAN_PRIMAL_ITER"
Number of primal clean iterations performed in the basis identi cation.

"MSK_LIINF_BI_DUAL_ITER"
Number of dual pivots performed in the basis identi cation.

"MSK_LIINF_BI_PRIMAL_ITER"
Number of primal pivots performed in the basis identi cation.

"MSK_LIINF_INTPNT_FACTOR_NUM_NZ"
Number of non-zeros in factorization.

"MSK_LIINF_MIO_ANZ"
Number of non-zero entries in the constraint matrix of the probelm to be solved by the mixed-integer optimizer.

"MSK_LIINF_MIO_INTPNT_ITER"
Number of interior-point iterations performed by the mixed-integer optimizer.

"MSK_LIINF_MIO_PRESOLVED_ANZ"
Number of non-zero entries in the constraint matrix of the problem after the mixed-integer optimizer's presolve.

"MSK_LIINF_MIO_SIMPLEX_ITER"
Number of simplex iterations performed by the mixed-integer optimizer.

"MSK_LIINF_RD_NUMANZ"
Number of non-zeros in A that is read.

"MSK_LIINF_RD_NUMQNZ"
Number of Q non-zeros.

iinfitem
Integer information items.

"MSK_IINF_ANA_PRO_NUM_CON"
Number of constraints in the problem.

"MSK_IINF_ANA_PRO_NUM_CON_EQ"
Number of equality constraints.

"MSK_IINF_ANA_PRO_NUM_CON_FR"
Number of unbounded constraints.

"MSK_IINF_ANA_PRO_NUM_CON_LO"
Number of constraints with a lower bound and an in nite upper bound.

"MSK_IINF_ANA_PRO_NUM_CON_RA"
Number of constraints with nite lower and upper bounds.

"MSK_IINF_ANA_PRO_NUM_CON_UP"
Number of constraints with an upper bound and an in nite lower bound.

"MSK_IINF_ANA_PRO_NUM_VAR"
Number of variables in the problem.

"MSK_IINF_ANA_PRO_NUM_VAR_BIN"
Number of binary (0-1) variables.

"MSK_IINF_ANA_PRO_NUM_VAR_CONT"
Number of continuous variables.

"MSK_IINF_ANA_PRO_NUM_VAR_EQ"
Number of xed variables.

"MSK_IINF_ANA_PRO_NUM_VAR_FR"
Number of free variables.

"MSK_IINF_ANA_PRO_NUM_VAR_INT"
Number of general integer variables.

"MSK_IINF_ANA_PRO_NUM_VAR_LO"
Number of variables with a lower bound and an in nite upper bound.

"MSK_IINF_ANA_PRO_NUM_VAR_RA"
Number of variables with nite lower and upper bounds.

"MSK_IINF_ANA_PRO_NUM_VAR_UP"
Number of variables with an upper bound and an in nite lower bound.

"MSK_IINF_INTPNT_FACTOR_DIM_DENSE"
Dimension of the dense sub system in factorization.

"MSK_IINF_INTPNT_ITER"
Number of interior-point iterations since invoking the interior-point optimizer.

"MSK_IINF_INTPNT_NUM_THREADS"
Number of threads that the interior-point optimizer is using.

"MSK_IINF_INTPNT_SOLVE_DUAL"
Non-zero if the interior-point optimizer is solving the dual problem.

"MSK_IINF_MIO_ABSGAP_SATISFIED"
Non-zero if absolute gap is within tolerances.

"MSK_IINF_MIO_CLIQUE_TABLE_SIZE"
Size of the clique table.

"MSK_IINF_MIO_CONSTRUCT_SOLUTION"
This item informs if MOSEK constructed an initial integer feasible solution.

- ˆ -1: tried, but failed,
- ˆ 0: no partial solution supplied by the user,
- ˆ 1: constructed feasible solution.

"MSK_IINF_MIO_NODE_DEPTH"
Depth of the last node solved.

"MSK_IINF_MIO_NUM_ACTIVE_NODES"
Number of active branch and bound nodes.

"MSK_IINF_MIO_NUM_BRANCH"
Number of branches performed during the optimization.

"MSK_IINF_MIO_NUM_CLIQUE_CUTS"
Number of clique cuts.

"MSK_IINF_MIO_NUM_CMIR_CUTS"
Number of Complemented Mixed Integer Rounding (CMIR) cuts.

"MSK_IINF_MIO_NUM_GOMORY_CUTS"
Number of Gomory cuts.

"MSK_IINF_MIO_NUM_IMPLIED_BOUND_CUTS"
Number of implied bound cuts.

"MSK_IINF_MIO_NUM_INT_SOLUTIONS"
Number of integer feasible solutions that have been found.

"MSK_IINF_MIO_NUM_KNAPSACK_COVER_CUTS"
Number of clique cuts.

"MSK_IINF_MIO_NUM_RELAX"
Number of relaxations solved during the optimization.

"MSK_IINF_MIO_NUM_REPEATED_PRESOLVE"
Number of times presolve was repeated at root.

"MSK_IINF_MIO_NUMBIN"
Number of binary variables in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMBINCONEVAR"
Number of binary cone variables in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMCON"
Number of constraints in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMCONE"
Number of cones in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMCONEVAR"
Number of cone variables in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMCONT"
Number of continuous variables in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMCONTCONEVAR"
Number of continuous cone variables in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMDEXPCONES"
Number of dual exponential cones in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMDPOWCONES"
Number of dual power cones in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMINT"
Number of integer variables in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMINTCONEVAR"
Number of integer cone variables in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMPEXPCONES"
Number of primal exponential cones in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMPPOWCONES"
Number of primal power cones in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMQCONES"
Number of quadratic cones in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMRQCONES"
Number of rotated quadratic cones in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_NUMVAR"
Number of variables in the problem to be solved by the mixed-integer optimizer.

"MSK_IINF_MIO_OBJ_BOUND_DEFINED"
Non-zero if a valid objective bound has been found, otherwise zero.

"MSK_IINF_MIO_PRESOLVED_NUMBIN"
Number of binary variables in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMBINCONEVAR"
Number of binary cone variables in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMCON"
Number of constraints in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMCONE"
Number of cones in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMCONEVAR"
Number of cone variables in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMCONT"
Number of continuous variables in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMCONTCONEVAR"
Number of continuous cone variables in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMDEXPCONES"
Number of dual exponential cones in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMDPOWCONES"
Number of dual power cones in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMINT"
Number of integer variables in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMINTCONEVAR"
Number of integer cone variables in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMPEXPCONES"
Number of primal exponential cones in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMPPOWCONES"
Number of primal power cones in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMQCONES"
Number of quadratic cones in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMRQCONES"
Number of rotated quadratic cones in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_PRESOLVED_NUMVAR"
Number of variables in the problem after the mixed-integer optimizer's presolve.

"MSK_IINF_MIO_RELGAP_SATISFIED"
Non-zero if relative gap is within tolerances.

"MSK_IINF_MIO_TOTAL_NUM_CUTS"
Total number of cuts generated by the mixed-integer optimizer.

"MSK_IINF_MIO_USER_OBJ_CUT"
If it is non-zero, then the objective cut is used.

"MSK_IINF_OPT_NUMCON"
Number of constraints in the problem solved when the optimizer is called.

"MSK_IINF_OPT_NUMVAR"
Number of variables in the problem solved when the optimizer is called

"MSK_IINF_OPTIMIZE_RESPONSE"
The response code returned by optimize.

"MSK_IINF_PURIFY_DUAL_SUCCESS"
Is nonzero if the dual solution is puri ed.

"MSK_IINF_PURIFY_PRIMAL_SUCCESS"
Is nonzero if the primal solution is puri ed.

"MSK_IINF_RD_NUMBARVAR"
Number of symmetric variables read.

"MSK_IINF_RD_NUMCON"
Number of constraints read.

"MSK_IINF_RD_NUMCONE"
Number of conic constraints read.

"MSK_IINF_RD_NUMINTVAR"
Number of integer-constrained variables read.

"MSK_IINF_RD_NUMQ"
Number of nonempty Q matrices read.

"MSK_IINF_RD_NUMVAR"
Number of variables read.

"MSK_IINF_RD_PROTYPE"
Problem type.

"MSK_IINF_SIM_DUAL_DEG_ITER"
The number of dual degenerate iterations.

"MSK_IINF_SIM_DUAL_HOTSTART"
If 1 then the dual simplex algorithm is solving from an advanced basis.

"MSK_IINF_SIM_DUAL_HOTSTART_LU"
If 1 then a valid basis factorization of full rank was located and used by the dual simplex algorithm.

"MSK_IINF_SIM_DUAL_INF_ITER"
The number of iterations taken with dual infeasibility.

"MSK_IINF_SIM_DUAL_ITER"
Number of dual simplex iterations during the last optimization.

"MSK_IINF_SIM_NUMCON"
Number of constraints in the problem solved by the simplex optimizer.

"MSK_IINF_SIM_NUMVAR"
Number of variables in the problem solved by the simplex optimizer.

"MSK_IINF_SIM_PRIMAL_DEG_ITER"
The number of primal degenerate iterations.

"MSK_IINF_SIM_PRIMAL_HOTSTART"
If 1 then the primal simplex algorithm is solving from an advanced basis.

"MSK_IINF_SIM_PRIMAL_HOTSTART_LU"
If 1 then a valid basis factorization of full rank was located and used by the primal simplex algorithm.

"MSK_IINF_SIM_PRIMAL_INF_ITER"
The number of iterations taken with primal infeasibility.

"MSK_IINF_SIM_PRIMAL_ITER"
Number of primal simplex iterations during the last optimization.

"MSK_IINF_SIM_SOLVE_DUAL"
Is non-zero if dual problem is solved.

"MSK_IINF_SOL_BAS_PROSTA"
Problem status of the basic solution. Updated after each optimization.

"MSK_IINF_SOL_BAS_SOLSTA"
Solution status of the basic solution. Updated after each optimization.

"MSK_IINF_SOL_ITG_PROSTA"
Problem status of the integer solution. Updated after each optimization.

"MSK_IINF_SOL_ITG_SOLSTA"
Solution status of the integer solution. Updated after each optimization.

"MSK_IINF_SOL_ITR_PROSTA"
Problem status of the interior-point solution. Updated after each optimization.

"MSK_IINF_SOL_ITR_SOLSTA"
Solution status of the interior-point solution. Updated after each optimization.

"MSK_IINF_STO_NUM_A_REALLOC"
Number of times the storage for storing A has been changed. A large value may indicates that memory fragmentation may occur.

inftype
Information item types

"MSK_INF_DOU_TYPE"
Is a double information type.

"MSK_INF_INT_TYPE"
Is an integer.

"MSK_INF_LINT_TYPE"
Is a long integer.

iomode
Input/output modes

"MSK_IOMODE_READ"
The le is read-only.

"MSK_IOMODE_WRITE"
The le is write-only. If the le exists then it is truncated when it is opened. Otherwise it is created when it is opened.

"MSK_IOMODE_READWRITE"
The le is to read and write.

branchdir

Speci es the branching direction.

"MSK_BRANCH_DIR_FREE"
The mixed-integer optimizer decides which branch to choose.

"MSK_BRANCH_DIR_UP"
The mixed-integer optimizer always chooses the up branch rst.

"MSK_BRANCH_DIR_DOWN"
The mixed-integer optimizer always chooses the down branch rst.

"MSK_BRANCH_DIR_NEAR"
Branch in direction nearest to selected fractional variable.

"MSK_BRANCH_DIR_FAR"
Branch in direction farthest from selected fractional variable.

"MSK_BRANCH_DIR_ROOT_LP"
Chose direction based on root lp value of selected variable.

"MSK_BRANCH_DIR_GUIDED"
Branch in direction of current incumbent.

"MSK_BRANCH_DIR_PSEUDOCOST"
Branch based on the pseudocost of the variable.

miocontsoltype

Continuous mixed-integer solution type

"MSK_MIO_CONT_SOL_NONE"
No interior-point or basic solution are reported when the mixed-integer optimizer is used.

"MSK_MIO_CONT_SOL_ROOT"
The reported interior-point and basic solutions are a solution to the root node problem when mixed-integer optimizer is used.

"MSK_MIO_CONT_SOL_ITG"
The reported interior-point and basic solutions are a solution to the problem with all integer variables xed at the value they have in the integer solution. A solution is only reported in case the problem has a primal feasible solution.

"MSK_MIO_CONT_SOL_ITG_REL"
In case the problem is primal feasible then the reported interior-point and basic solutions are a solution to the problem with all integer variables xed at the value they have in the integer solution. If the problem is primal infeasible, then the solution to the root node problem is reported.

miomode

Integer restrictions

"MSK_MIO_MODE_IGNORED"
The integer constraints are ignored and the problem is solved as a continuous problem.

"MSK_MIO_MODE_SATISFIED"
Integer restrictions should be satis ed.

mionodeseltype

Mixed-integer node selection types

"MSK_MIO_NODE_SELECTION_FREE"
The optimizer decides the node selection strategy.

"MSK_MIO_NODE_SELECTION_FIRST"
The optimizer employs a depth rst node selection strategy.

"MSK_MIO_NODE_SELECTION_BEST"
The optimizer employs a best bound node selection strategy.

"MSK_MIO_NODE_SELECTION_PSEUDO"
The optimizer employs selects the node based on a pseudo cost estimate.

mpsformat

MPS le format type

"MSK_MPS_FORMAT_STRICT"
It is assumed that the input le satis es the MPS format strictly.

"MSK_MPS_FORMAT_RELAXED"
It is assumed that the input le satis es a slightly relaxed version of the MPS format.

"MSK_MPS_FORMAT_FREE"
It is assumed that the input le satis es the free MPS format. This implies that spaces are not allowed in names. Otherwise the format is free.

"MSK_MPS_FORMAT_CPLEX"
The CPLEX compatible version of the MPS format is employed.

objsense
Objective sense types

"MSK_OBJECTIVE_SENSE_MINIMIZE"
The problem should be minimized.

"MSK_OBJECTIVE_SENSE_MAXIMIZE"
The problem should be maximized.

onoffkey
On/o

"MSK_ON"
Switch the option on.

"MSK_OFF"
Switch the option o .

optimizertype
Optimizer types

"MSK_OPTIMIZER_CONIC"
The optimizer for problems having conic constraints.

"MSK_OPTIMIZER_DUAL_SIMPLEX"
The dual simplex optimizer is used.

"MSK_OPTIMIZER_FREE"
The optimizer is chosen automatically.

"MSK_OPTIMIZER_FREE_SIMPLEX"
One of the simplex optimizers is used.

"MSK_OPTIMIZER_INTPNT"
The interior-point optimizer is used.

"MSK_OPTIMIZER_MIXED_INT"
The mixed-integer optimizer.

"MSK_OPTIMIZER_PRIMAL_SIMPLEX"
The primal simplex optimizer is used.

orderingtype
Ordering strategies

"MSK_ORDER_METHOD_FREE"
The ordering method is chosen automatically.

"MSK_ORDER_METHOD_APPMINLOC"
Approximate minimum local ll-in ordering is employed.

"MSK_ORDER_METHOD_EXPERIMENTAL"
This option should not be used.

"MSK_ORDER_METHOD_TRY_GRAPHPAR"
Always try the graph partitioning based ordering.

"MSK_ORDER_METHOD_FORCE_GRAPHPAR"
Always use the graph partitioning based ordering even if it is worse than the approximate minimum local ll ordering.

"MSK_ORDER_METHOD_NONE"
No ordering is used.

presolvemode

Presolve method.

"MSK_PRESOLVE_MODE_OFF"
The problem is not presolved before it is optimized.

"MSK_PRESOLVE_MODE_ON"
The problem is presolved before it is optimized.

"MSK_PRESOLVE_MODE_FREE"
It is decided automatically whether to presolve before the problem is optimized.

parametertype

Parameter type

"MSK_PAR_INVALID_TYPE"
Not a valid parameter.

"MSK_PAR_DOU_TYPE"
Is a double parameter.

"MSK_PAR_INT_TYPE"
Is an integer parameter.

"MSK_PAR_STR_TYPE"
Is a string parameter.

problemitem

Problem data items

"MSK_PI_VAR"
Item is a variable.

"MSK_PI_CON"
Item is a constraint.

"MSK_PI_CONE"
Item is a cone.

problemtype

Problem types

"MSK_PROBTYPE_LO"
The problem is a linear optimization problem.

"MSK_PROBTYPE_QO"
The problem is a quadratic optimization problem.

"MSK_PROBTYPE_QCQO"
The problem is a quadratically constrained optimization problem.

"MSK_PROBTYPE_CONIC"
A conic optimization.

"MSK_PROBTYPE_MIXED"
General nonlinear constraints and conic constraints. This combination can not be solved by **MOSEK**.

prosta

Problem status keys

"MSK_PRO_STA_UNKNOWN"
Unknown problem status.

"MSK_PRO_STA_PRIM_AND_DUAL_FEAS"
The problem is primal and dual feasible.

"MSK_PRO_STA_PRIM_FEAS"
The problem is primal feasible.

"MSK_PRO_STA_DUAL_FEAS"
The problem is dual feasible.

"MSK_PRO_STA_PRIM_INFEAS"
The problem is primal infeasible.

"MSK_PRO_STA_DUAL_INFEAS"
The problem is dual infeasible.

"MSK_PRO_STA_PRIM_AND_DUAL_INFEAS"
The problem is primal and dual infeasible.

"MSK_PRO_STA_ILL_POSED"
The problem is ill-posed. For example, it may be primal and dual feasible but have a positive duality gap.

"MSK_PRO_STA_PRIM_INFEAS_OR_UNBOUNDED"
The problem is either primal infeasible or unbounded. This may occur for mixed-integer problems.

xmlwriteroutputtype
XML writer output mode

"MSK_WRITE_XML_MODE_ROW"
Write in row order.

"MSK_WRITE_XML_MODE_COL"
Write in column order.

rescodetype
Response code type

"MSK_RESPONSE_OK"
The response code is OK.

"MSK_RESPONSE_WRN"
The response code is a warning.

"MSK_RESPONSE_TRM"
The response code is an optimizer termination status.

"MSK_RESPONSE_ERR"
The response code is an error.

"MSK_RESPONSE_UNK"
The response code does not belong to any class.

scalingtype
Scaling type

"MSK_SCALING_FREE"
The optimizer chooses the scaling heuristic.

"MSK_SCALING_NONE"
No scaling is performed.

"MSK_SCALING_MODERATE"
A conservative scaling is performed.

"MSK_SCALING_AGGRESSIVE"
A very aggressive scaling is performed.

scalingmethod
Scaling method

"MSK_SCALING_METHOD_POW2"
Scales only with power of 2 leaving the mantissa untouched.

"MSK_SCALING_METHOD_FREE"
The optimizer chooses the scaling heuristic.

sensitivitytype
Sensitivity types

"MSK_SENSITIVITY_TYPE_BASIS"
Basis sensitivity analysis is performed.

simseltype
Simplex selection strategy

"MSK_SIM_SELECTION_FREE"
The optimizer chooses the pricing strategy.

"MSK_SIM_SELECTION_FULL"
The optimizer uses full pricing.

"MSK_SIM_SELECTION_ASE"
The optimizer uses approximate steepest-edge pricing.

"MSK_SIM_SELECTION_DEVEX"
The optimizer uses devex steepest-edge pricing (or if it is not available an approximate steep-edge selection).

"MSK_SIM_SELECTION_SE"
The optimizer uses steepest-edge selection (or if it is not available an approximate steep-edge selection).

"MSK_SIM_SELECTION_PARTIAL"
The optimizer uses a partial selection approach. The approach is usually bene cial if the number of variables is much larger than the number of constraints.

solitem

Solution items

"MSK_SOL_ITEM_XC"
Solution for the constraints.

"MSK_SOL_ITEM_XX"
Variable solution.

"MSK_SOL_ITEM_Y"
Lagrange multipliers for equations.

"MSK_SOL_ITEM_SLC"
Lagrange multipliers for lower bounds on the constraints.

"MSK_SOL_ITEM_SUC"
Lagrange multipliers for upper bounds on the constraints.

"MSK_SOL_ITEM_SLX"
Lagrange multipliers for lower bounds on the variables.

"MSK_SOL_ITEM_SUX"
Lagrange multipliers for upper bounds on the variables.

"MSK_SOL_ITEM_SNX"
Lagrange multipliers corresponding to the conic constraints on the variables.

solsta

Solution status keys

"MSK_SOL_STA_UNKNOWN"
Status of the solution is unknown.

"MSK_SOL_STA_OPTIMAL"
The solution is optimal.

"MSK_SOL_STA_PRIM_FEAS"
The solution is primal feasible.

"MSK_SOL_STA_DUAL_FEAS"
The solution is dual feasible.

"MSK_SOL_STA_PRIM_AND_DUAL_FEAS"
The solution is both primal and dual feasible.

"MSK_SOL_STA_PRIM_INFEAS_CER"
The solution is a certi cate of primal infeasibility.

"MSK_SOL_STA_DUAL_INFEAS_CER"
The solution is a certi cate of dual infeasibility.

"MSK_SOL_STA_PRIM_ILLPOSED_CER"
The solution is a certi cate that the primal problem is illposed.

"MSK_SOL_STA_DUAL_ILLPOSED_CER"
The solution is a certi cate that the dual problem is illposed.

"MSK_SOL_STA_INTEGER_OPTIMAL"
The primal solution is integer optimal.

soltype
Solution types

"MSK_SOL_BAS"
The basic solution.

"MSK_SOL_ITR"
The interior solution.

"MSK_SOL_ITG"
The integer solution.

solveform
Solve primal or dual form

"MSK_SOLVE_FREE"
The optimizer is free to solve either the primal or the dual problem.

"MSK_SOLVE_PRIMAL"
The optimizer should solve the primal problem.

"MSK_SOLVE_DUAL"
The optimizer should solve the dual problem.

stakey
Status keys

"MSK_SK_UNK"
The status for the constraint or variable is unknown.

"MSK_SK_BAS"
The constraint or variable is in the basis.

"MSK_SK_SUPBAS"
The constraint or variable is super basic.

"MSK_SK_LOW"
The constraint or variable is at its lower bound.

"MSK_SK_UPR"
The constraint or variable is at its upper bound.

"MSK_SK_FIX"
The constraint or variable is xed.

"MSK_SK_INF"
The constraint or variable is infeasible in the bounds.

startpointtype
Starting point types

"MSK_STARTING_POINT_FREE"
The starting point is chosen automatically.

"MSK_STARTING_POINT_GUESS"
The optimizer guesses a starting point.

"MSK_STARTING_POINT_CONSTANT"
The optimizer constructs a starting point by assigning a constant value to all primal and dual variables. This starting point is normally robust.

"MSK_STARTING_POINT_SATISFY_BOUNDS"
The starting point is chosen to satisfy all the simple bounds on nonlinear variables. If this starting point is employed, then more care than usual should employed when choosing the bounds on the nonlinear variables. In particular very tight bounds should be avoided.

streamtype
Stream types

"MSK_STREAM_LOG"
Log stream. Contains the aggregated contents of all other streams. This means that a message written to any other stream will also be written to this stream.

"MSK_STREAM_MSG"
Message stream. Log information relating to performance and progress of the optimization is written to this stream.

"MSK_STREAM_ERR"
Error stream. Error messages are written to this stream.

"MSK_STREAM_WRN"
Warning stream. Warning messages are written to this stream.

value
Integer values

"MSK_MAX_STR_LEN"
Maximum string length allowed in **MOSEK**.

"MSK_LICENSE_BUFFER_LENGTH"
The length of a license key bu er.

variabletype
Variable types

"MSK_VAR_TYPE_CONT"
Is a continuous variable.

"MSK_VAR_TYPE_INT"
Is an integer variable.

15.8 Nonlinear interfaces (obsolete)

Important: This is a legacy document for users familiar with SCopt, DGopt, EXPopt, mskenopt, mskscopt and mskgpopt from previous versions of **MOSEK**. These interfaces have now been removed. We assume familiarity with documentation included in version 8. All problems expressible with this interface can (and should) be reformulated using the exponential cone and power cones.

New users should formulate problems involving powers, logarithms and exponentials directly in conic form.

Conversion tutorial

We recommend converting all nonlinear problems using SCopt, DGopt, EXPopt, mskenopt, mskscopt and mskgpopt into conic form. Depending on the values of f, g, h either the epigraph or hypograph of a SCopt function if convex, and a bounding variable can be introduced following the basic rules below. We assume all variables are within safe bounds where the SCopt operators are de ned and convex. We also assume $f > 0$.

A more comprehensive modeling guide for these types of problems can be found in the **MOSEK** Modeling Cookbook.

Powers

Consider $f(x+h)^g$. This can be reformulated using the power cone.

- If $g > 1$ then $t \geq f(x+h)^g$ is equivalent to $(t/f)^{1/g} \geq |x+h|$, that is $(t/f, 1, x+h) \in \mathcal{P}_3^{1/g,1-1/g}$.
- If $0 < g < 1$ then $|t| \leq f(x+h)^g$ is equivalent to $(x+h, 1, t/f) \in \mathcal{P}_3^{g,1-g}$.
- If $g < 0$ then $t \geq f(x+h)^g$ is equivalent to $(t/f)(x+h)^{-g} \geq 1$, that is $(t/f, x+h, 1) \in \mathcal{P}_3^{1/(1-g),-g/(1-g)}$.

Logarithm

The bound $t \leq f \log(gx+h)$ is equivalent to $(gx+h, 1, t/f) \in K_{\exp}$.

Chapter 16

Supported File Formats

MOSEK supports a range of problem and solution formats listed in Table 16.1 and Table 16.2. The **Task format** is **MOSEK**'s native binary format and it supports all features that **MOSEK** supports. The **OPF format** is **MOSEK**'s human-readable alternative that supports nearly all features (everything except semide nite problems). In general, text formats are signi cantly slower to read, but can be examined and edited directly in any text editor.

Problem formats

Table 16.1: List of supported le formats for optimization problems. The column *Conic* refers to conic problems involving the quadratic, rotated quadratic, power or exponential cone. The last two columns indicate if the format supports solutions and optimizer parameters.

Format Type	Ext.	Binary/Text	LP	QO	Conic	SDP	Sol	Param
LP	lp	plain text	X	X				
MPS	mps	plain text	X	X	X			
OPF	opf	plain text	X	X	X		X	X
PTF	ptf	plain text	X	X	X	X	X	
CBF	cbf	plain text	X		X	X		
Task format	task	binary	X	X	X	X	X	X
Jtask format	jtask	text	X	X	X	X	X	X

Solution formats

Table 16.2: List of supported solution formats.

Format Type	Ext.	Binary/Text	Description
SOL	sol	plain text	Interior Solution
	bas	plain text	Basic Solution
	int	plain text	Integer
Jsol format	jsol	text	Solution

Compression

MOSEK supports GZIP and Zstandard compression. Problem les with extension.gz (for GZIP) and .zst (for Zstandard) are assumed to be compressed when read, and are automatically compressed when written. For example, a le called

```
problem.mps.gz
```

will be considered as a GZIP compressed MPS le.

16.1 The LP File Format

MOSEK supports the LP le format with some extensions. The LP format is not a completely well-de ned standard and hence di erent optimization packages may interpret the same LP le in slightly di erent ways. **MOSEK** tries to emulate as closely as possible CPLEX's behavior, but tries to stay backward compatible.

The LP le format can specify problems of the form

$$\begin{array}{lcccc} \text{minimize/maximize} & & c^T x + \frac{1}{2} q^o(x) & & \\ \text{subject to} & l^c \leq & Ax + \frac{1}{2} q(x) & \leq & u^c, \\ & l^x \leq & x & \leq & u^x, \\ & & x_{\mathcal{J}} \text{ integer}, & & \end{array}$$

where

- $x \in \mathbb{R}^n$ is the vector of decision variables.
- $c \in \mathbb{R}^n$ is the linear term in the objective.
- $q^o :\in \mathbb{R}^n \to \mathbb{R}$ is the quadratic term in the objective where

$$q^o(x) = x^T Q^o x$$

and it is assumed that

$$Q^o = (Q^o)^T.$$

- $A \in \mathbb{R}^{m \times n}$ is the constraint matrix.
- $l^c \in \mathbb{R}^m$ is the lower limit on the activity for the constraints.
- $u^c \in \mathbb{R}^m$ is the upper limit on the activity for the constraints.
- $l^x \in \mathbb{R}^n$ is the lower limit on the activity for the variables.
- $u^x \in \mathbb{R}^n$ is the upper limit on the activity for the variables.
- $q : \mathbb{R}^n \to \mathbb{R}$ is a vector of quadratic functions. Hence,

$$q_i(x) = x^T Q^i x$$

where it is assumed that

$$Q^i = (Q^i)^T.$$

- $\mathcal{J} \subseteq \{1, 2, \ldots, n\}$ is an index set of the integer constrained variables.

16.1.1 File Sections

An LP formatted le contains a number of sections specifying the objective, constraints, variable bounds, and variable types. The section keywords may be any mix of upper and lower case letters.

Objective Function

The rst section beginning with one of the keywords

```
max
maximum
maximize
min
minimum
minimize
```

defines the objective sense and the objective function, i.e.

$$c^T x + \frac{1}{2} x^T Q^o x.$$

The objective may be given a name by writing

```
myname:
```

before the expressions. If no name is given, then the objective is named obj.

The objective function contains linear and quadratic terms. The linear terms are written as

```
4 x1 + x2 - 0.1 x3
```

and so forth. The quadratic terms are written in square brackets ([ ]/2) and are either squared or multiplied as in the examples

```
x1^2
```

and

```
x1 * x2
```

There may be zero or more pairs of brackets containing quadratic expressions.

An example of an objective section is

```
minimize
myobj: 4 x1 + x2 - 0.1 x3 + [ x1^2 + 2.1 x1 * x2 ]/2
```

Please note that the quadratic expressions are multiplied with $\frac{1}{2}$, so that the above expression means

$$\text{minimize} \quad 4x_1 + x_2 - 0.1 \cdot x_3 + \tfrac{1}{2}(x_1^2 + 2.1 \cdot x_1 \cdot x_2)$$

If the same variable occurs more than once in the linear part, the coefficients are added, so that 4 x1 + 2 x1 is equivalent to 6 x1. In the quadratic expressions x1 * x2 is equivalent to x2 * x1 and, as in the linear part, if the same variables multiplied or squared occur several times their coefficients are added.

Constraints

The second section beginning with one of the keywords

```
subj to
subject to
s.t.
st
```

defines the linear constraint matrix A and the quadratic matrices Q^i.

A constraint contains a name (optional), expressions adhering to the same rules as in the objective and a bound:

```
subject to
con1: x1 + x2 + [ x3^2 ]/2 <= 5.1
```

The bound type (here <=) may be any of <, <=, =, >, >= (< and <= mean the same), and the bound may be any number.

In the standard LP format it is not possible to define more than one bound per line, but **MOSEK** supports defining ranged constraints by using double-colon (::) instead of a single-colon ( ) after the constraint name, i.e.

$$-5 \leq x_1 + x_2 \leq 5 \tag{16.1}$$

may be written as

```
con:: -5 < x_1 + x_2 < 5
```

By default **MOSEK** writes ranged constraints this way.

If the les must adhere to the LP standard, ranged constraints must either be split into upper bounded and lower bounded constraints or be written as an equality with a slack variable. For example the expression (16.1) may be written as

$$x_1 + x_2 - sl_1 = 0, \ -5 \leq sl_1 \leq 5.$$

Bounds

Bounds on the variables can be speci ed in the bound section beginning with one of the keywords

```
bound
bounds
```

The bounds section is optional but should, if present, follow thesubject to section. All variables listed in the bounds section must occur in either the objective or a constraint.

The default lower and upper bounds are 0 and $+\infty$. A variable may be declared free with the keyword free , which means that the lower bound is $-\infty$ and the upper bound is $+\infty$. Furthermore it may be assigned a nite lower and upper bound. The bound de nitions for a given variable may be written in one or two lines, and bounds can be any number or $\pm\infty$ (written as +inf / -inf / +infinity / -infinity) as in the example

```
bounds
x1 free
x2 <= 5
0.1 <= x2
x3 = 42
2 <= x4 < +inf
```

Variable Types

The nal two sections are optional and must begin with one of the keywords

```
bin
binaries
binary
```

and

```
gen
general
```

Under general all integer variables are listed, and underbinary all binary (integer variables with bounds 0 and 1) are listed:

```
general
x1 x2
binary
x3 x4
```

Again, all variables listed in the binary or general sections must occur in either the objective or a constraint.

Terminating Section

Finally, an LP formatted le must be terminated with the keyword

```
end
```

16.1.2 LP File Examples

Linear example lo1.lp

```
\ File: lo1.lp
maximize
obj: 3 x1 + x2 + 5 x3 + x4
subject to
c1:  3 x1 + x2 + 2 x3 = 30
c2:  2 x1 + x2 + 3 x3 + x4 >= 15
c3:  2 x2 + 3 x4 <= 25
bounds
 0 <= x1 <= +infinity
 0 <= x2 <= 10
 0 <= x3 <= +infinity
 0 <= x4 <= +infinity
end
```

Mixed integer example milo1.lp

```
maximize
obj: x1 + 6.4e-01 x2
subject to
c1:  5e+01 x1 + 3.1e+01 x2 <= 2.5e+02
c2:  3e+00 x1 - 2e+00 x2 >= -4e+00
bounds
 0 <= x1 <= +infinity
 0 <= x2 <= +infinity
general
 x1 x2
end
```

16.1.3 LP Format peculiarities

Comments

Anything on a line after a \ is ignored and is treated as a comment.

Names

A name for an objective, a constraint or a variable may contain the letters a-z, A-Z, the digits 0-9 and the characters

```
!"#$%&()/,.;?@_'`|~
```

The first character in a name must not be a number, a period or the letter e or E. Keywords must not be used as names.

MOSEK accepts any character as valid for names, except \0. A name that is not allowed in LP file will be changed and a warning will be issued.

The algorithm for making names LP valid works as follows: The name is interpreted as an utf-8 string. For a Unicode character c:

- If c==_ (underscore), the output is __ (two underscores).
- If c is a valid LP name character, the output is just c.
- If c is another character in the ASCII range, the output is _XX, where XX is the hexadecimal code for the character.
- If c is a character in the range *127-65535*, the output is _uXXXX, where XXXX is the hexadecimal code for the character.

16.2 The MPS File Format

MOSEK supports the standard MPS format with some extensions. For a detailed description of the MPS format see the book by Nazareth[Naz87].

16.2.1 MPS File Structure

The version of the MPS format supported by **MOSEK** allows speci cation of an optimization problem of the form

$$\begin{array}{rcccl} \text{maximize/minimize} & & c^T x + q_0(x) & & \\ l^c & \leq & Ax + q(x) & \leq & u^c, \\ l^x & \leq & x & \leq & u^x, \\ & & x \in \mathcal{K}, & & \\ & & x_{\mathcal{J}} \ \text{integer}, & & \end{array} \tag{16.2}$$

where

- $x \in \mathbb{R}^n$ is the vector of decision variables.
- $A \in \mathbb{R}^{m \times n}$ is the constraint matrix.
- $l^c \in \mathbb{R}^m$ is the lower limit on the activity for the constraints.
- $u^c \in \mathbb{R}^m$ is the upper limit on the activity for the constraints.
- $l^x \in \mathbb{R}^n$ is the lower limit on the activity for the variables.
- $u^x \in \mathbb{R}^n$ is the upper limit on the activity for the variables.
- $q : \mathbb{R}^n \to \mathbb{R}$ is a vector of quadratic functions. Hence,

  $$q_i(x) = \frac{1}{2} x^T Q^i x$$

  where it is assumed that $Q^i = (Q^i)^T$. Please note the explicit $\frac{1}{2}$ in the quadratic term and that Q^i is required to be symmetric. The same applies to q_0.
- $\mathcal{K}$ is a convex cone.
- $\mathcal{J} \subseteq \{1, 2, \ldots, n\}$ is an index set of the integer-constrained variables.
- c is the vector of objective coe cients.

An MPS le with one row and one column can be illustrated like this:

```
*        1         2         3         4         5         6
*234567890123456789012345678901234567890123456789012345678901234567890
NAME          [name]
OBJSENSE
    [objsense]
OBJNAME       [objname]
ROWS
 ?  [cname1]
COLUMNS
    [vname1]  [cname1]  [value1]       [cname2]  [value2]
RHS
    [name]    [cname1]  [value1]       [cname2]  [value2]
RANGES
    [name]    [cname1]  [value1]       [cname2]  [value2]
QSECTION      [cname1]
    [vname1]  [vname2]  [value1]       [vname3]  [value2]
QMATRIX
    [vname1]  [vname2]  [value1]
```

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```
QUADOBJ
    [vname1]  [vname2]  [value1]
QCMATRIX      [cname1]
    [vname1]  [vname2]  [value1]
BOUNDS
 ?? [name]    [vname1]  [value1]
CSECTION      [kname1]  [value1]       [ktype]
    [vname1]
ENDATA
```

Here the names in capitals are keywords of the MPS format and names in brackets are custom de ned names or values. A couple of notes on the structure:

- Fields: All items surrounded by brackets appear in *fields*. The elds named valueN are numerical values. Hence, they must have the format

  ```
  [+|-]XXXXXXX.XXXXXX[[e|E][+|-]XXX]
  ```

  where

  ```
  X = [0|1|2|3|4|5|6|7|8|9].
  ```

- Sections: The MPS le consists of several sections where the names in capitals indicate the beginning of a new section. For example, COLUMNS denotes the beginning of the columns section.
- Comments: Lines starting with an * are comment lines and are ignored by **MOSEK**.
- Keys: The question marks represent keys to be speci ed later.
- Extensions: The sections QSECTION and CSECTION are speci c **MOSEK** extensions of the MPS format. The sections QMATRIX, QUADOBJ and QCMATRIX are included for sake of compatibility with other vendors extensions to the MPS format.
- The standard MPS format is a xed format, i.e. everything in the MPS le must be within certain xed positions. **MOSEK** also supports a *free format*. See Sec. 16.2.5 for details.

Linear example lo1.mps

A concrete example of a MPS le is presented below:

```
* File: lo1.mps
NAME          lo1
OBJSENSE
    MAX
ROWS
 N  obj
 E  c1
 G  c2
 L  c3
COLUMNS
    x1        obj       3
    x1        c1        3
    x1        c2        2
    x2        obj       1
    x2        c1        1
    x2        c2        1
    x2        c3        2
    x3        obj       5
    x3        c1        2
    x3        c2        3
    x4        obj       1
    x4        c2        1
```

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```
    x4        c3        3
RHS
    rhs       c1        30
    rhs       c2        15
    rhs       c3        25
RANGES
BOUNDS
 UP bound     x2        10
ENDATA
```

Subsequently each individual section in the MPS format is discussed.

NAME (optional)

In this section a name ([name]) is assigned to the problem.

OBJSENSE (optional)

This is an optional section that can be used to specify the sense of the objective function. The OBJSENSE section contains one line at most which can be one of the following:

```
MIN
MINIMIZE
MAX
MAXIMIZE
```

It should be obvious what the implication is of each of these four lines.

OBJNAME (optional)

This is an optional section that can be used to specify the name of the row that is used as objective function. objname should be a valid row name.

ROWS

A record in the ROWS section has the form

```
?  [cname1]
```

where the requirements for the fields are as follows:

Field	Starting Position	Max Width	required	Description
?	2	1	Yes	Constraint key
[cname1]	5	8	Yes	Constraint name

Hence, in this section each constraint is assigned a unique name denoted by [cname1]. Please note that [cname1] starts in position 5 and the field can be at most 8 characters wide. An initial key ? must be present to specify the type of the constraint. The key can have values E, G, L, or N with the following interpretation:

Constraint type	l_i^c	u_i^c
E (equal)	finite	$= l_i^c$
G (greater)	finite	∞
L (lower)	$-\infty$	finite
N (none)	$-\infty$	∞

In the MPS format the objective vector is not specified explicitly, but one of the constraints having the key N will be used as the objective vector c. In general, if multiple N type constraints are specified, then the first will be used as the objective vector c, unless something else was specified in the section OBJNAME

- Dual power cone (with parameter $0 < \alpha < 1$):

$$\mathcal{K}_t = \left\{ x \in \mathbb{R}^{n^t} : \left(\frac{x_1}{\alpha}\right)^{\alpha} \left(\frac{x_2}{1-\alpha}\right)^{1-\alpha} \geq \sqrt{\sum_{j=3}^{n^t} x_j^2}, \quad x_1, x_2 \geq 0 \right\}. \tag{16.9}$$

In general, membership in the $\mathbb{R}$ set is not speci ed. If a variable is not a member of any other cone then it is assumed to be a member of the $\mathbb{R}$ cone.

Next, let us study an example. Assume that the power cone

$$x_4^{1/3} x_5^{2/3} \geq |x_8|$$

and the rotated quadratic cone

$$2x_3x_7 \geq x_1^2 + x_0^2, \quad x_3, x_7 \geq 0,$$

should be speci ed in the MPS le. One CSECTION is required for each cone and they are speci ed as follows:

```
*         1         2         3         4         5         6
*234567890123456789012345678901234567890123456789012345678901234567890
CSECTION      konea     3e-1            PPOW
x4
x5
x8
CSECTION      koneb     0.0             RQUAD
x7
x3
x1
x0
```

In general, a CSECTION header has the format

```
CSECTION      [kname1]     [value1]     [ktype]
```

where the requirements for each eld are as follows:

Field	Starting Position	Max Width	Required	Description
[kname1]	15	8	Yes	Name of the cone
[value1]	25	12	No	Cone parameter
[ktype]	40		Yes	Type of the cone.

The possible cone type keys are:

[ktype]	Members	[value1]	Interpretation.
ZERO	≥ 0	unused	Zero cone (16.3).
QUAD	≥ 1	unused	Quadratic cone (16.4).
RQUAD	≥ 2	unused	Rotated quadratic cone (16.5).
PEXP	3	unused	Primal exponential cone (16.6).
PPOW	≥ 2	α	Primal power cone (16.7).
DEXP	3	unused	Dual exponential cone (16.8).
DPOW	≥ 2	α	Dual power cone (16.9).

A record in the CSECTION has the format

```
[vname1]
```

where the requirements for each eld are

Field	Starting Position	Max Width	required	Description
[vname1]	5	8	Yes	A valid variable name

A variable must occur in at most one CSECTION

ENDATA

This keyword denotes the end of the MPS file.

16.2.2 Integer Variables

Using special bound keys in the BOUNDS section it is possible to specify that some or all of the variables should be integer-constrained i.e. be members of $\mathbb{Z}$. However, an alternative method is available. This method is available only for backward compatibility and we recommend that it is not used. This method requires that markers are placed in the COLUMNS section as in the example:

```
COLUMNS
x1        obj       -10.0          c1        0.7
x1        c2         0.5           c3        1.0
x1        c4         0.1
* Start of integer-constrained variables.
MARK000  'MARKER'                 'INTORG'
x2        obj       -9.0           c1        1.0
x2        c2         0.8333333333  c3        0.66666667
x2        c4         0.25
x3        obj       1.0            c6        2.0
MARK001  'MARKER'                 'INTEND'
* End of integer-constrained variables.
```

Please note that special marker lines are used to indicate the start and the end of the integer variables. Furthermore be aware of the following

- All variables between the markers are assigned a default lower bound of 0 and a default upper bound of 1. This may not be what is intended. If it is not intended, the correct bounds should be defined in the BOUNDS section of the MPS formatted file.
- MOSEK ignores field 1, i.e. MARK0001 and MARK0011, however, other optimization systems require them.
- Field 2, i.e. 'MARKER', must be specified including the single quotes. This implies that no row can be assigned the name MARKER.
- Field 3 is ignored and should be left blank.
- Field 4, i.e. INTORG and INTEND, must be specified.
- It is possible to specify several such integer marker sections within the COLUMNS section.

16.2.3 General Limitations

- An MPS file should be an ASCII file.

16.2.4 Interpretation of the MPS Format

Several issues related to the MPS format are not well-defined by the industry standard. However, MOSEK uses the following interpretation:

- If a matrix element in the COLUMNS section is specified multiple times, then the multiple entries are added together.
- If a matrix element in a QSECTION section is specified multiple times, then the multiple entries are added together.

16.2.5 The Free MPS Format

MOSEK supports a free format variation of the MPS format. The free format is similar to the MPS le format but less restrictive, e.g. it allows longer names. However, a name must not contain any blanks.

Moreover, by default a line in the MPS le must not contain more than 1024 characters. By modifying the parameter *MSK_IPAR_READ_MPS_WIDTH* an arbitrary large line width will be accepted.

The free MPS format is default. To change to the strict and other formats use the parameter *MSK_IPAR_READ_MPS_FORMAT*.

16.3 The OPF Format

The *Optimization Problem Format (OPF)* is an alternative to LP and MPS les for specifying optimization problems. It is row-oriented, inspired by the CPLEX LP format.

Apart from containing objective, constraints, bounds etc. it may contain complete or partial solutions, comments and extra information relevant for solving the problem. It is designed to be easily read and modi ed by hand and to be forward compatible with possible future extensions.

Intended use

The OPF le format is meant to replace several other les:

- The LP le format: Any problem that can be written as an LP le can be written as an OPF le too; furthermore it naturally accommodates ranged constraints and variables as well as arbitrary characters in names, xed expressions in the objective, empty constraints, and conic constraints.
- Parameter les: It is possible to specify integer, double and string parameters along with the problem (or in a separate OPF le).
- Solution les: It is possible to store a full or a partial solution in an OPF le and later reload it.

16.3.1 The File Format

The format uses tags to structure data. A simple example with the basic sections may look like this:

```
[comment]
This is a comment. You may write almost anything here...
[/comment]

# This is a single-line comment.

[objective min 'myobj']
x + 3 y + x^2 + 3 y^2 + z + 1
[/objective]

[constraints]
[con 'con01'] 4 <= x + y  [/con]
[/constraints]

[bounds]
[b] -10 <= x,y <= 10  [/b]

[cone quad] x,y,z [/cone]
[/bounds]
```

A scope is opened by a tag of the form[tag] and closed by a tag of the form[/tag] . An opening tag may accept a list of unnamed and named arguments, for examples:

```
[tag value] tag with one unnamed argument [/tag]
[tag arg=value] tag with one named argument [/tag]
```

Unnamed arguments are identi ed by their order, while named arguments may appear in any order, but never before an unnamed argument. Thevalue can be a quoted, single-quoted or double-quoted text string, i.e.

```
[tag 'value']     single-quoted value [/tag]
[tag arg='value'] single-quoted value [/tag]
[tag "value"]     double-quoted value [/tag]
[tag arg="value"] double-quoted value [/tag]
```

16.3.2 Sections

The recognized tags are

[comment]

A comment section. This can contain *almost* any text: Between single quotes (') or double quotes (") any text may appear. Outside quotes the markup characters ([and]) must be pre xed by backslashes. Both single and double quotes may appear alone or inside a pair of quotes if it is pre xed by a backslash.

[objective]

The objective function: This accepts one or two parameters, where the rst one (in the above example min) is either min or max(regardless of case) and de nes the objective sense, and the second one (above myobj), if present, is the objective name. The section may contain linear and quadratic expressions.

If several objectives are speci ed, all but the last are ignored.

[constraints]

This does not directly contain any data, but may contain subsections con de ning a linear constraint.

[con]

De nes a single constraint; if an argument is present ([con NAME]) this is used as the name of the constraint, otherwise it is given a null-name. The section contains a constraint de nition written as linear and quadratic expressions with a lower bound, an upper bound, with both or with an equality. Examples:

```
[constraints]
[con 'con1'] 0 <= x + y       [/con]
[con 'con2'] 0 >= x + y       [/con]
[con 'con3'] 0 <= x + y <= 10 [/con]
[con 'con4']      x + y  = 10 [/con]
[/constraints]
```

Constraint names are unique. If a constraint is speci ed which has the same name as a previously de ned constraint, the new constraint replaces the existing one.

[bounds]

This does not directly contain any data, but may contain subsections b (linear bounds on variables) and cone (cones).

[b]

Bound de nition on one or several variables separated by comma (,). An upper or lower bound on a variable replaces any earlier de ned bound on that variable. If only one bound (upper or lower) is given only this bound is replaced. This means that upper and lower bounds can be speci ed separately. So the OPF bound de nition:

```
[b]  x,y >= -10  [/b]
[b]  x,y <= 10   [/b]
```

results in the bound $-10 \leq x, y \leq 10$.

[cone]

Specifies a cone. A cone is defined as a sequence of variables which belong to a single unique cone. The supported cone types are:

- quad: a quadratic cone of n variables $x_1, \ldots, x_n$ defines a constraint of the form

$$x_1^2 \geq \sum_{i=2}^{n} x_i^2, \quad x_1 \geq 0.$$

- rquad: a rotated quadratic cone of n variables $x_1, \ldots, x_n$ defines a constraint of the form

$$2x_1x_2 \geq \sum_{i=3}^{n} x_i^2, \quad x_1, x_2 \geq 0.$$

- pexp: primal exponential cone of 3 variables x_1, x_2, x_3 defines a constraint of the form

$$x_1 \geq x_2 \exp(x_3/x_2), \quad x_1, x_2 \geq 0.$$

- ppow with parameter $0 < \alpha < 1$: primal power cone of n variables $x_1, \ldots, x_n$ defines a constraint of the form

$$x_1^{\alpha} x_2^{1-\alpha} \geq \sqrt{\sum_{j=3}^{n} x_j^2}, \quad x_1, x_2 \geq 0.$$

- dexp: dual exponential cone of 3 variables x_1, x_2, x_3 defines a constraint of the form

$$x_1 \geq -x_3 e^{-1} \exp(x_2/x_3), \quad x_3 \leq 0, x_1 \geq 0.$$

- dpow with parameter $0 < \alpha < 1$: dual power cone of n variables $x_1, \ldots, x_n$ defines a constraint of the form

$$\left(\frac{x_1}{\alpha}\right)^{\alpha} \left(\frac{x_2}{1-\alpha}\right)^{1-\alpha} \geq \sqrt{\sum_{j=3}^{n^t} x_j^2}, \quad x_1, x_2 \geq 0.$$

- zero: zero cone of n variables $x_1, \ldots, x_n$ defines a constraint of the form

$$x_1 = \cdots = x_n = 0$$

A [bounds] -section example:

```
[bounds]
[b]  0 <= x,y <= 10  [/b] # ranged bound
[b] 10 >= x,y >=  0  [/b] # ranged bound
[b]  0 <= x,y <= inf [/b] # using inf
[b]       x,y free   [/b] # free variables
# Let (x,y,z,w) belong to the cone K
[cone rquad] x,y,z,w  [/cone] # rotated quadratic cone
[cone ppow '3e-01' 'a'] x1, x2, x3 [/cone] # power cone with alpha=1/3 and name 'a'
[/bounds]
```

By default all variables are free.

[variables]

This defines an ordering of variables as they should appear in the problem. This is simply a space-separated list of variable names.

[integer]

This contains a space-separated list of variables and de nes the constraint that the listed variables must be integer-valued.

[hints]

This may contain only non-essential data; for example estimates of the number of variables, constraints and non-zeros. Placed before all other sections containing data this may reduce the time spent reading the le.

In the hints section, any subsection which is not recognized by MOSEK is simply ignored. In this section a hint is de ned as follows:

```
[hint ITEM] value [/hint]
```

The hints recognized by MOSEK are:

- numvar (number of variables),
- numcon (number of linear/quadratic constraints),
- numanz (number of linear non-zeros in constraints),
- numqnz (number of quadratic non-zeros in constraints).

[solutions]

This section can contain a set of full or partial solutions to a problem. Each solution must be speci ed using a [solution] -section, i.e.

```
[solutions]
[solution]...[/solution] #solution 1
[solution]...[/solution] #solution 2
#other solutions....
[solution]...[/solution] #solution n
[/solutions]
```

The syntax of a [solution] -section is the following:

```
[solution SOLTYPE status=STATUS]...[/solution]
```

where SOLTYPE is one of the strings

- interior , a non-basic solution,
- basic , a basic solution,
- integer , an integer solution,

and STATUS is one of the strings

- UNKNOWN,
- OPTIMAL,
- INTEGER_OPTIMAL,
- PRIM_FEAS,
- DUAL_FEAS,
- PRIM_AND_DUAL_FEAS,
- NEAR_OPTIMAL,
- NEAR_PRIM_FEAS,

- NEAR_DUAL_FEAS
- NEAR_PRIM_AND_DUAL_FEAS
- PRIM_INFEAS_CER
- DUAL_INFEAS_CER
- NEAR_PRIM_INFEAS_CER
- NEAR_DUAL_INFEAS_CER
- NEAR_INTEGER_OPTIMAL

Most of these values are irrelevant for input solutions; when constructing a solution for simplex hot-start or an initial solution for a mixed integer problem the safe setting is UNKNOWN.

A [solution] -section contains [con] and [var] sections. Each [con] and [var] section defines solution information for a single variable or constraint, specified as list of KEYWORD=value pairs, in any order, written as

```
KEYWORD=value
```

Allowed keywords are as follows:

- sk. The status of the item, where the value is one of the following strings:
  - LOW, the item is on its lower bound.
  - UPR, the item is on its upper bound.
  - FIX, it is a fixed item.
  - BAS, the item is in the basis.
  - SUPBAS, the item is super basic.
  - UNK, the status is unknown.
  - INF, the item is outside its bounds (infeasible).
- lvl Defines the level of the item.
- sl Defines the level of the dual variable associated with its lower bound.
- su Defines the level of the dual variable associated with its upper bound.
- sn Defines the level of the variable associated with its cone.
- y Defines the level of the corresponding dual variable (for constraints only).

A [var] section should always contain the items sk, lvl, sl and su. Items sl and su are not required for integer solutions.

A [con] section should always contain sk, lvl, sl, su and y.

An example of a solution section

```
[solution basic status=UNKNOWN]
[var x0] sk=LOW    lvl=5.0      [/var]
[var x1] sk=UPR    lvl=10.0     [/var]
[var x2] sk=SUPBAS lvl=2.0  sl=1.5 su=0.0 [/var]

[con c0] sk=LOW    lvl=3.0 y=0.0 [/con]
[con c0] sk=UPR    lvl=0.0 y=5.0 [/con]
[/solution]
```

- [vendor] This contains solver/vendor specific data. It accepts one argument, which is a vendor ID for MOSEK the ID is simply mosek and the section contains the subsection parameters defining solver parameters. When reading a vendor section, any unknown vendor can be safely ignored. This is described later.

Comments using the # may appear anywhere in the file. Between the # and the following line-break any text may be written, including markup characters.

16.3.3 Numbers

Numbers, when used for parameter values or coe cients, are written in the usual way by the printf function. That is, they may be pre xed by a sign (+ or -) and may contain an integer part, decimal part and an exponent. The decimal point is always . (a dot). Some examples are

```
1
1.0
.0
1.
1e10
1e+10
1e-10
```

Some *invalid* examples are

```
e10   # invalid, must contain either integer or decimal part
.     # invalid
.e10  # invalid
```

More formally, the following standard regular expression describes numbers as used:

```
[+|-]?([0-9]+[.][0-9]*|[.][0-9]+)([eE][+|-]?[0-9]+)?
```

16.3.4 Names

Variable names, constraint names and objective name may contain arbitrary characters, which in some cases must be enclosed by quotes (single or double) that in turn must be preceded by a backslash. Unquoted names must begin with a letter (a-z or A-Z) and contain only the following characters: the letters a-z and A-Z, the digits 0-9, braces ({ and }) and underscore (_).

Some examples of legal names:

```
an_unquoted_name
another_name{123}
'single quoted name'
"double quoted name"
"name with \\"quote\\" in it"
"name with []s in it"
```

16.3.5 Parameters Section

In the vendor section solver parameters are de ned inside the parameters subsection. Each parameter is written as

```
[p PARAMETER_NAME] value [/p]
```

where PARAMETER_NAME is replaced by a **MOSEK** parameter name, usually of the form MSK_IPAR_... , MSK_DPAR_... or MSK_SPAR_..., and the value is replaced by the value of that parameter; both integer values and named values may be used. Some simple examples are

```
[vendor mosek]
[parameters]
[p MSK_IPAR_OPF_MAX_TERMS_PER_LINE] 10     [/p]
[p MSK_IPAR_OPF_WRITE_PARAMETERS]   MSK_ON [/p]
[p MSK_DPAR_DATA_TOL_BOUND_INF]     1.0e18 [/p]
[/parameters]
[/vendor]
```

16.3.6 Writing OPF Files from MOSEK

To write an OPF le then make sure the le extension is .opf.

Then modify the following parameters to de ne what the le should contain:

MSK_IPAR_OPF_WRITE_SOL_BAS	Include basic solution, if de ned.
MSK_IPAR_OPF_WRITE_SOL_ITG	Include integer solution, if de ned.
MSK_IPAR_OPF_WRITE_SOL_ITR	Include interior solution, if de ned.
MSK_IPAR_OPF_WRITE_SOLUTIONS	Include solutions if they are de ned. If this is o , no solutions are included.
MSK_IPAR_OPF_WRITE_HEADER	Include a small header with comments.
MSK_IPAR_OPF_WRITE_PROBLEM	Include the problem itself objective, constraints and bounds.
MSK_IPAR_OPF_WRITE_PARAMETERS	Include all parameter settings.
MSK_IPAR_OPF_WRITE_HINTS	Include hints about the size of the problem.

16.3.7 Examples

This section contains a set of small examples written in OPF and describing how to formulate linear, quadratic and conic problems.

Linear Example lo1.opf

Consider the example:

$$\begin{array}{lrcrcrcrcl} \text{maximize} & 3x_0 & + & 1x_1 & + & 5x_2 & + & 1x_3 & & \\ \text{subject to} & 3x_0 & + & 1x_1 & + & 2x_2 & & & = & 30, \\ & 2x_0 & + & 1x_1 & + & 3x_2 & + & 1x_3 & \geq & 15, \\ & & & 2x_1 & & & + & 3x_3 & \leq & 25, \end{array}$$

having the bounds

$$\begin{array}{rcrcl} 0 & \leq & x_0 & \leq & \infty, \\ 0 & \leq & x_1 & \leq & 10, \\ 0 & \leq & x_2 & \leq & \infty, \\ 0 & \leq & x_3 & \leq & \infty. \end{array}$$

In the OPFformat the example is displayed as shown in Listing 16.1.

Listing 16.1: Example of an OPF le for a linear problem.

```
[comment]
  The lo1 example in OPF format
[/comment]

[hints]
  [hint NUMVAR] 4 [/hint]
  [hint NUMCON] 3 [/hint]
  [hint NUMANZ] 9 [/hint]
[/hints]

[variables disallow_new_variables]
  x1 x2 x3 x4
[/variables]

[objective maximize 'obj']
   3 x1 + x2 + 5 x3 + x4
[/objective]

[constraints]
  [con 'c1'] 3 x1 +   x2 + 2 x3         = 30 [/con]
  [con 'c2'] 2 x1 +   x2 + 3 x3 +   x4 >= 15 [/con]
  [con 'c3']        2 x2        + 3 x4 <= 25 [/con]
[/constraints]

[bounds]
```

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```
  [b] 0 <= * [/b]
  [b] 0 <= x2 <= 10 [/b]
[/bounds]
```

Quadratic Example qo1.opf

An example of a quadratic optimization problem is

$$\begin{array}{lcl} \text{minimize} & & x_1^2 + 0.1x_2^2 + x_3^2 - x_1x_3 - x_2 \\ \text{subject to} & 1 \leq & x_1 + x_2 + x_3, \\ & & x \geq 0. \end{array}$$

This can be formulated in opf as shown below.

Listing 16.2: Example of an OPF le for a quadratic problem.

```
[comment]
  The qo1 example in OPF format
[/comment]

[hints]
  [hint NUMVAR] 3 [/hint]
  [hint NUMCON] 1 [/hint]
  [hint NUMANZ] 3 [/hint]
  [hint NUMQNZ] 4 [/hint]
[/hints]

[variables disallow_new_variables]
  x1 x2 x3
[/variables]

[objective minimize 'obj']
  # The quadratic terms are often written with a factor of 1/2 as here,
  # but this is not required.

   - x2 + 0.5 ( 2.0 x1 ^ 2 - 2.0 x3 * x1 + 0.2 x2 ^ 2 + 2.0 x3 ^ 2 )
[/objective]

[constraints]
  [con 'c1'] 1.0 <= x1 + x2 + x3 [/con]
[/constraints]

[bounds]
  [b] 0 <= * [/b]
[/bounds]
```

Conic Quadratic Example cqo1.opf

Consider the example:

$$\begin{array}{lcl} \text{minimize} & x_3 + x_4 + x_5 & \\ \text{subject to} & x_0 + x_1 + 2x_2 & = \quad 1, \\ & x_0, x_1, x_2 & \geq \quad 0, \\ & x_3 \geq \sqrt{x_0^2 + x_1^2}, & \\ & 2x_4x_5 \geq x_2^2. & \end{array}$$

Please note that the type of the cones is de ned by the parameter to [cone ...] ; the content of the cone-section is the names of variables that belong to the cone. The resulting OPF le is in Listing 16.3.

Listing 16.3: Example of an OPF le for a conic quadratic problem.

```
[comment]
  The cqo1 example in OPF format.
[/comment]

[hints]
  [hint NUMVAR] 6 [/hint]
  [hint NUMCON] 1 [/hint]
  [hint NUMANZ] 3 [/hint]
[/hints]

[variables disallow_new_variables]
  x1 x2 x3 x4 x5 x6
[/variables]

[objective minimize 'obj']
   x4 + x5 + x6
[/objective]

[constraints]
  [con 'c1']  x1 + x2 + 2e+00 x3 = 1e+00 [/con]
[/constraints]

[bounds]
  # We let all variables default to the positive orthant
  [b] 0 <= * [/b]

  # ...and change those that differ from the default
  [b] x4,x5,x6 free [/b]

  # Define quadratic cone: x4 >= sqrt( x1^2 + x2^2 )
  [cone quad 'k1'] x4, x1, x2 [/cone]

  # Define rotated quadratic cone: 2 x5 x6 >= x3^2
  [cone rquad 'k2'] x5, x6, x3 [/cone]
[/bounds]
```

Mixed Integer Example milo1.opf

Consider the mixed integer problem:

$$\begin{array}{lrcl} \text{maximize} & x_0 + 0.64x_1 & & \\ \text{subject to} & 50x_0 + 31x_1 & \leq & 250, \\ & 3x_0 - 2x_1 & \geq & -4, \\ & x_0, x_1 \geq 0 & & \text{and integer} \end{array}$$

This can be implemented in OPF with the le in Listing 16.4.

Listing 16.4: Example of an OPF le for a mixed-integer linear problem.

```
[comment]
  The milo1 example in OPF format
[/comment]

[hints]
  [hint NUMVAR] 2 [/hint]
  [hint NUMCON] 2 [/hint]
  [hint NUMANZ] 4 [/hint]
[/hints]
```

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```
[variables disallow_new_variables]
  x1 x2
[/variables]

[objective maximize 'obj']
   x1 + 6.4e-1 x2
[/objective]

[constraints]
  [con 'c1'] 5e+1 x1 + 3.1e+1 x2 <= 2.5e+2 [/con]
  [con 'c2'] -4 <= 3 x1 - 2 x2 [/con]
[/constraints]

[bounds]
  [b] 0 <= * [/b]
[/bounds]

[integer]
  x1 x2
[/integer]
```

16.4 The CBF Format

This document constitutes the technical reference manual of the *Conic Benchmark Format* with le extension: .cbf or .CBF. It uni es linear, second-order cone (also known as conic quadratic) and semide nite optimization with mixed-integer variables. The format has been designed with benchmark libraries in mind, and therefore focuses on compact and easily parsable representations. The problem structure is separated from the problem data, and the format moreover facilitates benchmarking of hotstart capability through sequences of changes.

16.4.1 How Instances Are Specified

This section de nes the spectrum of conic optimization problems that can be formulated in terms of the keywords of the CBF format.

In the CBF format, conic optimization problems are considered in the following form:

$$\begin{array}{lll} \min / \max & g^{obj} & \\ & g_i \in \mathcal{K}_i, & i \in \mathcal{I}, \\ \text{s.t.} & G_i \in \mathcal{K}_i, & i \in \mathcal{I}^{PSD}, \\ & x_j \in \mathcal{K}_j, & j \in \mathcal{J}, \\ & \overline{X}_j \in \mathcal{K}_j, & j \in \mathcal{J}^{PSD}. \end{array} \tag{16.10}$$

- **Variables** are either scalar variables, x_j for $j \in \mathcal{J}$, or variables, $\overline{X}_j$ for $j \in \mathcal{J}^{PSD}$. Scalar variables can also be declared as integer.
- **Constraints** are a ne expressions of the variables, either scalar-valued g_i for $i \in \mathcal{I}$, or matrix-valued G_i for $i \in \mathcal{I}^{PSD}$

$$g_i = \sum_{j \in \mathcal{J}^{PSD}} \langle F_{ij}, X_j \rangle + \sum_{j \in \mathcal{J}} a_{ij} x_j + b_i,$$

$$G_i = \sum_{j \in \mathcal{J}} x_j H_{ij} + D_i.$$

- The **objective function** is a scalar-valued a ne expression of the variables, either to be minimized or maximized. We refer to this expression as g^{obj}

$$g^{obj} = \sum_{j \in \mathcal{J}^{PSD}} \langle F_j^{obj}, X_j \rangle + \sum_{j \in \mathcal{J}} a_j^{obj} x_j + b^{obj}.$$

CBF format can represent the following cones $\mathcal{K}$:

- **Free domain** - A cone in the linear family de ned by

$$\{x \in \mathbb{R}^n\}, \text{ for } n \geq 1.$$

- **Positive orthant** - A cone in the linear family de ned by

$$\{x \in \mathbb{R}^n \mid x_j \geq 0 \text{ for } j = 1, \ldots, n\}, \text{ for } n \geq 1.$$

- **Negative orthant** - A cone in the linear family de ned by

$$\{x \in \mathbb{R}^n \mid x_j \leq 0 \text{ for } j = 1, \ldots, n\}, \text{ for } n \geq 1.$$

- **Fixpoint zero** - A cone in the linear family de ned by

$$\{x \in \mathbb{R}^n \mid x_j = 0 \text{ for } j = 1, \ldots, n\}, \text{ for } n \geq 1.$$

- **Quadratic cone** - A cone in the second-order cone family de ned by

$$\left\{ \begin{pmatrix} p \\ x \end{pmatrix} \in \mathbb{R} \times \mathbb{R}^{n-1},\ p^2 \geq x^T x,\ p \geq 0 \right\}, \text{ for } n \geq 2.$$

- **Rotated quadratic cone** - A cone in the second-order cone family de ned by

$$\left\{ \begin{pmatrix} p \\ q \\ x \end{pmatrix} \in \mathbb{R} \times \mathbb{R} \times \mathbb{R}^{n-2},\ 2pq \geq x^T x,\ p \geq 0,\ q \geq 0 \right\}, \text{ for } n \geq 3.$$

16.4.2 The Structure of CBF Files

This section de nes how information is written in the CBF format, without being speci c about the type of information being communicated.

All information items belong to exactly one of the three groups of information. These information groups, and the order they must appear in, are:

1. File format.
2. Problem structure.
3. Problem data.

The rst group, le format, provides information on how to interpret the le. The second group, problem structure, provides the information needed to deduce the type and size of the problem instance. Finally, the third group, problem data, speci es the coe cients and constants of the problem instance.

Information items

The format is composed as a list of information items. The rst line of an information item is the KEYWORD, revealing the type of information provided. The second line - of some keywords only - is the HEADER, typically revealing the size of information that follows. The remaining lines are the BODY, holding the actual information to be speci ed.

```
KEYWORD
BODY

KEYWORD
HEADER
BODY
```

The KEYWORD determines how each line in the HEADER and BODY is structured. Moreover, the number of lines in the BODY follows either from the KEYWORD, the HEADER, or from another information item required to precede it.

Embedded hotstart-sequences

A sequence of problem instances, based on the same problem structure, is within a single le. This is facilitated via the CHANGE within the problem data information group, as a separator between the information items of each instance. The information items following a CHANGE keyword are appending to, or changing (e.g., setting coe cients back to their default value of zero), the problem data of the preceding instance.

The sequence is intended for benchmarking of hotstart capability, where the solvers can reuse their internal state and solution (subject to the achieved accuracy) as warmpoint for the succeeding instance. Whenever this feature is unsupported or undesired, the keyword CHANGE should be interpreted as the end of le.

File encoding and line width restrictions

The format is based on the US-ASCII printable character set with two extensions as listed below. Note, by de nition, that none of these extensions can be misinterpreted as printable US-ASCII characters:

- A line feed marks the end of a line, carriage returns are ignored.
- Comment-lines may contain unicode characters in UTF-8 encoding.

The line width is restricted to 512 bytes, with 3 bytes reserved for the potential carriage return, line feed and null-terminator.

Integers and oating point numbers must follow the ISO C decimal string representation in the standard C locale. The format does not impose restrictions on the magnitude of, or number of signi cant digits in numeric data, but the use of 64-bit integers and 64-bit IEEE 754 oating point numbers should be su cient to avoid loss of precision.

Comment-line and whitespace rules

The format allows single-line comments respecting the following rule:

- Lines having rst byte equal to ' #' (US-ASCII 35) are comments, and should be ignored. Comments are only allowed between information items.

Given that a line is not a comment-line, whitespace characters should be handled according to the following rules:

- Leading and trailing whitespace characters should be ignored.
  - The seperator between multiple pieces of information on one line, is either one or more whitespace characters.
- Lines containing only whitespace characters are empty, and should be ignored. Empty lines are only allowed between information items.

16.4.3 Problem Specification

The problem structure

The problem structure de nes the objective sense, whether it is minimization and maximization. It also de nes the index sets, $\mathcal{J}$, $\mathcal{J}^{PSD}$, $\mathcal{I}$ and $\mathcal{I}^{PSD}$, which are all numbered from zero, $\{0, 1, \ldots\}$, and empty until explicitly constructed.

- **Scalar variables** are constructed in vectors restricted to a conic domain, such as $(x_0, x_1) \in \mathbb{R}^2_+$, $(x_2, x_3, x_4) \in \mathcal{Q}^3$, etc. In terms of the Cartesian product, this generalizes to

  $$x \in \mathcal{K}_1^{n_1} \times \mathcal{K}_2^{n_2} \times \cdots \times \mathcal{K}_k^{n_k}$$

  which in the CBF format becomes:

  ```
  VAR
  n k
  K1 n1
  K2 n2
  ...
  Kk nk
  ```

  where $\sum_i n_i = n$ is the total number of scalar variables. The list of supported cones is found in Table 16.3. Integrality of scalar variables can be speci ed afterwards.

- **PSD variables** are constructed one-by-one. That is, $X_j \succeq \mathbf{0}^{n_j \times n_j}$ for $j \in \mathcal{J}^{PSD}$, constructs a matrix-valued variable of size $n_j \times n_j$ restricted to be symmetric positive semide nite. In the CBF format, this list of constructions becomes:

  ```
  PSDVAR
  N
  n1
  n2
  ...
  nN
  ```

  where N is the total number of PSD variables.

- **Scalar constraints** are constructed in vectors restricted to a conic domain, such as $(g_0, g_1) \in \mathbb{R}^2_+$, $(g_2, g_3, g_4) \in \mathcal{Q}^3$, etc. In terms of the Cartesian product, this generalizes to

  $$g \in \mathcal{K}_1^{m_1} \times \mathcal{K}_2^{m_2} \times \cdots \times \mathcal{K}_k^{m_k}$$

  which in the CBF format becomes:

  ```
  CON
  m k
  K1 m1
  K2 m2
  ..
  Kk mk
  ```

  where $\sum_i m_i = m$ is the total number of scalar constraints. The list of supported cones is found in Table 16.3.

- **PSD constraints** are constructed one-by-one. That is, $G_i \succeq \mathbf{0}^{m_i \times m_i}$ for $i \in \mathcal{I}^{PSD}$, constructs a matrix-valued a ne expressions of size $m_i \times m_i$ restricted to be symmetric positive semide nite. In the CBF format, this list of constructions becomes

  ```
  PSDCON
  M
  m1
  m2
  ..
  mM
  ```

where M is the total number of PSD constraints.

With the objective sense, variables (with integer indications) and constraints, the de nitions of the many a ne expressions follow in problem data.

Problem data

The problem data de nes the coe cients and constants of the a ne expressions of the problem instance. These are considered zero until explicitly de ned, implying that instances with no keywords from this information group are, in fact, valid. Duplicating or con icting information is a failure to comply with the standard. Consequently, two coe cients written to the same position in a matrix (or to transposed positions in a symmetric matrix) is an error.

The a ne expressions of the objective, g^{obj}, of the scalar constraints, g_i, and of the PSD constraints, G_i, are de ned separately. The following notation uses the standard trace inner product for matrices, $\langle X, Y \rangle = \sum_{i,j} X_{ij} Y_{ij}$.

- The a ne expression of the objective is de ned as

$$g^{obj} = \sum_{j \in \mathcal{J}^{PSD}} \langle F_j^{obj}, X_j \rangle + \sum_{j \in \mathcal{J}} a_j^{obj} x_j + b^{obj},$$

  in terms of the symmetric matrices, F_j^{obj}, and scalars, a_j^{obj} and b^{obj}.

- The a ne expressions of the scalar constraints are de ned, for $i \in \mathcal{I}$, as

$$g_i = \sum_{j \in \mathcal{J}^{PSD}} \langle F_{ij}, X_j \rangle + \sum_{j \in \mathcal{J}} a_{ij} x_j + b_i,$$

  in terms of the symmetric matrices, F_{ij}, and scalars, a_{ij} and b_i.

- The a ne expressions of the PSD constraints are de ned, for $i \in \mathcal{I}^{PSD}$, as

$$G_i = \sum_{j \in \mathcal{J}} x_j H_{ij} + D_i,$$

  in terms of the symmetric matrices, H_{ij} and D_i.

List of cones

The format uses an explicit syntax for symmetric positive semide nite cones as shown above. For scalar variables and constraints, constructed in vectors, the supported conic domains and their minimum sizes are given as follows.

Table 16.3: Cones available in the CBF format

Name	CBF keyword	Cone family
Free domain	F	linear
Positive orthant	L+	linear
Negative orthant	L-	linear
Fixpoint zero	L=	linear
Quadratic cone	Q	second-order
Rotated quadratic cone	QR	second-order

16.4.4 File Format Keywords

VER

Description: The version of the Conic Benchmark Format used to write the le.
HEADER: None
BODY: One line formatted as:

```
INT
```

This is the version number.
Must appear exactly once in a le, as the rst keyword.

OBJSENSE

Description: De ne the objective sense.
HEADER: None
BODY: One line formatted as:

```
STR
```

having MIN indicates minimize, and MAX indicates maximize. Capital letters are required.
Must appear exactly once in a le.

PSDVAR

Description: Construct the PSD variables.
HEADER: One line formatted as:

```
INT
```

This is the number of PSD variables in the problem.
BODY: A list of lines formatted as:

```
INT
```

This indicates the number of rows (equal to the number of columns) in the matrix-valued PSD variable. The number of lines should match the number stated in the header.

VAR

Description: Construct the scalar variables.
HEADER: One line formatted as:

```
INT INT
```

This is the number of scalar variables, followed by the number of conic domains they are restricted to.
BODY: A list of lines formatted as:

```
STR INT
```

This indicates the cone name (see Table 16.3), and the number of scalar variables restricted to this cone. These numbers should add up to the number of scalar variables stated rst in the header. The number of lines should match the second number stated in the header.

INT

Description: Declare integer requirements on a selected subset of scalar variables.
HEADER: One line formatted as:

```
INT
```

This is the number of integer scalar variables in the problem.
BODY: a list of lines formatted as:

```
INT
```

This indicates the scalar variable index $j \in J$. The number of lines should match the number stated in the header.
Can only be used after the keyword VAR.

PSDCON

Description: Construct the PSD constraints.

HEADER: One line formatted as:

```
INT
```

This is the number of PSD constraints in the problem.

BODY: A list of lines formatted as:

```
INT
```

This indicates the number of rows (equal to the number of columns) in the matrix-valued affine expression of the PSD constraint. The number of lines should match the number stated in the header.

Can only be used after these keywords: PSDVAR, VAR.

CON

Description: Construct the scalar constraints.

HEADER: One line formatted as:

```
INT INT
```

This is the number of scalar constraints, followed by the number of conic domains they restrict to.

BODY: A list of lines formatted as:

```
STR INT
```

This indicates the cone name (see Table 16.3), and the number of affine expressions restricted to this cone. These numbers should add up to the number of scalar constraints stated first in the header. The number of lines should match the second number stated in the header.

Can only be used after these keywords: PSDVAR, VAR.

OBJFCOORD

Description: Input sparse coordinates (quadruplets) to define the symmetric matrices F_j^{obj}, as used in the objective.

HEADER: One line formatted as:

```
INT
```

This is the number of coordinates to be specified.

BODY: A list of lines formatted as:

```
INT INT INT REAL
```

This indicates the PSD variable index $j \in \mathcal{J}^{PSD}$, the row index, the column index and the coefficient value. The number of lines should match the number stated in the header.

OBJACOORD

Description: Input sparse coordinates (pairs) to define the scalars, a_j^{obj}, as used in the objective.

HEADER: One line formatted as:

```
INT
```

This is the number of coordinates to be specified.

BODY: A list of lines formatted as:

```
INT REAL
```

This indicates the scalar variable index $j \in \mathcal{J}$ and the coefficient value. The number of lines should match the number stated in the header.

OBJBCOORD

Description: Input the scalar, b^{obj}, as used in the objective.

HEADER: None.

BODY: One line formatted as:

```
REAL
```

This indicates the coe cient value.

FCOORD

Description: Input sparse coordinates (quintuplets) to de ne the symmetric matrices, F_{ij}, as used in the scalar constraints.

HEADER: One line formatted as:

```
INT
```

This is the number of coordinates to be speci ed.

BODY: A list of lines formatted as:

```
INT INT INT INT REAL
```

This indicates the scalar constraint index $i \in \mathcal{I}$, the PSD variable index $j \in \mathcal{J}^{PSD}$, the row index, the column index and the coe cient value. The number of lines should match the number stated in the header.

ACOORD

Description: Input sparse coordinates (triplets) to de ne the scalars, a_{ij}, as used in the scalar constraints.

HEADER: One line formatted as:

```
INT
```

This is the number of coordinates to be speci ed.

BODY: A list of lines formatted as:

```
INT INT REAL
```

This indicates the scalar constraint index $i \in \mathcal{I}$, the scalar variable index $j \in \mathcal{J}$ and the coe cient value. The number of lines should match the number stated in the header.

BCOORD

Description: Input sparse coordinates (pairs) to de ne the scalars, b_i, as used in the scalar constraints.

HEADER: One line formatted as:

```
INT
```

This is the number of coordinates to be speci ed.

BODY: A list of lines formatted as:

```
INT REAL
```

This indicates the scalar constraint index $i \in \mathcal{I}$ and the coe cient value. The number of lines should match the number stated in the header.

HCOORD

Description: Input sparse coordinates (quintuplets) to de ne the symmetric matrices, H_{ij}, as used in the PSD constraints.

HEADER: One line formatted as:

```
INT
```

This is the number of coordinates to be speci ed.
BODY: A list of lines formatted as

```
INT INT INT INT REAL
```

This indicates the PSD constraint index $i \in \mathcal{I}^{PSD}$, the scalar variable index $j \in \mathcal{J}$, the row index, the column index and the coe cient value. The number of lines should match the number stated in the header.

DCOORD

Description: Input sparse coordinates (quadruplets) to de ne the symmetric matrices, D_i, as used in the PSD constraints.
HEADER: One line formatted as

```
INT
```

This is the number of coordinates to be speci ed.
BODY: A list of lines formatted as:

```
INT INT INT REAL
```

This indicates the PSD constraint index $i \in \mathcal{I}^{PSD}$, the row index, the column index and the coe cient value. The number of lines should match the number stated in the header.

CHANGE

Start of a new instance speci cation based on changes to the previous. Can be interpreted as the end of le when the hotstart-sequence is unsupported or undesired.
BODY: None
Header: None

16.4.5 CBF Format Examples

Minimal Working Example

The conic optimization problem (16.11) , has three variables in a quadratic cone - rst one is integer - and an a ne expression in domain 0 (equality constraint).

$$\begin{array}{ll} \text{minimize} & 5.1\,x_0 \\ \text{subject to} & 6.2\,x_1 + 7.3\,x_2 - 8.4 \in \{0\} \\ & x \in \mathcal{Q}^3,\ x_0 \in \mathbb{Z}. \end{array} \tag{16.11}$$

Its formulation in the Conic Benchmark Format begins with the version of the CBF format used, to safeguard against later revisions.

```
VER
1
```

Next follows the problem structure, consisting of the objective sense, the number and domain of variables, the indices of integer variables, and the number and domain of scalar-valued a ne expressions (i.e., the equality constraint).

```
OBJSENSE
MIN

VAR
3 1
Q 3

INT
1
0
```

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```
CON
1 1
L= 1
```

Finally follows the problem data, consisting of the coe cients of the objective, the coe cients of the constraints, and the constant terms of the constraints. All data is speci ed on a sparse coordinate form.

```
OBJACOORD
1
0 5.1

ACOORD
2
0 1 6.2
0 2 7.3

BCOORD
1
0 -8.4
```

This concludes the example.

Mixing Linear, Second-order and Semidefinite Cones

The conic optimization problem (16.12), has a semide nite cone, a quadratic cone over unordered subindices, and two equality constraints.

$$
\begin{array}{lrcl}
\text{minimize} & \left\langle \begin{bmatrix} 2 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix}, X_1 \right\rangle + x_1 & & \\
\text{subject to} & \left\langle \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, X_1 \right\rangle + x_1 & = & 1.0\,, \\
& \left\langle \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, X_1 \right\rangle + x_0 + x_2 & = & 0.5\,, \\
& x_1 \geq \sqrt{x_0^2 + x_2^2}\,, & & \\
& X_1 \succeq \mathbf{0}\,. & &
\end{array}
\tag{16.12}
$$

The equality constraints are easily rewritten to the conic form, $(g_0, g_1) \in \{0\}^2$, by moving constants such that the right-hand-side becomes zero. The quadratic cone does not t under the VAR keyword in this variable permutation. Instead, it takes a scalar constraint $(g_2, g_3, g_4) = (x_1, x_0, x_2) \in \mathcal{Q}^3$, with scalar variables constructed as $(x_0, x_1, x_2) \in \mathbb{R}^3$. Its formulation in the CBF format is reported in the following list

```
# File written using this version of the Conic Benchmark Format:
#     | Version 1.
VER
1

# The sense of the objective is:
#     | Minimize.
OBJSENSE
MIN

# One PSD variable of this size:
#     | Three times three.
PSDVAR
1
3
```

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```
# Three scalar variables in this one conic domain:
#     | Three are free.
VAR
3 1
F 3

# Five scalar constraints with affine expressions in two conic domains:
#     | Two are fixed to zero.
#     | Three are in conic quadratic domain.
CON
5 2
L= 2
Q 3

# Five coordinates in F^{obj}_j coefficients:
#     | F^{obj}[0][0,0] = 2.0
#     | F^{obj}[0][1,0] = 1.0
#     | and more...
OBJFCOORD
5
0 0 0 2.0
0 1 0 1.0
0 1 1 2.0
0 2 1 1.0
0 2 2 2.0

# One coordinate in a^{obj}_j coefficients:
#     | a^{obj}[1] = 1.0
OBJACOORD
1
1 1.0

# Nine coordinates in F_ij coefficients:
#     | F[0,0][0,0] = 1.0
#     | F[0,0][1,1] = 1.0
#     | and more...
FCOORD
9
0 0 0 0 1.0
0 0 1 1 1.0
0 0 2 2 1.0
1 0 0 0 1.0
1 0 1 0 1.0
1 0 2 0 1.0
1 0 1 1 1.0
1 0 2 1 1.0
1 0 2 2 1.0

# Six coordinates in a_ij coefficients:
#     | a[0,1] = 1.0
#     | a[1,0] = 1.0
#     | and more...
ACOORD
6
0 1 1.0
1 0 1.0
1 2 1.0
2 1 1.0
3 0 1.0
4 2 1.0
```

(continues on next page)

(continued from previous page)

```
# Two coordinates in b_i coefficients:
#     | b[0] = -1.0
#     | b[1] = -0.5
BCOORD
2
0 -1.0
1 -0.5
```

Mixing Semidefinite Variables and Linear Matrix Inequalities

The standard forms in semide nite optimization are usually based either on semide nite variables or linear matrix inequalities. In the CBF format, both forms are supported and can even be mixed as shown in.

$$\begin{array}{lll} \text{minimize} & \left\langle \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, X_1 \right\rangle + x_1 + x_2 + 1 & \\ \text{subject to} & \left\langle \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, X_1 \right\rangle - x_1 - x_2 & \geq \quad 0.0\,, \\ & x_1 \begin{bmatrix} 0 & 1 \\ 1 & 3 \end{bmatrix} + x_2 \begin{bmatrix} 3 & 1 \\ 1 & 0 \end{bmatrix} - \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & \succeq \quad \mathbf{0}\,, \\ & X_1 \succeq \mathbf{0}\,. & \end{array} \tag{16.13}$$

Its formulation in the CBF format is written in what follows

```
# File written using this version of the Conic Benchmark Format:
#     | Version 1.
VER
1

# The sense of the objective is:
#     | Minimize.
OBJSENSE
MIN

# One PSD variable of this size:
#     | Two times two.
PSDVAR
1
2

# Two scalar variables in this one conic domain:
#     | Two are free.
VAR
2 1
F 2

# One PSD constraint of this size:
#     | Two times two.
PSDCON
1
2

# One scalar constraint with an affine expression in this one conic domain:
#     | One is greater than or equal to zero.
CON
1 1
L+ 1

# Two coordinates in F^{obj}_j coefficients:
```

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```
#     | F^{obj}[0][0,0] = 1.0
#     | F^{obj}[0][1,1] = 1.0
OBJFCOORD
2
0 0 0 1.0
0 1 1 1.0

# Two coordinates in a^{obj}_j coefficients:
#     | a^{obj}[0] = 1.0
#     | a^{obj}[1] = 1.0
OBJACOORD
2
0 1.0
1 1.0

# One coordinate in b^{obj} coefficient:
#     | b^{obj} = 1.0
OBJBCOORD
1.0

# One coordinate in F_ij coefficients:
#     | F[0,0][1,0] = 1.0
FCOORD
1
0 0 1 0 1.0

# Two coordinates in a_ij coefficients:
#     | a[0,0] = -1.0
#     | a[0,1] = -1.0
ACOORD
2
0 0 -1.0
0 1 -1.0

# Four coordinates in H_ij coefficients:
#     | H[0,0][1,0] = 1.0
#     | H[0,0][1,1] = 3.0
#     | and more...
HCOORD
4
0 0 1 0 1.0
0 0 1 1 3.0
0 1 0 0 3.0
0 1 1 0 1.0

# Two coordinates in D_i coefficients:
#     | D[0][0,0] = -1.0
#     | D[0][1,1] = -1.0
DCOORD
2
0 0 0 -1.0
0 1 1 -1.0
```

Optimization Over a Sequence of Objectives

The linear optimization problem (16.14), is de ned for a sequence of objectives such that hotstarting from one to the next might be advantages.

$$\begin{array}{lll} \text{maximize}_k & g_k^{obj} & \\ \text{subject to} & 50\,x_0 + 31 & \leq \quad 250\,, \\ & 3\,x_0 - 2x_1 & \geq \quad -4\,, \\ & x \in \mathbb{R}^2_+, & \end{array} \tag{16.14}$$

16.7 The JSON Format

MOSEK provides the possibility to read/write problems in valid JSON format.

JSON (JavaScript Object Notation) is a lightweight data-interchange format. It is easy for humans to read and write. It is easy for machines to parse and generate. It is based on a subset of the JavaScript Programming Language, Standard ECMA-262 3rd Edition - December 1999. JSON is a text format that is completely language independent but uses conventions that are familiar to programmers of the C-family of languages, including C, C++, C#, Java, JavaScript, Perl, Python, and many others. These properties make JSON an ideal data-interchange language.

The o cial JSON website http://www.json.org provides plenty of information along with the format de nition.

MOSEK de nes two JSON-like formats:

- jtask
- jsol

Despite being text-based human-readable formats *jtask* and *jsol* les will include no indentation and no new-lines, in order to keep the les as compact as possible. We therefore strongly advise to use JSON viewer tools to inspect *jtask* and *jsol* les.

16.7.1 *jtask* format

It stores a problem instance. The *jtask* format contains the same information as a *task format*. Even though a *jtask* le is human-readable, we do not recommend users to create it by hand, but to rely on **MOSEK**.

16.7.2 *jsol* format

It stores a problem solution. The *jsol* format contains all solutions and information items.

16.7.3 A *jtask* example

In Listing 16.6 we present a le in the *jtask* format that corresponds to the sample problem fromlo1.lp . The listing has been formatted for readability.

Listing 16.6: A formatted *jtask* le for the lo1.lp example.

```
{
    "$schema":"http://mosek.com/json/schema#",
    "Task/INFO":{
        "taskname":"lo1",
        "numvar":4,
        "numcon":3,
        "numcone":0,
        "numbarvar":0,
        "numanz":9,
        "numsymmat":0,
        "mosekver":[
            8,
            0,
            0,
            9
        ]
    },
    "Task/data":{
        "var":{
            "name":[
                "x1",
                "x2",
                "x3",
```

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```
                "x4"
            ],
            "bk":[
                "lo",
                "ra",
                "lo",
                "lo"
            ],
            "bl":[
                0.0,
                0.0,
                0.0,
                0.0
            ],
            "bu":[
                1e+30,
                1e+1,
                1e+30,
                1e+30
            ],
            "type":[
                "cont",
                "cont",
                "cont",
                "cont"
            ]
        },
        "con":{
            "name":[
                "c1",
                "c2",
                "c3"
            ],
            "bk":[
                "fx",
                "lo",
                "up"
            ],
            "bl":[
                3e+1,
                1.5e+1,
                    -1e+30
            ],
            "bu":[
                3e+1,
                1e+30,
                2.5e+1
            ]
        },
        "objective":{
            "sense":"max",
            "name":"obj",
            "c":{
                "subj":[
                    0,
                    1,
                    2,
                    3
                ],
                "val":[
                    3e+0,
```


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```
                    1e+0,
                    5e+0,
                    1e+0
                ]
            },
            "cfix":0.0
        },
        "A":{
            "subi":[
                0,
                0,
                0,
                1,
                1,
                1,
                1,
                2,
                2
            ],
            "subj":[
                0,
                1,
                2,
                0,
                1,
                2,
                3,
                1,
                3
            ],
            "val":[
                3e+0,
                1e+0,
                2e+0,
                2e+0,
                1e+0,
                3e+0,
                1e+0,
                2e+0,
                3e+0
            ]
        }
    },
    "Task/parameters":{
        "iparam":{
            "ANA_SOL_BASIS":"ON",
            "ANA_SOL_PRINT_VIOLATED":"OFF",
            "AUTO_SORT_A_BEFORE_OPT":"OFF",
            "AUTO_UPDATE_SOL_INFO":"OFF",
            "BASIS_SOLVE_USE_PLUS_ONE":"OFF",
            "BI_CLEAN_OPTIMIZER":"OPTIMIZER_FREE",
            "BI_IGNORE_MAX_ITER":"OFF",
            "BI_IGNORE_NUM_ERROR":"OFF",
            "BI_MAX_ITERATIONS":1000000,
            "CACHE_LICENSE":"ON",
            "CHECK_CONVEXITY":"CHECK_CONVEXITY_FULL",
            "COMPRESS_STATFILE":"ON",
            "CONCURRENT_NUM_OPTIMIZERS":2,
            "CONCURRENT_PRIORITY_DUAL_SIMPLEX":2,
            "CONCURRENT_PRIORITY_FREE_SIMPLEX":3,
            "CONCURRENT_PRIORITY_INTPNT":4,
```


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```
"CONCURRENT_PRIORITY_PRIMAL_SIMPLEX":1,
"FEASREPAIR_OPTIMIZE":"FEASREPAIR_OPTIMIZE_NONE",
"INFEAS_GENERIC_NAMES":"OFF",
"INFEAS_PREFER_PRIMAL":"ON",
"INFEAS_REPORT_AUTO":"OFF",
"INFEAS_REPORT_LEVEL":1,
"INTPNT_BASIS":"BI_ALWAYS",
"INTPNT_DIFF_STEP":"ON",
"INTPNT_FACTOR_DEBUG_LVL":0,
"INTPNT_FACTOR_METHOD":0,
"INTPNT_HOTSTART":"INTPNT_HOTSTART_NONE",
"INTPNT_MAX_ITERATIONS":400,
"INTPNT_MAX_NUM_COR":-1,
"INTPNT_MAX_NUM_REFINEMENT_STEPS":-1,
"INTPNT_OFF_COL_TRH":40,
"INTPNT_ORDER_METHOD":"ORDER_METHOD_FREE",
"INTPNT_REGULARIZATION_USE":"ON",
"INTPNT_SCALING":"SCALING_FREE",
"INTPNT_SOLVE_FORM":"SOLVE_FREE",
"INTPNT_STARTING_POINT":"STARTING_POINT_FREE",
"LIC_TRH_EXPIRY_WRN":7,
"LICENSE_DEBUG":"OFF",
"LICENSE_PAUSE_TIME":0,
"LICENSE_SUPPRESS_EXPIRE_WRNS":"OFF",
"LICENSE_WAIT":"OFF",
"LOG":10,
"LOG_ANA_PRO":1,
"LOG_BI":4,
"LOG_BI_FREQ":2500,
"LOG_CHECK_CONVEXITY":0,
"LOG_CONCURRENT":1,
"LOG_CUT_SECOND_OPT":1,
"LOG_EXPAND":0,
"LOG_FACTOR":1,
"LOG_FEAS_REPAIR":1,
"LOG_FILE":1,
"LOG_HEAD":1,
"LOG_INFEAS_ANA":1,
"LOG_INTPNT":4,
"LOG_MIO":4,
"LOG_MIO_FREQ":1000,
"LOG_OPTIMIZER":1,
"LOG_ORDER":1,
"LOG_PRESOLVE":1,
"LOG_RESPONSE":0,
"LOG_SENSITIVITY":1,
"LOG_SENSITIVITY_OPT":0,
"LOG_SIM":4,
"LOG_SIM_FREQ":1000,
"LOG_SIM_MINOR":1,
"LOG_STORAGE":1,
"MAX_NUM_WARNINGS":10,
"MIO_BRANCH_DIR":"BRANCH_DIR_FREE",
"MIO_CONSTRUCT_SOL":"OFF",
"MIO_CUT_CLIQUE":"ON",
"MIO_CUT_CMIR":"ON",
"MIO_CUT_GMI":"ON",
"MIO_CUT_KNAPSACK_COVER":"OFF",
"MIO_HEURISTIC_LEVEL":-1,
"MIO_MAX_NUM_BRANCHES":-1,
"MIO_MAX_NUM_RELAXS":-1,
```


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```
"MIO_MAX_NUM_SOLUTIONS":-1,
"MIO_MODE":"MIO_MODE_SATISFIED",
"MIO_MT_USER_CB":"ON",
"MIO_NODE_OPTIMIZER":"OPTIMIZER_FREE",
"MIO_NODE_SELECTION":"MIO_NODE_SELECTION_FREE",
"MIO_PERSPECTIVE_REFORMULATE":"ON",
"MIO_PROBING_LEVEL":-1,
"MIO_RINS_MAX_NODES":-1,
"MIO_ROOT_OPTIMIZER":"OPTIMIZER_FREE",
"MIO_ROOT_REPEAT_PRESOLVE_LEVEL":-1,
"MT_SPINCOUNT":0,
"NUM_THREADS":0,
"OPF_MAX_TERMS_PER_LINE":5,
"OPF_WRITE_HEADER":"ON",
"OPF_WRITE_HINTS":"ON",
"OPF_WRITE_PARAMETERS":"OFF",
"OPF_WRITE_PROBLEM":"ON",
"OPF_WRITE_SOL_BAS":"ON",
"OPF_WRITE_SOL_ITG":"ON",
"OPF_WRITE_SOL_ITR":"ON",
"OPF_WRITE_SOLUTIONS":"OFF",
"OPTIMIZER":"OPTIMIZER_FREE",
"PARAM_READ_CASE_NAME":"ON",
"PARAM_READ_IGN_ERROR":"OFF",
"PRESOLVE_ELIMINATOR_MAX_FILL":-1,
"PRESOLVE_ELIMINATOR_MAX_NUM_TRIES":-1,
"PRESOLVE_LEVEL":-1,
"PRESOLVE_LINDEP_ABS_WORK_TRH":100,
"PRESOLVE_LINDEP_REL_WORK_TRH":100,
"PRESOLVE_LINDEP_USE":"ON",
"PRESOLVE_MAX_NUM_REDUCTIONS":-1,
"PRESOLVE_USE":"PRESOLVE_MODE_FREE",
"PRIMAL_REPAIR_OPTIMIZER":"OPTIMIZER_FREE",
"QO_SEPARABLE_REFORMULATION":"OFF",
"READ_DATA_COMPRESSED":"COMPRESS_FREE",
"READ_DATA_FORMAT":"DATA_FORMAT_EXTENSION",
"READ_DEBUG":"OFF",
"READ_KEEP_FREE_CON":"OFF",
"READ_LP_DROP_NEW_VARS_IN_BOU":"OFF",
"READ_LP_QUOTED_NAMES":"ON",
"READ_MPS_FORMAT":"MPS_FORMAT_FREE",
"READ_MPS_WIDTH":1024,
"READ_TASK_IGNORE_PARAM":"OFF",
"SENSITIVITY_ALL":"OFF",
"SENSITIVITY_OPTIMIZER":"OPTIMIZER_FREE_SIMPLEX",
"SENSITIVITY_TYPE":"SENSITIVITY_TYPE_BASIS",
"SIM_BASIS_FACTOR_USE":"ON",
"SIM_DEGEN":"SIM_DEGEN_FREE",
"SIM_DUAL_CRASH":90,
"SIM_DUAL_PHASEONE_METHOD":0,
"SIM_DUAL_RESTRICT_SELECTION":50,
"SIM_DUAL_SELECTION":"SIM_SELECTION_FREE",
"SIM_EXPLOIT_DUPVEC":"SIM_EXPLOIT_DUPVEC_OFF",
"SIM_HOTSTART":"SIM_HOTSTART_FREE",
"SIM_HOTSTART_LU":"ON",
"SIM_INTEGER":0,
"SIM_MAX_ITERATIONS":10000000,
"SIM_MAX_NUM_SETBACKS":250,
"SIM_NON_SINGULAR":"ON",
"SIM_PRIMAL_CRASH":90,
"SIM_PRIMAL_PHASEONE_METHOD":0,
```


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```
            "SIM_PRIMAL_RESTRICT_SELECTION":50,
            "SIM_PRIMAL_SELECTION":"SIM_SELECTION_FREE",
            "SIM_REFACTOR_FREQ":0,
            "SIM_REFORMULATION":"SIM_REFORMULATION_OFF",
            "SIM_SAVE_LU":"OFF",
            "SIM_SCALING":"SCALING_FREE",
            "SIM_SCALING_METHOD":"SCALING_METHOD_POW2",
            "SIM_SOLVE_FORM":"SOLVE_FREE",
            "SIM_STABILITY_PRIORITY":50,
            "SIM_SWITCH_OPTIMIZER":"OFF",
            "SOL_FILTER_KEEP_BASIC":"OFF",
            "SOL_FILTER_KEEP_RANGED":"OFF",
            "SOL_READ_NAME_WIDTH":-1,
            "SOL_READ_WIDTH":1024,
            "SOLUTION_CALLBACK":"OFF",
            "TIMING_LEVEL":1,
            "WRITE_BAS_CONSTRAINTS":"ON",
            "WRITE_BAS_HEAD":"ON",
            "WRITE_BAS_VARIABLES":"ON",
            "WRITE_DATA_COMPRESSED":0,
            "WRITE_DATA_FORMAT":"DATA_FORMAT_EXTENSION",
            "WRITE_DATA_PARAM":"OFF",
            "WRITE_FREE_CON":"OFF",
            "WRITE_GENERIC_NAMES":"OFF",
            "WRITE_GENERIC_NAMES_IO":1,
            "WRITE_IGNORE_INCOMPATIBLE_CONIC_ITEMS":"OFF",
            "WRITE_IGNORE_INCOMPATIBLE_ITEMS":"OFF",
            "WRITE_IGNORE_INCOMPATIBLE_NL_ITEMS":"OFF",
            "WRITE_IGNORE_INCOMPATIBLE_PSD_ITEMS":"OFF",
            "WRITE_INT_CONSTRAINTS":"ON",
            "WRITE_INT_HEAD":"ON",
            "WRITE_INT_VARIABLES":"ON",
            "WRITE_LP_FULL_OBJ":"ON",
            "WRITE_LP_LINE_WIDTH":80,
            "WRITE_LP_QUOTED_NAMES":"ON",
            "WRITE_LP_STRICT_FORMAT":"OFF",
            "WRITE_LP_TERMS_PER_LINE":10,
            "WRITE_MPS_FORMAT":"MPS_FORMAT_FREE",
            "WRITE_MPS_INT":"ON",
            "WRITE_PRECISION":15,
            "WRITE_SOL_BARVARIABLES":"ON",
            "WRITE_SOL_CONSTRAINTS":"ON",
            "WRITE_SOL_HEAD":"ON",
            "WRITE_SOL_IGNORE_INVALID_NAMES":"OFF",
            "WRITE_SOL_VARIABLES":"ON",
            "WRITE_TASK_INC_SOL":"ON",
            "WRITE_XML_MODE":"WRITE_XML_MODE_ROW"
        },
        "dparam":{
            "ANA_SOL_INFEAS_TOL":1e-6,
            "BASIS_REL_TOL_S":1e-12,
            "BASIS_TOL_S":1e-6,
            "BASIS_TOL_X":1e-6,
            "CHECK_CONVEXITY_REL_TOL":1e-10,
            "DATA_TOL_AIJ":1e-12,
            "DATA_TOL_AIJ_HUGE":1e+20,
            "DATA_TOL_AIJ_LARGE":1e+10,
            "DATA_TOL_BOUND_INF":1e+16,
            "DATA_TOL_BOUND_WRN":1e+8,
            "DATA_TOL_C_HUGE":1e+16,
            "DATA_TOL_CJ_LARGE":1e+8,
```

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```
            "DATA_TOL_QIJ":1e-16,
            "DATA_TOL_X":1e-8,
            "FEASREPAIR_TOL":1e-10,
            "INTPNT_CO_TOL_DFEAS":1e-8,
            "INTPNT_CO_TOL_INFEAS":1e-10,
            "INTPNT_CO_TOL_MU_RED":1e-8,
            "INTPNT_CO_TOL_NEAR_REL":1e+3,
            "INTPNT_CO_TOL_PFEAS":1e-8,
            "INTPNT_CO_TOL_REL_GAP":1e-7,
            "INTPNT_NL_MERIT_BAL":1e-4,
            "INTPNT_NL_TOL_DFEAS":1e-8,
            "INTPNT_NL_TOL_MU_RED":1e-12,
            "INTPNT_NL_TOL_NEAR_REL":1e+3,
            "INTPNT_NL_TOL_PFEAS":1e-8,
            "INTPNT_NL_TOL_REL_GAP":1e-6,
            "INTPNT_NL_TOL_REL_STEP":9.95e-1,
            "INTPNT_QO_TOL_DFEAS":1e-8,
            "INTPNT_QO_TOL_INFEAS":1e-10,
            "INTPNT_QO_TOL_MU_RED":1e-8,
            "INTPNT_QO_TOL_NEAR_REL":1e+3,
            "INTPNT_QO_TOL_PFEAS":1e-8,
            "INTPNT_QO_TOL_REL_GAP":1e-8,
            "INTPNT_TOL_DFEAS":1e-8,
            "INTPNT_TOL_DSAFE":1e+0,
            "INTPNT_TOL_INFEAS":1e-10,
            "INTPNT_TOL_MU_RED":1e-16,
            "INTPNT_TOL_PATH":1e-8,
            "INTPNT_TOL_PFEAS":1e-8,
            "INTPNT_TOL_PSAFE":1e+0,
            "INTPNT_TOL_REL_GAP":1e-8,
            "INTPNT_TOL_REL_STEP":9.999e-1,
            "INTPNT_TOL_STEP_SIZE":1e-6,
            "LOWER_OBJ_CUT":-1e+30,
            "LOWER_OBJ_CUT_FINITE_TRH":-5e+29,
            "MIO_DISABLE_TERM_TIME":-1e+0,
            "MIO_MAX_TIME":-1e+0,
            "MIO_MAX_TIME_APRX_OPT":6e+1,
            "MIO_NEAR_TOL_ABS_GAP":0.0,
            "MIO_NEAR_TOL_REL_GAP":1e-3,
            "MIO_REL_GAP_CONST":1e-10,
            "MIO_TOL_ABS_GAP":0.0,
            "MIO_TOL_ABS_RELAX_INT":1e-5,
            "MIO_TOL_FEAS":1e-6,
            "MIO_TOL_REL_DUAL_BOUND_IMPROVEMENT":0.0,
            "MIO_TOL_REL_GAP":1e-4,
            "MIO_TOL_X":1e-6,
            "OPTIMIZER_MAX_TIME":-1e+0,
            "PRESOLVE_TOL_ABS_LINDEP":1e-6,
            "PRESOLVE_TOL_AIJ":1e-12,
            "PRESOLVE_TOL_REL_LINDEP":1e-10,
            "PRESOLVE_TOL_S":1e-8,
            "PRESOLVE_TOL_X":1e-8,
            "QCQO_REFORMULATE_REL_DROP_TOL":1e-15,
            "SEMIDEFINITE_TOL_APPROX":1e-10,
            "SIM_LU_TOL_REL_PIV":1e-2,
            "SIMPLEX_ABS_TOL_PIV":1e-7,
            "UPPER_OBJ_CUT":1e+30,
            "UPPER_OBJ_CUT_FINITE_TRH":5e+29
        },
        "sparam":{
            "BAS_SOL_FILE_NAME":"",
```


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```
            "DATA_FILE_NAME":"examples/tools/data/lo1.mps",
            "DEBUG_FILE_NAME":"",
            "INT_SOL_FILE_NAME":"",
            "ITR_SOL_FILE_NAME":"",
            "MIO_DEBUG_STRING":"",
            "PARAM_COMMENT_SIGN":"%%",
            "PARAM_READ_FILE_NAME":"",
            "PARAM_WRITE_FILE_NAME":"",
            "READ_MPS_BOU_NAME":"",
            "READ_MPS_OBJ_NAME":"",
            "READ_MPS_RAN_NAME":"",
            "READ_MPS_RHS_NAME":"",
            "SENSITIVITY_FILE_NAME":"",
            "SENSITIVITY_RES_FILE_NAME":"",
            "SOL_FILTER_XC_LOW":"",
            "SOL_FILTER_XC_UPR":"",
            "SOL_FILTER_XX_LOW":"",
            "SOL_FILTER_XX_UPR":"",
            "STAT_FILE_NAME":"",
            "STAT_KEY":"",
            "STAT_NAME":"",
            "WRITE_LP_GEN_VAR_NAME":"XMSKGEN"
        }
    }
}
```

16.8 The Solution File Format

MOSEK provides several solution files depending on the problem type and the optimizer used:

- *basis solution file* (extension .bas) if the problem is optimized using the simplex optimizer or basis identification is performed,
- *interior solution file* (extension .sol) if a problem is optimized using the interior-point optimizer and no basis identification is required,
- *integer solution file* (extension .int) if the problem contains integer constrained variables.

All solution files have the format:

```
NAME                : <problem name>
PROBLEM STATUS      : <status of the problem>
SOLUTION STATUS     : <status of the solution>
OBJECTIVE NAME      : <name of the objective function>
PRIMAL OBJECTIVE    : <primal objective value corresponding to the solution>
DUAL OBJECTIVE      : <dual objective value corresponding to the solution>
CONSTRAINTS
INDEX   NAME     AT ACTIVITY    LOWER LIMIT   UPPER LIMIT   DUAL LOWER   DUAL UPPER
?       <name>   ?? <a value>   <a value>     <a value>     <a value>    <a value>
VARIABLES
INDEX   NAME     AT ACTIVITY    LOWER LIMIT   UPPER LIMIT   DUAL LOWER   DUAL UPPER    CONIC␣
↪DUAL
?       <name>   ?? <a value>   <a value>     <a value>     <a value>    <a value>     <a value>
```

In the example the fields ? and <> will be filled with problem and solution specific information. As can be observed a solution report consists of three sections, i.e.

- HEADER In this section, first the name of the problem is listed and afterwards the problem and solution status are shown. Next the primal and dual objective values are displayed.

- CONSTRAINTS: For each constraint i of the form

$$l_i^c \quad \sum_{j=1}^{n} a_{ij} x_j \quad u_i^c; \tag{16.15}$$

the following information is listed:

INDEX: A sequential index assigned to the constraint by MOSEK.
NAME: The name of the constraint assigned by the user.
AT: The status of the constraint. In Table 16.4 the possible values of the status keys and their interpretation are shown.

Table 16.4: Status keys.

Status key	Interpretation
UN	Unknown status
BS	Is basic
SB	Is superbasic
LL	Is at the lower limit (bound)
UL	Is at the upper limit (bound)
EQ	Lower limit is identical to upper limit
**	Is infeasible i.e. the lower limit is greater than the upper limit.

ACTIVITY: the quantity $\sum_{j=1}^{n} a_{ij} x_j$, where x is the value of the primal solution.
LOWER LIMIT: The quantity l_i^c (see (16.15).)
UPPER LIMIT: The quantity u_i^c (see (16.15).)
DUAL LOWER: The dual multiplier corresponding to the lower limit on the constraint.
DUAL UPPER: The dual multiplier corresponding to the upper limit on the constraint.

- VARIABLES: The last section of the solution report lists information about the variables. This information has a similar interpretation as for the constraints. However, the column with the header CONIC DUAL is included for problems having one or more conic constraints. This column shows the dual variables corresponding to the conic constraints.

Example: lo1.sol

In Listing 16.7 we show the solution file for the lo1.opf problem.

Listing 16.7: An example of .sol file.

```
NAME                    :
PROBLEM STATUS          : PRIMAL_AND_DUAL_FEASIBLE
SOLUTION STATUS         : OPTIMAL
OBJECTIVE NAME          : obj
PRIMAL OBJECTIVE        : 8.33333333e+01
DUAL OBJECTIVE          : 8.33333332e+01

CONSTRAINTS
INDEX      NAME          AT ACTIVITY                LOWER LIMIT        UPPER LIMIT
. DUAL LOWER             DUAL UPPER
0          c1            EQ 3.00000000000000e+01    3.00000000e+01     3.00000000e+01     -0.
. 00000000000000e+00     -2.49999999741653e+00
1          c2            SB 5.33333333049187e+01    1.50000000e+01     NONE               2.
. 09159033069640e-10     -0.00000000000000e+00
2          c3            UL 2.49999999842049e+01    NONE               2.50000000e+01     -0.
. 00000000000000e+00     -3.33333332895108e-01

VARIABLES
INDEX      NAME          AT ACTIVITY                LOWER LIMIT        UPPER LIMIT
. DUAL LOWER             DUAL UPPER
0          x1            LL 1.67020427038537e-09    0.00000000e+00     NONE               -4.
. 49999999528054e+00     -0.00000000000000e+00
```

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```
1          x2             LL 2.93510446211883e-09     0.00000000e+00     1.00000000e+01     -2.
↪16666666494915e+00    6.20868657679896e-10
2          x3             SB 1.49999999899424e+01     0.00000000e+00     NONE               -8.
↪79123177245553e-10    -0.00000000000000e+00
3          x4             SB 8.33333332273115e+00     0.00000000e+00     NONE               -1.
↪69795978848200e-09    -0.00000000000000e+00
```

Chapter 17

List of examples

List of examples shipped in the distribution of Optimization Toolbox for MATLAB:

Table 17.1: List of distributed examples

File	Description
advs.m	Advanced simplex hot-start examples
affco1.m	A simple problem using a ne conic constraints
affco2.m	A simple problem using a ne conic constraints
callback.m	An example of data/progress callback
callback_handler.m	Log handler de nition for callback.m
ceo1.m	A simple conic exponential problem
cqo1.m	A simple conic quadratic problem
feasrepairex1.m	A simple example of how to repair an infeasible problem
gp1.m	A simple geometric program (GP) in conic form
lo1.m	A simple linear problem using msklpopt
lo2.m	A simple linear problem using mosekopt
lo3.m	A simple linear problem using linprog
mico1.m	A simple mixed-integer conic problem
milo1.m	A simple mixed-integer linear problem
mioinitsol.m	A simple mixed-integer linear problem with an initial guess
normex.m	Demonstrates least squares and other norm minimization problems
opt_server_sync.m	UsesMOSEK OptServer to solve an optimization problem synchronously
parameters.m	Shows how to set optimizer parameters and read information items
portfolio_1_basic.m	Portfolio optimization - basic Markowitz model
portfolio_2_frontier.m	Portfolio optimization - e cient frontier
portfolio_3_impact.m	Portfolio optimization - market impact costs
portfolio_4_transcost.m	Portfolio optimization - transaction costs
portfolio_5_card.m	Portfolio optimization - cardinality constraints
pow1.m	A simple power cone problem
qcqo1.m	A simple quadratically constrained quadratic problem
qo1.m	A simple quadratic problem
qo2.m	A simple quadratic problem
reoptimization.m	Demonstrate how to modify and re-optimize a linear problem

Continued on next page

Table 17.1 – continued from previous page

File	Description
response.m	Demonstrates proper response handling
rlo1.m	Robust linear optimization example, part 1
rlo2.m	Robust linear optimization example, part 2
sdo1.m	A simple semide nite problem with one matrix variable and a quadratic cone
sdo2.m	A simple semide nite problem with two matrix variables
sensitivity.m	Sensitivity analysis performed on a small linear problem
sensitivity2.m	Sensitivity analysis performed on a small linear problem
simple.m	A simple I/O example: read problem from a le, solve and write solutions
solutionquality.m	Demonstrates how to examine the quality of a solution

Additional examples can be found on the **MOSEK** website and in other **MOSEK** publications.

Chapter 18

Interface changes

The section shows interface-specific changes to the **MOSEK** Optimization Toolbox for MATLAB in version 9.2 compared to version 8. See the release notes for general changes and new features of the **MOSEK** Optimization Suite.

18.1 Backwards compatibility

- **Parameters.** Users who set parameters to tune the performance and numerical properties of the solver (termination criteria, tolerances, solving primal or dual, presolve etc.) are recommended to reevaluate such tuning. It may be that other, or default, parameter settings will be more beneficial in the current version. The hints in Sec. 8 may be useful for some cases.
- Remove all Near solution statuses i.e. MSK_SOL_STA_NEAR_OPTIMAL, MSK_SOL_STA_NEAR_PRIM_INFEASIBLE, etc. See Sec. 13.3.3.
- All functions related to the general nonlinear optimizer and Scopt have been removed. See Sec. 15.8.

18.2 New API

Introduced a possibility to specify *affine conic constraints* i.e. conic constraints of the form $Fx + g \in K$ directly. See Sec. 6.7 and Sec. 12.5 for details.

18.3 Parameters

Added

- *MSK_IPAR_INTPNT_ORDER_GP_NUM_SEEDS*
- *MSK_IPAR_INTPNT_PURIFY*
- *MSK_IPAR_LOG_INCLUDE_SUMMARY*
- *MSK_IPAR_LOG_LOCAL_INFO*
- *MSK_IPAR_MIO_CONIC_OUTER_APPROXIMATION*
- *MSK_IPAR_MIO_FEASPUMP_LEVEL*
- *MSK_IPAR_MIO_MAX_NUM_ROOT_CUT_ROUNDS*
- *MSK_IPAR_MIO_PROPAGATE_OBJECTIVE_CONSTRAINT*
- *MSK_IPAR_MIO_SEED*
- *MSK_IPAR_OPF_WRITE_LINE_LENGTH*

- *MSK_IPAR_PRESOLVE_MAX_NUM_PASS*
- *MSK_IPAR_PTF_WRITE_TRANSFORM*
- *MSK_IPAR_SIM_SEED*
- *MSK_IPAR_WRITE_COMPRESSION*

Removed

- MSK_DPAR_DATA_TOL_AIJ
- MSK_DPAR_INTPNT_NL_MERIT_BAL
- MSK_DPAR_INTPNT_NL_TOL_DFEAS
- MSK_DPAR_INTPNT_NL_TOL_MU_RED
- MSK_DPAR_INTPNT_NL_TOL_NEAR_REL
- MSK_DPAR_INTPNT_NL_TOL_PFEAS
- MSK_DPAR_INTPNT_NL_TOL_REL_GAP
- MSK_DPAR_INTPNT_NL_TOL_REL_STEP
- MSK_DPAR_MIO_DISABLE_TERM_TIME
- MSK_DPAR_MIO_NEAR_TOL_ABS_GAP
- MSK_DPAR_MIO_NEAR_TOL_REL_GAP
- MSK_IPAR_MIO_CONSTRUCT_SOL
- MSK_IPAR_MIO_MT_USER_CB
- MSK_IPAR_OPF_MAX_TERMS_PER_LINE
- MSK_IPAR_READ_DATA_COMPRESSED
- MSK_IPAR_READ_DATA_FORMAT
- MSK_IPAR_WRITE_DATA_COMPRESSED
- MSK_IPAR_WRITE_DATA_FORMAT

18.4 Constants

Added

- *"MSK_COMPRESS_ZSTD"*
- *"MSK_CT_DEXP"*
- *"MSK_CT_DPOW"*
- *"MSK_CT_PEXP"*
- *"MSK_CT_PPOW"*
- *"MSK_CT_ZERO"*
- *"MSK_DATA_FORMAT_PTF"*

- *"MSK_IINF_MIO_NUMBIN"*
- *"MSK_IINF_MIO_NUMBINCONEVAR"*
- *"MSK_IINF_MIO_NUMCONE"*
- *"MSK_IINF_MIO_NUMCONEVAR"*
- *"MSK_IINF_MIO_NUMCONT"*
- *"MSK_IINF_MIO_NUMCONTCONEVAR"*
- *"MSK_IINF_MIO_NUMDEXPCONES"*
- *"MSK_IINF_MIO_NUMDPOWCONES"*
- *"MSK_IINF_MIO_NUMINTCONEVAR"*
- *"MSK_IINF_MIO_NUMPEXPCONES"*
- *"MSK_IINF_MIO_NUMPPOWCONES"*
- *"MSK_IINF_MIO_NUMQCONES"*
- *"MSK_IINF_MIO_NUMRQCONES"*
- *"MSK_IINF_MIO_PRESOLVED_NUMBINCONEVAR"*
- *"MSK_IINF_MIO_PRESOLVED_NUMCONE"*
- *"MSK_IINF_MIO_PRESOLVED_NUMCONEVAR"*
- *"MSK_IINF_MIO_PRESOLVED_NUMCONTCONEVAR"*
- *"MSK_IINF_MIO_PRESOLVED_NUMDEXPCONES"*
- *"MSK_IINF_MIO_PRESOLVED_NUMDPOWCONES"*
- *"MSK_IINF_MIO_PRESOLVED_NUMINTCONEVAR"*
- *"MSK_IINF_MIO_PRESOLVED_NUMPEXPCONES"*
- *"MSK_IINF_MIO_PRESOLVED_NUMPPOWCONES"*
- *"MSK_IINF_MIO_PRESOLVED_NUMQCONES"*
- *"MSK_IINF_MIO_PRESOLVED_NUMRQCONES"*
- *"MSK_IINF_PURIFY_DUAL_SUCCESS"*
- *"MSK_IINF_PURIFY_PRIMAL_SUCCESS"*
- *"MSK_LIINF_MIO_ANZ"*

Removed

- MSK_DATAFORMAT_XML
- MSK_DINFITEM_MIO_HEURISTIC_TIME
- MSK_DINFITEM_MIO_OPTIMIZER_TIME
- MSK_IINFITEM_MIO_CONSTRUCT_NUM_ROUNDINGS
- MSK_IINFITEM_MIO_INITIAL_SOLUTION

- MSK_IINFITEM_MIO_NEAR_ABSGAP_SATISFIED
- MSK_IINFITEM_MIO_NEAR_RELGAP_SATISFIED
- MSK_LIINFITEM_MIO_SIM_MAXITER_SETBACKS
- MSK_MIONODESELTYPE_HYBRID
- MSK_MIONODESELTYPE_WORST
- MSK_PROBLEMTYPE_GECO
- MSK_PROSTA_NEAR_DUAL_FEAS
- MSK_PROSTA_NEAR_PRIM_AND_DUAL_FEAS
- MSK_PROSTA_NEAR_PRIM_FEAS
- MSK_SENSITIVITYTYPE_OPTIMAL_PARTITION
- MSK_SOLSTA_NEAR_DUAL_FEAS
- MSK_SOLSTA_NEAR_DUAL_INFEAS_CER
- MSK_SOLSTA_NEAR_INTEGER_OPTIMAL
- MSK_SOLSTA_NEAR_OPTIMAL
- MSK_SOLSTA_NEAR_PRIM_AND_DUAL_FEAS
- MSK_SOLSTA_NEAR_PRIM_FEAS
- MSK_SOLSTA_NEAR_PRIM_INFEAS_CER

18.5 Response Codes

Added

- *"MSK_RES_ERR_APPENDING_TOO_BIG_CONE"*
- *"MSK_RES_ERR_CBF_DUPLICATE_POW_CONES"*
- *"MSK_RES_ERR_CBF_DUPLICATE_POW_STAR_CONES"*
- *"MSK_RES_ERR_CBF_INVALID_DIMENSION_OF_CONES"*
- *"MSK_RES_ERR_CBF_INVALID_EXP_DIMENSION"*
- *"MSK_RES_ERR_CBF_INVALID_NUMBER_OF_CONES"*
- *"MSK_RES_ERR_CBF_INVALID_POWER"*
- *"MSK_RES_ERR_CBF_INVALID_POWER_CONE_INDEX"*
- *"MSK_RES_ERR_CBF_INVALID_POWER_STAR_CONE_INDEX"*
- *"MSK_RES_ERR_CBF_POWER_CONE_IS_TOO_LONG"*
- *"MSK_RES_ERR_CBF_POWER_CONE_MISMATCH"*
- *"MSK_RES_ERR_CBF_POWER_STAR_CONE_MISMATCH"*
- *"MSK_RES_ERR_CBF_UNHANDLED_POWER_CONE_TYPE"*
- *"MSK_RES_ERR_CBF_UNHANDLED_POWER_STAR_CONE_TYPE"*

- *"MSK_RES_ERR_CONE_PARAMETER"*
- *"MSK_RES_ERR_FORMAT_STRING"*
- *"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_CFIX"*
- *"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_FREE_CONSTRAINTS"*
- *"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_NONLINEAR"*
- *"MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_RANGED_CONSTRAINTS"*
- *"MSK_RES_ERR_NUM_ARGUMENTS"*
- *"MSK_RES_ERR_PTF_FORMAT"*
- *"MSK_RES_ERR_SERVER_PROBLEM_SIZE"*
- *"MSK_RES_ERR_SHAPE_IS_TOO_LARGE"*
- *"MSK_RES_ERR_SLICE_SIZE"*
- *"MSK_RES_ERR_TOO_SMALL_A_TRUNCATION_VALUE"*
- *"MSK_RES_WRN_EXP_CONES_WITH_VARIABLES_FIXED_AT_ZERO"*
- *"MSK_RES_WRN_POW_CONES_WITH_ROOT_FIXED_AT_ZERO"*

Removed

- MSK_RES_ERR_CANNOT_CLONE_NL
- MSK_RES_ERR_CANNOT_HANDLE_NL
- MSK_RES_ERR_INVALID_ACCMODE
- MSK_RES_ERR_INVALID_FILE_FORMAT_FOR_GENERAL_NL
- MSK_RES_ERR_NONLINEAR_FUNCTIONS_NOT_ALLOWED
- MSK_RES_ERR_NR_ARGUMENTS
- MSK_RES_ERR_OPEN_DL
- MSK_RES_ERR_USER_FUNC_RET
- MSK_RES_ERR_USER_FUNC_RET_DATA
- MSK_RES_ERR_USER_NLO_EVAL
- MSK_RES_ERR_USER_NLO_EVAL_HESSUBI
- MSK_RES_ERR_USER_NLO_EVAL_HESSUBJ
- MSK_RES_ERR_USER_NLO_FUNC
- MSK_RES_TRM_MIO_NEAR_ABS_GAP
- MSK_RES_TRM_MIO_NEAR_REL_GAP
- MSK_RES_WRN_CONSTRUCT_INVALID_SOL_ITG
- MSK_RES_WRN_CONSTRUCT_NO_SOL_ITG
- MSK_RES_WRN_CONSTRUCT_SOLUTION_INFEAS
- MSK_RES_WRN_NO_NONLINEAR_FUNCTION_WRITE

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Symbol Index

Enumerations

basindtype , 226
"MSK_BI_RESERVERED", 226
"MSK_BI_NO_ERROR", 226
"MSK_BI_NEVER", 226
"MSK_BI_IF_FEASIBLE", 226
"MSK_BI_ALWAYS", 226
boundkey, 226
"MSK_BK_UP", 226
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