

# JuMP

The JuMP core developers and contributors

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## **Part I**

### **Introduction**

# Chapter 1

## Introduction



Welcome to the documentation for JuMP.

### Note

This documentation is also available in PDF format: [JuMP.pdf](#).

### 1.1 What is JuMP?

JuMP is a domain-specific modeling language for [mathematical optimization](#) embedded in [Julia](#).

JuMP makes it easy to formulate and solve a range of problem classes, including linear programs, integer programs, conic programs, semidefinite programs, and constrained nonlinear programs. Here's an example:

```
julia> using JuMP, Ipopt

julia> function solve_constrained_least_squares_regression(A::Matrix, b::Vector)
       m, n = size(A)
       model = Model(Ipopt.Optimizer)
       set_silent(model)
       @variable(model, x[1:n])
       @variable(model, residuals[1:m])
       @constraint(model, residuals == A * x - b)
       @constraint(model, sum(x) == 1)
       @objective(model, Min, sum(residuals.^2))
       optimize!(model)
       return value.(x)
end
solve_constrained_least_squares_regression (generic function with 1 method)

julia> A, b = rand(10, 3), rand(10);
```

```
julia> x = solve_constrained_least_squares_regression(A, b)
3-element Vector{Float64}:
 0.4137624719002825
 0.09707679853084578
 0.48916072956887174
```

**Tip**

If you aren't sure if you should use JuMP, read [Should you use JuMP?](#).

## 1.2 Resources for getting started

There are a few ways to get started with JuMP:

- Read the [Installation Guide](#).
- Read the introductory tutorials [Getting started with Julia](#) and [Getting started with JuMP](#).
- Browse some of our modeling tutorials, including classics such as [The diet problem](#), or the [Maximum likelihood estimation](#) problem using nonlinear programming.

**Tip**

Need help? Join the [community forum](#) to search for answers to commonly asked questions.

Before asking a question, make sure to read the post [make it easier to help you](#), which contains a number of tips on how to ask a good question.

## 1.3 How the documentation is structured

Having a high-level overview of how this documentation is structured will help you know where to look for certain things.

- **Tutorials** contain worked examples of solving problems with JuMP. Start here if you are new to JuMP, or you have a particular problem class you want to model.
- The **Manual** contains short code-snippets that explain how to achieve specific tasks in JuMP. Look here if you want to know how to achieve a particular task, such as how to [Delete a variable](#) or how to [Modify an objective coefficient](#).
- The **API Reference** contains a complete list of the functions you can use in JuMP. Look here if you want to know how to use a particular function.
- The **Background information** section contains background reading material to provide context to JuMP. Look here if you want an understanding of what JuMP is and why we created it, rather than how to use it.



Figure 1.1: NumFOCUS logo

- The **Developer docs** section contains information for people contributing to JuMP development or writing JuMP extensions. Don't worry about this section if you are using JuMP to formulate and solve problems as a user.
- The **MathOptInterface** section is a self-contained copy of the documentation for MathOptInterface. Look here for functions and constants beginning with `MOI.`, as well as for general information on how MathOptInterface works.

## 1.4 Citing JuMP

If you find JuMP useful in your work, we kindly request that you cite the following paper ([preprint](#)):

```
@article{Lubin2023,
    author = {Miles Lubin and Oscar Dowson and Joaquim {Dias Garcia} and Joey Huchette and
              ↪ Beno{\^e}t Legat and Juan Pablo Vielma},
    title = {{JuMP} 1.0: {R}ecent improvements to a modeling language for mathematical
              ↪ optimization},
    journal = {Mathematical Programming Computation},
    year = {2023},
    doi = {10.1007/s12532-023-00239-3}
}
```

## 1.5 NumFOCUS

JuMP is a Sponsored Project of NumFOCUS, a 501(c)(3) nonprofit charity in the United States. NumFOCUS provides JuMP with fiscal, legal, and administrative support to help ensure the health and sustainability of the project. Visit [numfocus.org](http://numfocus.org) for more information.

You can support JuMP by [donating](#).

Donations to JuMP are managed by NumFOCUS. For donors in the United States, your gift is tax-deductible to the extent provided by law. As with any donation, you should consult with your tax adviser about your particular tax situation.

JuMP's largest expense is the annual JuMP-dev workshop. Donations will help us provide travel support for JuMP-dev attendees and take advantage of other opportunities that arise to support JuMP development.

## 1.6 License

JuMP is licensed under the [MPL-2.0 software license](#). Consult the [license](#) and the [Mozilla FAQ](#) for more information. In addition, JuMP is typically used in conjunction with solver packages and extensions which have their own licences. Consult their package repositories for the specific licenses that apply.

## Chapter 2

# Should you use JuMP?

JuMP is an [algebraic modeling language](#) for mathematical optimization written in the [Julia language](#).

This page explains when you should consider using JuMP, and importantly, when you should *not* use JuMP.

### 2.1 When should you use JuMP?

You should use JuMP if you have a constrained optimization problem that is formulated using the language of mathematical programming, that is, the problem has:

- a set of real- or complex-valued decision variables
- a scalar- or vector-valued real objective function
- a set of constraints.

Key reasons to use JuMP include:

- User friendliness
  - JuMP has syntax that mimics natural mathematical expressions. (See the section on [algebraic modeling languages](#).)
- Solver independence
  - JuMP uses a generic solver-independent interface provided by the [MathOptInterface](#) package, making it easy to change between a number of open-source and commercial optimization software packages ("solvers"). The [Supported solvers](#) section contains a table of the currently supported solvers.
- Ease of embedding
  - JuMP itself is written purely in Julia. Solvers are the only binary dependencies.
  - JuMP provides automatic installation of most solvers.
  - Because it is embedded in a general-purpose programming language, JuMP makes it easy to solve optimization problems as part of a larger workflow, for example, inside a simulation, behind a web server, or as a subproblem in a decomposition algorithm. As a trade-off, JuMP's syntax is constrained by the syntax and functionality available in Julia.

- JuMP is [MPL](#) licensed, meaning that it can be embedded in commercial software that complies with the terms of the license.
- Speed
  - Benchmarking has shown that JuMP can create problems at similar speeds to special-purpose modeling languages such as [AMPL](#).
  - JuMP communicates with most solvers in memory, avoiding the need to write intermediary files.
- Access to advanced algorithmic techniques
  - JuMP supports efficient *in-memory* re-solves of models.
  - JuMP provides access to solver-independent and solver-dependent [Callbacks](#).

## 2.2 When should you not use JuMP?

JuMP supports a broad range of optimization classes. However, there are still some that it doesn't support, or that are better supported by other software packages.

### You want to optimize a complicated Julia function

Packages in Julia compose well. It's common for people to pick two unrelated packages and use them in conjunction to create novel behavior. JuMP isn't one of those packages.

If you want to optimize an ordinary differential equation from [DifferentialEquations.jl](#) or tune a neural network from [Flux.jl](#), consider using other packages such as:

- [Optim.jl](#)
- [Optimization.jl](#)
- [NLPModels.jl](#)
- [Nonconvex.jl](#)

### Black-box, derivative free, or unconstrained optimization

JuMP supports nonlinear programs with constraints and objectives containing user-defined operators. However, the functions must be automatically differentiable, or you need to provide explicit derivatives. (See [User-defined operators](#) for more information.)

If your function is a black-box that is non-differentiable (for example, the function calls a simulation written in C++), JuMP is not the right tool for the job. This also applies if you want to use a derivative free method.

Even if your problem is differentiable, if it is unconstrained there is limited benefit (and downsides in the form of more overhead) to using JuMP over tools which are concerned only with function minimization.

Alternatives to consider are:

- [Optim.jl](#)
- [Optimization.jl](#)
- [NLopt.jl](#)

## Disciplined convex programming

JuMP does not support [disciplined convex programming \(DCP\)](#).

Alternatives to consider are:

- [Convex.jl](#)
- [CVXPY \[Python\]](#)
- [YALMIP \[MATLAB\]](#)

### Note

`Convex.jl` is also built on `MathOptInterface`, and shares the same set of underlying solvers. However, you input problems differently, and `Convex.jl` checks that the problem is DCP.

## Stochastic programming

JuMP requires deterministic input data.

If you have stochastic input data, consider using a JuMP extension such as:

- [InfiniteOpt.jl](#)
- [StochasticPrograms.jl](#)
- [SDDP.jl](#)

## Polyhedral computations

JuMP does not provide tools for working with the polyhedron formed by the set of linear constraints.

Alternatives to consider are:

- [Polyhedra.jl](#) (See the [documentation](#) to create a polyhedron from a JuMP model.)

## Chapter 3

# Installation Guide

This guide explains how to install Julia and JuMP. If you have installation troubles, read the [Common installation issues](#) section below.

### 3.1 Install Julia

JuMP is a package for [Julia](#). To use JuMP, first [download and install](#) Julia.

#### Tip

If you are new to Julia, read our [Getting started with Julia](#) tutorial.

### Choosing a version

You can install the "Current stable release" or the "Long-term support (LTS) release."

- The "Current stable release" is the latest release of Julia. It has access to newer features, and is likely faster.
- The "Long-term support release" is an older version of Julia that has continued to receive bug and security fixes. However, it may not have the latest features or performance improvements.

For most users, you should install the "Current stable release," and whenever Julia releases a new version of the current stable release, you should update your version of Julia. Note that any code you write on one version of the current stable release will continue to work on all subsequent releases.

For users in restricted software environments (for example, your enterprise IT controls what software you can install), you may be better off installing the long-term support release because you will not have to update Julia as frequently.

### 3.2 Install JuMP

JuMP is installed using the built-in Julia package manager. Launch Julia, and then enter the following at the `julia>` prompt:

```
julia> import Pkg  
julia> Pkg.add("JuMP")
```

**Tip**

We recommend you create a Pkg *environment* for each project you use JuMP for, instead of adding lots of packages to the global environment. The [Pkg manager documentation](#) has more information on this topic.

When we release a new version of JuMP, you can update with:

```
julia> import Pkg  
julia> Pkg.update("JuMP")
```

### 3.3 Install a solver

JuMP depends on solvers to solve optimization problems. Therefore, you will need to install one before you can solve problems with JuMP.

Install a solver using the Julia package manager, replacing "HiGHS" by the Julia package name as appropriate.

```
julia> import Pkg  
julia> Pkg.add("HiGHS")
```

Once installed, you can use HiGHS as a solver with JuMP as follows, using `set_attribute` to set solver-specific options:

```
julia> using JuMP  
julia> using HiGHS  
julia> model = Model(HiGHS.Optimizer);  
julia> set_attribute(model, "output_flag" => false)  
julia> set_attribute(model, "primal_feasibility_tolerance" => 1e-8)
```

**Note**

Most packages follow the `ModuleName.Optimizer` naming convention, but exceptions may exist. See the README of the Julia package's GitHub repository for more details on how to use a particular solver, including any solver-specific options.

### 3.4 Supported solvers

Most solvers are not written in Julia, and some require commercial licenses to use, so installation is often more complex.

- If a solver has Manual in the Installation column, the solver requires a manual installation step, such as downloading and installing a binary, or obtaining a commercial license. Consult the README of the relevant Julia package for more information.
- If the solver has Manual<sup>M</sup> in the Installation column, the solver requires an installation of MATLAB.
- If the Installation column is missing an entry, installing the Julia package will download and install any relevant solver binaries automatically, and you shouldn't need to do anything other than Pkg.add.

Solvers with a missing entry in the Julia Package column are written in Julia. The link in the Solver column is the corresponding Julia package.

Where:

- LP = Linear programming
- QP = Quadratic programming
- SOCP = Second-order conic programming (including problems with convex quadratic constraints or objective)
- MCP = Mixed-complementarity programming
- NLP = Nonlinear programming
- SDP = Semidefinite programming
- (MI)XXX = Mixed-integer equivalent of problem type XXX
- CP-SAT = Constraint programming and Boolean satisfiability

#### Note

Developed a solver or solver wrapper? This table is open for new contributions. Edit the [installation.md](#) file, and use the checklist [Adding a new solver to the documentation](#) when opening the pull request.

#### Note

Developing a solver or solver wrapper? See [Models](#) and the [MathOptInterface docs](#) for more details on how JuMP interacts with solvers. Please get in touch via the [Developer Chatroom](#) with any questions about connecting new solvers with JuMP.

## 3.5 AMPL-based solvers

Use [AmplNLWriter](#) to access solvers that support the [NL format](#).

Some solvers, such as [Bonmin](#), [Couenne](#) and [SHOT](#) can be installed via the Julia package manager. Others need to be manually installed.

Consult the AMPL documentation for a [complete list of supported solvers](#).

### 3.6 GAMS-based solvers

Use `GAMS.jl` to access solvers available through `GAMS`. Such solvers include: `AlphaECP`, `Antigone`, `BARON`, `CONOPT`, `Couenne`, `LocalSolver`, `PATHNLP`, `SHOT`, `SNOPT`, `SoPlex`. See a complete list [here](#).

#### Note

`GAMS.jl` requires an installation of the commercial software `GAMS` for which a [free community license](#) exists.

### 3.7 NEOS-based solvers

Use `NEOSServer.jl` to access solvers available through the `NEOS Server`.

### 3.8 Common installation issues

#### Tip

When in doubt, run `import Pkg; Pkg.update()` to see if updating your packages fixes the issue. Remember you will need to exit Julia and start a new session for the changes to take effect.

#### Check the version of your packages

Each package is versioned with a [three-part number](#) of the form vX.Y.Z. You can check which versions you have installed with `import Pkg; Pkg.status()`.

This should almost always be the most-recent release. You can check the releases of a package by going to the relevant GitHub page, and navigating to the "releases" page. For example, the list of JuMP releases is available at: <https://github.com/jump-dev/JuMP.jl/releases>.

If you post on the [community forum](#), please include the output of `Pkg.status()`.

#### Unsatisfiable requirements detected

Did you get an error like `Unsatisfiable requirements detected` for package JuMP? The `Pkg` documentation has a [section on how to understand and manage these conflicts](#).

#### Installing new packages can make JuMP downgrade to an earlier version

Another common complaint is that after adding a new package, code that previously worked no longer works.

This usually happens because the new package is not compatible with the latest version of JuMP. Therefore, the package manager rolls-back JuMP to an earlier version. Here's an example.

First, we add JuMP:

```
(jump_example) pkg> add JuMP
  Resolving package versions...
Updating `~/jump_example/Project.toml'
[4076af6c] + JuMP v0.21.5
Updating `~/jump_example/Manifest.toml'
... lines omitted ...
```

The `+ JuMP v0.21.5` line indicates that JuMP has been added at version 0.21.5. However, watch what happens when we add JuMPeR:

```
(jump_example) pkg> add JuMPeR
  Resolving package versions...
Updating `~/jump_example/Project.toml'
[4076af6c] + JuMP v0.21.5 => v0.18.6
[707a9f91] + JuMPeR v0.6.0
Updating `~/jump_example/Manifest.toml'
... lines omitted ...
```

JuMPeR gets added at version 0.6.0 (`+ JuMPeR v0.6.0`), but JuMP gets downgraded from 0.21.5 to 0.18.6 (`↓ JuMP v0.21.5 => v0.18.6`)! The reason for this is that JuMPeR doesn't support a version of JuMP newer than 0.18.6.

**Tip**

Pay careful attention to the output of the package manager when adding new packages, especially when you see a package being downgraded.

Solver	Julia Package	Installation	License	Supports
Alpine.jl			Triad NS	(MI)NLP
Artelys Knitro	KNITRO.jl	Manual	Comm.	(MI)LP, (MI)SOCP, (MI)NLP
BARON	BARON.jl	Manual	Comm.	(MI)NLP
Bonmin	AmpINLWriter.jl		EPL	(MI)NLP
Cbc	Cbc.jl		EPL	(MI)LP
CDCS	CDCS.jl	Manual <sup>M</sup>	GPL	LP, SOCP, SDP
CDD	CDDLib.jl		GPL	LP
Clarabel.jl			Apache	LP, QP, SOCP, SDP
Clp	Clp.jl		EPL	LP
COPT	COPT.jl		Comm.	(MI)LP, SOCP, SDP
COSMO.jl			Apache	LP, QP, SOCP, SDP
Couenne	AmpINLWriter.jl		EPL	(MI)NLP
CPLEX	CPLEX.jl	Manual	Comm.	(MI)LP, (MI)SOCP
CSDP	CSDP.jl		EPL	LP, SDP
DAQP	DAQP.jl		MIT	(Mixed-binary) QP
DSDP	DSDP.jl		DSDP	LP, SDP
EAGO.jl			MIT	(MI)NLP
ECOS	ECOS.jl		GPL	LP, SOCP
FICO Xpress	Xpress.jl	Manual	Comm.	(MI)LP, (MI)SOCP
GLPK	GLPK.jl		GPL	(MI)LP
Gurobi	Gurobi.jl	Manual	Comm.	(MI)LP, (MI)SOCP
HiGHS	HiGHS.jl		MIT	(MI)LP, QP
Hypatia.jl			MIT	LP, SOCP, SDP
Ipopt	Ipopt.jl		EPL	LP, QP, NLP
Juniper.jl			MIT	(MI)SOCP, (MI)NLP
Lorraine.jl			MIT	LP, SDP
MadNLP.jl			MIT	LP, QP, NLP
MAiNGO	MAiNGO.jl		EPL 2.0	(MI)NLP
Manopt.jl			MIT	NLP
MiniZinc	MiniZinc.jl	Manual	MPL-2	CP-SAT
Minotaur	AmpINLWriter.jl	Manual	BSD-like	(MI)NLP
MOSEK	MosekTools.jl	Manual	Comm.	(MI)LP, (MI)SOCP, SDP
NLopt	NLopt.jl		GPL	LP, QP, NLP
Octeract	AmpINLWriter.jl		Comm.	(MI)NLP
Optim.jl			MIT	NLP
OSQP	OSQP.jl		Apache	LP, QP
PATH	PATHSolver.jl		MIT	MCP
Pajarito.jl			MPL-2	(MI)NLP, (MI)SOCP, (MI)SDP
Pavito.jl			MPL-2	(MI)NLP
Penbmi	Penopt.jl		Comm.	Bilinear SDP
Percival.jl			MPL-2	NLP
PolyJuMP.KKT	PolyJuMP.jl		MIT	NLP
PolyJuMP.QCQP	PolyJuMP.jl		MIT	NLP
ProxSDP.jl			MIT	LP, SOCP, SDP
RAPOSa	AmpINLWriter.jl	Manual	RAPOSa	(MI)NLP
SCIP	SCIP.jl		Apache	(MI)LP, (MI)NLP
SCS	SCS.jl		MIT	LP, QP, SOCP, SDP
SDPA	SDPA.jl, SDPAFamily.jl		GPL	LP, SDP
SDPLR	SDPLR.jl		GPL	LP, SDP
SDPNAL	SDPNAL.jl	Manual <sup>M</sup>	CC BY-SA	LP, SDP
SDPT3	SDPT3.jl	Manual <sup>M</sup>	GPL	LP, SOCP, SDP
SeDuMi	SeDuMi.jl	Manual <sup>M</sup>	GPL	LP, SOCP, SDP
SHOT	AmpINLWriter.jl		EPL	(MI)NLP
StatusSwitchingQP.jl			MIT	LP, QP
Tulip.jl			MPL-2	LP
CATrustRegionMethod.il			MIT	NLP

## **Part II**

## **Tutorials**

## Chapter 4

# Getting started

### 4.1 Introduction

The purpose of these "Getting started" tutorials is to teach new users the basics of Julia and JuMP.

#### How these tutorials are structured

Having a high-level overview of how this part of the documentation is structured will help you know where to look for certain things.

- The "Getting started with" tutorials are basic introductions to different aspects of JuMP and Julia. If you are new to JuMP and Julia, start by reading them in the following order:
  - [Getting started with Julia](#)
  - [Getting started with JuMP](#)
  - [Getting started with sets and indexing](#)
  - [Getting started with data and plotting](#)
- Julia has a reputation for being "fast." Unfortunately, it is also easy to write *slow* Julia code. [Performance tips](#) contains a number of important tips on how to improve the performance of models you write in JuMP.
- [Design patterns for larger models](#) is a more advanced tutorial that is aimed at users writing large JuMP models. It's in the "Getting started" section to give you an early preview of how JuMP makes it easy to structure larger models. If you are new to JuMP you may want to skip or briefly skim this tutorial, and come back to it once you have written a few JuMP models.

### 4.2 Getting started with Julia

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

Because JuMP is embedded in Julia, knowing some basic Julia is important before you start learning JuMP.

#### Tip

This tutorial is designed to provide a minimalist crash course in the basics of Julia. You can find resources that provide a more comprehensive introduction to Julia [here](#).

## Installing Julia

To install Julia, [download the latest stable release](#), then follow the [platform specific install instructions](#).

### Tip

Unless you know otherwise, you probably want the 64-bit version.

Next, you need an IDE to develop in. VS Code is a popular choice, so follow [these install instructions](#).

Julia can also be used with [Jupyter notebooks](#) or the reactive notebooks of [Pluto.jl](#).

## The Julia REPL

The main way of interacting with Julia is via its REPL (Read Evaluate Print Loop). To access the REPL, start the Julia executable to arrive at the `julia>` prompt, and then start coding:

```
julia> 1 + 1  
2
```

As your programs become larger, write a script as a text file, and then run that file using:

```
julia> include("path/to/file.jl")
```

### Warning

Because of Julia's startup latency, running scripts from the command line like the following is slow:

```
$ julia path/to/file.jl
```

Use the REPL or a notebook instead.

## Code blocks in this documentation

In this documentation you'll see a mix of code examples with and without the `julia>`.

The Julia prompt is mostly used to demonstrate short code snippets, and the output is exactly what you will see if run from the REPL.

Blocks without the `julia>` can be copy-pasted into the REPL, but they are used because they enable richer output like plots or LaTeX to be displayed in the online and [PDF](#) versions of the documentation. If you run them from the REPL you may see different output.

## Where to get help

- Read the documentation
  - JuMP <https://jump.dev/JuMP.jl/stable/>
  - Julia <https://docs.julialang.org/en/v1/>
- Ask (or browse) the Julia community forum: <https://discourse.julialang.org>

- If the question is JuMP-related, ask in the [Optimization \(Mathematical\)](#) section, or tag your question with "jump"

To access the built-in help at the REPL, type ? to enter help-mode, followed by the name of the function to lookup:

```
help?> print
search: print println printstyled sprint isprint prevind parentindices precision escape_string

print([io::IO], xs...)

Write to io (or to the default output stream stdout if io is not given) a canonical
(un-decorated) text representation. The representation used by print includes minimal formatting
and tries to avoid Julia-specific details.

print falls back to calling show, so most types should just define show. Define print if your
type has a separate "plain" representation. For example, show displays strings with quotes, and
print displays strings without quotes.

string returns the output of print as a string.

Examples
=====

julia> print("Hello World!")
Hello World!
julia> io = IOBuffer();

julia> print(io, "Hello", ' ', :World!)
julia> String(take!(io))
"Hello World!"
```

## Numbers and arithmetic

Since we want to solve optimization problems, we're going to be using a lot of math. Luckily, Julia is great for math, with all the usual operators:

```
julia> 1 + 1
2

julia> 1 - 2
-1

julia> 2 * 2
4

julia> 4 / 5
0.8

julia> 3^2
9
```

Did you notice how Julia didn't print `.0` after some of the numbers? Julia is a dynamic language, which means you never have to explicitly declare the type of a variable. However, in the background, Julia is giving each variable a type. Check the type of something using the `typeof` function:

```
julia> typeof(1)
Int64

julia> typeof(1.0)
Float64
```

Here `1` is an `Int64`, which is an integer with 64 bits of precision, and `1.0` is a `Float64`, which is a floating point number with 64-bits of precision.

### Tip

If you aren't familiar with floating point numbers, make sure to read the [Floating point numbers](#) section.

We create complex numbers using `im`:

```
julia> x = 2 + 1im
2 + 1im

julia> real(x)
2

julia> imag(x)
1

julia> typeof(x)
Complex{Int64}

julia> x * (1 - 2im)
4 - 3im
```

### Info

The curly brackets surround what we call the *parameters* of a type. You can read `Complex{Int64}` as "a complex number, where the real and imaginary parts are represented by `Int64`." If we call `typeof(1.0 + 2.0im)` it will be `Complex{Float64}`, which a complex number with the parts represented by `Float64`.

There are also some cool things like an irrational representation of  $\pi$ .

```
julia> π
π = 3.1415926535897...
```

### Tip

To make  $\pi$  (and most other Greek letters), type `\pi` and then press [TAB].

```
julia> typeof(π)
Irrational{:π}
```

However, if we do math with irrational numbers, they get converted to Float64:

```
julia> typeof(2π / 3)
Float64
```

### Floating point numbers

#### Warning

If you aren't familiar with floating point numbers, make sure to read this section carefully.

A Float64 is a [floating point](#) approximation of a real number using 64-bits of information.

Because it is an approximation, things we know hold true in mathematics don't hold true in a computer. For example:

```
julia> 0.1 * 3 == 0.3
false
```

A more complicated example is:

```
julia> sin(2π / 3) == √3 / 2
false
```

#### Tip

Get  $\sqrt{}$  by typing `\sqrt` then press [TAB].

Let's see what the differences are:

```
julia> 0.1 * 3 - 0.3
5.551115123125783e-17

julia> sin(2π / 3) - √3 / 2
1.1102230246251565e-16
```

They are small, but not zero.

One way of explaining this difference is to consider how we would write  $1 / 3$  and  $2 / 3$  using only four digits after the decimal point. We would write  $1 / 3$  as 0.3333, and  $2 / 3$  as 0.6667. So, despite the fact that  $2 * (1 / 3) == 2 / 3$ ,  $2 * 0.3333 == 0.6666 != 0.6667$ .

Let's try that again using `≈ (\approx + [TAB])` instead of `==`:

```
julia> 0.1 * 3 ≈ 0.3
true

julia> sin(2π / 3) ≈ √3 / 2
true
```

`≈` is a clever way of calling the `isapprox` function:

```
julia> isapprox(sin(2π / 3), √3 / 2; atol = 1e-8)
true
```

### Warning

Floating point is the reason solvers use tolerances when they solve optimization models. A common mistake you're likely to make is checking whether a binary variable is 0 using `value(z) == 0`. Always remember to use something like `isapprox` when comparing floating point numbers.

Note that `isapprox` will always return `false` if one of the number being compared is 0 and `atol` is zero (its default value).

```
julia> 1e-300 ≈ 0.0
false
```

so always set a nonzero value of `atol` if one of the arguments can be zero.

```
julia> isapprox(1e-9, 0.0; atol = 1e-8)
true
```

### Tip

Gurobi has a [good series of articles](#) on the implications of floating point in optimization if you want to read more.

If you aren't careful, floating point arithmetic can throw up all manner of issues. For example:

```
julia> 1 + 1e-16 == 1
true
```

It even turns out that floating point numbers aren't associative:

```
julia> (1 + 1e-16) - 1e-16 == 1 + (1e-16 - 1e-16)
false
```

It's important to note that this issue isn't Julia-specific. It happens in every programming language (try it out in Python).

## Vectors, matrices, and arrays

Similar to MATLAB, Julia has native support for vectors, matrices and tensors; all of which are represented by arrays of different dimensions. Vectors are constructed by comma-separated elements surrounded by square brackets:

```
julia> b = [5, 6]
2-element Vector{Int64}:
 5
 6
```

Matrices can be constructed with spaces separating the columns, and semicolons separating the rows:

```
julia> A = [1.0 2.0; 3.0 4.0]
2×2 Matrix{Float64}:
 1.0  2.0
 3.0  4.0
```

We can do linear algebra:

```
julia> x = A \ b
2-element Vector{Float64}:
 -3.999999999999987
 4.499999999999999
```

### Info

Here is floating point at work again; x is approximately [-4, 4.5].

```
julia> A * x
2-element Vector{Float64}:
 5.0
 6.0

julia> A * x ≈ b
true
```

Note that when multiplying vectors and matrices, dimensions matter. For example, you can't multiply a vector by a vector:

```
julia> b * b
MethodError: no method matching *(::Vector{Int64}, ::Vector{Int64})
The function `*` exists, but no method is defined for this combination of argument types.

Closest candidates are:
  *(::Any, ::Any, !Matched::Any, !Matched::Any...)
  @ Base operators.jl:596
  *(!Matched::Type{<:LinearOperatorCollection.ProdOp}, ::Any, !Matched::Any)
  @ LinearOperatorCollection ~/julia/packages/LinearOperatorCollection/4Kgu1/src/ProdOp.jl:73
  *(!Matched::ChainRulesCore.NotImplemented, ::Any)
```

```
@ ChainRulesCore ~/.julia/packages/ChainRulesCore/U6wNx/src/tangent_arithmetic.jl:37
...

```

But multiplying transposes works:

```
julia> b' * b
61

julia> b * b'
2×2 Matrix{Int64}:
 25  30
 30  36
```

## Other common types

### Comments

Although not technically a type, code comments begin with the # character:

```
julia> 1 + 1 # This is a comment
2
```

Multiline comments begin with #= and end with =#:

```
#=
Here is a
multiline comment
#=
```

Comments can even be nested inside expressions. This is sometimes helpful when documenting inputs to functions:

```
julia> isapprox(
        sin(π),
        0.0;
        #= We need an explicit atol here because we are comparing with 0 =#
        atol = 0.001,
    )
true
```

### Strings

Double quotes are used for strings:

```
julia> typeof("This is Julia")
String
```

Unicode is fine in strings:

```
julia> typeof("π is about 3.1415")
String
```

Use `println` to print a string:

```
julia> println("Hello, World!")
Hello, World!
```

Use `$()` to interpolate values into a string:

```
julia> x = 123
123

julia> println("The value of x is: $(x)")
The value of x is: 123
```

Use triple-quotes for multiline strings:

```
julia> s = """
    Here is
    a
    multiline string
"""

"Here is\na\nmultiline string\n"
```

```
julia> println(s)
Here is
a
multiline string
```

## Symbols

Julia Symbols are a data structure from the compiler that represent Julia identifiers (that is, variable names).

```
julia> println("The value of x is: $(eval(:x))")
The value of x is: 123
```

### Warning

We used `eval` here to demonstrate how Julia links Symbols to variables. However, avoid calling `eval` in your code. It is usually a sign that your code is doing something that could be more easily achieved a different way. The [Community Forum](#) is a good place to ask for advice on alternative approaches.

```
julia> typeof(:x)
Symbol
```

You can think of a `Symbol` as a `String` that takes up less memory, and that can't be modified.

Convert between `String` and `Symbol` using their constructors:

```
julia> String(:abc)
"abc"

julia> Symbol("abc")
:abc
```

### Tip

Symbols are often (ab)used to stand in for a `String` or an `Enum`, when one of the latter is likely a better choice. The JuMP [Style guide](#) recommends reserving `Symbols` for identifiers. See [@enum vs. Symbol](#) for more.

## Tuples

Julia makes extensive use of a simple data structure called `Tuples`. `Tuples` are immutable collections of values. For example:

```
julia> t = ("hello", 1.2, :foo)
("hello", 1.2, :foo)

julia> typeof(t)
Tuple{String, Float64, Symbol}
```

`Tuples` can be accessed by index, similar to arrays:

```
julia> t[2]
1.2
```

And they can be "unpacked" like so:

```
julia> a, b, c = t
("hello", 1.2, :foo)

julia> b
1.2
```

The values can also be given names, which is a convenient way of making light-weight data structures.

```
julia> t = (word = "hello", num = 1.2, sym = :foo)
(word = "hello", num = 1.2, sym = :foo)
```

Values can be accessed using dot syntax:

```
julia> t.word
"hello"
```

## Dictionaries

Similar to Python, Julia has native support for dictionaries. Dictionaries provide a very generic way of mapping keys to values. For example, a map of integers to strings:

```
julia> d1 = Dict(1 => "A", 2 => "B", 4 => "D")
Dict{Int64, String} with 3 entries:
  4 => "D"
  2 => "B"
  1 => "A"
```

### Info

Type-stuff again: `Dict{Int64, String}` is a dictionary with `Int64` keys and `String` values.

Looking up a value uses the bracket syntax:

```
julia> d1[2]
"B"
```

Dictionaries support non-integer keys and can mix data types:

```
julia> Dict("A" => 1, "B" => 2.5, "D" => 2 - 3im)
Dict{String, Number} with 3 entries:
  "B" => 2.5
  "A" => 1
  "D" => 2-3im
```

### Info

Julia types form a hierarchy. Here the value type of the dictionary is `Number`, which is a generalization of `Int64`, `Float64`, and `Complex{Int}`. Leaf nodes in this hierarchy are called "concrete" types, and all others are called "Abstract." In general, having variables with abstract types like `Number` can lead to slower code, so you should try to make sure every element in a dictionary or vector is the same type. For example, in this case we could represent every element as a `Complex{Float64}`:

```
julia> Dict("A" => 1.0 + 0.0im, "B" => 2.5 + 0.0im, "D" => 2.0 - 3.0im)
Dict{String, ComplexF64} with 3 entries:
  "B" => 2.5+0.0im
  "A" => 1.0+0.0im
  "D" => 2.0-3.0im
```

Dictionaries can be nested:

```
julia> d2 = Dict("A" => 1, "B" => 2, "D" => Dict(:foo => 3, :bar => 4))
Dict{String, Any} with 3 entries:
  "B" => 2
  "A" => 1
  "D" => Dict(:bar=>4, :foo=>3)

julia> d2["B"]
2

julia> d2["D"][:foo]
3
```

## Structs

You can define custom datastructures with `struct`:

```
julia> struct MyStruct
    x::Int
    y::String
    z::Dict{Int,Int}
end

julia> a = MyStruct(1, "a", Dict(2 => 3))
Main.MyStruct(1, "a", Dict(2 => 3))

julia> a.x
1
```

By default, these are not mutable

```
julia> a.x = 2
setfield!: immutable struct of type MyStruct cannot be changed
```

However, you can declare a `mutable struct` which is mutable:

```
julia> mutable struct MyStructMutable
    x::Int
    y::String
    z::Dict{Int,Int}
end

julia> a = MyStructMutable(1, "a", Dict(2 => 3))
Main.MyStructMutable(1, "a", Dict(2 => 3))

julia> a.x
1

julia> a.x = 2
2
```

```
julia> a
Main.MyStructMutable(2, "a", Dict(2 => 3))
```

## Loops

Julia has native support for for-each style loops with the syntax `for <value> in <collection> end`:

```
julia> for i in 1:5
           println(i)
       end
1
2
3
4
5
```

### Info

Ranges are constructed as `start:stop`, or `start:step:stop`.

```
julia> for i in 1.2:1.1:5.6
           println(i)
       end
1.2
2.3
3.4
4.5
5.6
```

This for-each loop also works with dictionaries:

```
julia> for (key, value) in Dict("A" => 1, "B" => 2.5, "D" => 2 - 3im)
           println("$(key): $(value)")
       end
B: 2.5
A: 1
D: 2 - 3im
```

Note that in contrast to vector languages like MATLAB and R, loops do not result in a significant performance degradation in Julia.

## Control flow

Julia control flow is similar to MATLAB, using the keywords `if-elseif-else-end`, and the logical operators `||` and `&&` for **or** and **and** respectively:

```
julia> for i in 0:5:15
    if i < 5
        println!("$(i) is less than 5")
    elseif i < 10
        println!("$(i) is less than 10")
    else
        if i == 10
            println("the value is 10")
        else
            println!("$(i) is bigger than 10")
        end
    end
end
0 is less than 5
5 is less than 10
the value is 10
15 is bigger than 10
```

## Comprehensions

Similar to languages like Haskell and Python, Julia supports the use of simple loops in the construction of arrays and dictionaries, called comprehensions.

A list of increasing integers:

```
julia> [i for i in 1:5]
5-element Vector{Int64}:
1
2
3
4
5
```

Matrices can be built by including multiple indices:

```
julia> [i * j for i in 1:5, j in 5:10]
5×6 Matrix{Int64}:
 5   6   7   8   9   10
 10  12  14  16  18  20
 15  18  21  24  27  30
 20  24  28  32  36  40
 25  30  35  40  45  50
```

Conditional statements can be used to filter out some values:

```
julia> [i for i in 1:10 if i % 2 == 1]
5-element Vector{Int64}:
1
3
5
7
9
```

A similar syntax can be used for building dictionaries:

```
julia> Dict("$(i)" => i for i in 1:10 if i % 2 == 1)
Dict{String, Int64} with 5 entries:
  "1" => 1
  "5" => 5
  "7" => 7
  "9" => 9
  "3" => 3
```

## Functions

A simple function is defined as follows:

```
julia> function print_hello()
           return println("hello")
       end
print_hello (generic function with 1 method)

julia> print_hello()
hello
```

Arguments can be added to a function:

```
julia> function print_it(x)
           return println(x)
       end
print_it (generic function with 1 method)

julia> print_it("hello")
hello

julia> print_it(1.234)
1.234

julia> print_it(:my_id)
my_id
```

Optional keyword arguments are also possible:

```
julia> function print_it(x; prefix = "value:")
           return println("$(prefix) $(x)")
       end
print_it (generic function with 1 method)

julia> print_it(1.234)
value: 1.234

julia> print_it(1.234; prefix = "val:")
val: 1.234
```

The keyword `return` is used to specify the return values of a function:

```
julia> function mult(x; y = 2.0)
           return x * y
       end
mult (generic function with 1 method)

julia> mult(4.0)
8.0

julia> mult(4.0; y = 5.0)
20.0
```

### Anonymous functions

The syntax `input -> output` creates an anonymous function. These are most useful when passed to other functions. For example:

```
julia> f = x -> x^2
#11 (generic function with 1 method)

julia> f(2)
4

julia> map(x -> x^2, 1:4)
4-element Vector{Int64}:
 1
 4
 9
 16
```

### Type parameters

We can constrain the inputs to a function using type parameters, which are `::` followed by the type of the input we want. For example:

```
julia> function foo(x::Int)
           return x^2
       end
foo (generic function with 1 method)

julia> function foo(x::Float64)
           return exp(x)
       end
foo (generic function with 2 methods)

julia> function foo(x::Number)
           return x + 1
       end
foo (generic function with 3 methods)

julia> foo(2)
```

```
4

julia> foo(2.0)
7.38905609893065

julia> foo(1 + lim)
2 + lim
```

But what happens if we call `foo` with something we haven't defined it for?

```
julia> foo([1, 2, 3])
MethodError: no method matching foo(::Vector{Int64})
The function `foo` exists, but no method is defined for this combination of argument types.

Closest candidates are:
foo(!Matched::Float64)
@ Main REPL[2]:1
foo(!Matched::Int64)
@ Main REPL[1]:1
foo(!Matched::Number)
@ Main REPL[3]:1
```

A `MethodError` means that you passed a function something that didn't match the type that it was expecting. In this case, the error message says that it doesn't know how to handle an `Vector{Int64}`, but it does know how to handle `Float64`, `Int64`, and `Number`.

### Tip

Read the "Closest candidates" part of the error message carefully to get a hint as to what was expected.

## Broadcasting

In the example above, we didn't define what to do if `f` was passed a `Vector`. Luckily, Julia provides a convenient syntax for mapping `f` element-wise over arrays. Just add a `.` between the name of the function and the opening `(`. This works for *any* function, including functions with multiple arguments. For example:

```
julia> foo.([1, 2, 3])
3-element Vector{Int64}:
 1
 4
 9
```

### Tip

Get a `MethodError` when calling a function that takes a `Vector`, `Matrix`, or `Array`? Try broadcasting.

## Mutable vs immutable objects

Some types in Julia are *mutable*, which means you can change the values inside them. A good example is an array. You can modify the contents of an array without having to make a new array.

In contrast, types like `Float64` are *immutable*. You cannot modify the contents of a `Float64`.

This is something to be aware of when passing types into functions. For example:

```
julia> function mutability_example mutable_type::Vector{Int}, immutable_type::Int)
           mutable_type[1] += 1
           immutable_type += 1
       return
   end
mutability_example (generic function with 1 method)

julia> mutable_type = [1, 2, 3]
3-element Vector{Int64}:
 1
 2
 3

julia> immutable_type = 1
1

julia> mutability_example(mutable_type, immutable_type)

julia> println("mutable_type: $(mutable_type)")
mutable_type: [2, 2, 3]

julia> println("immutable_type: $(immutable_type)")
immutable_type: 1
```

Because `Vector{Int}` is a mutable type, modifying the variable inside the function changed the value outside of the function. In contrast, the change to `immutable_type` didn't modify the value outside the function.

You can check mutability with the `isimmutable` function:

```
julia> isimmutable([1, 2, 3])
false

julia> isimmutable(1)
true
```

## The package manager

### Installing packages

No matter how wonderful Julia's base language is, at some point you will want to use an extension package. Some of these are built-in, for example random number generation is available in the `Random` package in the standard library. These packages are loaded with the commands `using` and `import`.

```
julia> using Random # The equivalent of Python's `from Random import *`

julia> import Random # The equivalent of Python's `import Random`
```

```
julia> Random.seed!(33)
Random.TaskLocalRNG()

julia> [rand() for i in 1:10]
10-element Vector{Float64}:
 0.4745319377345316
 0.9650392357070774
 0.8194019096093067
 0.9297749959069098
 0.3127122336048005
 0.9684448191382753
 0.9063743823581542
 0.8386731983150535
 0.5103924401614957
 0.9296414851080324
```

The Package Manager is used to install packages that are not part of Julia's standard library.

For example the following can be used to install JuMP,

```
using Pkg
Pkg.add("JuMP")
```

For a complete list of registered Julia packages see the package listing at [JuliaHub](#).

From time to you may wish to use a Julia package that is not registered. In this case a git repository URL can be used to install the package.

```
using Pkg
Pkg.add("https://github.com/user-name/MyPackage.jl.git")
```

### Package environments

By default, `Pkg.add` will add packages to Julia's global environment. However, Julia also has built-in support for virtual environments.

Activate a virtual environment with:

```
import Pkg; Pkg.activate("/path/to/environment")
```

You can see what packages are installed in the current environment with `Pkg.status()`.

#### Tip

We *strongly* recommend you create a `Pkg` environment for each project that you create in Julia, and add only the packages that you need, instead of adding lots of packages to the global environment. The [Pkg manager documentation](#) has more information on this topic.

### 4.3 Getting started with JuMP

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

This tutorial is aimed at providing a quick introduction to writing and solving optimization models with JuMP.

If you're new to Julia, start by reading [Getting started with Julia](#).

#### What is JuMP?

JuMP ("Julia for Mathematical Programming") is an open-source modeling language that is embedded in Julia. It allows users to formulate various classes of optimization problems (linear, mixed-integer, quadratic, conic quadratic, semidefinite, and nonlinear) with easy-to-read code. These problems can then be solved using state-of-the-art open-source and commercial solvers.

JuMP also makes advanced optimization techniques easily accessible from a high-level language.

#### What is a solver?

A solver is a software package that incorporates algorithms for finding solutions to one or more classes of problem.

For example, HiGHS is a solver for linear programming (LP) and mixed integer programming (MIP) problems. It incorporates algorithms such as the simplex method and the interior-point method.

The [Supported-solvers](#) table lists the open-source and commercial solvers that JuMP currently supports.

#### What is MathOptInterface?

Each solver has its own concepts and data structures for representing optimization models and obtaining results.

[MathOptInterface](#) (MOI) is an abstraction layer that JuMP uses to convert from the problem written in JuMP to the solver-specific data structures for each solver.

MOI can be used directly, or through a higher-level modeling interface like JuMP.

Because JuMP is built on top of MOI, you'll often see the `MathOptInterface.` prefix displayed when JuMP types are printed. However, you'll only need to understand and interact with MOI to accomplish advanced tasks such as creating [solver-independent callbacks](#).

#### Installation

JuMP is a package for Julia. From Julia, JuMP is installed by using the built-in package manager.

```
import Pkg
Pkg.add("JuMP")
```

You also need to include a Julia package which provides an appropriate solver. One such solver is `HiGHS.Optimizer`, which is provided by the [HiGHS.jl package](#).

```
import Pkg
Pkg.add("HiGHS")
```

See [Installation Guide](#) for a list of other solvers you can use.

### An example

Let's solve the following linear programming problem using JuMP and HiGHS. We will first look at the complete code to solve the problem and then go through it step by step.

Here's the problem:

$$\begin{aligned} \text{min} \quad & 12x + 20y \\ \text{s.t.} \quad & 6x + 8y \geq 100 \\ & 7x + 12y \geq 120 \\ & x \geq 0 \\ & y \in [0, 3] \end{aligned}$$

And here's the code to solve this problem:

```
julia> using JuMP

julia> using HiGHS

julia> model = Model(HiGHS.Optimizer)
A JuMP Model
└ solver: HiGHS
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> @variable(model, x >= 0)
x

julia> @variable(model, 0 <= y <= 3)
y

julia> @objective(model, Min, 12x + 20y)
12 x + 20 y

julia> @constraint(model, c1, 6x + 8y >= 100)
c1 : 6 x + 8 y ≥ 100

julia> @constraint(model, c2, 7x + 12y >= 120)
c2 : 7 x + 12 y ≥ 120

julia> print(model)
Min 12 x + 20 y
Subject to
c1 : 6 x + 8 y ≥ 100
c2 : 7 x + 12 y ≥ 120
x ≥ 0
y ≥ 0
y ≤ 3

julia> optimize!(model)
```

```

Running HiGHS 1.8.0 (git hash: fcfb534146): Copyright (c) 2024 HiGHS under MIT licence terms
Coefficient ranges:
  Matrix [6e+00, 1e+01]
  Cost   [1e+01, 2e+01]
  Bound  [3e+00, 3e+00]
  RHS    [1e+02, 1e+02]
Presolving model
2 rows, 2 cols, 4 nonzeros 0s
2 rows, 2 cols, 4 nonzeros 0s
Presolve : Reductions: rows 2(-0); columns 2(-0); elements 4(-0) - Not reduced
Problem not reduced by presolve: solving the LP
Using EKK dual simplex solver - serial
  Iteration      Objective      Infeasibilities num(sum)
    0            0.0000000000e+00 Pr: 2(220) 0s
    2            2.0500000000e+02 Pr: 0(0) 0s
Model status : Optimal
Simplex iterations: 2
Objective value : 2.0500000000e+02
HiGHS run time : 0.00

>julia> termination_status(model)
OPTIMAL::TerminationStatusCode = 1

>julia> primal_status(model)
FEASIBLE_POINT::ResultStatusCode = 1

>julia> dual_status(model)
FEASIBLE_POINT::ResultStatusCode = 1

>julia> objective_value(model)
204.9999999999997

>julia> value(x)
15.00000000000005

>julia> value(y)
1.249999999999996

>julia> shadow_price(c1)
-0.2499999999999922

>julia> shadow_price(c2)
-1.5000000000000007

```

### Step-by-step

Once JuMP is installed, to use JuMP in your programs write:

```

>julia> using JuMP

```

We also need to include a Julia package which provides an appropriate solver. We want to use `HiGHS.Optimizer` here which is provided by the `HiGHS.jl` package:

```
julia> using HiGHS
```

JuMP builds problems incrementally in a `Model` object. Create a model by passing an optimizer to the `Model` function:

```
julia> model = Model(HiGHS.Optimizer)
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none
```

Variables are modeled using `@variable`:

```
julia> @variable(model, x >= 0)
x
```

### Info

The macro creates a new Julia object, `x`, in the current scope. We could have made this more explicit by writing:

```
x = @variable(model, x >= 0)
```

but the macro does this automatically for us to save writing `x` twice.

Variables can have lower and upper bounds:

```
julia> @variable(model, 0 <= y <= 30)
y
```

The objective is set using `@objective`:

```
julia> @objective(model, Min, 12x + 20y)
12 x + 20 y
```

Constraints are modeled using `@constraint`. Here, `c1` and `c2` are the names of our constraint:

```
julia> @constraint(model, c1, 6x + 8y >= 100)
c1 : 6 x + 8 y ≥ 100

julia> @constraint(model, c2, 7x + 12y >= 120)
c2 : 7 x + 12 y ≥ 120
```

Call `print` to display the model:

```
julia> print(model)
Min 12 x + 20 y
Subject to
c1 : 6 x + 8 y ≥ 100
c2 : 7 x + 12 y ≥ 120
x ≥ 0
y ≥ 0
y ≤ 30
```

To solve the optimization problem, call the `optimize!` function:

```
julia> optimize!(model)
Running HiGHS 1.8.0 (git hash: fcfb534146): Copyright (c) 2024 HiGHS under MIT licence terms
Coefficient ranges:
    Matrix [6e+00, 1e+01]
    Cost   [1e+01, 2e+01]
    Bound  [3e+01, 3e+01]
    RHS    [1e-02, 1e+02]
Presolving model
2 rows, 2 cols, 4 nonzeros  0s
2 rows, 2 cols, 4 nonzeros  0s
Presolve : Reductions: rows 2(-0); columns 2(-0); elements 4(-0) - Not reduced
Problem not reduced by presolve: solving the LP
Using EKK dual simplex solver - serial
    Iteration      Objective      Infeasibilities num(sum)
        0          0.0000000000e+00 Pr: 2(220) 0s
        2          2.0500000000e+02 Pr: 0(0) 0s
Model  status      : Optimal
Simplex iterations: 2
Objective value     :  2.0500000000e+02
HiGHS run time      :          0.00
```

### Info

The `!` after `optimize` is part of the name. It's nothing special. Julia has a convention that functions which mutate their arguments should end in `!`. A common example is `push!`.

Now let's see what information we can query about the solution, starting with `is_solved_and_feasible`:

```
julia> is_solved_and_feasible(model)
true
```

We can get more information about the solution by querying the three types of statuses.

`termination_status` tells us why the solver stopped:

```
julia> termination_status(model)
OPTIMAL::TerminationStatusCode = 1
```

In this case, the solver found an optimal solution.

Check `primal_status` to see if the solver found a primal feasible point:

```
julia> primal_status(model)
FEASIBLE_POINT::ResultStatusCode = 1
```

and `dual_status` to see if the solver found a dual feasible point:

```
julia> dual_status(model)
FEASIBLE_POINT::ResultStatusCode = 1
```

Now we know that our solver found an optimal solution, and that it has a primal and a dual solution to query.

Query the objective value using `objective_value`:

```
julia> objective_value(model)
205.0
```

the primal solution using `value`:

```
julia> value(x)
15.00000000000004

julia> value(y)
1.249999999999976
```

and the dual solution using `shadow_price`:

```
julia> shadow_price(c1)
-0.2499999999999917

julia> shadow_price(c2)
-1.5000000000000007
```

### Warning

You should always check whether the solver found a solution before calling solution functions like `value` or `objective_value`. A common workflow is:

```
optimize!(model)
if !is_solved_and_feasible(model)
    error("Solver did not find an optimal solution")
end
```

That's it for our simple model. In the rest of this tutorial, we expand on some of the basic JuMP operations.

## Model basics

Create a model by passing an optimizer:

```
julia> model = Model(HiGHS.Optimizer)
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

Alternatively, call `set_optimizer` at any point before calling `optimize!`:

```
julia> model = Model()
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none

julia> set_optimizer(model, HiGHS.Optimizer)
```

For some solvers, you can also use `direct_model`, which offers a more efficient connection to the underlying solver:

```
julia> model = direct_model(HiGHS.Optimizer())
A JuMP Model
├ mode: DIRECT
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

### Warning

Some solvers do not support `direct_model`!

## Solver Options

Pass options to solvers with `optimizer_with_attributes`:

```
julia> model =
        Model(optimizer_with_attributes(HiGHS.Optimizer, "output_flag" => false))
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
```

```
| num_constraints: 0
└ Names registered in the model: none
```

**Note**

These options are solver-specific. To find out the various options available, see the GitHub README of the individual solver packages. The link to each solver's GitHub page is in the [Supported solvers](#) table.

You can also pass options with `set_attribute`:

```
julia> model = Model(HiGHS.Optimizer)
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none

julia> set_attribute(model, "output_flag", false)
```

**Solution basics**

We saw above how to use `termination_status` and `primal_status` to understand the solution returned by the solver.

However, only query solution attributes like `value` and `objective_value` if there is an available solution. Here's a recommended way to check:

```
julia> function solve_infeasible()
    model = Model(HiGHS.Optimizer)
    @variable(model, 0 <= x <= 1)
    @variable(model, 0 <= y <= 1)
    @constraint(model, x + y >= 3)
    @objective(model, Max, x + 2y)
    optimize!(model)
    if !is_solved_and_feasible(model)
        @warn("The model was not solved correctly.")
        return
    end
    return value(x), value(y)
end
solve_infeasible (generic function with 1 method)

julia> solve_infeasible()
Running HiGHS 1.8.0 (git hash: fcfb534146): Copyright (c) 2024 HiGHS under MIT licence terms
Coefficient ranges:
  Matrix [1e+00, 1e+00]
  Cost   [1e+00, 2e+00]
  Bound  [1e+00, 1e+00]
  RHS    [3e+00, 3e+00]
Presolving model
```

```
Problem status detected on presolve: Infeasible
Model  status      : Infeasible
Objective value   :  0.0000000000e+00
HiGHS run time    :          0.00
ERROR: No LP invertible representation for getDualRay
r Warning: The model was not solved correctly.
└ @ Main REPL[1]:9
```

## Variable basics

Let's create a new empty model to explain some of the variable syntax:

```
julia> model = Model()
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

## Variable bounds

All of the variables we have created till now have had a bound. We can also create a free variable.

```
julia> @variable(model, free_x)
free_x
```

While creating a variable, instead of using the `<=` and `>=` syntax, we can also use the `lower_bound` and `upper_bound` keyword arguments.

```
julia> @variable(model, keyword_x, lower_bound = 1, upper_bound = 2)
keyword_x
```

We can query whether a variable has a bound using the `has_lower_bound` and `has_upper_bound` functions. The values of the bound can be obtained using the `lower_bound` and `upper_bound` functions.

```
julia> has_upper_bound(keyword_x)
true

julia> upper_bound(keyword_x)
2.0
```

Note querying the value of a bound that does not exist will result in an error.

```
julia> lower_bound(free_x)
Variable free_x does not have a lower bound.
```

## Containers

We have already seen how to add a single variable to a model using the `@variable` macro. Now let's look at ways to add multiple variables to a model.

JuMP provides data structures for adding collections of variables to a model. These data structures are referred to as *containers* and are of three types: `Arrays`, `DenseAxisArrays`, and `SparseAxisArrays`.

### Arrays

JuMP arrays are created when you have integer indices that start at 1:

```
julia> @variable(model, a[1:2, 1:2])
2×2 Matrix{VariableRef}:
 a[1,1]  a[1,2]
 a[2,1]  a[2,2]
```

Index elements in `a` as follows:

```
julia> a[1, 1]
a[1,1]
```

```
julia> a[2, :]
2-element Vector{VariableRef}:
 a[2,1]
 a[2,2]
```

Create an n-dimensional variable  $x \in R^n$  with bounds  $l \leq x \leq u$  ( $l, u \in R^n$ ) as follows:

```
julia> n = 10
10

julia> l = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10];

julia> u = [10, 11, 12, 13, 14, 15, 16, 17, 18, 19];

julia> @variable(model, l[i] <= x[i = 1:n] <= u[i])
10-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]
 x[4]
 x[5]
 x[6]
 x[7]
 x[8]
 x[9]
 x[10]
```

We can also create variable bounds that depend upon the indices:

```
julia> @variable(model, y[i = 1:2, j = 1:2] >= 2i + j)
2×2 Matrix{VariableRef}:
 y[1,1]  y[1,2]
 y[2,1]  y[2,2]
```

### DenseAxisArrays

DenseAxisArrays are used when the indices are not one-based integer ranges. The syntax is similar except with an arbitrary vector as an index as opposed to a one-based range:

```
julia> @variable(model, z[i = 2:3, j = 1:2:3] >= 0)
2-dimensional DenseAxisArray{VariableRef,2,...} with index sets:
    Dimension 1, 2:3
    Dimension 2, 1:2:3
And data, a 2×2 Matrix{VariableRef}:
z[2,1]  z[2,3]
z[3,1]  z[3,3]
```

Indices do not have to be integers. They can be any Julia type:

```
julia> @variable(model, w[1:5, ["red", "blue"]] <= 1)
2-dimensional DenseAxisArray{VariableRef,2,...} with index sets:
    Dimension 1, Base.OneTo(5)
    Dimension 2, ["red", "blue"]
And data, a 5×2 Matrix{VariableRef}:
w[1,red]  w[1,blue]
w[2,red]  w[2,blue]
w[3,red]  w[3,blue]
w[4,red]  w[4,blue]
w[5,red]  w[5,blue]
```

Index elements in a DenseAxisArray as follows:

```
julia> z[2, 1]
z[2,1]
```

```
julia> w[2:3, ["red", "blue"]]
2-dimensional DenseAxisArray{VariableRef,2,...} with index sets:
    Dimension 1, [2, 3]
    Dimension 2, ["red", "blue"]
And data, a 2×2 Matrix{VariableRef}:
w[2,red]  w[2,blue]
w[3,red]  w[3,blue]
```

See [Forcing the container type](#) for more details.

### SparseAxisArrays

SparseAxisArrays are created when the indices do not form a Cartesian product. For example, this applies when indices have a dependence upon previous indices (called triangular indexing):

```
julia> @variable(model, u[i = 1:2, j = i:3])
SparseAxisArray{VariableRef, 2, Tuple{Int64, Int64}} with 5 entries:
 [1, 1] = u[1,1]
 [1, 2] = u[1,2]
 [1, 3] = u[1,3]
 [2, 2] = u[2,2]
 [2, 3] = u[2,3]
```

We can also conditionally create variables by adding a comparison check that depends upon the named indices and is separated from the indices by a semi-colon ;:

```
julia> @variable(model, v[i = 1:9; mod(i, 3) == 0])
SparseAxisArray{VariableRef, 1, Tuple{Int64}} with 3 entries:
 [3] = v[3]
 [6] = v[6]
 [9] = v[9]
```

Index elements in a DenseAxisArray as follows:

```
julia> u[1, 2]
u[1,2]
```

```
julia> v[[3, 6]]
SparseAxisArray{VariableRef, 1, Tuple{Int64}} with 2 entries:
 [3] = v[3]
 [6] = v[6]
```

### Integrality

JuMP can create binary and integer variables. Binary variables are constrained to the set  $\{0, 1\}$ , and integer variables are constrained to the set  $\mathbb{Z}$ .

#### Integer variables

Create an integer variable by passing Int:

```
julia> @variable(model, integer_x, Int)
integer_x
```

or setting the integer keyword to true:

```
julia> @variable(model, integer_z, integer = true)
integer_z
```

### Binary variables

Create a binary variable by passing `Bin`:

```
julia> @variable(model, binary_x, Bin)
binary_x
```

or setting the `binary` keyword to `true`:

```
julia> @variable(model, binary_z, binary = true)
binary_z
```

### Constraint basics

We'll need a new model to explain some of the constraint basics:

```
julia> model = Model()
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none

julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> @variable(model, z[1:10]);
```

### Containers

Just as we had containers for variables, JuMP also provides `Arrays`, `DenseAxisArrays`, and `SparseAxisArrays` for storing collections of constraints. Examples for each container type are given below.

#### Arrays

Create an Array of constraints:

```
julia> @constraint(model, [i = 1:3], i * x <= i + 1)
3-element Vector{ConstraintRef{Model,
    ↳ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↳ MathOptInterface.LessThan{Float64}}, ScalarShape}}:
    x ≤ 2
    2 x ≤ 3
    3 x ≤ 4
```

## DenseAxisArrays

Create an DenseAxisArray of constraints:

```
julia> @constraint(model, [i = 1:2, j = 2:3], i * x <= j + 1)
2-dimensional DenseAxisArray{ConstraintRef{Model},
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape},2,...} with index sets:
    Dimension 1, Base.OneTo(2)
    Dimension 2, 2:3
And data, a 2x2 Matrix{ConstraintRef{Model},
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}:
    x ≤ 3      x ≤ 4
    2 x ≤ 3   2 x ≤ 4
```

## SparseAxisArrays

Create an SparseAxisArray of constraints:

```
julia> @constraint(model, [i = 1:2, j = 1:2; i != j], i * x <= j + 1)
SparseAxisArray{ConstraintRef{Model},
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}, 2, Tuple{Int64, Int64}} with 2 entries:
    [1, 2] = x ≤ 3
    [2, 1] = 2 x ≤ 2
```

## Constraints in a loop

We can add constraints using regular Julia loops:

```
julia> for i in 1:3
        @constraint(model, 6x + 4y >= 5i)
    end
```

or use for each loops inside the @constraint macro:

```
julia> @constraint(model, [i in 1:3], 6x + 4y >= 5i)
3-element Vector{ConstraintRef{Model},
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.GreaterThan{Float64}}, ScalarShape}:
    6 x + 4 y ≥ 5
    6 x + 4 y ≥ 10
    6 x + 4 y ≥ 15
```

We can also create constraints such as  $\sum_{i=1}^{10} z_i \leq 1$ :

```
julia> @constraint(model, sum(z[i] for i in 1:10) <= 1)
z[1] + z[2] + z[3] + z[4] + z[5] + z[6] + z[7] + z[8] + z[9] + z[10] ≤ 1
```

## Objective functions

Set an objective function with `@objective`:

```
julia> model = Model(HiGHS.Optimizer)
A JuMP Model
└ solver: HiGHS
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> @variable(model, x >= 0)
x

julia> @variable(model, y >= 0)
y

julia> @objective(model, Min, 2x + y)
2 x + y
```

Create a maximization objective using Max:

```
julia> @objective(model, Max, 2x + y)
2 x + y
```

### Tip

Calling `@objective` multiple times will over-write the previous objective. This can be useful when you want to solve the same problem with different objectives.

## Vectorized syntax

We can also add constraints and an objective to JuMP using vectorized linear algebra. We'll illustrate this by solving an LP in standard form that is,

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \end{aligned}$$

```
julia> vector_model = Model(HiGHS.Optimizer)
A JuMP Model
└ solver: HiGHS
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> A = [1 1 9 5; 3 5 0 8; 2 0 6 13]
```

```

3x4 Matrix{Int64}:
1 1 9 5
3 5 0 8
2 0 6 13

julia> b = [7, 3, 5]
3-element Vector{Int64}:
7
3
5

julia> c = [1, 3, 5, 2]
4-element Vector{Int64}:
1
3
5
2

julia> @variable(vector_model, x[1:4] >= 0)
4-element Vector{VariableRef}:
x[1]
x[2]
x[3]
x[4]

julia> @constraint(vector_model, A * x .== b)
3-element Vector{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↪ MathOptInterface.EqualTo{Float64}}, ScalarShape}}:
x[1] + x[2] + 9 x[3] + 5 x[4] = 7
3 x[1] + 5 x[2] + 8 x[4] = 3
2 x[1] + 6 x[3] + 13 x[4] = 5

julia> @objective(vector_model, Min, c' * x)
x[1] + 3 x[2] + 5 x[3] + 2 x[4]

julia> optimize!(vector_model)
Running HiGHS 1.8.0 (git hash: fcfb534146): Copyright (c) 2024 HiGHS under MIT licence terms
Coefficient ranges:
Matrix [1e+00, 1e+01]
Cost [1e+00, 5e+00]
Bound [0e+00, 0e+00]
RHS [3e+00, 7e+00]
Presolving model
3 rows, 4 cols, 10 nonzeros 0s
3 rows, 4 cols, 10 nonzeros 0s
Presolve : Reductions: rows 3(-0); columns 4(-0); elements 10(-0) - Not reduced
Problem not reduced by presolve: solving the LP
Using EKK dual simplex solver - serial
Iteration      Objective      Infeasibilities num(sum)
0          0.0000000000e+00 Pr: 3(13.5) 0s
4          4.9230769231e+00 Pr: 0(0) 0s
Model  status      : Optimal
Simplex iterations: 4
Objective value      : 4.9230769231e+00

```

```
HiGHS run time      :      0.00
julia> assert_is_solved_and_feasible(vector_model)

julia> objective_value(vector_model)
4.923076923076922
```

## 4.4 Getting started with sets and indexing

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

Most introductory courses to linear programming will teach you to identify sets over which the decision variables and constraints are indexed. Therefore, it is common to write variables such as  $x_i$  for all  $i \in I$ .

A common stumbling block for new users to JuMP is that JuMP *does not provide specialized syntax for constructing and manipulating these sets*.

We made this decision because Julia already provides a wealth of data structures for working with sets.

In contrast, because tools like AMPL are stand-alone software packages, they had to define their own syntax for set construction and manipulation. Indeed, the [AMPL Book](#) has two entire chapters devoted to sets and indexing (Chapter 5, "Simple Sets and Indexing," and Chapter 6, "Compound Sets and Indexing").

The purpose of this tutorial is to demonstrate a variety of ways in which you can construct and manipulate sets for optimization models.

If you haven't already, you should first read [Getting started with JuMP](#).

```
using JuMP
```

### Unordered sets

Unordered sets are useful to describe non-numeric indices, such as the names of cities or types of products.

The most common way to construct a set is by creating a vector:

```
animals = ["dog", "cat", "chicken", "cow", "pig"]
model = Model()
@variable(model, x[animals])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, ["dog", "cat", "chicken", "cow", "pig"]
And data, a 5-element Vector{VariableRef}:
  x[dog]
  x[cat]
  x[chicken]
  x[cow]
  x[pig]
```

We can also use things like the keys of a dictionary:

```
weight_of_animals = Dict(
    "dog" => 20.0,
    "cat" => 5.0,
    "chicken" => 2.0,
    "cow" => 720.0,
    "pig" => 150.0,
)
animal_keys = keys(weight_of_animals)
model = Model()
@variable(model, x[animal_keys])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
Dimension 1, ["cow", "chicken", "cat", "pig", "dog"]
And data, a 5-element Vector{VariableRef}:
x[cow]
x[chicken]
x[cat]
x[pig]
x[dog]
```

A third option is to use Julia's Set object.

```
animal_set = Set()
for animal in keys(weight_of_animals)
    push!(animal_set, animal)
end
animal_set
```

```
Set{Any} with 5 elements:
"cow"
"chicken"
"cat"
"pig"
"dog"
```

The nice thing about Sets is that they automatically remove duplicates:

```
push!(animal_set, "dog")
animal_set
```

```
Set{Any} with 5 elements:
"cow"
"chicken"
"cat"
"pig"
"dog"
```

Note how dog does not appear twice.

```
model = Model()
@variable(model, x[animal_set])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
Dimension 1, ["cow", "chicken", "cat", "pig", "dog"]
And data, a 5-element Vector{VariableRef}:
x[cow]
x[chicken]
x[cat]
x[pig]
x[dog]
```

## Sets of numbers

Sets of numbers are useful to describe sets that are ordered, such as years or elements in a vector. The easiest way to create sets of numbers is to use Julia's range syntax.

These can start at 1:

```
model = Model()
@variable(model, x[1:4])
```

```
4-element Vector{VariableRef}:
x[1]
x[2]
x[3]
x[4]
```

but they don't have to:

```
model = Model()
@variable(model, x[2012:2021])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
Dimension 1, 2012:2021
And data, a 10-element Vector{VariableRef}:
x[2012]
x[2013]
x[2014]
x[2015]
x[2016]
x[2017]
x[2018]
x[2019]
x[2020]
x[2021]
```

Ranges also have a `start:step:stop` syntax. So the Olympic years are:

```
model = Model()
@variable(model, x[1896:4:2020])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, 1896:4:2020
And data, a 32-element Vector{VariableRef}:
x[1896]
x[1900]
x[1904]
x[1908]
x[1912]
x[1916]
x[1920]
x[1924]
x[1928]
x[1932]
⋮
x[1988]
x[1992]
x[1996]
x[2000]
x[2004]
x[2008]
x[2012]
x[2016]
x[2020]
```

## Sets of other things

An important observation is that you can have *any* Julia type as the element of a set. It doesn't have to be a String or a Number. For example, you can have tuples:

```
sources = ["A", "B", "C"]
sinks = ["D", "E"]
S = [(source, sink) for source in sources, sink in sinks]
model = Model()
@variable(model, x[S])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, [("A", "D"), ("B", "D"), ("C", "D"), ("A", "E"), ("B", "E"), ("C", "E")]
And data, a 6-element Vector{VariableRef}:
x[("A", "D")]
x[("B", "D")]
x[("C", "D")]
x[("A", "E")]
x[("B", "E")]
x[("C", "E")]
```

```
x[("A", "D")]
```

$x(A, D)$

For multi-dimensional sets, you can use JuMP's syntax for constructing [Containers](#):

```
model = Model()
@variable(model, x[sources, sinks])
```

```
2-dimensional DenseAxisArray{VariableRef,2,...} with index sets:
    Dimension 1, ["A", "B", "C"]
    Dimension 2, ["D", "E"]
And data, a 3x2 Matrix{VariableRef}:
x[A,D]  x[A,E]
x[B,D]  x[B,E]
x[C,D]  x[C,E]
```

```
x["A", "D"]
```

$x_{A,D}$

#### Info

Note how we indexed `x["A", "D"]` instead of `x[("A", "D")]` as above.

### Sets to watch out for

JuMP supports any sets which are [iterable](#), that is, the set `set` supports a for-loop like: `[i for i in set]`. This causes a few common errors.

First, if `T = 3`, you may pass the integer `T` by mistake instead of a range like `1:T`:

```
model = Model()
T = 3
@variable(model, x[T])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
    Dimension 1, [3]
And data, a 1-element Vector{VariableRef}:
x[3]
```

This results in a single variable being created, instead of three as desired. Because this is a common error, a warning is printed, advising you to pass a `Vector{Int}` instead:

```
@variable(model, x_fixed[[T]])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, [3]
And data, a 1-element Vector{VariableRef}:
  x_fixed[3]
```

Second, because Strings are iterable, passing a "index" as a singleton index is the same as passing ['i', 'n', 'd', 'e', 'x']:

```
@variable(model, y["index"])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, ['i', 'n', 'd', 'e', 'x']
And data, a 5-element Vector{VariableRef}:
  y[i]
  y[n]
  y[d]
  y[e]
  y[x]
```

This time, a warning is not printed, but the work-around is similar, pass a Vector{String} instead:

```
@variable(model, y_fixed[["index"]])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, ["index"]
And data, a 1-element Vector{VariableRef}:
  y_fixed[index]
```

### Tip

As a rule of thumb, if you want an index with one element, avoid confusion by passing [index] instead of index.

## Set operations

Julia has built-in support for set operations such as `union`, `intersect`, and `setdiff`.

Therefore, to create a set of all years in which the summer Olympics were held, we can use:

```
baseline = 1896:4:2020
cancelled = [1916, 1940, 1944, 2020]
off_year = [2021]
olympic_years = union(setdiff(baseline, cancelled), off_year)
```

```
29-element Vector{Int64}:
1896
1900
1904
1908
1912
1920
1924
1928
1932
1936
    □
1988
1992
1996
2000
2004
2008
2012
2016
2021
```

You can also find the number of elements (that is, the cardinality) in a set using `length`:

```
length(olympic_years)
```

```
29
```

## Set membership operations

To compute membership of sets, use the `in` function.

```
2000 in olympic_years
```

```
true
```

```
2001 in olympic_years
```

```
false
```

## Indexing expressions

Use Julia's generator syntax to compute new sets, such as the list of Olympic years that are divisible by 3:

```
olympic_3_years = [year for year in olympic_years if mod(year, 3) == 0]
model = Model()
@variable(model, x[olympic_3_years])
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, [1896, 1908, 1920, 1932, 1956, 1968, 1980, 1992, 2004, 2016]
And data, a 10-element Vector{VariableRef}:
x[1896]
x[1908]
x[1920]
x[1932]
x[1956]
x[1968]
x[1980]
x[1992]
x[2004]
x[2016]
```

Alternatively, use JuMP's syntax for constructing [Containers](#):

```
model = Model()
@variable(model, x[year in olympic_years; mod(year, 3) == 0])
```

```
SparseAxisArray{VariableRef, 1, Tuple{Int64}} with 10 entries:
[1896]  =  x[1896]
[1908]  =  x[1908]
[1920]  =  x[1920]
[1932]  =  x[1932]
[1956]  =  x[1956]
[1968]  =  x[1968]
[1980]  =  x[1980]
[1992]  =  x[1992]
  □
[2004]  =  x[2004]
[2016]  =  x[2016]
```

## Compound sets

Consider a transportation problem in which we need to ship goods between cities. We have been provided a list of cities:

```
cities = ["Auckland", "Wellington", "Christchurch", "Dunedin"]
```

```
4-element Vector{String}:
"Auckland"
"Wellington"
"Christchurch"
"Dunedin"
```

and a distance matrix which records the shipping distance between pairs of cities. If we can't ship between two cities, the distance is 0.

```
distances = [0 643 1071 1426; 0 0 436 790; 0 0 0 360; 1426 0 0 0]
```

```
4x4 Matrix{Int64}:
 0 643 1071 1426
 0 0 436 790
 0 0 0 360
1426 0 0 0
```

Let's have a look at ways we could write a model with an objective function to minimize the total shipping cost. For simplicity, we'll ignore all constraints.

### Fix unused variables

One approach is to fix all variables that we can't use to zero. Most solvers are smart-enough to remove these during a presolve phase, so it has a very small impact on performance:

```
N = length(cities)
model = Model()
@variable(model, x[1:N, 1:N] >= 0)
for i in 1:N, j in 1:N
    if distances[i, j] == 0
        fix(x[i, j], 0.0; force = true)
    end
end
@objective(model, Min, sum(distances[i, j] * x[i, j] for i in 1:N, j in 1:N))
```

$$643x_{1,2} + 1071x_{1,3} + 1426x_{1,4} + 436x_{2,3} + 790x_{2,4} + 360x_{3,4} + 1426x_{4,1}$$

### Filtered summation

Another approach is to define filters whenever we want to sum over our decision variables:

```
N = length(cities)
model = Model()
@variable(model, x[1:N, 1:N] >= 0)
@objective(
    model,
    Min,
    sum(
```

```

        distances[i, j] * x[i, j] for i in 1:N, j in 1:N if distances[i, j] > 0
    ),
)

```

$$643x_{1,2} + 1071x_{1,3} + 1426x_{1,4} + 436x_{2,3} + 790x_{2,4} + 360x_{3,4} + 1426x_{4,1}$$

### Filtered indexing

We could also use JuMP's support for [Containers](#):

```

N = length(cities)
model = Model()
@variable(model, x[i = 1:N, j = 1:N; distances[i, j] > 0])
@objective(model, Min, sum(distances[i...] * x[i] for i in eachindex(x)))

```

$$643x_{1,2} + 1071x_{1,3} + 1426x_{1,4} + 436x_{2,3} + 790x_{2,4} + 360x_{3,4} + 1426x_{4,1}$$

#### Note

The `i...` is called a "splat." It converts a tuple like `(1, 2)` into two indices like `distances[1, 2]`.

### Converting to a different data structure

Another approach, and one that is often the most readable, is to convert the data you have into something that is easier to work with. Originally, we had a vector of strings and a matrix of distances. What we really need is something that maps usable origin-destination pairs to distances. A dictionary is an obvious choice:

```

routes = Dict(
    (a, b) => distances[i, j] for
        (i, a) in enumerate(cities), (j, b) in enumerate(cities) if
            distances[i, j] > 0
)

```

```

Dict{Tuple{String, String}, Int64} with 7 entries:
("Auckland", "Wellington")    => 643
("Wellington", "Christchurch") => 436
("Wellington", "Dunedin")     => 790
("Christchurch", "Dunedin")   => 360
("Auckland", "Dunedin")       => 1426
("Dunedin", "Auckland")       => 1426
("Auckland", "Christchurch")  => 1071

```

Then, we can create our model like so:

```

model = Model()
@variable(model, x[keys(routes)])
@objective(model, Min, sum(v * x[k] for (k, v) in routes))

```

$$643x("Auckland", "Wellington") + 436x("Wellington", "Christchurch") + 790x("Wellington", "Dunedin") + 360x("Christchurch", "Dunedin") \\ 1426x("Auckland", "Dunedin") + 1426x("Dunedin", "Auckland") + 1071x("Auckland", "Christchurch")$$

This has a number of benefits over the other approaches, including a compacter algebraic model and variables that are named in a more meaningful way.

### Tip

If you're struggling to formulate a problem using the available syntax in JuMP, it's probably a sign that you should convert your data into a different form.

### Next steps

The purpose of this tutorial was to show how JuMP does not have specialized syntax for set creation and manipulation. Instead, you should use the tools provided by Julia itself.

This is both an opportunity and a challenge, because you are free to pick the syntax and data structures that best suit your problem, but for new users it can be daunting to decide which structure to use.

Read through some of the other JuMP tutorials to get inspiration and ideas for how you can use Julia's syntax and data structures to your advantage.

## 4.5 Getting started with data and plotting

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

In this tutorial we will learn how to read tabular data into Julia, and some of the basics of plotting.

If you're new to Julia, start by reading [Getting started with Julia](#) and [Getting started with JuMP](#) first.

### Note

There are multiple ways to read the same kind of data into Julia. This tutorial focuses on `DataFrames.jl` because it provides the ecosystem to work with most of the required file types in a straightforward manner.

Before we get started, we need this constant to point to where the data files are.

```
import JuMP
const DATA_DIR = joinpath(
    dirname(pathof(JuMP)),
    joinpath("../", "docs", "src", "tutorials", "getting_started", "data"),
);
```

### Where to get help

Read the documentation

- Plots.jl: <http://docs.juliaplots.org/latest/>
- CSV.jl: <http://csv.juliadata.org/stable>
- DataFrames.jl: <https://dataframes.juliadata.org/stable/>

## Preliminaries

To get started, we need to install some packages.

### DataFrames.jl

The `DataFrames` package provides a set of tools for working with tabular data. It is available through the Julia package manager.

```
using Pkg  
Pkg.add("DataFrames")
```

```
import DataFrames
```

#### What is a DataFrame?

A `DataFrame` is a data structure like a table or spreadsheet. You can use it for storing and exploring a set of related data values. Think of it as a smarter array for holding tabular data.

### Plots.jl

The `Plots` package provides a set of tools for plotting. It is available through the Julia package manager.

```
using Pkg  
Pkg.add("Plots")
```

```
import Plots
```

### CSV.jl

CSV and other delimited text files can be read by the `CSV.jl` package.

```
Pkg.add("CSV")
```

```
import CSV
```

### DataFrame basics

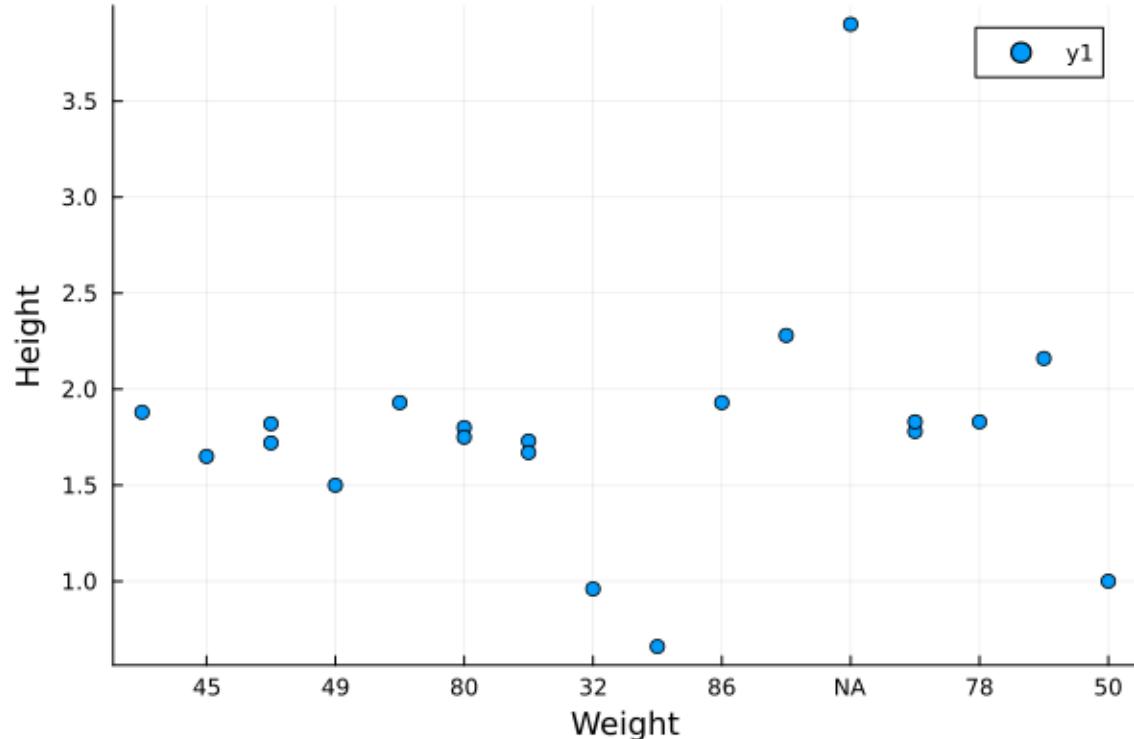
To read a CSV file into a `DataFrame`, we use the `CSV.read` function.

```
csv_df = CSV.read(joinpath(DATA_DIR, "StarWars.csv"), DataFrames.DataFrame)
```

Let's try plotting some of this data

	Name	Gender	Height	Weight	Eyecolor	Haircolor	Skincolor	Homeland	Born	Died	Jedi	Species	Weapon
	String31	String7	Float64	String7	String15	String7	String15	String15	String15	String15	String7	String15	String15
1	Anakin Skywalker	male	1.88	84	blue	blond	fair	Tatooine	41.9BBY	4ABY	jedi	human	lightsaber
2	Padme Amidala	female	1.65	45	brown	brown	light	Naboo	46BBY	19BBY	no_jedi	human	unarmed
3	Luke Skywalker	male	1.72	77	blue	blond	fair	Tatooine	19BBY	unk_died	jedi	human	lightsaber
4	Leia Skywalker	female	1.5	49	brown	brown	light	Alderaan	19BBY	unk_died	no_jedi	human	blaster
5	Qui-Gon Jinn	male	1.93	88.5	blue	brown	light	unk_planet	92BBY	32BBY	jedi	human	lightsaber
6	Obi-Wan Kenobi	male	1.82	77	bluegray	auburn	fair	Stewjon	57BBY	0BBY	jedi	human	lightsaber
7	Han Solo	male	1.8	80	brown	brown	light	Corellia	29BBY	unk_died	no_jedi	human	blaster
8	Sheev Palpatine	male	1.73	75	blue	red	pale	Naboo	82BBY	10ABY	no_jedi	human	force-lightning
9	R2-D2	male	0.96	32	NA	NA	NA	Naboo	33BBY	unk_died	no_jedi	droid	unarmed
10	C-3PO	male	1.67	75	NA	NA	NA	Tatooine	112BBY	3ABY	no_jedi	droid	unarmed
11	Yoda	male	0.66	17	brown	brown	green	unk_planet	896BBY	4ABY	jedi	yoda	lightsaber
12	Darth Maul	male	1.75	80	yellow	none	red	Dathomir	54BBY	unk_died	no_jedi	dathomirian	lightsaber
13	Dooku	male	1.93	86	brown	brown	light	Serenno	102BBY	19BBY	jedi	human	lightsaber
14	Chewbacca	male	2.28	112	blue	brown	NA	Kashyyyk	200BBY	25ABY	no_jedi	wookiee	bowcaster
15	Jabba	male	3.9	NA	yellow	none	tan-green	Tatooine	unk_born	4ABY	no_jedi	hutt	unarmed
16	Lando Calrissian	male	1.78	79	brown	blank	dark	Socorro	31BBY	unk_died	no_jedi	human	blaster
17	Boba Fett	male	1.83	78	brown	black	brown	Kamino	31.5BBY	unk_died	no_jedi	human	blaster
18	Jango Fett	male	1.83	79	brown	black	brown	ConcordDawn	66BBY	22BBY	no_jedi	human	blaster
19	Grievous	male	2.16	159	gold	black	orange	Kalee	unk_born	19BBY	no_jedi	kaleesh	slugthrower
20	Chief Chirpa	male	1.0	50	black	gray	brown	Endor	unk_born	4ABY	no_jedi	ewok	spear

```
Plots.scatter(
    csv_df.Weight,
    csv_df.Height;
    xlabel = "Weight",
    ylabel = "Height",
)
```



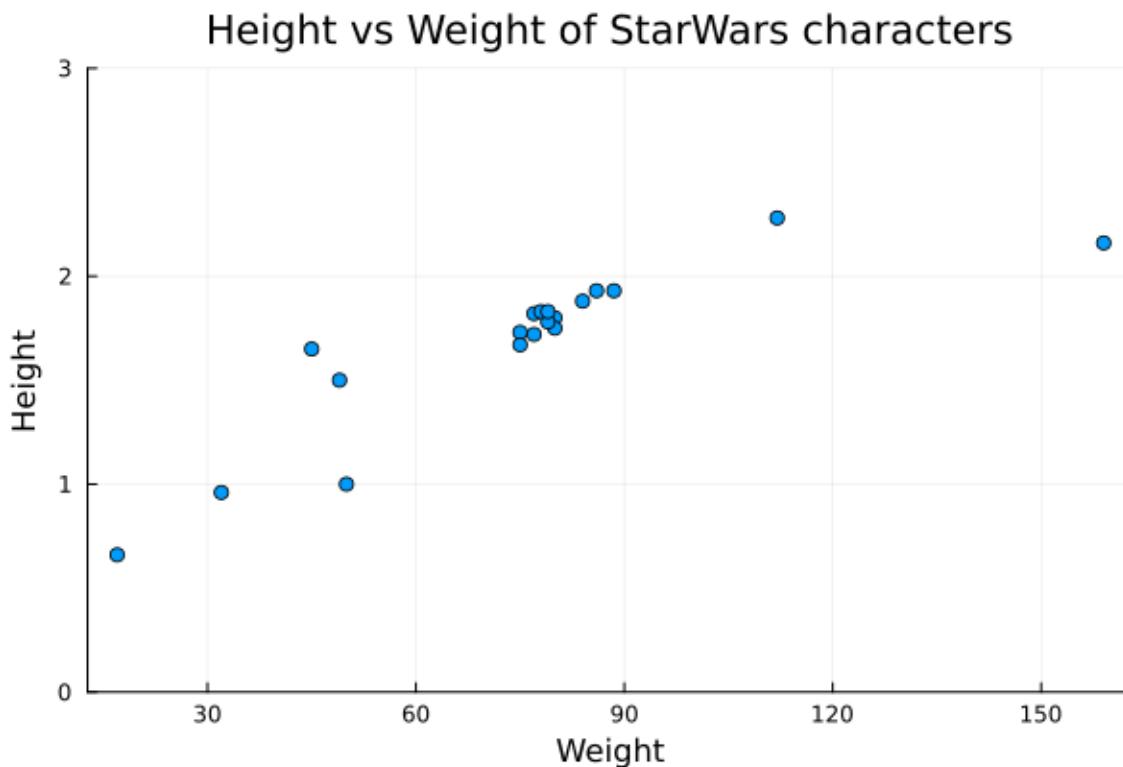
That doesn't look right. What happened? If you look at the dataframe above, it read Weight in as a String column because there are "NA" fields. Let's correct that, by telling CSV to consider "NA" as missing.

```
csv_df = CSV.read(
    joinpath(DATA_DIR, "StarWars.csv"),
    DataFrames.DataFrame;
    missingstring = "NA",
)
```

	Name	Gender	Height	Weight	Eyecolor	Haircolor	Skincolor	Homeland	Born	Died	Jedi	Species	Weapon
	String31	String7	Float64	Float64?	String15?	String7?	String15?	String15	String15	String15	String7	String15	String15
1	Anakin Skywalker	male	1.88	84.0	blue	blond	fair	Tatooine	41.9BBY	4ABY	jedi	human	lightsaber
2	Padme Amidala	female	1.65	45.0	brown	brown	light	Naboo	46BBY	19BBY	no_jedi	human	unarmed
3	Luke Skywalker	male	1.72	77.0	blue	blond	fair	Tatooine	19BBY	unk_died	jedi	human	lightsaber
4	Leia Skywalker	female	1.5	49.0	brown	brown	light	Alderaan	19BBY	unk_died	no_jedi	human	blaster
5	Qui-Gon Jinn	male	1.93	88.5	blue	brown	light	unk_planet	92BBY	32BBY	jedi	human	lightsaber
6	Obi-Wan Kenobi	male	1.82	77.0	bluegray	auburn	fair	Stewjon	57BBY	0BBY	jedi	human	lightsaber
7	Han Solo	male	1.8	80.0	brown	brown	light	Corellia	29BBY	unk_died	no_jedi	human	blaster
8	Sheev Palpatine	male	1.73	75.0	blue	red	pale	Naboo	82BBY	10ABY	no_jedi	human	force-lightning
9	R2-D2	male	0.96	32.0	missing	missing	missing	Naboo	33BBY	unk_died	no_jedi	droid	unarmed
10	C-3PO	male	1.67	75.0	missing	missing	missing	Tatooine	112BBY	3ABY	no_jedi	droid	unarmed
11	Yoda	male	0.66	17.0	brown	brown	green	unk_planet	896BBY	4ABY	jedi	yoda	lightsaber
12	Darth Maul	male	1.75	80.0	yellow	none	red	Dathomir	54BBY	unk_died	no_jedi	dathomirian	lightsaber
13	Dooku	male	1.93	86.0	brown	brown	light	Serenno	102BBY	19BBY	jedi	human	lightsaber
14	Chewbacca	male	2.28	112.0	blue	brown	missing	Kashyyyk	200BBY	25ABY	no_jedi	wookiee	bowcaster
15	Jabba	male	3.9	missing	yellow	none	tan-green	Tatooine	unk_born	4ABY	no_jedi	hutt	unarmed
16	Lando Calrissian	male	1.78	79.0	brown	blank	dark	Socorro	31BBY	unk_died	no_jedi	human	blaster
17	Boba Fett	male	1.83	78.0	brown	black	brown	Kamino	31.5BBY	unk_died	no_jedi	human	blaster
18	Jango Fett	male	1.83	79.0	brown	black	brown	ConcordDawn	66BBY	22BBY	no_jedi	human	blaster
19	Grievous	male	2.16	159.0	gold	black	orange	Kalee	unk_born	19BBY	no_jedi	kaleesh	slugthrower
20	Chief Chirpa	male	1.0	50.0	black	gray	brown	Endor	unk_born	4ABY	no_jedi	ewok	spear

Then let's re-plot our data

```
Plots.scatter(
    csv_df.Weight,
    csv_df.Height;
    title = "Height vs Weight of StarWars characters",
    xlabel = "Weight",
    ylabel = "Height",
    label = false,
    ylims = (0, 3),
)
```



That looks better.

**Tip**

Read the [CSV documentation](#) for other parsing options.

DataFrames.jl supports manipulation using functions similar to pandas. For example, split the dataframe into groups based on eye-color:

```
by_eyecolor = DataFrames.groupby(csv_df, :Eyecolor)
```

GroupedDataFrame with 7 groups based on key: Eyecolor

First Group (5 rows): Eyecolor = "blue"

	Name	Gender	Height	Weight	Eyecolor	Haircolor	Skincolor	Homeland	Born	Died
	String31	String7	Float64	Float64?	String15?	String7?	String15?	String15	String15	String15
1	Anakin Skywalker	male	1.88	84.0	blue	blond	fair	Tatooine	41.9BBY	4ABY
2	Luke Skywalker	male	1.72	77.0	blue	blond	fair	Tatooine	19BBY	unk_d
3	Qui-Gon Jinn	male	1.93	88.5	blue	brown	light	unk_planet	92BBY	32BB
4	Sheev Palpatine	male	1.73	75.0	blue	red	pale	Naboo	82BBY	10AB
5	Chewbacca	male	2.28	112.0	blue	brown	missing	Kashyyyk	200BBY	25AB
...										

Last Group (1 row): Eyecolor = "black"

	Name	Gender	Height	Weight	Eyecolor	Haircolor	Skincolor	Homeland	Born	Died
1	String31	String7	Float64	Float64?	String15?	String7?	String15?	String15	String15	String15
Chief Chirpa	male	1.0	50.0	black	gray	brown	Endor	unk_born	4ABY	

Then recombine into a single dataframe based on a function operating over the split dataframes:

```
eyecolor_count = DataFrames.combine(by_eyecolor) do df
    return DataFrames.nrow(df)
end
```

	Eyecolor	x1
	String15?	Int64
1	blue	5
2	brown	8
3	bluegray	1
4	<i>missing</i>	2
5	yellow	2
6	gold	1
7	black	1

We can rename columns:

```
DataFrames.rename!(eyecolor_count, :x1 => :count)
```

	Eyecolor	count
	String15?	Int64
1	blue	5
2	brown	8
3	bluegray	1
4	<i>missing</i>	2
5	yellow	2
6	gold	1
7	black	1

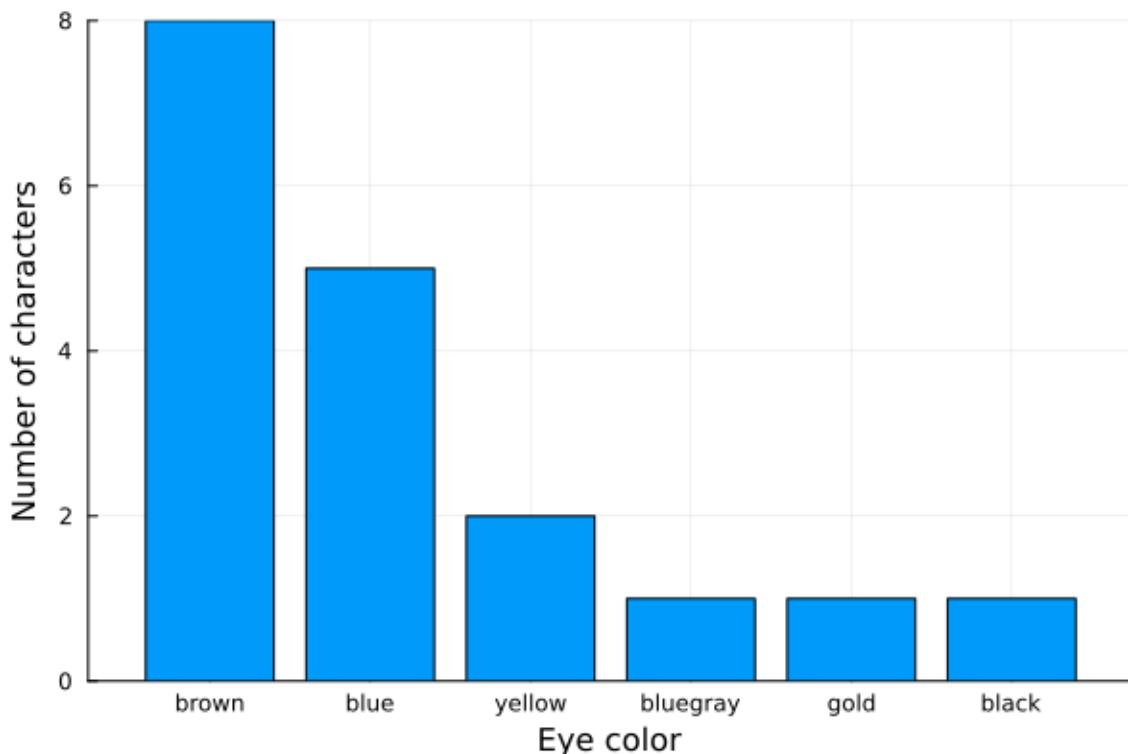
Drop some missing rows:

```
DataFrames.dropmissing!(eyecolor_count, :Eyecolor)
```

	Eyecolor	count
	String15	Int64
1	blue	5
2	brown	8
3	bluegray	1
4	yellow	2
5	gold	1
6	black	1

Then we can visualize the data:

```
sort!(eyecolor_count, :count; rev = true)
Plots.bar(
    eyecolor_count.Eyecolor,
    eyecolor_count.count;
    xlabel = "Eye color",
    ylabel = "Number of characters",
    label = false,
)
```



### Other Delimited Files

We can also use the CSV.jl package to read any other delimited text file format.

By default, CSV.File will try to detect a file's delimiter from the first 10 lines of the file.

Candidate delimiters include ',', '\t', ' ', '|', ';', and ':'. If it can't auto-detect the delimiter, it will assume ','.

Let's take the example of space separated data.

```
ss_df = CSV.read(joinpath(DATA_DIR, "Cereal.txt"), DataFrame)
```

We can also specify the delimiter as follows:

```
delim_df = CSV.read(
    joinpath(DATA_DIR, "Soccer.txt"),
```

	Name	Cups	Calories	Carbs	Fat	Fiber	Potassium	Protein	Sodium	Sugars
	String31	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
1	CapnCrunch	0.75	120	12.0	2	0.0	35	1	220	12
2	CocoaPuffs	1.0	110	12.0	1	0.0	55	1	180	13
3	Trix	1.0	110	13.0	1	0.0	25	1	140	12
4	AppleJacks	1.0	110	11.0	0	1.0	30	2	125	14
5	CornChex	1.0	110	22.0	0	0.0	25	2	280	3
6	CornFlakes	1.0	100	21.0	0	1.0	35	2	290	2
7	Nut&Honey	0.67	120	15.0	1	0.0	40	2	190	9
8	Smacks	0.75	110	9.0	1	1.0	40	2	70	15
9	MultiGrain	1.0	100	15.0	1	2.0	90	2	220	6
10	CracklinOat	0.5	110	10.0	3	4.0	160	3	140	7
11	GrapeNuts	0.25	110	17.0	0	3.0	90	3	179	3
12	HoneyNutCheerios	0.75	110	11.5	1	1.5	90	3	250	10
13	NutriGrain	0.67	140	21.0	2	3.0	130	3	220	7
14	Product19	1.0	100	20.0	0	1.0	45	3	320	3
15	TotalRaisinBran	1.0	140	15.0	1	4.0	230	3	190	14
16	WheatChex	0.67	100	17.0	1	3.0	115	3	230	3
17	Oatmeal	0.5	130	13.5	2	1.5	120	3	170	10
18	Life	0.67	100	12.0	2	2.0	95	4	150	6
19	Maypo	1.0	100	16.0	1	0.0	95	4	0	3
20	QuakerOats	0.5	100	14.0	1	2.0	110	4	135	6
21	Muesli	1.0	150	16.0	3	3.0	170	4	150	11
22	Cheerios	1.25	110	17.0	2	2.0	105	6	290	1
23	SpecialK	1.0	110	16.0	0	1.0	55	6	230	3

```
DataFrames.DataFrame;
delim = ":";
```

## Working with DataFrames

Now that we have read the required data into a DataFrame, let us look at some basic operations we can perform on it.

### Querying Basic Information

The size function gets us the dimensions of the DataFrame:

```
DataFrames.size(ss_df)
```

```
(23, 10)
```

We can also use the nrow and ncol functions to get the number of rows and columns respectively:

```
DataFrames.nrow(ss_df),  DataFrames.ncol(ss_df)
```

	Team	Played	Wins	Draws	Losses	Goals_for	Goals_against
	String31	Int64	Int64	Int64	Int64	String15	String15
1	Barcelona	38	30	4	4	110 goals	21 goals
2	Real Madrid	38	30	2	6	118 goals	38 goals
3	Atletico Madrid	38	23	9	6	67 goals	29 goals
4	Valencia	38	22	11	5	70 goals	32 goals
5	Seville	38	23	7	8	71 goals	45 goals
6	Villarreal	38	16	12	10	48 goals	37 goals
7	Athletic Bilbao	38	15	10	13	42 goals	41 goals
8	Celta Vigo	38	13	12	13	47 goals	44 goals
9	Malaga	38	14	8	16	42 goals	48 goals
10	Espanyol	38	13	10	15	47 goals	51 goals
11	Rayo Vallecano	38	15	4	19	46 goals	68 goals
12	Real Sociedad	38	11	13	14	44 goals	51 goals
13	Elche	38	11	8	19	35 goals	62 goals
14	Levante	38	9	10	19	34 goals	67 goals
15	Getafe	38	10	7	21	33 goals	64 goals
16	Deportivo La Coruna	38	7	14	17	35 goals	60 goals
17	Granada	38	7	14	17	29 goals	64 goals
18	Eibar	38	9	8	21	34 goals	55 goals
19	Almeria	38	8	8	22	35 goals	64 goals
20	Cordoba	38	3	11	24	22 goals	68 goals

(23, 10)

The describe function gives basic summary statistics of data in a DataFrame:

```
DataFrames.describe(ss_df)
```

	variable	mean	min	median	max	nmissing	eltype
	Symbol	Union...	Any	Union...	Any	Int64	DataType
1	Name		AppleJacks		WheatChex	0	String31
2	Cups	0.823043	0.25	1.0	1.25	0	Float64
3	Calories	113.043	100	110.0	150	0	Int64
4	Carbs	15.0435	9.0	15.0	22.0	0	Float64
5	Fat	1.13043	0	1.0	3	0	Int64
6	Fiber	1.56522	0.0	1.5	4.0	0	Float64
7	Potassium	86.3043	25	90.0	230	0	Int64
8	Protein	2.91304	1	3.0	6	0	Int64
9	Sodium	189.957	0	190.0	320	0	Int64
10	Sugars	7.52174	1	7.0	15	0	Int64

Names of every column can be obtained by the names function:

```
DataFrames.names(ss_df)
```

```
10-element Vector[String]:
"Name"
"Cups"
"Calories"
"Carbs"
"Fat"
"Fiber"
"Potassium"
"Protein"
"Sodium"
"Sugars"
```

Corresponding data types are obtained using the broadcasted eltype function:

```
eltype(ss_df)
```

	Name	Cups	Calories	Carbs	Fat	Fiber	Potassium	Protein	Sodium	Sugars
	DataType	DataType	DataType	DataType						
1	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
2	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
3	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
4	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
5	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
6	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
7	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
8	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
9	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
10	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
11	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
12	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
13	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
14	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
15	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
16	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
17	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
18	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
19	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
20	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
21	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
22	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64
23	Char	Float64	Int64	Float64	Int64	Float64	Int64	Int64	Int64	Int64

### Accessing the Data

Similar to regular arrays, we use numerical indexing to access elements of a DataFrame:

```
csv_df[1, 1]
```

```
"Anakin Skywalker"
```

The following are different ways to access a column:

```
csv_df[!, 1]
```

```
20-element Vector{InlineStrings.String31}:
"Anakin Skywalker"
"Padme Amidala"
"Luke Skywalker"
"Leia Skywalker"
"Qui-Gon Jinn"
"Obi-Wan Kenobi"
"Han Solo"
"Sheev Palpatine"
"R2-D2"
"C-3PO"
"Yoda"
"Darth Maul"
"Dooku"
"Chewbacca"
"Jabba"
"Lando Calrissian"
"Boba Fett"
"Jango Fett"
"Grievous"
"Chief Chirpa"
```

```
csv_df[!, :Name]
```

```
20-element Vector{InlineStrings.String31}:
"Anakin Skywalker"
"Padme Amidala"
"Luke Skywalker"
"Leia Skywalker"
"Qui-Gon Jinn"
"Obi-Wan Kenobi"
"Han Solo"
"Sheev Palpatine"
"R2-D2"
"C-3PO"
"Yoda"
"Darth Maul"
"Dooku"
"Chewbacca"
"Jabba"
"Lando Calrissian"
"Boba Fett"
"Jango Fett"
"Grievous"
"Chief Chirpa"
```

```
csv_df.Name
```

```
20-element Vector{InlineStrings.String31}:
"Anakin Skywalker"
"Padme Amidala"
"Luke Skywalker"
"Leia Skywalker"
"Qui-Gon Jinn"
"Obi-Wan Kenobi"
"Han Solo"
"Sheev Palpatine"
"R2-D2"
"C-3PO"
"Yoda"
"Darth Maul"
"Dooku"
"Chewbacca"
"Jabba"
"Lando Calrissian"
"Boba Fett"
"Jango Fett"
"Grievous"
"Chief Chirpa"
```

```
csv_df[:, 1] # Note that this creates a copy.
```

```
20-element Vector{InlineStrings.String31}:
"Anakin Skywalker"
"Padme Amidala"
"Luke Skywalker"
"Leia Skywalker"
"Qui-Gon Jinn"
"Obi-Wan Kenobi"
"Han Solo"
"Sheev Palpatine"
"R2-D2"
"C-3PO"
"Yoda"
"Darth Maul"
"Dooku"
"Chewbacca"
"Jabba"
"Lando Calrissian"
"Boba Fett"
"Jango Fett"
"Grievous"
"Chief Chirpa"
```

The following are different ways to access a row:

```
csv_df[1:1, :]
```

	Name	Gender	Height	Weight	Eyecolor	Haircolor	Skincolor	Homeland	Born	Died	Jedi	Species	Weapon
1	String31	String7	Float64	Float64?	String15?	String7?	String15?	String15	String15	String15	String7	String15	String15
1	Anakin Skywalker	male	1.88	84.0	blue	blond	fair	Tatooine	41.9BBY	4ABY	jedi	human	lightsaber

```
csv_df[1, :] # This produces a DataFrameRow.
```

	Name	Gender	Height	Weight	Eyecolor	Haircolor	Skincolor	Homeland	Born	Died	Jedi	Species	Weapon
1	String31	String7	Float64	Float64?	String15?	String7?	String15?	String15	String15	String15	String7	String15	String15
1	Anakin Skywalker	male	1.88	84.0	blue	blond	fair	Tatooine	41.9BBY	4ABY	jedi	human	lightsaber

We can change the values just as we normally assign values.

Assign a range to scalar:

```
csv_df[1:3, :Height] .= 1.83
```

```
3-element view(::Vector{Float64}, 1:3) with eltype Float64:
1.83
1.83
1.83
```

Assign a vector:

```
csv_df[4:6, :Height] = [1.8, 1.6, 1.8]
```

```
3-element Vector{Float64}:
1.8
1.6
1.8
```

```
csv_df
```

### Tip

There are a lot more things which can be done with a DataFrame. Read the [docs](#) for more information.

For information on dplyr-type syntax:

- Read the [DataFrames.jl documentation](#)
- Check out [DataFramesMeta.jl](#)

	Name	Gender	Height	Weight	Eyecolor	Haircolor	Skincolor	Homeland	Born	Died	Jedi	Species	Weapon
	String31	String7	Float64	Float64?	String15?	String7?	String15?	String15	String15	String15	String7	String15	String15
1	Anakin Skywalker	male	1.83	84.0	blue	blond	fair	Tatooine	41.9BBY	4ABY	jedi	human	lightsaber
2	Padme Amidala	female	1.83	45.0	brown	brown	light	Naboo	46BBY	19BBY	no_jedi	human	unarmed
3	Luke Skywalker	male	1.83	77.0	blue	blond	fair	Tatooine	19BBY	unk_died	jedi	human	lightsaber
4	Leia Skywalker	female	1.8	49.0	brown	brown	light	Alderaan	19BBY	unk_died	no_jedi	human	blaster
5	Qui-Gon Jinn	male	1.6	88.5	blue	brown	light	unk_planet	92BBY	32BBY	jedi	human	lightsaber
6	Obi-Wan Kenobi	male	1.8	77.0	bluegray	auburn	fair	Stewjon	57BBY	0BBY	jedi	human	lightsaber
7	Han Solo	male	1.8	80.0	brown	brown	light	Corellia	29BBY	unk_died	no_jedi	human	blaster
8	Sheev Palpatine	male	1.73	75.0	blue	red	pale	Naboo	82BBY	10ABY	no_jedi	human	force-lightning
9	R2-D2	male	0.96	32.0	missing	missing	missing	Naboo	33BBY	unk_died	no_jedi	droid	unarmed
10	C-3PO	male	1.67	75.0	missing	missing	missing	Tatooine	112BBY	3ABY	no_jedi	droid	unarmed
11	Yoda	male	0.66	17.0	brown	brown	green	unk_planet	896BBY	4ABY	jedi	yoda	lightsaber
12	Darth Maul	male	1.75	80.0	yellow	none	red	Dathomir	54BBY	unk_died	no_jedi	dathomirian	lightsaber
13	Dooku	male	1.93	86.0	brown	brown	light	Serenno	102BBY	19BBY	jedi	human	lightsaber
14	Chewbacca	male	2.28	112.0	blue	brown	missing	Kashyyyk	200BBY	25ABY	no_jedi	wookiee	bowcaster
15	Jabba	male	3.9	missing	yellow	none	tan-green	Tatooine	unk_born	4ABY	no_jedi	hatt	unarmed
16	Lando Calrissian	male	1.78	79.0	brown	blank	dark	Socorro	31BBY	unk_died	no_jedi	human	blaster
17	Boba Fett	male	1.83	78.0	brown	black	brown	Kamino	31.5BBY	unk_died	no_jedi	human	blaster
18	Jango Fett	male	1.83	79.0	brown	black	brown	ConcordDawn	66BBY	22BBY	no_jedi	human	blaster
19	Grievous	male	2.16	159.0	gold	black	orange	Kalee	unk_born	19BBY	no_jedi	kaleesh	slugthrower
20	Chief Chirpa	male	1.0	50.0	black	gray	brown	Endor	unk_born	4ABY	no_jedi	ewok	spear

### Example: the passport problem

Let's now apply what we have learned to solve a real problem.

#### Data manipulation

The [Passport Index Dataset](#) lists travel visa requirements for 199 countries, in .csv format. Our task is to find the minimum number of passports required to visit all countries.

```
passport_data = CSV.read(
    joinpath(DATA_DIR, "passport-index-matrix.csv"),
    DataFrames.DataFrame,
)
```

In this dataset, the first column represents a passport (=from) and each remaining column represents a foreign country (=to).

The values in each cell are as follows:

- 3 = visa-free travel
- 2 = eTA is required
- 1 = visa can be obtained on arrival
- 0 = visa is required
- -1 is for all instances where passport and destination are the same

Our task is to find out the minimum number of passports needed to visit every country without requiring a visa.

The values we are interested in are -1 and 3. Let's modify the dataframe so that the -1 and 3 are 1 (true), and all others are 0 (false):

```
function modifier(x)
    if x == -1 || x == 3
        return 1
    else
```

```

        return 0
    end
end

for country in passport_data.Passport
    passport_data[!, country] = modifier.(passport_data[!, country])
end

```

The values in the cells now represent:

- 1 = no visa required for travel
- 0 = visa required for travel

### JuMP Modeling

To model the problem as a mixed-integer linear program, we need a binary decision variable  $x_c$  for each country  $c$ .  $x_c$  is 1 if we select passport  $c$  and 0 otherwise. Our objective is to minimize the sum  $\sum x_c$  over all countries.

Since we wish to visit all the countries, for every country, we must own at least one passport that lets us travel to that country visa free. For one destination, this can be mathematically represented as  $\sum_{c \in C} a_{c,d} \cdot x_d \geq 1$ , where  $a$  is the `passport_data` dataframe.

Thus, we can represent this problem using the following model:

$$\begin{aligned} \min \quad & \sum_{c \in C} x_c \\ \text{s.t.} \quad & \sum_{c \in C} a_{c,d} x_c \geq 1 \quad \forall d \in C \\ & x_c \in \{0, 1\} \quad \forall c \in C. \end{aligned}$$

We'll now solve the problem using JuMP:

```

using JuMP
import HiGHS

```

First, create the set of countries:

```
C = passport_data.Passport
```

```

199-element Vector{String}:
"Afghanistan"
"Albania"
"Algeria"
"Andorra"
"Angola"
"Antigua and Barbuda"
"Argentina"

```

```
"Armenia"
"Australia"
"Austria"
[]
"Uruguay"
"Uzbekistan"
"Vanuatu"
"Vatican"
"Venezuela"
"Viet Nam"
"Yemen"
"Zambia"
"Zimbabwe"
```

Then, create the model and initialize the decision variables:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[C], Bin)
@objective(model, Min, sum(x))
@constraint(model, [d in C], passport_data[!, d]' * x >= 1)
model
```

```
A JuMP Model
├ solver: HiGHS
├ objective_sense: MIN_SENSE
|└ objective_function_type: AffExpr
├ num_variables: 199
├ num_constraints: 398
|└ AffExpr in MOI.GreaterThan{Float64}: 199
|└ VariableRef in MOI.ZeroOne: 199
└ Names registered in the model
  └ :x
```

Now optimize:

```
optimize!(model)
```

We can use the `solution_summary` function to get an overview of the solution:

```
solution_summary(model)
```

```
* Solver : HiGHS
* Status
  Result count      : 1
  Termination status : OPTIMAL
```

```

Message from the solver:
"kHighsModelStatusOptimal"

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : NO_SOLUTION
Objective value   : 2.30000e+01
Objective bound    : 2.30000e+01
Relative gap       : 0.00000e+00
Dual objective value : NaN

* Work counters
Solve time (sec)   : 6.53458e-03
Simplex iterations : 26
Barrier iterations : -1
Node count         : 1

```

Just to be sure, check that the solver found an optimal solution:

```
assert_is_solved_and_feasible(model)
```

## Solution

Let's have a look at the solution in more detail:

```
println("Minimum number of passports needed: ", objective_value(model))
```

```
Minimum number of passports needed: 23.0
```

```

println("Optimal passports:")
for c in C
    if value(x[c]) > 0.5
        println(" * ", c)
    end
end

```

```

Optimal passports:
* Afghanistan
* Chad
* Comoros
* Djibouti
* Georgia
* Hong Kong
* India
* Luxembourg

```

```
* Madagascar
* Maldives
* Mali
* New Zealand
* North Korea
* Papua New Guinea
* Singapore
* Somalia
* Sri Lanka
* Tunisia
* Turkey
* Uganda
* United Arab Emirates
* United States
* Zimbabwe
```

We need some passports, like New Zealand and the United States, which have widespread access to a large number of countries. However, we also need passports like North Korea which only have visa-free access to a very limited number of countries.

**Note**

We use `value(x[c]) > 0.5` rather than `value(x[c]) == 1` to avoid excluding solutions like `x[c] = 0.99999` that are "1" to some tolerance.

## 4.6 Debugging

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

Dealing with bugs is an unavoidable part of coding optimization models in any framework, including JuMP. Sources of bugs include not only generic coding errors (method errors, typos, off-by-one issues), but also semantic mistakes in the formulation of an optimization problem and the incorrect use of a solver.

This tutorial explains some common sources of bugs and modeling issues that you might encounter when writing models in JuMP, and it suggests a variety of strategies to deal with them.

**Tip**

This tutorial is more advanced than the other "Getting started" tutorials. It's in the "Getting started" section to give you an early preview of how to debug JuMP models. However, if you are new to JuMP, you may want to briefly skim the tutorial, and come back to it once you have written a few JuMP models.

```
julia> using JuMP
julia> import HiGHS
```

## Getting help

Debugging can be a frustrating part of modeling, particularly if you're new to optimization and programming. If you're stuck, join the [community forum](#) to search for answers to commonly asked questions.

Before asking a new question, make sure to read the post [Make it easier to help you](#), which contains a number of tips on how to ask a good question.

Above all else, take time to simplify your code as much as possible. The fewer lines of code you can post that reproduces the same issue, the faster someone can answer your question.

## Debugging Julia code

Read the [Debugging chapter](#) in the book [ThinkJulia.jl](#). It has a number of great tips and tricks for debugging Julia code.

## Solve failures

When a solver experiences an issue that prevents it from finding an optimal solution (or proving that one does not exist), JuMP may return one of a number of [termination\\_statuses](#).

For example, if the solver found a solution, but experienced numerical imprecision, it may return a status such as [ALMOST\\_OPTIMAL](#) or [ALMOST\\_LOCALLY\\_SOLVED](#) indicating that the problem was solved to a relaxed set of tolerances. Alternatively, the solver may return a problematic status such as [NUMERICAL\\_ERROR](#), [SLOW\\_PROGRESS](#), or [OTHER\\_ERROR](#), indicating that it could not find a solution to the problem.

Most solvers can experience numerical imprecision because they use [floating-point arithmetic](#) to perform operations such as addition, subtraction, and multiplication. These operations aren't exact, and small errors can accrue between the theoretical value and the value that the computer computes. For example:

```
julia> 0.1 * 3 == 0.3
false
```

### Tip

Read the [Guidelines for numerical issues](#) section of the Gurobi documentation, along with the [Debugging numerical problems](#) section of the YALMIP documentation.

## Common sources

Common sources of solve failures are:

- Very large numbers and very small numbers as problem coefficients. Exactly what "large" is depends on the solver and the problem, but in general, values above 1e6 or smaller than 1e-6 cause problems.
- Nonlinear problems with functions that are not defined in parts of their domain. For example, minimizing  $\log(x)$  where  $x \geq 0$  is undefined when  $x = 0$  (a common starting value).

## Strategies

Strategies to debug sources of solve failures include:

- Rescale variables in the problem and their associated coefficients to make the magnitudes of all coefficients in the  $1e-4$  to  $1e4$  range. For example, that might mean rescaling a variable from measuring distance in centimeters to kilometers.
- Try a different solver. Some solvers might be more robust than others for a particular problem.
- Read the documentation of your solver, and try settings that encourage numerical robustness.
- Set bounds or add constraints so that all nonlinear functions are defined across all of the feasible region. This particularly applies for functions like  $1 / x$  and  $\log(x)$  which are not defined for  $x = 0$ .

### Incorrect results

Sometimes, you might find that the solver returns an "optimal" solution that is incorrect according to the model you are trying to solve (perhaps the solution is suboptimal, or it doesn't satisfy some of the constraints).

Incorrect results can be hard to detect and debug, because the solver gives no hints that there is a problem. Indeed, the `termination_status` will likely be `OPTIMAL` and a solution will be available.

### Common sources

Common sources of incorrect results are:

- A modeling error, so that your JuMP model does not match the formulation you have on paper
- Not accounting for the tolerances that solvers use (for example, if  $x$  is binary, a value like  $x = 1.0000001$  may still be considered feasible)
- A bug in JuMP or the solver.

The probability of the issue being a bug in JuMP or the solver is much smaller than a modeling error. When in doubt, first assume there is a bug in your code before assuming that there is a bug in JuMP.

### Strategies

Strategies to debug sources of incorrect results include:

- Print your JuMP model to see if it matches the formulation you have on paper. Look out for incorrect signs `+` instead of `-`, and off-by-one errors such as `x[t]` instead of `x[t-1]`.
- Check that you are not using exact comparisons like `value(x) == 1.0`; always use `isapprox(value(x), 1.0; atol = 1e-6)` where you manually specify the comparison tolerance.
- Try a different solver. If one solver succeeds where another doesn't this is a sign that the problem is a numerical issue or a bug in the solver.

### Debugging an infeasible model

A model is infeasible if there is no primal solution that satisfies all of the constraints. In general, an infeasible model means one of two things:

- Your problem really has no feasible solution
- There is a mistake in your model.

### Example

A simple example of an infeasible model is:

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0)
x

julia> @objective(model, Max, 2x + 1)
2 x + 1

julia> @constraint(model, con, 2x - 1 <= -2)
con : 2 x ≤ -1
```

because the bound says that  $x \geq 0$ , but we can rewrite the constraint to be  $x \leq -1/2$ . When the problem is infeasible, JuMP may return one of a number of statuses. The most common is [INFEASIBLE](#):

```
julia> optimize!(model)

julia> termination_status(model)
INFEASIBLE::TerminationStatusCode = 2
```

Depending on the solver, you may also receive [INFEASIBLE\\_OR\\_UNBOUNDED](#) or [LOCALLY\\_INFEASIBLE](#).

A termination status of [INFEASIBLE\\_OR\\_UNBOUNDED](#) means that the solver could not prove if the solver was infeasible or unbounded, only that the model does not have a finite feasible optimal solution.

Nonlinear optimizers such as Ipopt may return the status [LOCALLY\\_INFEASIBLE](#). This does not mean that the solver *proved* no feasible solution exists, only that it could not find one. If you know a primal feasible point, try providing it as a starting point using [set\\_start\\_value](#) and re-optimize.

### Common sources

Common sources of infeasibility are:

- Incorrect units, for example, using a lower bound of megawatts and an upper bound of kilowatts
- Using `+` instead of `-` in a constraint
- Off-by-one and related errors, for example, using `x[t]` instead of `x[t-1]` in part of a constraint
- Otherwise invalid mathematical formulations

### Strategies

Strategies to debug sources of infeasibility include:

- Iteratively comment out a constraint (or block of constraints) and re-solve the problem. When you find a constraint that makes the problem infeasible when added, check the constraint carefully for errors.

- If the problem is still infeasible with all constraints commented out, check all variable bounds. Do they use the right data?
- If you have a known feasible solution, use `primal_feasibility_report` to evaluate the constraints and check for violations. You'll probably find that you have a typo in one of the constraints.
- Try a different solver. Sometimes, solvers have bugs, and they can incorrectly report a problem as infeasible when it isn't. If you find such a case where one solver reports the problem is infeasible and another can find an optimal solution, please report it by opening an issue on the GitHub repository of the solver that reports infeasibility.

**Tip**

Some solvers also have specialized support for debugging sources of infeasibility via an [irreducible infeasible subsystem](#). To see if your solver has support, try calling `compute_conflict!`:

```
julia> compute_conflict!(model)
ERROR: ArgumentError: The optimizer HiGHS.Optimizer does not support `compute_conflict!`
```

In this case, HiGHS does not support computing conflicts, but other solvers such as Gurobi and CPLEX do. If the solver does support computing conflicts, read [Conflicts](#) for more details.

**Penalty relaxation**

Another strategy to debug sources of infeasibility is the `relax_with_penalty!` function.

The penalty relaxation modifies constraints of the form  $f(x) \in S$  into  $f(x) + y - z \in S$ , where  $y, z \geq 0$ , and then it introduces a penalty term into the objective of  $a \times (y + z)$  (if minimizing, else  $-a$ ), where  $a$  is a penalty.

```
julia> map = relax_with_penalty!(model)
⠑ Warning: Skipping PenaltyRelaxation for
⠄ ConstraintIndex{MathOptInterface.VariableIndex,MathOptInterface.GreaterThan{Float64}}
⠄ @ MathOptInterface.Utilities
⠄ ~/julia/packages/MathOptInterface/MQX8C/src/Utilities/penalty_relaxation.jl:289
Dict{ConstraintRef{Model},
⠄ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
⠄ MathOptInterface.LessThan{Float64}}, ScalarShape}, AffExpr} with 1 entry:
con : 2 x - _[2] ≤ -1 => _[2]
```

Here `map` is a dictionary which maps constraint indices to an affine expression representing  $(y + z)$ .

If we optimize the relaxed model, this time we get a feasible solution:

```
julia> optimize!(model)

julia> termination_status(model)
OPTIMAL::TerminationStatusCode = 1
```

Iterate over the contents of `map` to see which constraints are violated:

```
julia> for (con, penalty) in map
    violation = value(penalty)
    if violation > 0
        println("Constraint `$(name(con))` is violated by $violation")
    end
end
Constraint `con` is violated by 1.0
```

Once you find a violated constraint in the relaxed problem, take a look to see if there is a typo or other common mistake in that particular constraint.

Consult the docstring [relax\\_with\\_penalty!](#) for information on how to modify the penalty cost term  $a$ , either for every constraint in the model or a particular subset of the constraints.

When using [relax\\_with\\_penalty!](#), you should be aware that:

- Variable bounds and integrality restrictions are not relaxed. If the problem is still infeasible after calling [relax\\_with\\_penalty!](#), check the variable bounds.
- You cannot undo the penalty relaxation. If you need an unmodified model, rebuild the problem, or call [copy\\_model](#) before calling [relax\\_with\\_penalty!](#).

## Debugging an unbounded model

A model is unbounded if there is no limit on how good the objective value can get. Most often, an unbounded model means that you have an error in your modeling, because all physical systems have limits. (You cannot make an infinite amount of profit.)

### Example

A simple example of an unbounded model is:

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0)
x

julia> @objective(model, Max, 2x + 1)
2 x + 1
```

because we can increase  $x$  without limit, and the objective value  $2x + 1$  gets better as  $x$  increases.

When the problem is unbounded, JuMP may return one of a number of statuses. The most common is [DUAL\\_INFEASIBLE](#):

```
julia> optimize!(model)

julia> termination_status(model)
DUAL_INFEASIBLE::TerminationStatusCode = 3
```

Depending on the solver, you may also receive `INFEASIBLE_OR_UNBOUNDED` or an error code like `NORM_LIMIT`.

### Common sources

Common sources of unboundedness are:

- Using Max instead of Min
- Omitting variable bounds, such as  $0 \leq x \leq 1$
- Using + instead of - in a term of the objective function.

### Strategies

Strategies to debug sources of unboundedness include:

- Double check whether you intended Min or Max in the `@objective` line.
- Print the objective function with `print(objective_function(model))` and verify that the value and sign of each coefficient is as you expect.
- Add large bounds to all variables that are free or have one-sided bounds, then re-solve the problem. Because all variables are now bounded, the problem will have a finite optimal solution. Look at the value of each variable in the optimal solution to see if it is at one of the new bounds. If it is, you either need to specify a better bound for that variable, or there might be a mistake in the objective function associated with that variable (for example, a + instead of a -).

If there are too many variables to add bounds to, or there are too many terms to examine by hand, another strategy is to create a new variable with a large upper bound (if maximizing, lower bound if minimizing) and a constraint that the variable must be less-than or equal to the expression of the objective function. For example:

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0)
# @objective(model, Max, 2x + 1)
x

julia> @variable(model, objective <= 10_000)
objective

julia> @constraint(model, objective <= 2x + 1)
-2 x + objective ≤ 1

julia> @objective(model, Max, objective)
objective
```

This new model has a finite optimal solution, so we can solve it and then look for variables with large positive or negative values in the optimal solution.

```
julia> optimize!(model)

julia> assert_is_solved_and_feasible(model)

julia> for var in all_variables(model)
        if var == objective
            continue
        end
        if abs(value(var)) > 1e3
            println("Variable `$(name(var))` may be unbounded")
        end
    end
Variable `x` may be unbounded
```

## Debugging performance problems

There are two common sources for a model that takes a long time to solve:

1. JuMP builds the problem quickly, but the solver takes a long time to run or prove optimality. This commonly happens for mixed-integer programs, and you should see the solver print logs indicating slow but steady progress. There is no easy fix for this, other than choosing a different solver or reformulating your model.
2. JuMP builds the problem slowly, and even if you wait a while, the solver may ever start running or displaying output.

This section explains how to debug the second case.

As a rule of thumb, we never expect JuMP to be the bottleneck in the solution process. If your model takes longer to build than to solve, or if it takes longer than a small number of minutes to build, then you have a fixable performance problem. JuMP models should never take hours to build.

### Common sources

Common sources of performance problems are:

- Writing Julia code that has  $O(N^2)$  or worse scaling behavior. As one common example, see [Performance problems with sum-if formulations](#).
- Building a model with a very large ( $> 10^8$ ) number of variables or constraints. Here the most likely cause of the performance problem is that you do not have enough memory to store the model. Use a computer with more RAM.

### Strategies

The strategy to debug JuMP models that have performance problems depends on how long your model takes to build.

As a first step, encapsulate everything you want to debug into a single function `foo`, so you can run it with `@time foo()`.

Can you run `@time foo()` in seconds to minutes?

If the answer is "yes," then you can use [ProfileView.jl](#) to find the bottleneck.

To use ProfileView, do:

```
julia> using ProfileView

julia> @profview foo(); # run once to trigger compilation. Ignore the output.

julia> @profview foo()
```

This will open a flamegraph. The x-axis of the graph is time, so that wider bars take more time. The bars are stacked so that the `foo()` call is on the bottom, and subsequent calls within `foo` are stacked on top.

Reading a flamegraph can take some experience, but if you click on a bar it will print the line number to the REPL. Hunt around until you find the widest bar that points to a line of code that you have written, then ask yourself if it makes sense for this line to be the bottleneck.

If a wide bar points to code inside JuMP or a related Julia package, please open an issue on GitHub or post on the [community forum](#).

If `@time foo()` takes longer than a few minutes to run, then either make the problem smaller by using a smaller dataset, or do the following.

1. Comment out everything in the function, then, line by line (or block by block):
2. Un-comment some code and re-run `@time foo()`
3. If the time increases by a lot (from seconds or minutes to hours), look for  $O(N^2)$  or worse scaling behavior. Is there a better way to write the code that you are trying to execute?
4. If the time increases by more than expected, but it still takes seconds or minutes to execute, use [ProfileView](#) to look for obvious bottlenecks.

## 4.7 Tolerances and numerical issues

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

Optimization solvers can seem like magic black boxes that take in an algebraic formulation of a problem and return a solution. It is tempting to treat their solutions at face value, since we often have little ability to verify that the solution is in fact optimal. However, like all numerical algorithms that use floating point arithmetic, optimization solvers use tolerances to check whether a solution satisfies the constraints. In the best case, the solution satisfies the original constraints to [machine precision](#). In most cases, the solution satisfies the constraints to some very small tolerance that has no noticeable impact on the quality of the optimal solution. In the worst case, the solver can return a "wrong" solution, or fail to find one even if it exists. (The solution is "wrong" only in the sense of user expectation. It will satisfy the solution to the tolerances that are provided.)

The purpose of this tutorial is to explain the various types of tolerances that are used in optimization solvers and what you can reasonably expect from a solution.

There are a few sources of additional information:

- Ambros Gleixner has an excellent YouTube talk [Numerics in LP & MIP Solvers](#)
- Gurobi has a series of articles in their documentation called [Guidelines for Numerical Issues](#)

**Tip**

This tutorial is more advanced than the other "Getting started" tutorials. It's in the "Getting started" section to give you an early preview of how tolerances affect JuMP models. However, if you are new to JuMP, you may want to briefly skim the tutorial, and come back to it once you have written a few JuMP models.

**Required packages**

This tutorial uses the following packages:

```
using JuMP
import HiGHS
import SCS
```

**Background**

Optimization solvers use tolerances to check the feasibility of constraints.

There are four main types of tolerances:

1. primal feasibility: controls how feasibility of the primal solution is measured
2. dual feasibility: controls how feasibility of the dual solution is measured
3. integrality: controls how feasibility of the binary and integer variables are measured
4. optimality: controls how close the primal and dual solutions must be.

Solvers may use absolute tolerances, relative tolerances, or some mixture of both. The definition and default value of each tolerance is solver-dependent.

The dual feasibility tolerance is much the same as the primal feasibility tolerance, only that operates on the space of dual solutions instead of the primal. HiGHS has `dual_feasibility_tolerance`, but some solvers have only a single feasibility tolerance that uses the same value for both.

The optimality tolerance is a more technical tolerance that is used to test the equivalence of the primal and dual objectives in the KKT system if you are solving a continuous problem via interior point. HiGHS has `ipm_optimality_tolerance`, but some solvers will not have such a tolerance. Note that the optimality tolerance is different to the relative MIP gap that controls early termination of a MIP solution during branch-and-bound.

Because the dual and optimality tolerances are less used, this tutorial focuses on the primal feasibility and integrality tolerances.

**Primal feasibility**

The primal feasibility tolerance controls how primal constraints are evaluated. For example, the constraint  $2x = 1$  is actually implemented as  $|2x - 1| \leq \varepsilon$ , where  $\varepsilon$  is a small solver-dependent primal feasibility tolerance that is typically on the order of `1e-8`.

Here's an example in practice. This model should be infeasible, since  $x$  must be non-negative, but there is also an equality constraint that  $x$  is equal to a small negative number. Yet when we solve this problem, we get:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x >= 0)
@constraint(model, x == -1e-8)
optimize!(model)
is_solved_and_feasible(model)
```

true

value(x)

0.0

In other words, HiGHS thinks that the solution  $x = 0$  satisfies the constraint  $x == -1e-8$ . The value of  $\epsilon$  in HiGHS is controlled by the `primal_feasibility_tolerance` option. The default is  $1e-7$ . If we set this to a smaller value, HiGHS will now correctly deduce that the problem is infeasible:

```
set_attribute(model, "primal_feasibility_tolerance", 1e-10)
optimize!(model)
is_solved_and_feasible(model)
```

false

### Realistic example

Here's a more realistic example, which was reported in the [SCS.jl](#) repository:

```
n, ε = 13, 0.0234
N = 2^n
model = Model(SCS.Optimizer)
@variable(model, x[1:N] >= 0)
@objective(model, Min, x[1])
@constraint(model, sum(x) == 1)
z = [((-1)^(i & (1 << j)) >> j) for j in 0:n-1, i in 0:N-1]
@constraint(model, z * x .≥= 1 - ε)
optimize!(model)
```

```
-----
^I      SCS v3.2.7 - Splitting Conic Solver
^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
problem: variables n: 8192, constraints m: 8206
```

```

cones: ^I z: primal zero / dual free vars: 1
^I l: linear vars: 8205
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^I acceleration_lookback: 10, acceleration_interval: 10
^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^I nnz(A): 122880, nnz(P): 0
-----
iter | pri res | dua res |   gap   |   obj   |   scale   | time (s)
-----
 0| 2.00e+01  1.00e+00  2.00e+01 -9.98e+00  1.00e-01  3.51e-02
 100| 6.92e-05  7.92e-05  7.33e-06  2.41e-05  1.00e-01  9.39e-02
-----
status: solved
timings: total: 9.39e-02s = setup: 3.39e-02s + solve: 6.00e-02s
^I lin-sys: 5.07e-02s, cones: 2.14e-03s, accel: 7.95e-04s
-----
objective = 0.000024
-----
```

SCS reports that it solved the problem to optimality:

```
is_solved_and_feasible(model)
```

```
true
```

and that the solution for  $x[1]$  is nearly zero:

```
value(x[1])
```

```
2.04406873858532e-5
```

However, the analytic solution for  $x[1]$  is:

```
1 - n * ε / 2
```

```
0.8479
```

The answer is very wrong, and there is no indication from the solver that anything untoward happened. What's going on?

One useful debugging tool is [primal\\_feasibility\\_report](#):

```
report = primal_feasibility_report(model)
```

```
Dict{Any, Float64} with 8192 entries:
x[7341] ≥ 0 => 1.8669e-5
x[1023] ≥ 0 => 2.17278e-5
x[3662] ≥ 0 => 1.8669e-5
x[5715] ≥ 0 => 1.71395e-5
x[705] ≥ 0 => 1.25513e-5
x[3075] ≥ 0 => 1.25513e-5
x[3634] ≥ 0 => 1.71395e-5
x[5909] ≥ 0 => 1.71395e-5
x[956] ≥ 0 => 2.01984e-5
x[6499] ≥ 0 => 1.71395e-5
x[5110] ≥ 0 => 2.17278e-5
x[504] ≥ 0 => 2.01984e-5
x[3319] ≥ 0 => 2.01984e-5
x[6091] ≥ 0 => 2.01984e-5
x[7685] ≥ 0 => 1.56101e-5
x[1726] ≥ 0 => 2.01984e-5
x[2026] ≥ 0 => 2.01984e-5
x[5325] ≥ 0 => 1.71395e-5
x[6720] ≥ 0 => 2.17278e-5
[]          => []
```

`report` is a dictionary which maps constraints to the violation. The largest violation is approximately `1e-5`:

```
maximum(values(report))
```

```
6.92133754155444e-5
```

This makes sense, because the default primal feasibility tolerance for SCS is `1e-4`.

Most of the entries are lower bound constraints on the variables. Here are all the variables which violate their lower bound:

```
violated_variables = filter(xi -> value(xi) < 0, x)
```

```
8178-element Vector{VariableRef}:
x[4]
x[6]
x[7]
x[8]
x[10]
x[11]
x[12]
x[13]
x[14]
```

```
x[15]
[]
x[8184]
x[8185]
x[8186]
x[8187]
x[8188]
x[8189]
x[8190]
x[8191]
x[8192]
```

The first one is:

```
y = first(violated_variables)
```

$x_4$

It has a primal value of:

```
value(y)
```

```
-1.1021914231743998e-5
```

which matches the value in the feasibility report:

```
report[LowerBoundRef(y)]
```

```
1.1021914231743998e-5
```

Despite the small primal feasibility tolerance and the small actual violations of the constraints, our optimal solution is very far from the theoretical optimum.

We can "fix" our model by decreasing `eps_abs` and `eps_rel`, which SCS uses to control the absolute and relative feasibility tolerances. Now the solver finds the correct solution:

```
set_attribute(model, "eps_abs", 1e-5)
set_attribute(model, "eps_rel", 1e-5)
optimize!(model)
```

```
-----
^I      SCS v3.2.7 - Splitting Conic Solver
^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
```

```

problem: variables n: 8192, constraints m: 8206
cones: ^I z: primal zero / dual free vars: 1
^I l: linear vars: 8205
settings: eps_abs: 1.0e-05, eps_rel: 1.0e-05, eps_infeas: 1.0e-07
^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^I acceleration_lookback: 10, acceleration_interval: 10
^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^I nnz(A): 122880, nnz(P): 0
-----
iter | pri res | dua res | gap | obj | scale | time (s)
-----
0| 2.00e+01 1.00e+00 2.00e+01 -9.98e+00 1.00e-01 3.45e-02
250| 2.01e-02 2.85e-04 2.00e-02 3.01e-02 3.86e-01 1.85e-01
500| 3.69e-04 5.93e-04 8.84e-05 8.48e-01 6.13e-01 3.38e-01
550| 2.66e-06 6.58e-10 1.27e-05 8.48e-01 6.13e-01 3.69e-01
-----
status: solved
timings: total: 3.69e-01s = setup: 3.34e-02s + solve: 3.35e-01s
^I lin-sys: 2.74e-01s, cones: 1.16e-02s, accel: 6.39e-03s
-----
objective = 0.847906
-----
```

```

assert_is_solved_and_feasible(model)
value(x[1])
```

```
0.8479127435814551
```

### Why you shouldn't use a small tolerance

There is no direct relationship between the size of feasibility tolerance and the quality of the solution.

You might surmise from this section that you should set the tightest feasibility tolerance possible. However, tighter tolerances come at the cost of increased solve time.

For example, SCS is a first-order solver. This means it uses only local gradient information at update each iteration. SCS took 100 iterations to solve the problem with the default tolerance of 1e-4, and 550 iterations to solve the problem with 1e-5. SCS may not be able to find a solution to our problem with a tighter tolerance in a reasonable amount of time.

### Integrality

Integrality tolerances control how the solver decides if a variable satisfies an integrality or binary constraint. The tolerance is typically defined as:  $|x - \lfloor x + 0.5 \rfloor| \leq \varepsilon$ , which you can read as the absolute distance to the nearest integer.

Here's a simple example:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x == 1 + 1e-6, Int)
optimize!(model)
is_solved_and_feasible(model)
```

```
true
```

HiGHS found an optimal solution, and the value of  $x$  is:

```
value(x)
```

```
1.000001
```

In other words, HiGHS thinks that the solution  $x = 1.000001$  satisfies the constraint that  $x$  must be an integer. `primal_feasibility_report` shows that indeed, the integrality constraint is violated:

```
primal_feasibility_report(model)
```

```
Dict{Any, Float64} with 1 entry:
 x integer => 1.0e-6
```

The value of  $\varepsilon$  in HiGHS is controlled by the `mip_feasibility_tolerance` option. The default is  $1e-6$ . If we set the attribute to a smaller value, HiGHS will now correctly deduce that the problem is infeasible:

```
set_attribute(model, "mip_feasibility_tolerance", 1e-10)
optimize!(model)
is_solved_and_feasible(model)
```

```
false
```

### Realistic example

Integrality tolerances are particularly important when you have big-M type constraints. Small non-integer values in the integer variables can cause "leakage" flows even when the big-M switch is "off." Consider this example:

```
M = 1e6
model = Model()
@variable(model, x >= 0)
@variable(model, y, Bin)
@constraint(model, x <= M * y)
print(model)
```

```

Feasibility
Subject to
x - 1000000 y ≤ 0
x ≥ 0
y binary

```

This model has a feasible solution (to tolerances) of  $(x, y) = (1, 1e-6)$ ; there can be a non-zero value of  $x$  even when  $y$  is (approximately) 0.

```
primal_feasibility_report(model, Dict(x => 1.0, y => 1e-6))
```

```

Dict{Any, Float64} with 1 entry:
y binary => 1.0e-6

```

### Rounding the solution

Integrality tolerances are the reason why JuMP does not return `::Int` for `value(x)` of an integer variable or `::Bool` for `value(x)` of a binary variable.

In most cases, it is safe to post-process the solution using `y_int = round(Int, value(y))`. However, in some cases "fixing" the integrality like this can cause violations in primal feasibility that exceed the primal feasibility tolerance. For example, if we rounded our  $(x, y) = (1, 1e-6)$  solution to  $(x, y) = (1, 0)$ , then the constraint  $x \leq M * y$  is now violated by a value of 1.0, which is much greater than a typical feasibility tolerance of  $1e-8$ .

```
primal_feasibility_report(model, Dict(x => 1.0, y => 0.0))
```

```

Dict{Any, Float64} with 1 entry:
x - 1000000 y ≤ 0 => 1.0

```

### Why you shouldn't use a small tolerance

Just like primal feasibility tolerances, using a smaller value for the integrality tolerance can lead to greatly increased solve times.

### Contradictory results

The distinction between feasible and infeasible can be surprisingly nuanced. Solver A might decide the problem is feasible while solver B might decide it is infeasible. Different algorithms *within* solver A (like simplex and barrier) may also come to different conclusions. Even changing settings like turning presolve on and off can make a difference.

Here is an example where HiGHS reports the problem is infeasible, but there exists a feasible (to tolerance) solution:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x >= 0)
@variable(model, y >= 0)
@constraint(model, x + 1e8 * y == -1)
optimize!(model)
is_solved_and_feasible(model)
```

```
false
```

The feasible solution  $(x, y) = (0.0, -1e-8)$  has a maximum primal violation of  $1e-8$  which is smaller than the HiGHS feasibility tolerance:

```
primal_feasibility_report(model, Dict(x => 0.0, y => -1e-8))
```

```
Dict{Any, Float64} with 1 entry:
y ≥ 0 => 1.0e-8
```

This happens because there are two basic solutions. The first is infeasible at  $(x, y) = (-1, 0)$  and the second is feasible  $(x, y) = (0, -1e-8)$ . Different algorithms may terminate at either of these bases.

Another example is a variation on our integrality example, but this time, there are constraints that  $x \geq 1$  and  $y \leq 0.5$ :

```
M = 1e6
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x >= 1)
@variable(model, y, Bin)
@constraint(model, y ≤ 0.5)
@constraint(model, x ≤ M * y)
optimize!(model)
is_solved_and_feasible(model)
```

```
false
```

HiGHS reports the problem is infeasible, but there is a feasible (to tolerance) solution of:

```
primal_feasibility_report(model, Dict(x => 1.0, y => 1e-6))
```

```
Dict{Any, Float64} with 1 entry:
y binary => 1.0e-6
```

This happens because the presolve routine deduces that the  $y \leq 0.5$  constraint forces the binary variable  $y$  to take the value 0. Substituting the value for  $y$  into the last constraint, presolve may also deduce that  $x \leq 0$ , which violates the bound of  $x \geq 1$  and so the problem is infeasible.

We can work around this by providing HiGHS with the feasible starting solution:

```
set_start_value(x, 1)
set_start_value(y, 1e-6)
```

Now HiGHS will report that the problem is feasible:

```
optimize!(model)
is_solved_and_feasible(model)
```

```
true
```

### Contradictory results are not a bug in the solver

These contradictory examples are not bugs in the HiGHS solver. They are an expected result of the interaction between the tolerances and the solution algorithm. There will always be models in the gray boundary at the edge of feasibility, for which the question of feasibility is not a clear true or false.

### Problem scaling

Problem scaling refers to the absolute magnitudes of the data in your problem. The data is any numbers in the objective, the constraints, or the variable bounds.

We say that a problem is poorly scaled if there are very small ( $< 10^{-3}$ ) or very large ( $> 10^6$ ) coefficients in the problem, or if the ratio of the largest to smallest coefficient is large.

Numerical issues related to the feasibility tolerances most commonly arise because of poor problem scaling. The next examples assume a primal feasibility tolerance of  $1e-8$ , but actual tolerances may vary from one solver to another.

### Small magnitudes

If the problem data is too small, then the feasibility tolerance can be too easily satisfied. For example, consider:

```
model = Model()
@variable(model, x)
@constraint(model, 1e-8 * x == 1e-4)
```

$$1.0 \times 10^{-8}x = 0.0001$$

This should have the solution that  $x = 10^4$ , but because the feasibility tolerance of this constraint is  $|10^{-4} - 10^{-8}x| < 10^{-8}$ , it actually permits any value of  $x$  between 9999 and 10,001, which is a larger range of feasible values than you might have expected.

### Large magnitudes

If the problem data is too large, then the feasibility tolerance can be too difficult to satisfy.

```
model = Model()
@variable(model, x)
@constraint(model, 1e12 * x == 1e4)
```

$$1000000000000x = 10000$$

This should have the solution that  $x = 10^{-8}$ , but because the feasibility tolerance of this constraint is  $|10^{12}x - 10^4| < 10^{-8}$ , it actually permits any value of  $x$  in  $10^{-8} \pm 10^{-20}$ , which is a smaller range of feasible values than you might have expected.

### Large magnitude ratios

If the ratio of the smallest to the largest magnitude is too large, then the tolerances or small changes in the input data can lead to large changes in the optimal solution. We have already seen an example with the integrality tolerance, but we can exacerbate the behavior by putting a small coefficient on  $x$ :

```
model = Model()
@variable(model, x >= 0)
@variable(model, y, Bin)
@constraint(model, 1e-6x <= 1e6 * y)
```

$$1.0 \times 10^{-6}x - 1000000y \leq 0$$

This problem has a feasible (to tolerance) solution of:

```
primal_feasibility_report(model, Dict(x => 1_000_000.01, y => 1e-6))
```

```
Dict{Any, Float64} with 2 entries:
  1.0e-6 x - 1000000 y ≤ 0 => 1.0e-8
  y binary              => 1.0e-6
```

If you intended the constraint to read that if  $x$  is non-zero then  $y = 1$ , this solution might be unexpected.

### Recommended values

There are no hard rules that you must follow, and the interaction between tolerances, problem scaling, and the solution is problem dependent. You should always check the solution returned by the solver to check it makes sense for your application.

With that caveat in mind, a general rule of thumb to follow is:

Try to keep the ratio of the smallest to largest coefficient less than  $10^6$  in any row and column, and try to keep most values between  $10^{-3}$  and  $10^6$ .

### Choosing the correct units

The best way to fix problem scaling is by changing the units of your variables and constraints. Here's an example. Suppose we are choosing the level of capacity investment in a new power plant. We can install up to 1 GW of capacity at a cost of \$1.78/W, and we have a budget of \$200 million.

```
model = Model()
@variable(model, 0 <= x_capacity_W <= 10^9)
@constraint(model, 1.78 * x_capacity_W <= 200e6)
```

$$1.78x\_capacity\_W \leq 200000000$$

This constraint violates the recommendations because there are values greater than  $10^6$ , and the ratio of the coefficients in the constraint is  $10^8$ .

One fix is the convert our capacity variable from Watts to Megawatts. This yields:

```
model = Model()
@variable(model, 0 <= x_capacity_MW <= 10^3)
@constraint(model, 1.78e6 * x_capacity_MW <= 200e6)
```

$$1780000x\_capacity\_MW \leq 200000000$$

We can improve our model further by dividing the constraint by  $10^6$  to change the units from dollars to million dollars.

```
model = Model()
@variable(model, 0 <= x_capacity_MW <= 10^3)
@constraint(model, 1.78 * x_capacity_MW <= 200)
```

$$1.78x\_capacity\_MW \leq 200$$

This problem is equivalent to the original problem, but it has much better problem scaling.

As a general rule, to fix problem scaling you must simultaneously scale both variables and constraints. It is usually not sufficient to scale variables or constraints in isolation.

## 4.8 Design patterns for larger models

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

JuMP makes it easy to build and solve optimization models. However, once you start to construct larger models, and especially ones that interact with external data sources or have customizable sets of variables and constraints based on client choices, you may find that your scripts become unwieldy. This tutorial demonstrates a variety of ways in which you can structure larger JuMP models to improve their readability and maintainability.

**Tip**

This tutorial is more advanced than the other "Getting started" tutorials. It's in the "Getting started" section to give you an early preview of how JuMP makes it easy to structure larger models. However, if you are new to JuMP you may want to briefly skim the tutorial, and come back to it once you have written a few JuMP models.

**Overview**

This tutorial uses explanation-by-example. We're going to start with a simple [knapsack model](#), and then expand it to add various features and structure.

**A simple script**

Your first prototype of a JuMP model is probably a script that uses a small set of hard-coded data.

```
using JuMP, HiGHS
profit = [5, 3, 2, 7, 4]
weight = [2, 8, 4, 2, 5]
capacity = 10
N = 5
model = Model(HiGHS.Optimizer)
@variable(model, x[1:N], Bin)
@objective(model, Max, sum(profit[i] * x[i] for i in 1:N))
@constraint(model, sum(weight[i] * x[i] for i in 1:N) <= capacity)
optimize!(model)
assert_is_solved_and_feasible(model)
value.(x)
```

```
5-element Vector{Float64}:
 1.0
 0.0
 -0.0
 1.0
 1.0
```

The benefits of this approach are:

- it is quick to code
- it is quick to make changes.

The downsides include:

- all variables are global (read [Performance tips](#))
- it is easy to introduce errors, for example, having `profit` and `weight` be vectors of different lengths, or not match `N`
- the solution, `x[i]`, is hard to interpret without knowing the order in which we provided the data.

## Wrap the model in a function

A good next step is to wrap your model in a function. This is useful for a few reasons:

- it removes global variables
- it encapsulates the JuMP model and forces you to clarify your inputs and outputs
- we can add some error checking.

```
function solve_knapsack_1(profit::Vector, weight::Vector, capacity::Real)
    if length(profit) != length(weight)
        throw(DimensionMismatch("profit and weight are different sizes"))
    end
    N = length(weight)
    model = Model(HiGHS.Optimizer)
    @variable(model, x[1:N], Bin)
    @objective(model, Max, sum(profit[i] * x[i] for i in 1:N))
    @constraint(model, sum(weight[i] * x[i] for i in 1:N) <= capacity)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(x)
end

solve_knapsack_1([5, 3, 2, 7, 4], [2, 8, 4, 2, 5], 10)
```

```
5-element Vector{Float64}:
 1.0
 0.0
 -0.0
 1.0
 1.0
```

## Create better data structures

Although we can check for errors like mis-matched vector lengths, if you start to develop models with a lot of data, keeping track of vectors and lengths and indices is fragile and a common source of bugs. A good solution is to use Julia's type system to create an abstraction over your data.

For example, we can create a struct that represents a single object, with a constructor that lets us validate assumptions on the input data:

```
struct KnapsackObject
    profit::Float64
    weight::Float64
    function KnapsackObject(profit::Float64, weight::Float64)
        if weight < 0
            throw(DomainError("Weight of object cannot be negative"))
        end
        return new(profit, weight)
    end
end
```

as well as a struct that holds a dictionary of objects and the knapsack's capacity:

```
struct KnapsackData
    objects::Dict{String,KnapsackObject}
    capacity::Float64
end
```

Here's what our data might look like now:

```
objects = Dict(
    "apple" => KnapsackObject(5.0, 2.0),
    "banana" => KnapsackObject(3.0, 8.0),
    "cherry" => KnapsackObject(2.0, 4.0),
    "date" => KnapsackObject(7.0, 2.0),
    "eggplant" => KnapsackObject(4.0, 5.0),
)
data = KnapsackData(objects, 10.0)
```

```
Main.KnapsackData(Dict{String, Main.KnapsackObject}("cherry" => Main.KnapsackObject(2.0, 4.0),
    "banana" => Main.KnapsackObject(3.0, 8.0), "date" => Main.KnapsackObject(7.0, 2.0), "eggplant"
    => Main.KnapsackObject(4.0, 5.0), "apple" => Main.KnapsackObject(5.0, 2.0)), 10.0)
```

If you want, you can add custom printing to make it easier to visualize:

```
function Base.show(io::IO, data::KnapsackData)
    println(io, "A knapsack with capacity $(data.capacity) and possible items:")
    for (k, v) in data.objects
        println(
            io,
            " $(rpad(k, 8)) : profit = $(v.profit), weight = $(v.weight)",
        )
    end
    return
end

data
```

```
A knapsack with capacity 10.0 and possible items:
cherry   : profit = 2.0, weight = 4.0
banana   : profit = 3.0, weight = 8.0
date     : profit = 7.0, weight = 2.0
eggplant : profit = 4.0, weight = 5.0
apple    : profit = 5.0, weight = 2.0
```

Then, we can re-write our `solve_knapsack` function to take our `KnapsackData` as input:

```

function solve_knapsack_2(data::KnapsackData)
    model = Model(HiGHS.Optimizer)
    @variable(model, x[keys(data.objects)], Bin)
    @objective(model, Max, sum(v.profit * x[k] for (k, v) in data.objects))
    @constraint(
        model,
        sum(v.weight * x[k] for (k, v) in data.objects) <= data.capacity,
    )
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(x)
end

solve_knapsack_2(data)

```

```

1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
-0.0
0.0
1.0
1.0
1.0

```

## Read in data from files

Having a data structure is a good step. But it is still annoying that we have to hard-code the data into Julia. A good next step is to separate the data into an external file format; JSON is a common choice.

```

json_data = """
{
    "objects": {
        "apple": {"profit": 5.0, "weight": 2.0},
        "banana": {"profit": 3.0, "weight": 8.0},
        "cherry": {"profit": 2.0, "weight": 4.0},
        "date": {"profit": 7.0, "weight": 2.0},
        "eggplant": {"profit": 4.0, "weight": 5.0}
    },
    "capacity": 10.0
}
"""

temp_dir = mktempdir()
knapsack_json_filename = joinpath(temp_dir, "knapsack.json")
# Instead of writing a new file here you could replace `knapsack_json_filename`
# with the path to a local file.
write(knapsack_json_filename, json_data);

```

Now let's write a function that reads this file and builds a KnapsackData object:

```

import JSON

function read_data(filename)
    d = JSON.parsefile(filename)
    return KnapsackData(
        Dict(
            k => KnapsackObject(v["profit"], v["weight"]) for
            (k, v) in d["objects"]
        ),
        d["capacity"],
    )
end

data = read_data(knapsack_json_filename)

```

A knapsack with capacity 10.0 and possible items:

cherry	:	profit = 2.0, weight = 4.0
banana	:	profit = 3.0, weight = 8.0
date	:	profit = 7.0, weight = 2.0
eggplant	:	profit = 4.0, weight = 5.0
apple	:	profit = 5.0, weight = 2.0

### Add options via if-else

At this point, we have data in a file format which we can load and solve a single problem. For many users, this might be sufficient. However, at some point you may be asked to add features like "but what if we want to take more than one of a particular item?"

If this is the first time that you've been asked to add a feature, adding options via if-else statements is a good approach. For example, we might write:

```

function solve_knapsack_3(data::KnapsackData; binary_knapsack::Bool)
    model = Model(HiGHS.Optimizer)
    if binary_knapsack
        @variable(model, x[keys(data.objects)], Bin)
    else
        @variable(model, x[keys(data.objects)] >= 0, Int)
    end
    @objective(model, Max, sum(v.profit * x[k] for (k, v) in data.objects))
    @constraint(
        model,
        sum(v.weight * x[k] for (k, v) in data.objects) <= data.capacity,
    )
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(x)
end

```

```
solve_knapsack_3 (generic function with 1 method)
```

Now we can solve the binary knapsack:

```
solve_knapsack_3(data; binary_knapsack = true)
```

```
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
-0.0
0.0
1.0
1.0
1.0
```

And an integer knapsack where we can take more than one copy of each item:

```
solve_knapsack_3(data; binary_knapsack = false)
```

```
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
0.0
0.0
5.0
0.0
0.0
```

## Add configuration options via dispatch

If you get repeated requests to add different options, you'll quickly find yourself in a mess of different flags and if-else statements. It's hard to write, hard to read, and hard to ensure you haven't introduced any bugs. A good solution is to use Julia's type dispatch to control the configuration of the model. The easiest way to explain this is by example.

First, start by defining a new abstract type, as well as new subtypes for each of our options. These types are going to control the configuration of the knapsack model.

```
abstract type AbstractConfiguration end

struct BinaryKnapsackConfig <: AbstractConfiguration end

struct IntegerKnapsackConfig <: AbstractConfiguration end
```

Then, we rewrite our `solve_knapsack` function to take a `config` argument, and we introduce an `add_knapsack_variables` function to abstract the creation of our variables.

```
function solve_knapsack_4(data::KnapsackData, config::AbstractConfiguration)
    model = Model(HiGHS.Optimizer)
    x = add_knapsack_variables(model, data, config)
    @objective(model, Max, sum(v.profit * x[k] for (k, v) in data.objects))
    @constraint(
        model,
        sum(v.weight * x[k] for (k, v) in data.objects) <= data.capacity,
    )
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(x)
end
```

solve\_knapsack\_4 (generic function with 1 method)

For the binary knapsack problem, add\_knapsack\_variables looks like this:

```
function add_knapsack_variables(
    model::Model,
    data::KnapsackData,
    ::BinaryKnapsackConfig,
)
    return @variable(model, x[keys(data.objects)], Bin)
end
```

add\_knapsack\_variables (generic function with 1 method)

For the integer knapsack problem, add\_knapsack\_variables looks like this:

```
function add_knapsack_variables(
    model::Model,
    data::KnapsackData,
    ::IntegerKnapsackConfig,
)
    return @variable(model, x[keys(data.objects)] >= 0, Int)
end
```

add\_knapsack\_variables (generic function with 2 methods)

Now we can solve the binary knapsack:

solve\_knapsack\_4(data, BinaryKnapsackConfig())

```
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
-0.0
0.0
1.0
1.0
1.0
```

and the integer knapsack problem:

```
solve_knapsack_4(data, IntegerKnapsackConfig())
```

```
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
0.0
0.0
5.0
0.0
0.0
```

The main benefit of the dispatch approach is that you can quickly add new options without needing to modify the existing code. For example:

```
struct UpperBoundedKnapsackConfig <: AbstractConfiguration
    limit::Int
end

function add_knapsack_variables(
    model::Model,
    data::KnapsackData,
    config::UpperBoundedKnapsackConfig,
)
    return @variable(model, 0 <= x[keys(data.objects)] <= config.limit, Int)
end

solve_knapsack_4(data, UpperBoundedKnapsackConfig(3))
```

```
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
0.0
0.0
3.0
0.0
2.0
```

## Generalize constraints and objectives

It's easy to extend the dispatch approach to constraints and objectives as well. The key points to notice in the next two functions are that:

- we can access registered variables via `model[:x]`
- we can define generic functions which accept any `AbstractConfiguration` as a configuration argument. That means we can implement a single method and have it apply to multiple configuration types.

```

function add_knapsack_constraints(
    model::Model,
    data::KnapsackData,
    ::AbstractConfiguration,
)
    x = model[:x]
    @constraint(
        model,
        capacity_constraint,
        sum(v.weight * x[k] for (k, v) in data.objects) <= data.capacity,
    )
    return
end

function add_knapsack_objective(
    model::Model,
    data::KnapsackData,
    ::AbstractConfiguration,
)
    x = model[:x]
    @objective(model, Max, sum(v.profit * x[k] for (k, v) in data.objects))
    return
end

function solve_knapsack_5(data::KnapsackData, config::AbstractConfiguration)
    model = Model(HiGHS.Optimizer)
    add_knapsack_variables(model, data, config)
    add_knapsack_constraints(model, data, config)
    add_knapsack_objective(model, data, config)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(model[:x])
end

solve_knapsack_5(data, BinaryKnapsackConfig())

```

```

1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
-0.0
0.0
1.0

```

```
1.0
1.0
```

### Remove solver dependence, add error checks

Compared to where we started, our knapsack model is now significantly different. We've wrapped it in a function, defined some data types, and introduced configuration options to control the variables and constraints that get added. There are a few other steps we can do to further improve things:

- remove the dependence on HiGHS
- add checks that we found an optimal solution
- add a helper function to avoid the need to explicitly construct the data.

```
function solve_knapsack_6(
    optimizer,
    data::KnapsackData,
    config::AbstractConfiguration,
)
    model = Model(optimizer)
    add_knapsack_variables(model, data, config)
    add_knapsack_constraints(model, data, config)
    add_knapsack_objective(model, data, config)
    optimize!(model)
    if !is_solved_and_feasible(model)
        @warn("Model not solved to optimality")
        return nothing
    end
    return value.(model[:x])
end

function solve_knapsack_6(
    optimizer,
    data::String,
    config::AbstractConfiguration,
)
    return solve_knapsack_6(optimizer, read_data(data), config)
end

solution = solve_knapsack_6(
    HiGHS.Optimizer,
    knapsack_json_filename,
    BinaryKnapsackConfig(),
)
```

```
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
 -0.0
```

```
0.0
1.0
1.0
1.0
```

## Create a module

Now we're ready to expose our model to the wider world. That might be as part of a larger Julia project that we're contributing to, or as a stand-alone script that we can run on-demand. In either case, it's good practice to wrap everything in a module. This further encapsulates our code into a single namespace, and we can add documentation in the form of [docstrings](#).

Some good rules to follow when creating a module are:

- use `import` in a module instead of using `to` make it clear which functions are from which packages
- use `_` to start function and type names that are considered private
- add docstrings to all public variables and functions.

```
module KnapsackModel

import JuMP
import JSON

struct _KnapsackObject
    profit::Float64
    weight::Float64
    function _KnapsackObject(profit::Float64, weight::Float64)
        if weight < 0
            throw(DomainError("Weight of object cannot be negative"))
        end
        return new(profit, weight)
    end
end

struct _KnapsackData
    objects::Dict{String,_KnapsackObject}
    capacity::Float64
end

function _read_data(filename)
    d = JSON.parsefile(filename)
    return _KnapsackData(
        Dict(
            k => _KnapsackObject(v["profit"], v["weight"]) for
            (k, v) in d["objects"]
        ),
        d["capacity"],
    )
end
```

```
abstract type _AbstractConfiguration end

"""
    BinaryKnapsackConfig()

Create a binary knapsack problem where each object can be taken 0 or 1 times.
"""

struct BinaryKnapsackConfig <: _AbstractConfiguration end

"""
    IntegerKnapsackConfig()

Create an integer knapsack problem where each object can be taken any number of
times.
"""

struct IntegerKnapsackConfig <: _AbstractConfiguration end

function _add_knapsack_variables(
    model::JuMP.Model,
    data::_KnapsackData,
    ::BinaryKnapsackConfig,
)
    return JuMP.@variable(model, x[keys(data.objects)], Bin)
end

function _add_knapsack_variables(
    model::JuMP.Model,
    data::_KnapsackData,
    ::IntegerKnapsackConfig,
)
    return JuMP.@variable(model, x[keys(data.objects)] >= 0, Int)
end

function _add_knapsack_constraints(
    model::JuMP.Model,
    data::_KnapsackData,
    ::_AbstractConfiguration,
)
    x = model[:x]
    JuMP.@constraint(
        model,
        capacity_constraint,
        sum(v.weight * x[k] for (k, v) in data.objects) <= data.capacity,
    )
    return
end

function _add_knapsack_objective(
    model::JuMP.Model,
    data::_KnapsackData,
    ::_AbstractConfiguration,
)
    x = model[:x]
    JuMP.@objective(model, Max, sum(v.profit * x[k] for (k, v) in data.objects))
    return

```

```

end

function _solve_knapsack(
    optimizer,
    data::_KnapsackData,
    config::_AbstractConfiguration,
)
    model = JuMP.Model(optimizer)
    _add_knapsack_variables(model, data, config)
    _add_knapsack_constraints(model, data, config)
    _add_knapsack_objective(model, data, config)
    JuMP.optimize!(model)
    if !JuMP.is_solved_and_feasible(model)
        @warn("Model not solved to optimality")
        return nothing
    end
    return JuMP.value.(model[:x])
end

"""
solve_knapsack(
    optimizer,
    knapsack_json_filename::String,
    config::_AbstractConfiguration,
)
"""

Solve the knapsack problem and return the optimal primal solution

# Arguments

* `optimizer` : an object that can be passed to `JuMP.Model` to construct a new JuMP model.
* `knapsack_json_filename` : the filename of a JSON file containing the data for the problem.
* `config` : an object to control the type of knapsack model constructed.
  Valid options are:
  * `BinaryKnapsackConfig()`
  * `IntegerKnapsackConfig()`

# Returns

* If an optimal solution exists: a `JuMP.DenseAxisArray` that maps the `String` name of each object to the number of objects to pack into the knapsack.
* Otherwise, `nothing`, indicating that the problem does not have an optimal solution.

# Example

```julia
solution = solve_knapsack(
    HiGHS.Optimizer,
    "path/to/data.json",
    BinaryKnapsackConfig(),
)
```

```

```
```julia
solution = solve_knapsack(
    MOI.OptimizerWithAttributes(HiGHS.Optimizer, "output_flag" => false),
    "path/to/data.json",
    IntegerKnapsackConfig(),
)
```
```
function solve_knapsack(
    optimizer,
    knapsack_json_filename::String,
    config::AbstractConfiguration,
)
    data = _read_data(knapsack_json_filename)
    return _solve_knapsack(optimizer, data, config)
end
end
```

Main.KnapsackModel

Finally, you can call your model:

```
import .KnapsackModel

KnapsackModel.solve_knapsack(
    HiGHS.Optimizer,
    knapsack_json_filename,
    KnapsackModel.BinaryKnapsackConfig(),
)
```

```
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, ["cherry", "banana", "date", "eggplant", "apple"]
And data, a 5-element Vector{Float64}:
-0.0
0.0
1.0
1.0
1.0
```

**Note**

The `.` in `.KnapsackModel` denotes that it is a submodule and not a separate package that we installed with `Pkg.add`. If you put the `KnapsackModel` in a separate file, load it with:

```
include("path/to/KnapsackModel.jl")
import .KnapsackModel
```

**Add tests**

As a final step, you should add tests for your model. This often means testing on a small problem for which you can work out the optimal solution by hand. The Julia standard library `Test` has good unit-testing functionality.

```
import .KnapsackModel
using Test

@testset "KnapsackModel" begin
    @testset "feasible_binary_knapsack" begin
        x = KnapsackModel.solve_knapsack(
            HiGHS.Optimizer,
            knapsack_json_filename,
            KnapsackModel.BinaryKnapsackConfig(),
        )
        @test isapprox(x["apple"], 1, atol = 1e-5)
        @test isapprox(x["banana"], 0, atol = 1e-5)
        @test isapprox(x["cherry"], 0, atol = 1e-5)
        @test isapprox(x["date"], 1, atol = 1e-5)
        @test isapprox(x["eggplant"], 1, atol = 1e-5)
    end
    @testset "feasible_integer_knapsack" begin
        x = KnapsackModel.solve_knapsack(
            HiGHS.Optimizer,
            knapsack_json_filename,
            KnapsackModel.IntegerKnapsackConfig(),
        )
        @test isapprox(x["apple"], 0, atol = 1e-5)
        @test isapprox(x["banana"], 0, atol = 1e-5)
        @test isapprox(x["cherry"], 0, atol = 1e-5)
        @test isapprox(x["date"], 5, atol = 1e-5)
        @test isapprox(x["eggplant"], 0, atol = 1e-5)
    end
    @testset "infeasible_binary_knapsack" begin
        dir = mktempdir()
        infeasible_filename = joinpath(dir, "infeasible.json")
        write(
            infeasible_filename,
            """
            "objects": {
                "apple": {"profit": 5.0, "weight": 2.0},
                "banana": {"profit": 3.0, "weight": 8.0},
                "cherry": {"profit": 2.0, "weight": 4.0},
                "date": {"profit": 7.0, "weight": 2.0},
                "eggplant": {"profit": 4.0, "weight": 5.0}
            }
        """
    end
end
```

```

        },
        "capacity": -10.0
    }"",
)
x = KnapsackModel.solve_knapsack(
    HiGHS.Optimizer,
    infeasible_filename,
    KnapsackModel.BinaryKnapsackConfig(),
)
@test x === nothing
end
end

```

```

Test.DefaultTestSet("KnapsackModel", Any[Test.DefaultTestSet("feasible_binary_knapsack", Any[], 5,
    false, false, true, 1.738701845960475e9, 1.738701845962445e9, false,
    "design_patterns_for_larger_models.md"), Test.DefaultTestSet("feasible_integer_knapsack",
    Any[], 5, false, false, true, 1.73870184596248e9, 1.738701846085925e9, false,
    "design_patterns_for_larger_models.md"), Test.DefaultTestSet("infeasible_binary_knapsack",
    Any[], 1, false, false, true, 1.738701846085972e9, 1.73870184608792e9, false,
    "design_patterns_for_larger_models.md")], 0, false, false, true, 1.738701845960439e9,
    1.73870184608793e9, false, "design_patterns_for_larger_models.md")

```

### Tip

Place these tests in a separate file `test_knapsack_model.jl` so that you can run the tests by adding `include("test_knapsack_model.jl")` to any file where needed.

### Next steps

We've only briefly scratched the surface of ways to create and structure large JuMP models, so consider this tutorial a starting point, rather than a comprehensive list of all the possible ways to structure JuMP models. If you are embarking on a large project that uses JuMP, a good next step is to look at ways people have written large JuMP projects "in the wild."

Here are some good examples (all co-incidentally related to energy):

- AnyMOD.jl
  - JuMP-dev 2021 talk
  - source code
- PowerModels.jl
  - JuMP-dev 2021 talk
  - source code
- PowerSimulations.jl
  - JuliaCon 2021 talk

- [source code](#)
- UnitCommitment.jl
  - [JuMP-dev 2021 talk](#)
  - [source code](#)

## 4.9 Performance tips

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

By now you should have read the other "getting started" tutorials. You're almost ready to write your own models, but before you do so there are some important things to be aware of.

The Julia manual has an excellent section on [Performance tips](#). The purpose of this tutorial is to highlight a number of performance issues that are specific to JuMP.

### Required packages

This tutorial uses the following packages:

```
julia> using JuMP

julia> import HiGHS
```

### Use macros to build expressions

Use JuMP's macros to build expressions.

Constructing an expression outside the macro results in intermediate copies of the expression. For example,

```
x[1] + x[2] + x[3]
```

is equivalent to

```
a = x[1]
b = a + x[2]
c = b + x[3]
```

Since we only care about `c`, the `a` and `b` expressions are not needed and constructing them slows the program down.

JuMP's macros rewrite the expressions to operate in-place and avoid these extra copies. Because they allocate less memory, they are faster, particularly for large expressions.

Here's an example.

```
julia> model = Model()
A JuMP Model
└ solver: none
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> @variable(model, x[1:3])
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]
```

Here's what happens if we construct the expression outside the macro:

```
julia> @allocated x[1] + x[2] + x[3]
1296
```

### Info

The `@allocated` measures how many bytes were allocated during the evaluation of an expression.  
Fewer is better.

If we use the `@expression` macro, we get many fewer allocations:

```
julia> @allocated @expression(model, x[1] + x[2] + x[3])
640
```

### Use `add_to_expression!` to build summations

If you don't want to use the expression macros, use `add_to_expression!` to build summations. For example, instead of:

```
julia> expr = zero(AffExpr)
0

julia> for i in 1:3
           expr += x[i]
       end

julia> expr
x[1] + x[2] + x[3]
```

do

```
julia> expr = zero(AffExpr)
0

julia> for i in 1:3
           add_to_expression!(expr, x[i])
       end

julia> expr
x[1] + x[2] + x[3]
```

The former is equivalent to:

```
julia> expr0 = zero(AffExpr)
0

julia> expr1 = expr0 + x[1]
x[1]

julia> expr2 = expr1 + x[2]
x[1] + x[2]

julia> expr = expr2 + x[3]
x[1] + x[2] + x[3]
```

which allocates four unique `AffExpr` objects. The latter efficiently updates `expr` in-place so that only one `AffExpr` object is allocated.

The function `add_to_expression!` also supports terms like `y += a * x` where `a` is a constant. For example, instead of:

```
julia> expr = zero(AffExpr)
0

julia> for i in 1:3
           expr += i * x[i]
       end

julia> expr
x[1] + 2 x[2] + 3 x[3]
```

do

```
julia> expr = zero(AffExpr)
0

julia> for i in 1:3
           add_to_expression!(expr, i, x[i])
       end
```

```
julia> expr
x[1] + 2 x[2] + 3 x[3]
```

Don't do this, because `i * x[i]` will allocate a new `AffExpr` in each iteration:

```
julia> expr = zero(AffExpr)
0

julia> for i in 1:3
           add_to_expression!(expr, i * x[i])
       end

julia> expr
x[1] + 2 x[2] + 3 x[3]
```

### Disable string names

By default, JuMP creates String names for variables and constraints and passes these to the solver. The benefit of passing names is that it improves the readability of log messages from the solver (for example, "variable `x` has invalid bounds" instead of "variable `v1203` has invalid bounds"), but for larger models the overhead of passing names can be non-trivial.

Disable the creation of String names by setting `set_string_name = false` in the `@variable` and `@constraint` macros, or by calling `set_string_names_on_creation` to disable all names for a particular model:

```
julia> model = Model();

julia> set_string_names_on_creation(model, false)

julia> @variable(model, x)
_[1]

julia> @constraint(model, c, 2x <= 1)
2 _[1] ≤ 1
```

Note that this doesn't change how symbolic names and bindings are stored:

```
julia> x
_[1]

julia> model[:x]
_[1]

julia> x === model[:x]
true
```

But you can no longer look up the variable by the string name:

```
julia> variable_by_name(model, "x") === nothing
true
```

**Info**

For more information on the difference between string names, symbolic names, and bindings, see [String names, symbolic names, and bindings](#).

## 4.10 Performance problems with sum-if formulations

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to explain a common performance issue that can arise with summations like `sum(x[a] for a in list if condition(a))`. This issue is particularly common in models with graph or network structures.

**Tip**

This tutorial is more advanced than the other "Getting started" tutorials. It's in the "Getting started" section because it is one of the most common causes of performance problems that users experience when they first start using JuMP to write large scale programs. If you are new to JuMP, you may want to briefly skim the tutorial and come back to it once you have written a few JuMP models.

### Required packages

This tutorial uses the following packages

```
using JuMP
import Plots
```

### Data

As a motivating example, we consider a network flow problem, like the examples in [Network flow problems](#) or [The network multi-commodity flow problem](#).

Here is a function that builds a random graph. The specifics do not matter.

```
function build_random_graph(num_nodes::Int, num_edges::Int)
    nodes = 1:num_nodes
    edges = Pair{Int,Int}[i - 1 => i for i in 2:num_nodes]
    while length(edges) < num_edges
        edge = rand(nodes) => rand(nodes)
        if !(edge in edges)
            push!(edges, edge)
        end
    end
    function demand(n)
        if n == 1
            return -1
        end
    end
end
```

```

        elseif n == num_nodes
            return 1
        else
            return 0
        end
    end
    return nodes, edges, demand
end

nodes, edges, demand = build_random_graph(4, 8)

```

```
(1:4, [1 => 2, 2 => 3, 3 => 4, 2 => 2, 3 => 3, 1 => 1, 3 => 2, 1 => 4], Main.demand)
```

The goal is to decide the flow of a commodity along each edge in edges to satisfy the `demand(n)` of each node `n` in `nodes`.

The mathematical formulation is:

$$\begin{aligned} s.t. \quad & \sum_{(i,n) \in E} x_{i,n} - \sum_{(n,j) \in E} x_{n,j} = d_n \quad \forall n \in N \\ & x_e \geq 0 \quad \forall e \in E \end{aligned}$$

### Naïve model

The first model you might write down is:

```

model = Model()
@variable(model, flows[e in edges] >= 0)
@constraint(
    model,
    [n in nodes],
    sum(flows[(i, j)] for (i, j) in edges if j == n) -
    sum(flows[(i, j)] for (i, j) in edges if i == n) == demand(n)
);

```

The benefit of this formulation is that it looks very similar to the mathematical formulation of a network flow problem.

The downside to this formulation is subtle. Behind the scenes, the JuMP `@constraint` macro expands to something like:

```

model = Model()
@variable(model, flows[e in edges] >= 0)
for n in nodes
    flow_in = AffExpr(0.0)
    for (i, j) in edges
        if j == n
            add_to_expression!(flow_in, flows[(i, j)])
        end

```

```

    end
    flow_out = AffExpr(0.0)
    for (i, j) in edges
        if i == n
            add_to_expression!(flow_out, flows[(i, j)])
        end
    end
    @constraint(model, flow_in - flow_out == demand(n))
end

```

This formulation includes two for-loops, with a loop over every edge (twice) for every node. The big-O notation of the runtime is  $O(|nodes| \times |edges|)$ . If you have a large number of nodes and a large number of edges, the runtime of this loop can be large.

Let's build a function to benchmark our formulation:

```

function build_naive_model(nodes, edges, demand)
    model = Model()
    @variable(model, flows[e in edges] >= 0)
    @constraint(
        model,
        [n in nodes],
        sum(flows[(i, j)] for (i, j) in edges if j == n) -
        sum(flows[(i, j)] for (i, j) in edges if i == n) == demand(n)
    )
    return model
end

nodes, edges, demand = build_random_graph(1_000, 2_000)
@elapsed build_naive_model(nodes, edges, demand)

```

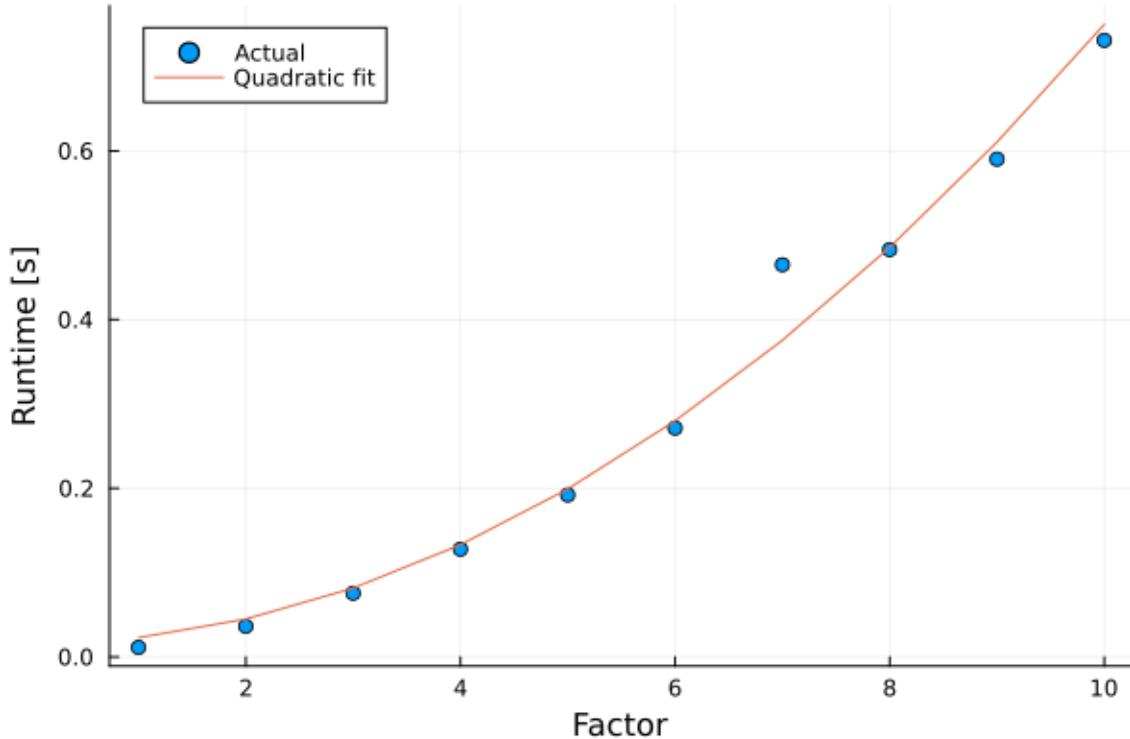
0.126908497

A good way to benchmark is to measure the runtime across a wide range of input sizes. From our big-O analysis, we should expect that doubling the number of nodes and edges results in a 4x increase in the runtime.

```

run_times = Float64[]
factors = 1:10
for factor in factors
    graph = build_random_graph(1_000 * factor, 5_000 * factor)
    push!(run_times, @elapsed build_naive_model(graph...))
end
Plots.plot(; xlabel = "Factor", ylabel = "Runtime [s]")
Plots.scatter!(factors, run_times; label = "Actual")
a, b = hcat(ones(10), factors .^ 2) \ run_times
Plots.plot!(factors, a .+ b * factors .^ 2; label = "Quadratic fit")

```



As expected, the runtimes demonstrate quadratic scaling: if we double the number of nodes and edges, the runtime increases by a factor of four.

### Caching

We can improve our formulation by caching the list of incoming and outgoing nodes for each node  $n$ :

```
out_nodes = Dict(n => Int[] for n in nodes)
in_nodes = Dict(n => Int[] for n in nodes)
for (i, j) in edges
    push!(out_nodes[i], j)
    push!(in_nodes[j], i)
end
```

with the corresponding change to our model:

```
model = Model()
@variable(model, flows[e in edges] >= 0)
@constraint(
    model,
    [n in nodes],
    sum(flows[(i, n)] for i in in_nodes[n]) -
    sum(flows[(n, j)] for j in out_nodes[n]) == demand(n)
);
```

The benefit of this formulation is that we now loop over  $\text{out}_\text{nodes}[n]$  rather than edges for each node  $n$ , and so the runtime is  $O(|edges|)$ .

Let's build a new function to benchmark our formulation:

```
function build_cached_model(nodes, edges, demand)
    out_nodes = Dict(n => Int[] for n in nodes)
    in_nodes = Dict(n => Int[] for n in nodes)
    for (i, j) in edges
        push!(out_nodes[i], j)
        push!(in_nodes[j], i)
    end
    model = Model()
    @variable(model, flows[e in edges] >= 0)
    @constraint(
        model,
        [n in nodes],
        sum(flows[(i, n)] for i in in_nodes[n]) -
        sum(flows[(n, j)] for j in out_nodes[n]) == demand(n)
    )
    return model
end

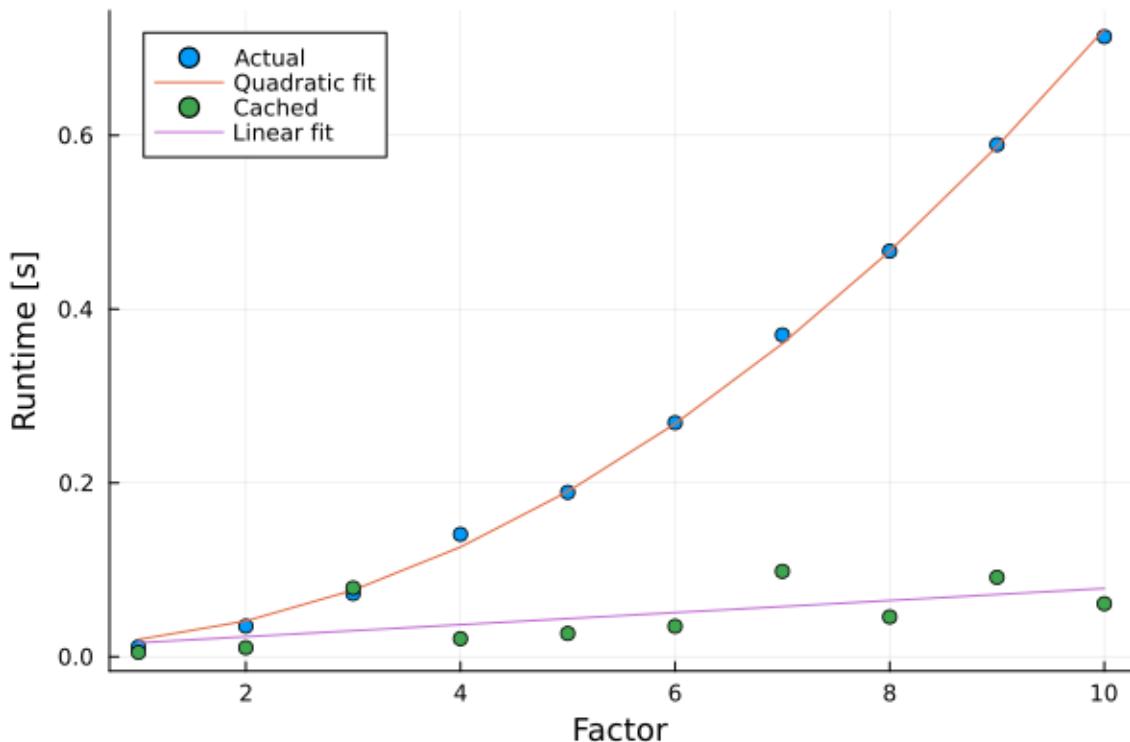
nodes, edges, demand = build_random_graph(1_000, 2_000)
@elapsed build_cached_model(nodes, edges, demand)
```

0.175075108

## Analysis

Now we can analyse the difference in runtime of the two formulations:

```
run_times_naive = Float64[]
run_times_cached = Float64[]
factors = 1:10
for factor in factors
    graph = build_random_graph(1_000 * factor, 5_000 * factor)
    push!(run_times_naive, @elapsed build_naive_model(graph...))
    push!(run_times_cached, @elapsed build_cached_model(graph...))
end
Plots.plot(; xlabel = "Factor", ylabel = "Runtime [s]")
Plots.scatter!(factors, run_times_naive; label = "Actual")
a, b = hcat(ones(10), factors .^ 2) \ run_times_naive
Plots.plot!(factors, a .+ b * factors .^ 2; label = "Quadratic fit")
Plots.scatter!(factors, run_times_cached; label = "Cached")
a, b = hcat(ones(10), factors) \ run_times_cached
Plots.plot!(factors, a .+ b * factors; label = "Linear fit")
```



Even though the cached model needs to build `in_nodes` and `out_nodes`, it is asymptotically faster than the naïve model, scaling linearly with `factor` rather than quadratically.

### Lesson

If you write code with `sum-if` type conditions, for example, `@constraint(model, [a in set], sum(x[b] for b in list if condition(a, b))`, you can improve the performance by caching the elements for which `condition(a, b)` is true.

Finally, you should understand that this behavior is not specific to JuMP, and that it applies more generally to all computer programs you might write. (Python programs that use Pyomo or gurobipy would similarly benefit from this caching approach.)

Understanding big-O notation and algorithmic complexity is a useful debugging skill to have, regardless of the type of program that you are writing.

# Chapter 5

## Transitioning

### 5.1 Transitioning from MATLAB

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

`YALMIP` and `CVX` are two packages for mathematical optimization in MATLAB®. They are independently developed and are in no way affiliated with JuMP.

The purpose of this tutorial is to help new users to JuMP who have previously used YALMIP or CVX by comparing and contrasting their different features.

#### Tip

If you have not used Julia before, read the [Getting started with Julia](#) tutorial.

### Namespaces

Julia has namespaces, which MATLAB lacks. Therefore one needs to either use the command:

```
using JuMP
```

in order bring all names exported by JuMP into scope, or:

```
import JuMP
```

in order to merely make the JuMP package available. `import` requires prefixing everything you use from JuMP with `JuMP. .` In this tutorial we use the former.

### Models

YALMIP and CVX have a single, implicit optimization model that you build by defining variables and constraints.

In JuMP, we create an explicit model first, and then, when you declare variables, constraints, or the objective function, you specify to which model they are being added.

Create a new JuMP model with the command:

```
model = Model()
```

```
A JuMP Model
└ solver: none
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none
```

## Variables

In most cases there is a direct translation between variable declarations. The following table shows some common examples:

JuMP	YALMIP	CVX
@variable(model, x)	x = sdpvar	variable x
@variable(model, x, Int)	x = intvar	variable x integer
@variable(model, x, Bin)	x = binvar	variable x binary
@variable(model, v[1:d])	v = sdpvar(d, 1)	variable v(d)
@variable(model, m[1:d, 1:d])	m = sdpvar(d,d,'full')	variable m(d, d)
@variable(model, m[1:d, 1:d] in ComplexPlane())	m = sdpvar(d,d,'full','complex')	complex
@variable(model, m[1:d, 1:d], Symmetric)	m = sdpvar(d)	variable m(d,d)
@variable(model, m[1:d, 1:d], Hermitian)	m = sdpvar(d,d,'hermitian','complexHermitian')	symmetric

Like CVX, but unlike YALMIP, JuMP can also constrain variables upon creation:

JuMP	CVX
@variable(model, v[1:d] >= 0)	variable v(d) nonnegative
@variable(model, m[1:d, 1:d], PSD)	variable m(d,d) semidefinite
@variable(model, m[1:d, 1:d] in PSDCone())	variable m(d,d) semidefinite
@variable(model, m[1:d, 1:d] in HermitianPSDCone())	variable m(d,d) complex

JuMP can additionally set variable bounds, which may be handled more efficiently by a solver than an equivalent linear constraint. For example:

```
@variable(model, -1 <= x[i in 1:3] <= i)
upper_bound.(x)
```

```
3-element Vector{Float64}:
1.0
2.0
3.0
```

A more interesting case is when you want to declare, for example,  $n$  real symmetric matrices. Both YALMIP and CVX allow you to put the matrices as the slices of a 3-dimensional array, via the commands `m = sdpvar(d, d, n)` and variable `m(d, d, n)` `Symmetric`, respectively. With JuMP this is not possible. Instead, to achieve the same result one needs to declare a vector of  $n$  matrices:

```
d, n = 3, 2
m = [@variable(model, [1:d, 1:d], Symmetric) for _ in 1:n]
```

```
2-element Vector{LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}}:
 [_[4] _[5] _[7]; _[5] _[6] _[8]; _[7] _[8] _[9]]
 [_[10] _[11] _[13]; _[11] _[12] _[14]; _[13] _[14] _[15]]
```

```
m[1]
```

```
3x3 LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}:
 _[4] _[5] _[7]
 _[5] _[6] _[8]
 _[7] _[8] _[9]
```

```
m[2]
```

```
3x3 LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}:
 _[10] _[11] _[13]
 _[11] _[12] _[14]
 _[13] _[14] _[15]
```

The analogous construct in MATLAB would be a cell array containing the optimization variables, which every discerning programmer avoids as cell arrays are rather slow. This is not a problem in Julia: a vector of matrices is almost as fast as a 3-dimensional array.

## Constraints

As in the case of variables, in most cases there is a direct translation between the packages:

Like YALMIP and CVX, JuMP is smart enough to not generate redundant constraints when declaring equality constraints between `Symmetric` or `Hermitian` matrices. In these cases `@constraint(model, m == c)` will not generate constraints for the lower diagonal and the imaginary part of the diagonal (in the complex case).

Experienced MATLAB users will probably be relieved to see that you must pass `PSDCone()` or `HermitianPSDCone()` to make a matrix positive semidefinite, because the `>=` ambiguity in YALMIP and CVX is common source of bugs.

## Setting the objective

Like CVX, but unlike YALMIP, JuMP has a specific command for setting an objective function:

JuMP	YALMIP	CVX
@constraint(model, v == c)	v == c	v == c
@constraint(model, v >= 0)	v >= 0	v >= 0
@constraint(model, m >= 0, PSDCone())	m >= 0	m == semidefinite(length(m))
@constraint(model, m >= 0, HermitianPSDCone())	m >= 0	m ==
@constraint(model, [t; v] in SecondOrderCone())	cone(v, t)	hermitian_semidefinite(length(m))
@constraint(model, [x, y, z] in MOI.ExponentialCone())	expcone([x, y, z])	{x, y, z} == exponential(1)

```
@objective(model, Min, sum(i * x[i] for i in 1:3))
```

$$x_1 + 2x_2 + 3x_3$$

Here the third argument is any expression you want to optimize, and Min is an objective sense (the other possibility is Max).

### Setting solver and options

In order to set an optimizer with JuMP, do:

```
import Clarabel
set_optimizer(model, Clarabel.Optimizer)
```

where "Clarabel" is an example solver. See the list of [Supported solvers](#) for other choices.

To configure the solver options you use the command:

```
set_attribute(model, "verbose", true)
```

where verbose is an option specific to Clarabel.

A crucial difference is that with JuMP you must explicitly choose a solver before optimizing. Both YALMIP and CVX allow you to leave it empty and will try to guess an appropriate solver for the problem.

### Optimizing

Like YALMIP, but unlike CVX, with JuMP you need to explicitly start the optimization, with the command:

```
optimize!(model)
```

```

problem:
variables      = 15
constraints    = 6
nnz(P)         = 0
nnz(A)         = 6
cones (total) = 1
: Nonnegative = 1,  numel = 6

settings:
linear algebra: direct / qdldl, precision: Float64
max iter = 200, time limit = Inf, max step = 0.990
tol_feas = 1.0e-08, tol_gap_abs = 1.0e-08, tol_gap_rel = 1.0e-08,
static reg : on, ε1 = 1.0e-08, ε2 = 4.9e-32
dynamic reg: on, ε = 1.0e-13, δ = 2.0e-07
iter refine: on, reltol = 1.0e-13, abstol = 1.0e-12,
             max iter = 10, stop ratio = 5.0
equilibrate: on, min_scale = 1.0e-04, max_scale = 1.0e+04
             max iter = 10

iter      pcost      dcost      gap      pres      dres      k/t      μ      step
-----
0  1.0000e+01 -1.2500e+01  2.25e+00  0.00e+00  0.00e+00  1.00e+00  3.36e+00  -----
1  3.9744e+00 -5.5968e-01  4.53e+00  1.43e-16  1.27e-16  3.10e-01  6.92e-01  8.38e-01
2  1.1590e-01 -1.2437e-01  2.40e-01  4.88e-17  3.27e-17  2.81e-02  3.83e-02  9.73e-01
3  1.1746e-03 -1.2507e-03  2.43e-03  1.06e-16  7.36e-17  2.83e-04  3.87e-04  9.90e-01
4  1.1746e-05 -1.2507e-05  2.43e-05  1.44e-16  3.68e-17  2.83e-06  3.87e-06  9.90e-01
5  1.1746e-07 -1.2507e-07  2.43e-07  5.05e-15  4.78e-15  2.83e-08  3.87e-08  9.90e-01
6  1.1746e-09 -1.2507e-09  2.43e-09  1.59e-16  6.59e-17  2.83e-10  3.87e-10  9.90e-01
-----
Terminated with status = solved
solve time = 641μs

```

The exclamation mark here is a Julia-ism that means the function is modifying its argument, `model`.

### Querying solution status

After the optimization is done, you should check for the solution status to see what solution (if any) the solver found.

Like YALMIP and CVX, JuMP provides a solver-independent way to check it, via the command:

```
is_solved_and_feasible(model)
```

```
true
```

If the return value is `false`, you should investigate with `termination_status`, `primal_status`, and `raw_status`. See [Solutions](#) for more details on how to query and interpret solution statuses.

### Extracting variables

Like YALMIP, but unlike CVX, with JuMP you need to explicitly ask for the value of your variables after optimization is done, with the function call `value(x)` to obtain the value of variable `x`.

```
value.(m[1][1, 1])
```

```
0.0
```

A subtlety is that, unlike YALMIP, the function `value` is only defined for scalars. For vectors and matrices you need to use Julia broadcasting: `value.(v)`.

```
value.(m[1])
```

```
3x3 Matrix{Float64}:
 0.0  0.0  0.0
 0.0  0.0  0.0
 0.0  0.0  0.0
```

There is also a specialized function for extracting the value of the objective, `objective_value(model)`, which is useful if your objective doesn't have a convenient expression.

```
objective_value(model)
```

```
-5.99999998825352
```

## Dual variables

Like YALMIP and CVX, JuMP allows you to recover the dual variables. In order to do that, the simplest method is to name the constraint you're interested in, for example, `@constraint(model, bob, sum(v) == 1)` and then, after the optimization is done, call `dual(bob)`. See [Duality](#) for more details.

## Reformulating problems

Perhaps the biggest difference between JuMP and YALMIP and CVX is how far the package is willing to go in reformulating the problems you give to it.

CVX is happy to reformulate anything it can, even using approximations if your solver cannot handle the problem.

YALMIP will only do exact reformulations, but is still fairly adventurous, for example, being willing to reformulate a nonlinear objective in terms of conic constraints.

JuMP does no such thing: it only reformulates objectives into objectives, and constraints into constraints, and is fairly conservative at that. As a result, you might need to do some reformulations manually, for which a good guide is the [Modeling with cones](#) tutorial.

## Vectorization

In MATLAB, it is absolutely essential to "vectorize" your code to obtain acceptable performance. This is because MATLAB is a slow interpreted language, which sends your commands to fast libraries. When you "vectorize" your code you are minimizing the MATLAB part of the work and sending it to the fast libraries instead.

There's no such duality with Julia.

Everything you write and most libraries you use will compile down to LLVM, so "vectorization" has no effect.

For example, if you are writing a linear program in MATLAB and instead of the usual constraints = [v >= 0] you write:

```
for i = 1:n
    constraints = [constraints, v(i) >= 0];
end
```

performance will be poor.

With Julia, on the other hand, there is hardly any difference between

```
@constraint(model, v >= 0)
```

and

```
for i in 1:n
    @constraint(model, v[i] >= 0)
end
```

## Symmetric and Hermitian matrices

Julia has specialized support for symmetric and Hermitian matrices in the `LinearAlgebra` package:

```
import LinearAlgebra
```

If you have a matrix that is numerically symmetric:

```
x = [1 2; 2 3]
```

```
2×2 Matrix{Int64}:
 1  2
 2  3
```

```
LinearAlgebra.issymmetric(x)
```

```
true
```

then you can wrap it in a `LinearAlgebra.Symmetric` matrix to tell Julia's type system that the matrix is symmetric.

```
LinearAlgebra.Symmetric(x)
```

```
2×2 LinearAlgebra.Symmetric{Int64, Matrix{Int64}}:
 1  2
 2  3
```

Using a `Symmetric` matrix lets Julia and JuMP use more efficient algorithms when they are working with symmetric matrices.

If you have a matrix that is nearly but not exactly symmetric:

```
x = [1.0 2.0; 2.001 3.0]
LinearAlgebra.issymmetric(x)
```

```
false
```

then you could, as you might do in MATLAB, make it numerically symmetric as follows:

```
x_sym = 0.5 * (x + x')
```

```
2×2 Matrix{Float64}:
 1.0      2.0005
 2.0005   3.0
```

In Julia, you can explicitly choose whether to use the lower or upper triangle of the matrix:

```
x_sym = LinearAlgebra.Symmetric(x, :L)
```

```
2×2 LinearAlgebra.Symmetric{Float64, Matrix{Float64}}:
 1.0      2.001
 2.001    3.0
```

```
x_sym = LinearAlgebra.Symmetric(x, :U)
```

```
2×2 LinearAlgebra.Symmetric{Float64, Matrix{Float64}}:
1.0  2.0
2.0  3.0
```

The same applies for Hermitian matrices, using `LinearAlgebra.Hermitian` and `LinearAlgebra.ishermitian`.

### Primal versus dual form

When you translate some optimization problems from YALMIP or CVX to JuMP, you might be surprised to see it get much faster or much slower, even if you're using exactly the same solver. The most likely reason is that YALMIP will always interpret the problem as the dual form, whereas CVX and JuMP will try to interpret the problem in the form most appropriate to the solver. If the problem is more naturally formulated in the primal form it is likely that YALMIP's performance will suffer, or if JuMP gets it wrong, its performance will suffer. It might be worth trying both primal and dual forms if you're having trouble, which can be done automatically with the package [Dualization.jl](#).

For an in-depth explanation of this issue, see the [Dualization](#) tutorial.

### Rosetta stone

In this section, we show a complete example of the same optimization problem being solved with JuMP, YALMIP, and CVX. It is a semidefinite program that computes a lower bound on the random robustness of entanglement using the partial transposition criterion.

The code is complete, apart from the function that does partial transposition. With both YALMIP and CVX we use the function `PartialTranspose` from [QETLAB](#). With JuMP, we could use the function `Convex.partialtranspose` from [Convex.jl](#), but we reproduce it here for simplicity:

```
function partial_transpose(x::AbstractMatrix, sys::Int, dims::Vector)
    @assert size(x, 1) == size(x, 2) == prod(dims)
    @assert 1 <= sys <= length(dims)
    n = length(dims)
    s = n - sys + 1
    p = collect(1:2n)
    p[s], p[n+s] = n + s, s
    r = reshape(x, (reverse(dims)..., reverse(dims)...))
    return reshape(permutedims(r, p), size(x))
end
```

`partial_transpose` (generic function with 1 method)

### JuMP

The JuMP code to solve this problem is:

```
using JuMP
import Clarabel
import LinearAlgebra
```

```

function random_state_pure(d)
    x = randn(Complex{Float64}, d)
    y = x * x'
    return LinearAlgebra.Hermitian(y / LinearAlgebra.tr(y))
end

function robustness_jump(d)
    rho = random_state_pure(d^2)
    id = LinearAlgebra.Hermitian(LinearAlgebra.I(d^2))
    rhoT = LinearAlgebra.Hermitian(partial_transpose(rho, 1, [d, d]))
    model = Model(Clarabel.Optimizer)
    set_attribute(model, "verbose", false)
    @variable(model, λ)
    @constraint(model, PPT, rhoT + λ * id ∈ HermitianPSDCone())
    @objective(model, Min, λ)
    optimize!(model)
    assert_is_solved_and_feasible(model; allow_almost = true)
    WT = dual(PPT)
    return value(λ), real(LinearAlgebra.dot(WT, rhoT))
end

robustness_jump(3)

```

```
(0.43174978781546347, -0.43174978731622865)
```

## YALMIP

The corresponding YALMIP code is:

```

function robustness_yalmip(d)
    rho = random_state_pure(d^2);
    % PartialTranspose from https://github.com/nathanieljohnston/QETLAB
    rhoT = PartialTranspose(rho, 1, [d d]);
    lambda = sdpvar;
    constraints = [(rhoT + lambda*eye(d^2) >= 0)':'PPT'];
    ops = sdpsettings(sdpsettings, 'verbose', 0, 'solver', 'sedumi');
    sol = optimize(constraints, lambda, ops);
    if sol.problem == 0
        WT = dual(constraints('PPT'));
        value(lambda)
        real(WT(:)' * rhoT(:))
    else
        display(['Something went wrong: ', sol.info])
    end
end

function rho = random_state_pure(d)
    x = randn(d, 1) + li * randn(d, 1);
    y = x * x';
    rho = y / trace(y);
end

```

**CVX**

The corresponding CVX code is:

```
function robustness_cvx(d)
    rho = random_state_pure(d^2);
    % PartialTranspose from https://github.com/nathanieljohnston/QETLAB
    rhoT = PartialTranspose(rho, 1, [d d]);
    cvx_begin
        variable lambda
        dual variable WT
        WT : rhoT + lambda * eye(d^2) == hermitian_semidefinite(d^2)
        minimise lambda
    cvx_end
    if strcmp(cvx_status, 'Solved')
        lambda
        real(WT(:)' * rhoT(:))
    else
        display('Something went wrong.')
    end
end

function rho = random_state_pure(d)
    x = randn(d, 1) + li * randn(d, 1);
    y = x * x';
    rho = y / trace(y);
end
```

# Chapter 6

## Linear programs

### 6.1 Introduction

Linear programs (LPs) are a fundamental class of optimization problems of the form:

$$\min_{x \in \mathbb{R}^n} \sum_{i=1}^n c_i x_i \quad (6.1)$$

$$\text{s.t. } l_j \leq \sum_{i=1}^n a_{ij} x_i \leq u_j \quad j = 1 \dots m \quad (6.2)$$

$$l_i \leq x_i \leq u_i \quad i = 1 \dots n. \quad (6.3)$$

The most important thing to note is that all terms are of the form coefficient \* variable, and that there are no nonlinear terms or multiplications between variables.

Mixed-integer linear programs (MILPs) are extensions of linear programs in which some (or all) of the decision variables take discrete values.

### How to choose a solver

Almost all solvers support linear programs; look for "LP" in the list of [Supported solvers](#). However, fewer solvers support mixed-integer linear programs. Solvers supporting discrete variables start with "(MI)" in the list of [Supported solvers](#).

### How these tutorials are structured

Having a high-level overview of how this part of the documentation is structured will help you know where to look for certain things.

- The following tutorials are worked examples that present a problem in words, then formulate it in mathematics, and then solve it in JuMP. This usually involves some sort of visualization of the solution. Start here if you are new to JuMP.
  - [The diet problem](#)
  - [The cannery problem](#)
  - [The facility location problem](#)

- [Financial modeling problems](#)
- [Network flow problems](#)
- [N-Queens](#)
- [Sudoku](#)
- The [Tips and tricks](#) tutorial contains a number of helpful reformulations and tricks you can use when modeling linear programs. Look here if you are stuck trying to formulate a problem as a linear program.
- The [Sensitivity analysis of a linear program](#) tutorial explains how to create sensitivity reports like those produced by the Excel Solver.
- The [Callbacks](#) tutorial explains how to write a variety of solver-independent callbacks. Look here if you want to write a callback.
- The remaining tutorials are less verbose and styled in the form of short code examples. These tutorials have less explanation, but may contain useful code snippets, particularly if they are similar to a problem you are trying to solve.

## 6.2 The knapsack problem example

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to demonstrate how to formulate and solve a simple optimization problem.

### Required packages

This tutorial requires the following packages:

```
using JuMP
import HiGHS
```

### Formulation

The [knapsack problem](#) is a classical optimization problem: given a set of items and a container with a fixed capacity, choose a subset of items having the greatest combined value that will fit within the container without exceeding the capacity.

The name of the problem suggests its analogy to packing for a trip, where the baggage weight limit is the capacity and the goal is to pack the most profitable combination of belongings.

We can formulate the knapsack problem as the integer linear program:

$$\begin{aligned} \max \quad & \sum_{i=1}^n c_i x_i \\ \text{s.t.} \quad & \sum_{i=1}^n w_i x_i \leq C, \\ & x_i \in \{0, 1\}, \quad \forall i = 1, \dots, n, \end{aligned}$$

where  $C$  is the capacity, and there is a choice between  $n$  items, with item  $i$  having weight  $w_i$ , profit  $c_i$ . Decision variable  $x_i$  is equal to 1 if the item is chosen and 0 if not.

This formulation can be written more compactly as:

$$\begin{aligned} \max & c^\top x \\ \text{s.t. } & w^\top x \leq C \\ & x \text{ binary} . \end{aligned}$$

## Data

The data for the problem consists of two vectors (one for the profits and one for the weights) along with a capacity.

There are five objects:

```
n = 5;
```

For our example, we use a capacity of 10 units:

```
capacity = 10.0;
```

and the profit and cost data:

```
profit = [5.0, 3.0, 2.0, 7.0, 4.0];
weight = [2.0, 8.0, 4.0, 2.0, 5.0];
```

## JuMP formulation

Let's begin constructing the JuMP model for our knapsack problem.

First, we'll create a `Model` object for holding model elements as we construct each part. We'll also set the solver that will ultimately be called to solve the model, once it's constructed.

```
model = Model(HiGHS.Optimizer)
```

```
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

Next we need the decision variables representing which items are chosen:

```
@variable(model, x[1:n], Bin)
```

```
5-element Vector{VariableRef}:
x[1]
x[2]
x[3]
x[4]
x[5]
```

We now want to constrain those variables so that their combined weight is less than or equal to the given capacity:

```
@constraint(model, sum(weight[i] * x[i] for i in 1:n) <= capacity)
```

$$2x_1 + 8x_2 + 4x_3 + 2x_4 + 5x_5 \leq 10$$

Finally, our objective is to maximize the combined profit of the chosen items:

```
@objective(model, Max, sum(profit[i] * x[i] for i in 1:n))
```

$$5x_1 + 3x_2 + 2x_3 + 7x_4 + 4x_5$$

Let's print a human-readable description of the model and check that the model looks as expected:

```
print(model)
```

```
Max 5 x[1] + 3 x[2] + 2 x[3] + 7 x[4] + 4 x[5]
Subject to
 2 x[1] + 8 x[2] + 4 x[3] + 2 x[4] + 5 x[5] ≤ 10
  x[1] binary
  x[2] binary
  x[3] binary
  x[4] binary
  x[5] binary
```

We can now solve the optimization problem and inspect the results.

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : HiGHS
* Status
  Result count      : 1
  Termination status : OPTIMAL
```

```

Message from the solver:
"kHighsModelStatusOptimal"

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : NO_SOLUTION
Objective value   : 1.60000e+01
Objective bound    : 1.60000e+01
Relative gap       : 0.00000e+00
Dual objective value : NaN

* Work counters
Solve time (sec)   : 5.15938e-04
Simplex iterations : 1
Barrier iterations : -1
Node count         : 1

```

The items chosen are

```
items_chosen = [i for i in 1:n if value(x[i]) > 0.5]
```

```

3-element Vector{Int64}:
1
4
5

```

## Writing a function

After working interactively, it is good practice to implement your model in a function.

The function can be used to ensure that the model is given well-defined input data with validation checks, and that the solution process went as expected.

```

function solve_knapsack_problem();
    profit::Vector{Float64},
    weight::Vector{Float64},
    capacity::Float64,
)
    n = length(weight)
    # The profit and weight vectors must be of equal length.
    @assert length(profit) == n
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, x[1:n], Bin)
    @objective(model, Max, profit' * x)
    @constraint(model, weight' * x <= capacity)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    println("Objective is: ", objective_value(model))

```

```

println("Solution is:")
for i in 1:n
    print("x[$i] = ", round(Int, value(x[i])))
    println(", c[$i] / w[$i] = ", profit[i] / weight[i])
end
chosen_items = [i for i in 1:n if value(x[i]) > 0.5]
return chosen_items
end

solve_knapsack_problem(; profit = profit, weight = weight, capacity = capacity)

```

```

3-element Vector{Int64}:
1
4
5

```

We observe that the chosen items (1, 4, and 5) have the best profit to weight ratio in this particular example.

### Next steps

Here are some things to try next:

- Call the function with different data. What happens as the capacity increases?
- What happens if the profit and weight vectors are different lengths?
- Instead of creating a binary variable with `Bin`, we could have written `@variable(model, 0 <= x[1:n] <= 1, Int)`. Verify that this formulation finds the same solution. What happens if we are allowed to take more than one of each item?

## 6.3 The diet problem

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to demonstrate how to incorporate DataFrames into a JuMP model. As an example, we use classic [Stigler diet problem](#).

### Required packages

This tutorial requires the following packages:

```

using JuMP
import CSV
import DataFrames
import HiGHS
import Test

```

## Formulation

We wish to cook a nutritionally balanced meal by choosing the quantity of each food  $f$  to eat from a set of foods  $F$  in our kitchen.

Each food  $f$  has a cost,  $c_f$ , as well as a macro-nutrient profile  $a_{m,f}$  for each macro-nutrient  $m \in M$ .

Because we care about a nutritionally balanced meal, we set some minimum and maximum limits for each nutrient, which we denote  $l_m$  and  $u_m$  respectively.

Furthermore, because we are optimizers, we seek the minimum cost solution.

With a little effort, we can formulate our dinner problem as the following linear program:

$$\begin{aligned} \min \quad & \sum_{f \in F} c_f x_f \\ \text{s.t.} \quad & l_m \leq \sum_{f \in F} a_{m,f} x_f \leq u_m, \quad \forall m \in M \\ & x_f \geq 0, \quad \forall f \in F. \end{aligned}$$

In the rest of this tutorial, we will create and solve this problem in JuMP, and learn what we should cook for dinner.

## Data

First, we need some data for the problem. For this tutorial, we'll write CSV files to a temporary directory from Julia. If you have existing files, you could change the filenames to point to them instead.

```
dir = mktempdir()
```

```
"/tmp/jl_F77ZWK"
```

The first file is a list of foods with their macro-nutrient profile:

```
food_csv_filename = joinpath(dir, "diet_foods.csv")
open(food_csv_filename, "w") do io
    write(
        io,
        """
        name,cost,calories,protein,fat,sodium
        hamburger,2.49,410,24,26,730
        chicken,2.89,420,32,10,1190
        hot dog,1.50,560,20,32,1800
        fries,1.89,380,4,19,270
        macaroni,2.09,320,12,10,930
        pizza,1.99,320,15,12,820
        salad,2.49,320,31,12,1230
        milk,0.89,100,8,2.5,125
        ice cream,1.59,330,8,10,180
        """,
    )
```

```

    return
end
foods = CSV.read(food_csv_filename, DataFrames.DataFrame)

```

	name	cost	calories	protein	fat	sodium
	String15	Float64	Int64	Int64	Float64	Int64
1	hamburger	2.49	410	24	26.0	730
2	chicken	2.89	420	32	10.0	1190
3	hot dog	1.5	560	20	32.0	1800
4	fries	1.89	380	4	19.0	270
5	macaroni	2.09	320	12	10.0	930
6	pizza	1.99	320	15	12.0	820
7	salad	2.49	320	31	12.0	1230
8	milk	0.89	100	8	2.5	125
9	ice cream	1.59	330	8	10.0	180

Here,  $F$  is `foods.name` and  $c_f$  is `foods.cost`. (We're also playing a bit loose the term "macro-nutrient" by including calories and sodium.)

We also need our minimum and maximum limits:

```

nutrient_csv_filename = joinpath(dir, "diet_nutrient.csv")
open(nutrient_csv_filename, "w") do io
    write(
        io,
        """
        nutrient,min,max
        calories,1800,2200
        protein,91,
        fat,0,65
        sodium,0,1779
        """,
    )
    return
end
limits = CSV.read(nutrient_csv_filename, DataFrames.DataFrame)

```

	nutrient	min	max
	String15	Int64	Int64?
1	calories	1800	2200
2	protein	91	missing
3	fat	0	65
4	sodium	0	1779

Protein is missing data for the maximum. Let's fix that using `coalesce`:

```

limits.max = coalesce.(limits.max, Inf)
limits

```

	nutrient	min	max
	String15	Int64	Real
1	calories	1800	2200
2	protein	91	Inf
3	fat	0	65
4	sodium	0	1779

### JuMP formulation

Now we're ready to convert our mathematical formulation into a JuMP model.

First, create a new JuMP model. Since we have a linear program, we'll use HiGHS as our optimizer:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
```

Next, we create a set of decision variables  $x$ , with one element for each row in the DataFrame, and each  $x$  has a lower bound of 0:

```
@variable(model, x[foods.name] >= 0)
```

```
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, InlineStrings.String15["hamburger", "chicken", "hot dog", "fries", "macaroni",
    ↳ "pizza", "salad", "milk", "ice cream"]
And data, a 9-element Vector{VariableRef}:
x[hamburger]
x[chicken]
x[hot dog]
x[fries]
x[macaroni]
x[pizza]
x[salad]
x[milk]
x[ice cream]
```

To simplify things later on, we store the vector as a new column  $x$  in the DataFrame `foods`. Since  $x$  is a `DenseAxisArray`, we first need to convert it to an `Array`:

```
foods.x = Array(x)
```

```
9-element Vector{VariableRef}:
x[hamburger]
x[chicken]
x[hot dog]
x[fries]
x[macaroni]
x[pizza]
x[salad]
```

```
x[milk]
x[ice cream]
```

Our objective is to minimize the total cost of purchasing food:

```
@objective(model, Min, sum(foods.cost .* foods.x));
```

For the next component, we need to add a constraint that our total intake of each component is within the limits contained in the `limits` DataFrame:

```
@constraint(
    model,
    [row in eachrow(limits)],
    row.min <= sum(foods[!, row.nutrient] .* foods.x) <= row.max,
);
```

What does our model look like?

```
print(model)
```

```
Min 2.49 x[hamburger] + 2.89 x[chicken] + 1.5 x[hot dog] + 1.89 x[fries] + 2.09 x[macaroni] + 1.99
↪ x[pizza] + 2.49 x[salad] + 0.89 x[milk] + 1.59 x[ice cream]
Subject to
410 x[hamburger] + 420 x[chicken] + 560 x[hot dog] + 380 x[fries] + 320 x[macaroni] + 320 x[pizza]
↪ + 320 x[salad] + 100 x[milk] + 330 x[ice cream] ∈ [1800, 2200]
24 x[hamburger] + 32 x[chicken] + 20 x[hot dog] + 4 x[fries] + 12 x[macaroni] + 15 x[pizza] + 31
↪ x[salad] + 8 x[milk] + 8 x[ice cream] ∈ [91, Inf]
26 x[hamburger] + 10 x[chicken] + 32 x[hot dog] + 19 x[fries] + 10 x[macaroni] + 12 x[pizza] + 12
↪ x[salad] + 2.5 x[milk] + 10 x[ice cream] ∈ [0, 65]
730 x[hamburger] + 1190 x[chicken] + 1800 x[hot dog] + 270 x[fries] + 930 x[macaroni] + 820
↪ x[pizza] + 1230 x[salad] + 125 x[milk] + 180 x[ice cream] ∈ [0, 1779]
x[hamburger] ≥ 0
x[chicken] ≥ 0
x[hot dog] ≥ 0
x[fries] ≥ 0
x[macaroni] ≥ 0
x[pizza] ≥ 0
x[salad] ≥ 0
x[milk] ≥ 0
x[ice cream] ≥ 0
```

## Solution

Let's optimize and take a look at the solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : HIGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 1.18289e+01
  Objective bound    : 1.18289e+01
  Relative gap       : 0.00000e+00
  Dual objective value : 1.18289e+01

* Work counters
  Solve time (sec)   : 2.11239e-04
  Simplex iterations : 6
  Barrier iterations : 0
  Node count         : -1
```

We found an optimal solution. Let's see what the optimal solution is:

```
for row in eachrow(foods)
    println(row.name, " = ", value(row.x))
end
```

```
hamburger = 0.6045138888888871
chicken = 0.0
hot dog = 0.0
fries = 0.0
macaroni = 0.0
pizza = 0.0
salad = 0.0
milk = 6.9701388888888935
ice cream = 2.5913194444444447
```

That's a lot of milk and ice cream, and sadly, we only get 0.6 of a hamburger.

We can also use the function `Containers.rowtable` to easily convert the result into a DataFrame:

```
table = Containers.rowtable(value, x; header = [:food, :quantity])
solution = DataFrames.DataFrame(table)
```

This makes it easy to perform analyses our solution:

	food	quantity
	String15	Float64
1	hamburger	0.604514
2	chicken	0.0
3	hot dog	0.0
4	fries	0.0
5	macaroni	0.0
6	pizza	0.0
7	salad	0.0
8	milk	6.97014
9	ice cream	2.59132

```
filter!(row -> row.quantity > 0.0, solution)
```

	food	quantity
	String15	Float64
1	hamburger	0.604514
2	milk	6.97014
3	ice cream	2.59132

## Problem modification

JuMP makes it easy to take an existing model and modify it by adding extra constraints. Let's see what happens if we add a constraint that we can buy at most 6 units of milk or ice cream combined.

```
dairy_foods = ["milk", "ice cream"]
is_dairy = map(name -> name in dairy_foods, foods.name)
dairy_constraint = @constraint(model, sum(foods[is_dairy, :x]) <= 6)
optimize!(model)
Test.@test !is_solved_and_feasible(model)
Test.@test termination_status(model) == INFEASIBLE
Test.@test primal_status(model) == NO_SOLUTION
solution_summary(model)
```

```
* Solver : HiGHS

* Status
Result count      : 1
Termination status : INFEASIBLE
Message from the solver:
"kHighsModelStatusInfeasible"

* Candidate solution (result #1)
Primal status      : NO_SOLUTION
Dual status        : INFEASIBILITY_CERTIFICATE
Objective value    : 1.18289e+01
Objective bound    : 0.00000e+00
Relative gap       : Inf
Dual objective value : 3.56146e+00
```

```
* Work counters
Solve time (sec)    : 1.43766e-04
Simplex iterations : 0
Barrier iterations : 0
Node count          : -1
```

There exists no feasible solution to our problem. Looks like we're stuck eating ice cream for dinner.

### Next steps

- You can delete a constraint using `delete(model, dairy_constraint)`. Can you add a different constraint to provide a diet with less dairy?
- Some food items (like hamburgers) are discrete. You can use `set_integer` to force a variable to take integer values. What happens to the solution if you do?

## 6.4 The cannery problem

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

**This tutorial was originally contributed by Louis Luangkesorn.**

This tutorial solves the cannery problem from Dantzig, *Linear Programming and Extensions*, Princeton University Press, Princeton, NJ, 1963. This class of problem is known as a transshipment problem.

The purpose of this tutorial is to demonstrate how to use JSON data in the formulation of a JuMP model.

### Required packages

This tutorial requires the following packages:

```
using JuMP
import HiGHS
import JSON
import Test
```

### Formulation

The cannery problem assumes we are optimizing the shipment of cases of cans from production plants  $p \in P$  to markets  $m \in M$ .

Each production plant  $p$  has a capacity  $c_p$ , and each market  $m$  has a demand  $d_m$ . The shipping cost per case of cans from plant  $p$  to market  $m$  is  $d_{p,m}$ .

We wish to find the distribution plan  $x_{p,m}$ , the number of cases of cans to ship from plant  $p$  to market  $m$ , for  $p \in P$  and  $m \in M$  that minimizes the shipping costs. We can formulate our problem as the following linear program:

$$\begin{aligned}
 & \min \sum_{p \in P} \sum_{m \in M} d_{p,m} x_{p,m} \\
 \text{s.t. } & \sum_{m \in M} x_{p,m} \leq c_p, \quad \forall p \in P \\
 & \sum_{p \in P} x_{p,m} \geq d_m, \quad \forall m \in M \\
 & x_{p,m} \geq 0, \quad \forall p \in P, m \in M
 \end{aligned}$$

## Data

A key feature of the tutorial is to demonstrate how to load data from JSON.

For simplicity, we've hard-coded it below. But if the data was available as a .json file, we could use `data = JSON.parsefile(filename)` to read in the data.

```

data = JSON.parse("""
{
    "plants": {
        "Seattle": {"capacity": 350},
        "San-Diego": {"capacity": 600}
    },
    "markets": {
        "New-York": {"demand": 300},
        "Chicago": {"demand": 300},
        "Topeka": {"demand": 300}
    },
    "distances": {
        "Seattle => New-York": 2.5,
        "Seattle => Chicago": 1.7,
        "Seattle => Topeka": 1.8,
        "San-Diego => New-York": 2.5,
        "San-Diego => Chicago": 1.8,
        "San-Diego => Topeka": 1.4
    }
}
""")
  
```

```

Dict{String, Any} with 3 entries:
"plants"    => Dict{String, Any}("Seattle"=>Dict{String, Any}("capacity"=>350...
"distances" => Dict{String, Any}("San-Diego => New-York"=>2.5, "Seattle => To...
"markets"   => Dict{String, Any}("Chicago"=>Dict{String, Any}("demand"=>300),...
  
```

Create the set of plants:

```
P = keys(data["plants"])
```

```
KeySet for a Dict{String, Any} with 2 entries. Keys:
"Seattle"
"San-Diego"
```

Create the set of markets:

```
M = keys(data["markets"])
```

```
KeySet for a Dict{String, Any} with 3 entries. Keys:
"Chicago"
"Topeka"
"New-York"
```

We also need a function to compute the distance from plant to market:

```
distance(p::String, m::String) = data["distances"][$(p) => $(m)]
```

```
distance (generic function with 1 method)
```

## JuMP formulation

Now we're ready to convert our mathematical formulation into a JuMP model.

First, create a new JuMP model. Since we have a linear program, we'll use HiGHS as our optimizer:

```
model = Model(HiGHS.Optimizer)
```

```
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none
```

Our decision variables are indexed over the set of plants and markets:

```
@variable(model, x[P, M] >= 0)
```

```
2-dimensional DenseAxisArray{VariableRef,2,...} with index sets:
    Dimension 1, ["Seattle", "San-Diego"]
    Dimension 2, ["Chicago", "Topeka", "New-York"]
And data, a 2x3 Matrix{VariableRef}:
  x[Seattle,Chicago]   x[Seattle,Topeka]   x[Seattle,New-York]
  x[San-Diego,Chicago] x[San-Diego,Topeka] x[San-Diego,New-York]
```

We need a constraint that each plant can ship no more than its capacity:

```
@constraint(model, [p in P], sum(x[p, :]) <= data["plants"][p]["capacity"])
```

```
1-dimensional DenseAxisArray{ConstraintRef{Model,
    ↵ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↵ MathOptInterface.LessThan{Float64}}, ScalarShape},1,...} with index sets:
    Dimension 1, ["Seattle", "San-Diego"]
And data, a 2-element Vector{ConstraintRef{Model,
    ↵ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↵ MathOptInterface.LessThan{Float64}}, ScalarShape}}:
  x[Seattle,Chicago] + x[Seattle,Topeka] + x[Seattle,New-York] ≤ 350
  x[San-Diego,Chicago] + x[San-Diego,Topeka] + x[San-Diego,New-York] ≤ 600
```

and each market must receive at least its demand:

```
@constraint(model, [m in M], sum(x[:, m]) >= data["markets"][m]["demand"])
```

```
1-dimensional DenseAxisArray{ConstraintRef{Model,
    ↵ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↵ MathOptInterface.GreaterThan{Float64}}, ScalarShape},1,...} with index sets:
    Dimension 1, ["Chicago", "Topeka", "New-York"]
And data, a 3-element Vector{ConstraintRef{Model,
    ↵ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↵ MathOptInterface.GreaterThan{Float64}}, ScalarShape}}:
  x[Seattle,Chicago] + x[San-Diego,Chicago] ≥ 300
  x[Seattle,Topeka] + x[San-Diego,Topeka] ≥ 300
  x[Seattle,New-York] + x[San-Diego,New-York] ≥ 300
```

Finally, our objective is to minimize the transportation distance:

```
@objective(model, Min, sum(distance(p, m) * x[p, m] for p in P, m in M));
```

## Solution

Let's optimize and look at the solution:

```

optimize!(model)
solution_summary(model)

* Solver : HiGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 1.68000e+03
  Objective bound    : 1.68000e+03
  Relative gap       : 0.00000e+00
  Dual objective value : 1.68000e+03

* Work counters
  Solve time (sec)   : 2.22683e-04
  Simplex iterations : 3
  Barrier iterations : 0
  Node count         : -1

```

What's the optimal shipment?

```

assert_is_solved_and_feasible(model)
for p in P, m in M
    println(p, " => ", m, ": ", value(x[p, m]))
end

```

```

Seattle => Chicago: 300.0
Seattle => Topeka: 0.0
Seattle => New-York: 0.0
San-Diego => Chicago: 0.0
San-Diego => Topeka: 300.0
San-Diego => New-York: 300.0

```

## 6.5 The factory schedule example

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

**This tutorial was originally contributed by @Crghilardi.**

This tutorial is a Julia translation of Part 5 from [Introduction to Linear Programming with Python](#).

The purpose of this tutorial is to demonstrate how to use `DataFrames` and delimited files, and to structure your code that is robust to infeasibilities and permits running with different datasets.

## Required packages

This tutorial requires the following packages:

```
using JuMP
import CSV
import DataFrames
import HiGHS
import StatsPlots
```

## Formulation

The Factory Scheduling Problem assumes we are optimizing the production of a good from factories  $f \in F$  over the course of 12 months  $m \in M$ .

If a factory  $f$  runs during a month  $m$ , a fixed cost of  $a_f$  is incurred, the factory must produce  $x_{m,f}$  units that is within some minimum and maximum production levels  $l_f$  and  $u_f$  respectively, and each unit of production incurs a variable cost  $c_f$ . Otherwise, the factory can be shut for the month with zero production and no fixed-cost is incurred. We denote the run/not-run decision by  $z_{m,f} \in \{0, 1\}$ , where  $z_{m,f}$  is 1 if factory  $f$  runs in month  $m$ . The factory must produce enough units to satisfy demand  $d_m$ .

With a little effort, we can formulate our problem as the following linear program:

$$\begin{aligned} \min \quad & \sum_{f \in F, m \in M} a_f z_{m,f} + c_f x_{m,f} \\ \text{s.t.} \quad & x_{m,f} \leq u_f z_{m,f} \quad \forall f \in F, m \in M \\ & x_{m,f} \geq l_f z_{m,f} \quad \forall f \in F, m \in M \\ & \sum_{f \in F} x_{m,f} = d_m \quad \forall f \in F, m \in M \\ & z_{m,f} \in \{0, 1\} \quad \forall f \in F, m \in M. \end{aligned}$$

However, this formulation has a problem: if demand is too high, we may be unable to satisfy the demand constraint, and the problem will be infeasible.

### Tip

When modeling, consider ways to formulate your model such that it always has a feasible solution. This greatly simplifies debugging data errors that would otherwise result in an infeasible solution. In practice, most practical decisions have a feasible solution. In our case, we could satisfy demand (at a high cost) by buying replacement items for the buyer, or running the factories in overtime to make up the difference.

We can improve our model by adding a new variable,  $\delta_m$ , which represents the quantity of unmet demand in each month  $m$ . We penalize  $\delta_m$  by an arbitrarily large value of \$10,000/unit in the objective.

$$\begin{aligned}
 \min \quad & \sum_{f \in F, m \in M} a_f z_{m,f} + c_f x_{m,f} + \sum_{m \in M} 10000\delta_m \\
 \text{s.t.} \quad & x_{m,f} \leq u_f z_{m,f} \quad \forall f \in F, m \in M \\
 & x_{m,f} \geq l_f z_{m,f} \quad \forall f \in F, m \in M \\
 & \sum_{f \in F} x_{m,f} - \delta_m = d_m \quad \forall f \in F, m \in M \\
 & z_{m,f} \in \{0, 1\} \quad \forall f \in F, m \in M \\
 & \delta_m \geq 0 \quad \forall m \in M.
 \end{aligned}$$

## Data

The JuMP GitHub repository contains two text files with the data we need for this tutorial.

The first file contains a dataset of our factories, A and B, with their production and cost levels for each month. For the documentation, the file is located at:

```
factories_filename = joinpath(@__DIR__, "factory_schedule_factories.txt");
```

To run locally, download `factory_schedule_factories.txt` and update `factories_filename` appropriately.

The file has the following contents:

```
print(read(factories_filename, String))
```

factory	month	min_production	max_production	fixed_cost	variable_cost
A	1	20000	100000	500	10
A	2	20000	110000	500	11
A	3	20000	120000	500	12
A	4	20000	145000	500	9
A	5	20000	160000	500	8
A	6	20000	140000	500	8
A	7	20000	155000	500	5
A	8	20000	200000	500	7
A	9	20000	210000	500	9
A	10	20000	197000	500	10
A	11	20000	80000	500	8
A	12	20000	150000	500	8
B	1	20000	50000	600	5
B	2	20000	55000	600	4
B	3	20000	60000	600	3
B	4	20000	100000	600	5
B	5	0	0	0	0
B	6	20000	70000	600	6
B	7	20000	60000	600	4
B	8	20000	100000	600	6
B	9	20000	100000	600	8
B	10	20000	100000	600	11
B	11	20000	120000	600	10
B	12	20000	150000	600	12

We use the CSV and DataFrames packages to read it into Julia:

```
factory_df = CSV.read(
    factories_filename,
    DataFrames.DataFrame;
    delim = ' ',
    ignorerepeated = true,
)
```

	factory	month	min_production	max_production	fixed_cost	variable_cost
	String1	Int64	Int64	Int64	Int64	Int64
1	A	1	20000	100000	500	10
2	A	2	20000	110000	500	11
3	A	3	20000	120000	500	12
4	A	4	20000	145000	500	9
5	A	5	20000	160000	500	8
6	A	6	20000	140000	500	8
7	A	7	20000	155000	500	5
8	A	8	20000	200000	500	7
9	A	9	20000	210000	500	9
10	A	10	20000	197000	500	10
11	A	11	20000	80000	500	8
12	A	12	20000	150000	500	8
13	B	1	20000	50000	600	5
14	B	2	20000	55000	600	4
15	B	3	20000	60000	600	3
16	B	4	20000	100000	600	5
17	B	5	0	0	0	0
18	B	6	20000	70000	600	6
19	B	7	20000	60000	600	4
20	B	8	20000	100000	600	6
21	B	9	20000	100000	600	8
22	B	10	20000	100000	600	11
23	B	11	20000	120000	600	10
24	B	12	20000	150000	600	12

The second file contains the demand data by month:

```
demand_filename = joinpath(@__DIR__, "factory_schedule_demand.txt");
```

To run locally, download `factory_schedule_demand.txt` and update `demand_filename` appropriately.

```
demand_df = CSV.read(
    demand_filename,
    DataFrames.DataFrame;
    delim = ' ',
    ignorerepeated = true,
)
```

	month	demand
	Int64	Int64
1	1	120000
2	2	100000
3	3	130000
4	4	130000
5	5	140000
6	6	130000
7	7	150000
8	8	170000
9	9	200000
10	10	190000
11	11	140000
12	12	100000

### Data validation

Before moving on, it's always good practice to validate the data you read from external sources. The more effort you spend here, the fewer issues you will have later. The following function contains a few simple checks, but we could add more. For example, you might want to check that none of the values are too large (or too small), which might indicate a typo or a unit conversion issue (perhaps the variable costs are in \$/1000 units instead of \$/unit).

```
function validate_data(
    demand_df::DataFrames.DataFrame,
    factory_df::DataFrames.DataFrame,
)
    # Minimum production must not exceed maximum production.
    @assert all(factory_df.min_production .≤ factory_df.max_production)
    # Demand, minimum production, fixed costs, and variable costs must all be
    # non-negative.
    @assert all(demand_df.demand .≥ 0)
    @assert all(factory_df.min_production .≥ 0)
    @assert all(factory_df.fixed_cost .≥ 0)
    @assert all(factory_df.variable_cost .≥ 0)
    return
end

validate_data(demand_df, factory_df)
```

### JuMP formulation

Next, we need to code our JuMP formulation. As shown in [Design patterns for larger models](#), it's always good practice to code your model in a function that accepts well-defined input and returns well-defined output.

```
function solve_factory_scheduling(
    demand_df::DataFrames.DataFrame,
    factory_df::DataFrames.DataFrame,
)
    # Even though we validated the data above, it's good practice to do it here
    # too.
    validate_data(demand_df, factory_df)
```

```

months, factories = unique(factory_df.month), unique(factory_df.factory)
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, status[months, factories], Bin)
@variable(model, production[months, factories], Int)
@variable(model, unmet_demand[months] >= 0)
# We use `eachrow` to loop through the rows of the dataframe and add the
# relevant constraints.
for r in eachrow(factory_df)
    m, f = r.month, r.factory
    @constraint(model, production[m, f] <= r.max_production * status[m, f])
    @constraint(model, production[m, f] >= r.min_production * status[m, f])
end
@constraint(
    model,
    [r in eachrow(demand_df)],
    sum(production[r.month, :]) + unmet_demand[r.month] == r.demand,
)
@objective(
    model,
    Min,
    10_000 * sum(unmet_demand) + sum(
        r.fixed_cost * status[r.month, r.factory] +
        r.variable_cost * production[r.month, r.factory] for
        r in eachrow(factory_df)
    )
)
optimize!(model)
assert_is_solved_and_feasible(model)
schedules = Dict{Symbol,Vector{Float64}}()
Symbol(f) => value.(production[:, f]) for f in factories
)
schedules[:unmet_demand] = value.(unmet_demand)
return (
    termination_status = termination_status(model),
    cost = objective_value(model),
    # This `select` statement re-orders the columns in the DataFrame.
    schedules = DataFrames.select(
        DataFrames.DataFrame(schedules),
        [:unmet_demand, :A, :B],
    ),
)
)
end

```

```
solve_factory_scheduling (generic function with 1 method)
```

## Solution

Now we can call our `solve_factory_scheduling` function using the data we read in above.

```
solution = solve_factory_scheduling(demand_df, factory_df);
```

Let's see what `solution` contains:

```
solution.termination_status
```

```
OPTIMAL::TerminationStatusCode = 1
```

```
solution.cost
```

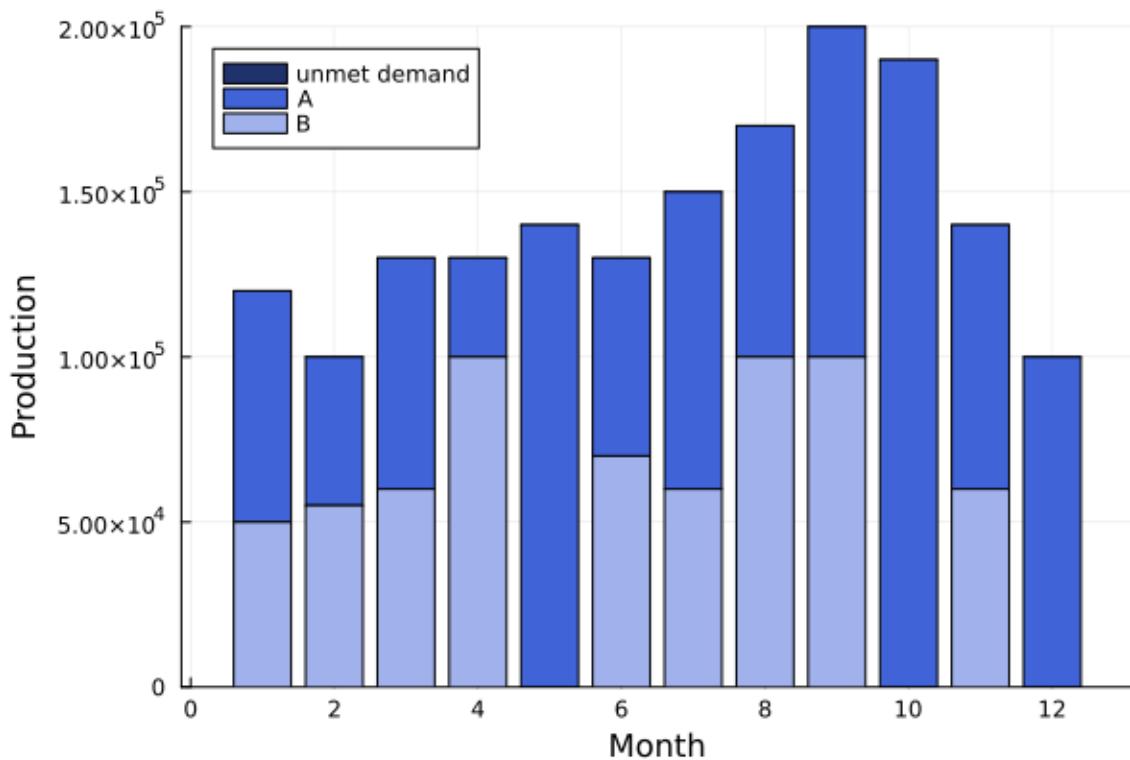
```
1.29064e7
```

```
solution.schedules
```

	unmet_demand	A	B
	Float64	Float64	Float64
1	0.0	70000.0	50000.0
2	0.0	45000.0	55000.0
3	0.0	70000.0	60000.0
4	0.0	30000.0	100000.0
5	0.0	140000.0	-0.0
6	0.0	60000.0	70000.0
7	0.0	90000.0	60000.0
8	0.0	70000.0	100000.0
9	0.0	100000.0	100000.0
10	0.0	190000.0	-0.0
11	0.0	80000.0	60000.0
12	0.0	100000.0	-0.0

These schedules will be easier to visualize as a graph:

```
StatsPlots.groupedbar(
    Matrix(solution.schedules),
    bar_position = :stack,
    labels = ["unmet demand" "A" "B"],
    xlabel = "Month",
    ylabel = "Production",
    legend = :topleft,
    color = ["#20326c" "#4063d8" "#a0blec"],
)
```



Note that we don't have any unmet demand.

### What happens if demand increases?

Let's run an experiment by increasing the demand by 50% in all time periods:

```
demand_df.demand *= 1.5
```

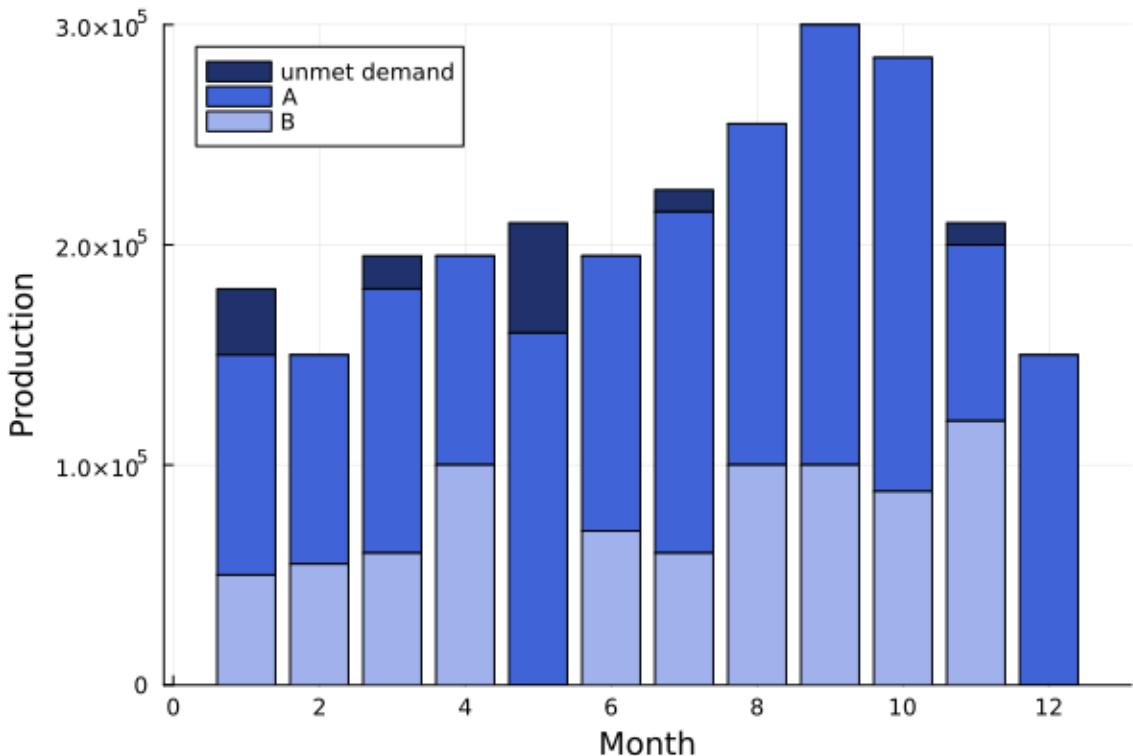
```
12-element Vector{Float64}:
180000.0
150000.0
195000.0
195000.0
210000.0
195000.0
195000.0
225000.0
255000.0
300000.0
285000.0
210000.0
150000.0
```

Now we resolve the problem:

```
high_demand_solution = solve_factory_scheduling(demand_df, factory_df);
```

and visualize the solution:

```
StatsPlots.groupedbar(
    Matrix(high_demand_solution.schedules);
    bar_position = :stack,
    labels = ["unmet demand" "A" "B"],
    xlabel = "Month",
    ylabel = "Production",
    legend = :topleft,
    color = ["#20326c" "#4063d8" "#a0b1ec"],
)
```



Uh oh, we can't satisfy all of the demand.

### How sensitive is the solution to changes in variable cost?

Let's run another experiment, this time seeing how the optimal objective value changes as we vary the variable costs of each factory.

First though, let's reset the demand to its original level:

```
demand_df.demand ./= 1.5;
```

For our experiment, we're going to scale the variable costs of both factories by a set of values from 0.0 to 1.5:

```
scale_factors = 0:0.1:1.5
```

```
0.0:0.1:1.5
```

At a high level, we're going to loop over the scale factors for A, then the scale factors for B, rescale the input data, call our `solve_factory_scheduling` example, and then store the optimal objective value in the following cost matrix:

```
cost = zeros(length(scale_factors), length(scale_factors));
```

Because we're modifying `factory_df` in-place, we need to store the original variable costs in a new column:

```
factory_df[!, :old_variable_cost] = copy(factory_df.variable_cost);
```

Then, we need a function to scale the `:variable_cost` column for a particular factory by a value `scale`:

```
function scale_variable_cost(df, factory, scale)
    rows = df.factory .== factory
    df[rows, :variable_cost] .=
        round.(Int, df[rows, :old_variable_cost] .* scale)
    return
end
```

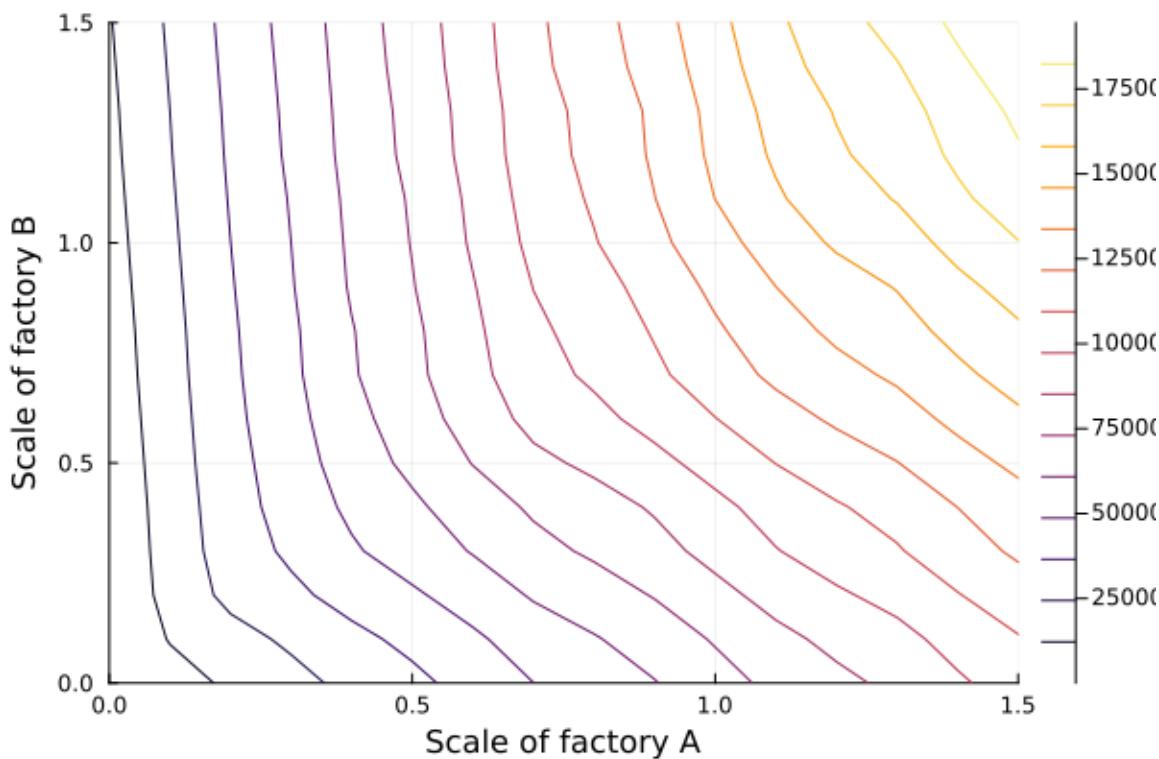
```
scale_variable_cost (generic function with 1 method)
```

Our experiment is just a nested for-loop, modifying A and B and storing the cost:

```
for (j, a) in enumerate(scale_factors)
    scale_variable_cost(factory_df, "A", a)
    for (i, b) in enumerate(scale_factors)
        scale_variable_cost(factory_df, "B", b)
        cost[i, j] = solve_factory_scheduling(demand_df, factory_df).cost
    end
end
```

Let's visualize the cost matrix:

```
StatsPlots.contour(
    scale_factors,
    scale_factors,
    cost;
    xlabel = "Scale of factory A",
    ylabel = "Scale of factory B",
)
```



What can you infer from the solution?

#### Info

The [Power Systems](#) tutorial explains a number of other ways you can structure a problem to perform a parametric analysis of the solution. In particular, you can use in-place modification to reduce the time it takes to build and solve the resulting models.

## 6.6 The multi-commodity flow problem

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

**This tutorial was originally contributed by Louis Luangkesorn.**

This tutorial is a JuMP implementation of the multi-commodity transportation model described in [AMPL: A Modeling Language for Mathematical Programming](#), by R. Fourer, D.M. Gay and B.W. Kernighan.

The purpose of this tutorial is to demonstrate creating a JuMP model from an SQLite database.

## Required packages

This tutorial uses the following packages

```
using JuMP
import DataFrames
import HiGHS
import SQLite
import Tables
import Test

const DBInterface = SQLite.DBInterface
```

DBInterface

## Formulation

The multi-commodity flow problem is a simple extension of [The transportation problem](#) to multiple types of products. Briefly, we start with the formulation of the transportation problem:

$$\begin{aligned} \min \quad & \sum_{i \in O, j \in D} c_{i,j} x_{i,j} \\ \text{s.t.} \quad & \sum_{j \in D} x_{i,j} \leq s_i \quad \forall i \in O \\ & \sum_{i \in O} x_{i,j} = d_j \quad \forall j \in D \\ & x_{i,j} \geq 0 \quad \forall i \in O, j \in D \end{aligned}$$

but introduce a set of products  $P$ , resulting in:

$$\begin{aligned} \min \quad & \sum_{i \in O, j \in D, k \in P} c_{i,j,k} x_{i,j,k} \\ \text{s.t.} \quad & \sum_{j \in D} x_{i,j,k} \leq s_{i,k} \quad \forall i \in O, k \in P \\ & \sum_{i \in O} x_{i,j,k} = d_{j,k} \quad \forall j \in D, k \in P \\ & x_{i,j,k} \geq 0 \quad \forall i \in O, j \in D, k \in P \\ & \sum_{k \in P} x_{i,j,k} \leq u_{i,j} \quad \forall i \in O, j \in D \end{aligned}$$

Note that the last constraint is new; it says that there is a maximum quantity of goods (of any type) that can be transported from origin  $i$  to destination  $j$ .

## Data

For the purpose of this tutorial, the JuMP repository contains an example database called `multi.sqlite`.

```
filename = joinpath(@__DIR__, "multi.sqlite");
```

To run locally, download `multi.sqlite` and update `filename` appropriately.

Load the database using `SQLite.DB`:

```
db = SQLite.DB(filename)
```

```
SQLite.DB("/home/runner/work/JuMP.jl/JuMP.jl/docs/latex_build/tutorials/linear/multi.sqlite")
```

A quick way to see the schema of the database is via `SQLite.tables`:

```
SQLite.tables(db)
```

```
5-element Vector{SQLite.DBTable}:
SQLite.DBTable("locations", Tables.Schema:
:location Union{Missing, String}
:type Union{Missing, String})
SQLite.DBTable("products", Tables.Schema:
:product Union{Missing, String})
SQLite.DBTable("supply", Tables.Schema:
:origin Union{Missing, String}
:product Union{Missing, String}
:supply Union{Missing, Float64})
SQLite.DBTable("demand", Tables.Schema:
:destination Union{Missing, String}
:product Union{Missing, String}
:demand Union{Missing, Float64})
SQLite.DBTable("cost", Tables.Schema:
:origin Union{Missing, String}
:destination Union{Missing, String}
:product Union{Missing, String}
:cost Union{Missing, Float64})
```

We interact with the database by executing queries, and then piping the results to an appropriate table. One example is a `DataFrame`:

```
DBInterface.execute(db, "SELECT * FROM locations") |> DataFrames.DataFrame
```

But other table types are supported, such as `Tables.rowtable`:

	location	type
	String	String
1	GARY	origin
2	CLEV	origin
3	PITT	origin
4	FRA	destination
5	DET	destination
6	LAN	destination
7	WIN	destination
8	STL	destination
9	FRE	destination
10	LAF	destination

```
DBInterface.execute(db, "SELECT * FROM locations") |> Tables.rowtable
```

```
10-element Vector{@NamedTuple{location::String, type::String}}:
(location = "GARY", type = "origin")
(location = "CLEV", type = "origin")
(location = "PITT", type = "origin")
(location = "FRA", type = "destination")
(location = "DET", type = "destination")
(location = "LAN", type = "destination")
(location = "WIN", type = "destination")
(location = "STL", type = "destination")
(location = "FRE", type = "destination")
(location = "LAF", type = "destination")
```

A rowtable is a Vector of NamedTuples.

You can construct more complicated SQL queries:

```
origins =
    DBInterface.execute(
        db,
        "SELECT location FROM locations WHERE type = \"origin\"",
    ) |> Tables.rowtable
```

```
3-element Vector{@NamedTuple{location::String}}:
(location = "GARY",)
(location = "CLEV",)
(location = "PITT",)
```

But for our purpose, we just want the list of strings:

```
origins = map(y -> y.location, origins)
```

```
3-element Vector{String}:
"GARY"
"CLEV"
"PITT"
```

We can compose these two operations to get a list of destinations:

```
destinations =
    DBInterface.execute(
        db,
        "SELECT location FROM locations WHERE type = \"destination\"",
    ) |>
Tables.rowtable |>
x -> map(y -> y.location, x)
```

```
7-element Vector{String}:
"FRA"
"DET"
"LAN"
"WIN"
"STL"
"FRG"
"LAJ"
```

And a list of products from our products table:

```
products =
    DBInterface.execute(db, "SELECT product FROM products") |>
Tables.rowtable |>
x -> map(y -> y.product, x)
```

```
3-element Vector{String}:
"bands"
"coils"
"plate"
```

## JuMP formulation

We start by creating a model and our decision variables:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[origins, destinations, products] >= 0)
```

```

3-dimensional DenseAxisArray{VariableRef,3,...} with index sets:
  Dimension 1, ["GARY", "CLEV", "PITT"]
  Dimension 2, ["FRA", "DET", "LAN", "WIN", "STL", "FRE", "LAF"]
  Dimension 3, ["bands", "coils", "plate"]
And data, a 3x7x3 Array{VariableRef, 3}:
[:, :, "bands"] =
x[GARY,FRA,bands] x[GARY,DET,bands] ... x[GARY,LAF,bands]
x[CLEV,FRA,bands] x[CLEV,DET,bands] x[CLEV,LAF,bands]
x[PITT,FRA,bands] x[PITT,DET,bands] x[PITT,LAF,bands]

[:, :, "coils"] =
x[GARY,FRA,coils] x[GARY,DET,coils] ... x[GARY,LAF,coils]
x[CLEV,FRA,coils] x[CLEV,DET,coils] x[CLEV,LAF,coils]
x[PITT,FRA,coils] x[PITT,DET,coils] x[PITT,LAF,coils]

[:, :, "plate"] =
x[GARY,FRA,plate] x[GARY,DET,plate] ... x[GARY,LAF,plate]
x[CLEV,FRA,plate] x[CLEV,DET,plate] x[CLEV,LAF,plate]
x[PITT,FRA,plate] x[PITT,DET,plate] x[PITT,LAF,plate]

```

One approach when working with databases is to extract all of the data into a Julia datastructure. For example, let's pull the cost table into a DataFrame and then construct our objective by iterating over the rows of the DataFrame:

```

cost = DBInterface.execute(db, "SELECT * FROM cost") |> DataFrames.DataFrame
@objective(
    model,
    Max,
    sum(r.cost * x[r.origin, r.destination, r.product] for r in eachrow(cost)),
)

```

If we don't want to use a DataFrame, we can use a Tables.rowtable instead:

```

supply = DBInterface.execute(db, "SELECT * FROM supply") |> Tables.rowtable
for r in supply
    @constraint(model, sum(x[r.origin, :, r.product]) <= r.supply)
end

```

Another approach is to execute the query, and then to iterate through the rows of the query using Tables.rows:

```

demand = DBInterface.execute(db, "SELECT * FROM demand")
for r in Tables.rows(demand)
    @constraint(model, sum(x[:, r.destination, r.product]) == r.demand)
end

```

### Warning

Iterating through the rows of a query result works by incrementing a cursor inside the database. As a consequence, you cannot call Tables.rows twice on the same query result.

The SQLite queries can be arbitrarily complex. For example, here's a query which builds every possible origin-destination pair:

```
od_pairs = DBInterface.execute(
    db,
    """
    SELECT a.location as 'origin',
           b.location as 'destination'
    FROM locations a
    INNER JOIN locations b
    ON a.type = 'origin' AND b.type = 'destination'
    """,
)
```

```
SQLite.Query{false}(SQLite.Stmt(SQLite.DB("/home/runner/work/JuMP.jl/JuMP.jl/docs/latex_build/tutorials/linear/multi.s
→ Base.RefValue{Ptr{SQLite.C.sqlite3_stmt}}(Ptr{SQLite.C.sqlite3_stmt} @0x000000007598db18),
→ Dict{Int64, Any}()), Base.RefValue{Int32}(100), [:origin, :destination], Type[Union{Missing,
→ String}, Union{Missing, String}], Dict(:origin => 1, :destination => 2),
→ Base.RefValue{Int64}(0))
```

With a constraint that we cannot send more than 625 units between each pair:

```
for r in Tables.rows(od_pairs)
    @constraint(model, sum(x[r.origin, r.destination, :]) <= 625)
end
```

## Solution

Finally, we can optimize the model:

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : HiGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 2.25700e+05
  Objective bound    : 2.25700e+05
  Relative gap       : 0.00000e+00
```

```
Dual objective value : 2.25700e+05

* Work counters
  Solve time (sec)   : 6.88791e-04
  Simplex iterations : 54
  Barrier iterations : 0
  Node count         : -1
```

and print the solution:

```
begin
    println("      ", join(products, ' '))
    for o in origins, d in destinations
        v = lpad.([round(Int, value(x[o, d, p])) for p in products], 5)
        println(o, " ", d, " ", join(replace.(v, " 0" => ". "), " "))
    end
end
```

	bands	coils	plate
GARY FRA	25	500	100
GARY DET	125	.	50
GARY LAN	.	.	.
GARY WIN	.	.	50
GARY STL	250	300	.
GARY FRE	.	.	.
GARY LAF	.	.	.
CLEV FRA	275	.	.
CLEV DET	100	200	50
CLEV LAN	100	.	.
CLEV WIN	.	.	.
CLEV STL	.	625	.
CLEV FRE	225	400	.
CLEV LAF	.	375	250
PITT FRA	.	.	.
PITT DET	75	550	.
PITT LAN	.	400	.
PITT WIN	75	250	.
PITT STL	400	25	200
PITT FRE	.	450	100
PITT LAF	250	125	.

## 6.7 The network multi-commodity flow problem

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

This tutorial is a variation of [The multi-commodity flow problem](#) where the graph is a network instead of a bipartite graph.

The purpose of this tutorial is to demonstrate a style of modeling that uses relational algebra.

## Required packages

This tutorial uses the following packages:

```
using JuMP
import DataFrames
import HiGHS
import SQLite
import SQLite.DBInterface
import Test
```

## Formulation

The network multi-commodity flow problem is an extension of the [The multi-commodity flow problem](#), where instead of having a bipartite graph of supply and demand nodes, the graph can contain a set of nodes,  $i \in \mathcal{N}$ , which each have a (potentially zero) supply capacity,  $u_{i,p}^s$ , and (potentially zero) a demand,  $d_{i,p}$  for each commodity  $p \in P$ . The nodes are connected by a set of edges  $(i, j) \in \mathcal{E}$ , which have a shipment cost  $c_{i,j,p}^x$  and a total flow capacity of  $u_{i,j}^x$ .

Our take is to choose an optimal supply for each node  $s_{i,p}$ , as well as the optimal transshipment  $x_{i,j,p}$  that minimizes the total cost.

The mathematical formulation is:

$$\begin{aligned} \min \quad & \sum_{(i,j) \in \mathcal{E}, p \in P} c_{i,j,p}^x x_{i,j,p} + \sum_{i \in \mathcal{N}, p \in P} c_{i,p}^s s_{i,p} \\ \text{s.t.} \quad & s_{i,p} + \sum_{(j,i) \in \mathcal{E}} x_{j,i,p} - \sum_{(i,j) \in \mathcal{E}} x_{i,j,p} = d_{i,p} \quad \forall i \in \mathcal{N}, p \in P \\ & x_{i,j,p} \geq 0 \quad \forall (i,j) \in \mathcal{E}, p \in P \\ & \sum_{p \in P} x_{i,j,p} \leq u_{i,j}^x \quad \forall (i,j) \in \mathcal{E} \\ & 0 \leq s_{i,p} \leq u_{i,p}^s \quad \forall i \in \mathcal{N}, p \in P. \end{aligned}$$

The purpose of this tutorial is to demonstrate how this model can be built using relational algebra instead of a direct math-to-code translation of the summations.

## Data

For the purpose of this tutorial, the JuMP repository contains an example database called `commodity_nz.db`:

```
filename = joinpath(@__DIR__, "commodity_nz.db");
```

To run locally, download `commodity_nz.db` and update `filename` appropriately.

Load the database using `SQLite.DB`:

```
db = SQLite.DB(filename)
```

```
SQLite.DB("/home/runner/work/JuMP.jl/JuMP.jl/docs/latex_build/tutorials/linear/commodity_nz.db")
```

A quick way to see the schema of the database is via `SQLite.tables`:

```
SQLite.tables(db)
```

```
4-element Vector{SQLite.DBTable}:
 SQLite.DBTable("products", Tables.Schema:
 :product      Union{Missing, String}
 :cost_per_km  Union{Missing, Float64})
 SQLite.DBTable("shipping", Tables.Schema:
 :origin       Union{Missing, String}
 :destination  Union{Missing, String}
 :product      Union{Missing, String}
 :distance_km  Union{Missing, Float64})
 SQLite.DBTable("supply", Tables.Schema:
 :origin      Union{Missing, String}
 :product     Union{Missing, String}
 :capacity    Union{Missing, Float64}
 :cost        Union{Missing, Float64})
 SQLite.DBTable("demand", Tables.Schema:
 :destination Union{Missing, String}
 :product     Union{Missing, String}
 :demand      Union{Missing, Float64})
```

We interact with the database by executing queries and then loading the results into a DataFrame:

```
function get_table(db, table)
    query = DBInterface.execute(db, "SELECT * FROM $table")
    return DataFrames.DataFrame(query)
end
```

```
get_table (generic function with 1 method)
```

The `shipping` table contains the set of arcs and their distances:

```
df_shipping = get_table(db, "shipping")
```

The `products` table contains the shipping cost per kilometer of each product:

```
df_products = get_table(db, "products")
```

The `supply` table contains the supply capacity of each node, as well as the cost:

	origin	destination	product	distance_km
	String	String	String	Float64
1	auckland	waikato	milk	112.0
2	auckland	tauranga	milk	225.0
3	auckland	christchurch	milk	1070.0
4	waikato	auckland	milk	112.0
5	waikato	tauranga	milk	107.0
6	waikato	wellington	milk	392.0
7	tauranga	auckland	milk	225.0
8	tauranga	waikato	milk	107.0
9	christchurch	auckland	milk	1070.0
10	auckland	waikato	kiwifruit	112.0
11	auckland	christchurch	kiwifruit	1070.0
12	waikato	auckland	kiwifruit	112.0
13	waikato	wellington	kiwifruit	392.0
14	tauranga	auckland	kiwifruit	225.0
15	tauranga	waikato	kiwifruit	107.0
16	christchurch	auckland	kiwifruit	1070.0

	product	cost_per_km
	String	Float64
1	milk	0.001
2	kiwifruit	0.01

```
df_supply = get_table(db, "supply")
```

	origin	product	capacity	cost
	String	String	Float64	Float64
1	waikato	milk	10.0	0.5
2	tauranga	milk	6.0	1.0
3	tauranga	kiwifruit	26.0	1.0
4	christchurch	milk	10.0	0.6

The demand table contains the demand of each node:

```
df_demand = get_table(db, "demand")
```

	destination	product	demand
	String	String	Float64
1	auckland	milk	16.0
2	auckland	kiwifruit	16.0
3	tauranga	milk	2.0
4	tauranga	kiwifruit	2.0
5	wellington	milk	2.0
6	wellington	kiwifruit	2.0
7	christchurch	milk	4.0
8	christchurch	kiwifruit	4.0

### JuMP formulation

We start by creating a model and our decision variables:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
```

For the shipping decisions, we create a new column in `df_shipping` called `x_flow`, which has one non-negative decision variable for each row:

```
df_shipping.x_flow = @variable(model, x[1:size(df_shipping, 1)] >= 0)
df_shipping
```

	origin	destination	product	distance_km	x_flow
	String	String	String	Float64	GenericV...
1	auckland	waikato	milk	112.0	$x_1$
2	auckland	tauranga	milk	225.0	$x_2$
3	auckland	christchurch	milk	1070.0	$x_3$
4	waikato	auckland	milk	112.0	$x_4$
5	waikato	tauranga	milk	107.0	$x_5$
6	waikato	wellington	milk	392.0	$x_6$
7	tauranga	auckland	milk	225.0	$x_7$
8	tauranga	waikato	milk	107.0	$x_8$
9	christchurch	auckland	milk	1070.0	$x_9$
10	auckland	waikato	kiwifruit	112.0	$x_{10}$
11	auckland	christchurch	kiwifruit	1070.0	$x_{11}$
12	waikato	auckland	kiwifruit	112.0	$x_{12}$
13	waikato	wellington	kiwifruit	392.0	$x_{13}$
14	tauranga	auckland	kiwifruit	225.0	$x_{14}$
15	tauranga	waikato	kiwifruit	107.0	$x_{15}$
16	christchurch	auckland	kiwifruit	1070.0	$x_{16}$

For the supply, we add a variable to each row, and then set the upper bound to the capacity of each supply node:

```
df_supply.x_supply = @variable(model, s[1:size(df_supply, 1)] >= 0)
set_upper_bound.(df_supply.x_supply, df_supply.capacity)
df_supply
```

	origin	product	capacity	cost	x_supply
	String	String	Float64	Float64	GenericV...
1	waikato	milk	10.0	0.5	$s_1$
2	tauranga	milk	6.0	1.0	$s_2$
3	tauranga	kiwifruit	26.0	1.0	$s_3$
4	christchurch	milk	10.0	0.6	$s_4$

Our objective is to minimize the shipping cost plus the supply cost. To compute the flow cost, we need to join the shipping table, which contains `distance_km` with the products table, which contains `cost_per_km`:

```
df_cost = DataFrames.leftjoin(df_shipping, df_products; on = [:product])
df_cost.flow_cost = df_cost.cost_per_km .* df_cost.distance_km
df_cost
```

	origin	destination	product	distance_km	x_flow	cost_per_km	flow_cost
	String	String	String	Float64	GenericV...	Float64?	Float64
1	auckland	waikato	milk	112.0	$x_1$	0.001	0.112
2	auckland	tauranga	milk	225.0	$x_2$	0.001	0.225
3	auckland	christchurch	milk	1070.0	$x_3$	0.001	1.07
4	waikato	auckland	milk	112.0	$x_4$	0.001	0.112
5	waikato	tauranga	milk	107.0	$x_5$	0.001	0.107
6	waikato	wellington	milk	392.0	$x_6$	0.001	0.392
7	tauranga	auckland	milk	225.0	$x_7$	0.001	0.225
8	tauranga	waikato	milk	107.0	$x_8$	0.001	0.107
9	christchurch	auckland	milk	1070.0	$x_9$	0.001	1.07
10	auckland	waikato	kiwifruit	112.0	$x_{10}$	0.01	1.12
11	auckland	christchurch	kiwifruit	1070.0	$x_{11}$	0.01	10.7
12	waikato	auckland	kiwifruit	112.0	$x_{12}$	0.01	1.12
13	waikato	wellington	kiwifruit	392.0	$x_{13}$	0.01	3.92
14	tauranga	auckland	kiwifruit	225.0	$x_{14}$	0.01	2.25
15	tauranga	waikato	kiwifruit	107.0	$x_{15}$	0.01	1.07
16	christchurch	auckland	kiwifruit	1070.0	$x_{16}$	0.01	10.7

Then we can use linear algebra to compute the inner product between two columns:

```
@objective(
    model,
    Min,
    df_cost.flow_cost' * df_shipping.x_flow +
    df_supply.cost' * df_supply.x_supply
);
```

For the flow capacities on each arc, we use `DataFrames.groupby` to partition the flow variables based on `:origin` and `:destination`, and then we constrain their sum to be less than a fixed capacity.

```
capacity = 30
for df in DataFrames.groupby(df_shipping, [:origin, :destination])
    @constraint(model, sum(df.x_flow) <= capacity)
end
```

For each node in the graph, we need to compute a mass balance constraint which says that for each product, the supply, plus the flow into the node, and less the flow out of the node is equal to the demand.

We can compute an expression for the flow out of each node using `DataFrames.groupby` on the `origin` and `product` columns of the `df_shipping` table:

```
df_flow_out = DataFrames.DataFrame(
    (node = i.origin, product = i.product, x_flow_out = sum(df.x_flow)) for
    (i, df) in pairs(DataFrames.groupby(df_shipping, [:origin, :product])))
)
```

	node	product	x_flow_out
	String	String	AffExpr
1	auckland	milk	$x_1 + x_2 + x_3$
2	waikato	milk	$x_4 + x_5 + x_6$
3	tauranga	milk	$x_7 + x_8$
4	christchurch	milk	$x_9$
5	auckland	kiwifruit	$x_{10} + x_{11}$
6	waikato	kiwifruit	$x_{12} + x_{13}$
7	tauranga	kiwifruit	$x_{14} + x_{15}$
8	christchurch	kiwifruit	$x_{16}$

We can compute an expression for the flow into each node using `DataFrames.groupby` on the destination and product columns of the `df_shipping` table:

```
df_flow_in = DataFrame.DataFrame(
    (node = i.destination, product = i.product, x_flow_in = sum(df.x_flow))
    for (i, df) in
    pairs(DataFrames.groupby(df_shipping, [:destination, :product]))
)
```

	node	product	x_flow_in
	String	String	AffExpr
1	waikato	milk	$x_1 + x_8$
2	tauranga	milk	$x_2 + x_5$
3	christchurch	milk	$x_3$
4	auckland	milk	$x_4 + x_7 + x_9$
5	wellington	milk	$x_6$
6	waikato	kiwifruit	$x_{10} + x_{15}$
7	christchurch	kiwifruit	$x_{11}$
8	auckland	kiwifruit	$x_{12} + x_{14} + x_{16}$
9	wellington	kiwifruit	$x_{13}$

We can join the two tables together using `DataFrames.outerjoin`. We need to use `outerjoin` here because there might be missing rows.

```
df = DataFrame.outerjoin(df_flow_in, df_flow_out; on = [:node, :product])
```

Next, we need to join the supply column:

```
df = DataFrame.leftjoin(
    df,
    DataFrame.select(df_supply, [:origin, :product, :x_supply]);
    on = [:node => :origin, :product],
)
```

and then the demand column

	node	product	x_flow_in	x_flow_out	
	String	String	AffExpr?	AffExpr?	
1	waikato	milk	$x_1 + x_8$	$x_4 + x_5 + x_6$	
2	tauranga	milk	$x_2 + x_5$	$x_7 + x_8$	
3	christchurch	milk	$x_3$	$x_9$	
4	auckland	milk	$x_4 + x_7 + x_9$	$x_1 + x_2 + x_3$	
5	waikato	kiwifruit	$x_{10} + x_{15}$	$x_{12} + x_{13}$	
6	christchurch	kiwifruit	$x_{11}$	$x_{16}$	
7	auckland	kiwifruit	$x_{12} + x_{14} + x_{16}$	$x_{10} + x_{11}$	
8	wellington	milk	$x_6$	<i>missing</i>	
9	wellington	kiwifruit	$x_{13}$	<i>missing</i>	
10	tauranga	kiwifruit	<i>missing</i>	$x_{14} + x_{15}$	

	node	product	x_flow_in	x_flow_out	x_supply	
	String	String	AffExpr?	AffExpr?	GenericV...?	
1	waikato	milk	$x_1 + x_8$	$x_4 + x_5 + x_6$	$s_1$	
2	tauranga	milk	$x_2 + x_5$	$x_7 + x_8$	$s_2$	
3	christchurch	milk	$x_3$	$x_9$	$s_4$	
4	tauranga	kiwifruit	<i>missing</i>	$x_{14} + x_{15}$	$s_3$	
5	auckland	milk	$x_4 + x_7 + x_9$	$x_1 + x_2 + x_3$	<i>missing</i>	
6	waikato	kiwifruit	$x_{10} + x_{15}$	$x_{12} + x_{13}$	<i>missing</i>	
7	christchurch	kiwifruit	$x_{11}$	$x_{16}$	<i>missing</i>	
8	auckland	kiwifruit	$x_{12} + x_{14} + x_{16}$	$x_{10} + x_{11}$	<i>missing</i>	
9	wellington	milk	$x_6$	<i>missing</i>	<i>missing</i>	
10	wellington	kiwifruit	$x_{13}$	<i>missing</i>	<i>missing</i>	

```
df = DataFrames.leftjoin(
    df,
    DataFrames.select(df_demand, [:destination, :product, :demand]);
    on = [:node => :destination, :product],
)
```

	node	product	x_flow_in	x_flow_out	x_supply	demand
	String	String	AffExpr?	AffExpr?	GenericV...?	Float64?
1	tauranga	milk	$x_2 + x_5$	$x_7 + x_8$	$s_2$	2.0
2	christchurch	milk	$x_3$	$x_9$	$s_4$	4.0
3	tauranga	kiwifruit	<i>missing</i>	$x_{14} + x_{15}$	$s_3$	2.0
4	auckland	milk	$x_4 + x_7 + x_9$	$x_1 + x_2 + x_3$	<i>missing</i>	16.0
5	christchurch	kiwifruit	$x_{11}$	$x_{16}$	<i>missing</i>	4.0
6	auckland	kiwifruit	$x_{12} + x_{14} + x_{16}$	$x_{10} + x_{11}$	<i>missing</i>	16.0
7	wellington	milk	$x_6$	<i>missing</i>	<i>missing</i>	2.0
8	wellington	kiwifruit	$x_{13}$	<i>missing</i>	<i>missing</i>	2.0
9	waikato	milk	$x_1 + x_8$	$x_4 + x_5 + x_6$	$s_1$	<i>missing</i>
10	waikato	kiwifruit	$x_{10} + x_{15}$	$x_{12} + x_{13}$	<i>missing</i>	<i>missing</i>

Now we're ready to add our mass balance constraint. Because some rows contain *missing* values, we need to use `coalesce` to convert any *missing* into a numeric value:

```
@constraint(
    model,
    [r in eachrow(df)],
    coalesce(r.x_supply, 0.0) + coalesce(r.x_flow_in, 0.0) -
    coalesce(r.x_flow_out, 0.0) == coalesce(r.demand, 0.0),
);
```

## Solution

Finally, we can optimize the model:

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : HiGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 1.43228e+02
  Objective bound    : 1.43228e+02
  Relative gap       : 3.96874e-16
  Dual objective value : 1.43228e+02

* Work counters
  Solve time (sec)   : 3.48091e-04
  Simplex iterations : 8
  Barrier iterations : 0
  Node count         : -1
```

update the solution in the DataFrames:

```
df_shipping.x_flow = value.(df_shipping.x_flow)
df_supply.x_supply = value.(df_supply.x_supply);
```

and display the optimal solution for flows:

```
DataFrames.select(
    filter!(row -> row.x_flow > 0.0, df_shipping),
    [:origin, :destination, :product, :x_flow],
)
```

	origin	destination	product	x_flow
	String	String	String	Float64
1	waikato	auckland	milk	10.0
2	waikato	wellington	milk	2.0
3	tauranga	auckland	milk	2.0
4	tauranga	waikato	milk	2.0
5	christchurch	auckland	milk	4.0
6	auckland	christchurch	kiwifruit	4.0
7	waikato	auckland	kiwifruit	20.0
8	waikato	wellington	kiwifruit	2.0
9	tauranga	waikato	kiwifruit	22.0

## 6.8 Tips and tricks

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

**This tutorial was originally contributed by Arpit Bhatia.**

### Tip

A good source of tips is the [Mosek Modeling Cookbook](#).

This tutorial collates some tips and tricks you can use when formulating mixed-integer programs. It uses the following packages:

```
julia> using JuMP
```

### Absolute value

To model the absolute value function  $t \geq |x|$ , there are a few options. In all cases, these reformulations only work if you are minimizing  $t$  "down" into  $|x|$ . They do not work if you are trying to maximize  $|x|$ .

#### Option 1

This option adds two linear inequality constraints:

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, t)
t

julia> @constraint(model, t >= x)
-x + t ≥ 0

julia> @constraint(model, t >= -x)
x + t ≥ 0
```

**Option 2**

This option uses two non-negative variables and forms expressions for  $x$  and  $t$ :

```
julia> model = Model();

julia> @variable(model, z[1:2] >= 0)
2-element Vector{VariableRef}:
z[1]
z[2]

julia> @expression(model, t, z[1] + z[2])
z[1] + z[2]

julia> @expression(model, x, z[1] - z[2])
z[1] - z[2]
```

**Option 3**

This option uses `MOI.NormOneCone` and lets JuMP choose the reformulation:

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, t)
t

julia> @constraint(model, [t; x] in MOI.NormOneCone(2))
[t, x] ∈ MathOptInterface.NormOneCone(2)
```

**L1-norm**

To model  $\min ||x||_1$ , that is,  $\min \sum_i |x_i|$ , use the `MOI.NormOneCone`:

```
julia> model = Model();

julia> @variable(model, x[1:3])
3-element Vector{VariableRef}:
x[1]
x[2]
x[3]

julia> @variable(model, t)
t

julia> @constraint(model, [t; x] in MOI.NormOneCone(1 + length(x)))
[t, x[1], x[2], x[3]] ∈ MathOptInterface.NormOneCone(4)
```

```
julia> @objective(model, Min, t)
t
```

### Infinity-norm

To model  $\min \|x\|_\infty$ , that is,  $\min \max_i |x_i|$ , use the `MOI.NormInfinityCone`:

```
julia> model = Model();

julia> @variable(model, x[1:3])
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]

julia> @variable(model, t)
t

julia> @constraint(model, [t; x] in MOI.NormInfinityCone(1 + length(x)))
[t, x[1], x[2], x[3]] ∈ MathOptInterface.NormInfinityCone(4)

julia> @objective(model, Min, t)
t
```

### Max

To model  $t \geq \max\{x, y\}$ , do:

```
julia> model = Model();

julia> @variable(model, t)
t

julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> @constraint(model, t >= x)
t - x ≥ 0

julia> @constraint(model, t >= y)
t - y ≥ 0
```

This reformulation does not work for  $t \geq \min\{x, y\}$ .

## Min

To model  $t \leq \min\{x, y\}$ , do:

```
julia> model = Model();

julia> @variable(model, t)
t

julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> @constraint(model, t <= x)
t - x ≤ 0

julia> @constraint(model, t <= y)
t - y ≤ 0
```

This reformulation does not work for  $t \leq \max\{x, y\}$ .

## Modulo

To model  $y = x \bmod n$ , where  $n$  is a constant modulus, we use the relationship  $x = n \cdot z + y$ , where  $z \in \mathbb{Z}_+$  is the number of times that  $n$  can be divided by  $x$  and  $y$  is the remainder.

```
julia> n = 4
4

julia> model = Model();

julia> @variable(model, x >= 0, Int)
x

julia> @variable(model, 0 <= y <= n - 1, Int)
y

julia> @variable(model, z >= 0, Int)
z

julia> @constraint(model, x == n * z + y)
x - y - 4 z = 0
```

The modulo reformulation is often useful for subdividing a time increment into units of time like hours and days:

```
julia> model = Model();
```

```
julia> @variable(model, t >= 0, Int)
t

julia> @variable(model, 0 <= hours <= 23, Int)
hours

julia> @variable(model, days >= 0, Int)
days

julia> @constraint(model, t == 24 * days + hours)
t - hours - 24 days = 0
```

## Boolean operators

Binary variables can be used to construct logical operators. Here are some example.

### Or

$$x_3 = x_1 \vee x_2$$

```
julia> model = Model();

julia> @variable(model, x[1:3], Bin)
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]

julia> @constraints(model, begin
           x[1] <= x[3]
           x[2] <= x[3]
           x[3] <= x[1] + x[2]
       end)
(x[1] - x[3] ≤ 0, x[2] - x[3] ≤ 0, -x[1] - x[2] + x[3] ≤ 0)
```

### And

$$x_3 = x_1 \wedge x_2$$

```
julia> model = Model();

julia> @variable(model, x[1:3], Bin)
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]

julia> @constraints(model, begin
```

```

        x[3] <= x[1]
        x[3] <= x[2]
        x[3] >= x[1] + x[2] - 1
    end)
(-x[1] + x[3] ≤ 0, -x[2] + x[3] ≤ 0, -x[1] - x[2] + x[3] ≥ -1)

```

**Not**

$$x_1 \neg x_2$$

```

julia> model = Model();

julia> @variable(model, x[1:2], Bin)
2-element Vector{VariableRef}:
x[1]
x[2]

julia> @constraint(model, x[1] == 1 - x[2])
x[1] + x[2] = 1

```

**Implies**

$$x_1 \implies x_2$$

```

julia> model = Model();

julia> @variable(model, x[1:2], Bin)
2-element Vector{VariableRef}:
x[1]
x[2]

julia> @constraint(model, x[1] <= x[2])
x[1] - x[2] ≤ 0

```

**Disjunctions****Problem**

Suppose that we have two constraints  $a^\top x \leq b$  and  $c^\top x \leq d$ , and we want at least one to hold.

**Trick 1**

Use an [indicator constraint](#).

**Example** Either  $x_1 \leq 1$  or  $x_2 \leq 2$ .

```
julia> model = Model();

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
x[1]
x[2]

julia> @variable(model, y[1:2], Bin)
2-element Vector{VariableRef}:
y[1]
y[2]

julia> @constraint(model, y[1] --> {x[1] <= 1})
y[1] --> {x[1] ≤ 1}

julia> @constraint(model, y[2] --> {x[2] <= 2})
y[2] --> {x[2] ≤ 2}

julia> @constraint(model, sum(y) == 1) # Exactly one branch must be true
y[1] + y[2] = 1
```

## Trick 2

Introduce a "big-M" multiplied by a binary variable to relax one of the constraints.

**Example** Either  $x_1 \leq 1$  or  $x_2 \leq 2$ .

```
julia> model = Model();

julia> @variable(model, x[1:2] <= 10)
2-element Vector{VariableRef}:
x[1]
x[2]

julia> @variable(model, y[1:2], Bin)
2-element Vector{VariableRef}:
y[1]
y[2]

julia> M = 100
100

julia> @constraint(model, x[1] <= 1 + M * y[1])
x[1] - 100 y[1] ≤ 1

julia> @constraint(model, x[2] <= 2 + M * y[2])
x[2] - 100 y[2] ≤ 2

julia> @constraint(model, sum(y) == 1)
y[1] + y[2] = 1
```

**Warning**

If  $M$  is too small, the solution may be suboptimal. If  $M$  is too big, the solver may encounter numerical issues. Try to use domain knowledge to choose an  $M$  that is just right. Gurobi has a [good documentation section](#) on this topic.

**Indicator constraints****Problem**

Suppose we want to model that a certain linear inequality must be satisfied when some other event occurs, that is, for a binary variable  $z$ , we want to model the implication:

$$z = 1 \implies a^\top x \leq b$$

**Trick 1**

Some solvers have native support for indicator constraints. In addition, if the variables involved have finite domains, then JuMP can automatically reformulate an indicator into a mixed-integer program.

**Example**  $x_1 + x_2 \leq 1$  if  $z = 1$ .

```
julia> model = Model();

julia> @variable(model, 0 <= x[1:2] <= 10)
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> @variable(model, z, Bin)
z

julia> @constraint(model, z --> {sum(x) <= 1})
z --> {x[1] + x[2] ≤ 1}
```

**Example**  $x_1 + x_2 \leq 1$  if  $z = 0$ .

```
julia> model = Model();

julia> @variable(model, 0 <= x[1:2] <= 10)
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> @variable(model, z, Bin)
z

julia> @constraint(model, !z --> {sum(x) <= 1})
!z --> {x[1] + x[2] ≤ 1}
```

**Trick 2**

If the solver doesn't support indicator constraints and the variables do not have a finite domain, you can use the big-M trick.

**Example**  $x_1 + x_2 \leq 1$  if  $z = 1$ .

```
julia> model = Model();

julia> @variable(model, x[1:2] <= 10)
2-element Vector{VariableRef}:
x[1]
x[2]

julia> @variable(model, z, Bin)
z

julia> M = 100
100

julia> @constraint(model, sum(x) <= 1 + M * (1 - z))
x[1] + x[2] + 100 z ≤ 101
```

**Example**  $x_1 + x_2 \leq 1$  if  $z = 0$ .

```
julia> model = Model();

julia> @variable(model, x[1:2] <= 10)
2-element Vector{VariableRef}:
x[1]
x[2]

julia> @variable(model, z, Bin)
z

julia> M = 100
100

julia> @constraint(model, sum(x) <= 1 + M * z)
x[1] + x[2] - 100 z ≤ 1
```

**Semi-continuous variables**

A semi-continuous variable is a continuous variable between bounds  $[l, u]$  that also can assume the value zero, that is:  $x \in \{0\} \cup [l, u]$ .

**Example**  $x \in \{0\} \cup [1, 2]$

```
julia> model = Model();
```

```
julia> @variable(model, x in Semicontinuous(1.0, 2.0))
x
```

You can also represent a semi-continuous variable using the reformulation:

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, z, Bin)
z

julia> @constraint(model, x <= 2 * z)
x - 2 z ≤ 0

julia> @constraint(model, x >= 1 * z)
x - z ≥ 0
```

When  $z = 0$  the two constraints are equivalent to  $0 \leq x \leq 0$ . When  $z = 1$ , the two constraints are equivalent to  $1 \leq x \leq 2$ .

### Semi-integer variables

A semi-integer variable is a variable which assumes integer values between bounds  $[l, u]$  and can also assume the value zero:  $x \in \{0\} \cup [l, u] \cap \mathbb{Z}$ .

```
julia> model = Model();

julia> @variable(model, x in Semiinteger(5.0, 10.0))
x
```

You can also represent a semi-integer variable using the reformulation:

```
julia> model = Model();

julia> @variable(model, x, Int)
x

julia> @variable(model, z, Bin)
z

julia> @constraint(model, x <= 10 * z)
x - 10 z ≤ 0

julia> @constraint(model, x >= 5 * z)
x - 5 z ≥ 0
```

When  $z = 0$  the two constraints are equivalent to  $0 \leq x \leq 0$ . When  $z = 1$ , the two constraints are equivalent to  $5 \leq x \leq 10$ .

### Special Ordered Sets of Type 1

A Special Ordered Set of Type 1 is a set of variables, at most one of which can take a non-zero value, all others being at 0.

They most frequently apply where a set of variables are actually binary variables. In other words, we have to choose at most one from a set of possibilities.

```
julia> model = Model();

julia> @variable(model, x[1:3], Bin)
3-element Vector{VariableRef}:
x[1]
x[2]
x[3]

julia> @constraint(model, x in SOS1())
[x[1], x[2], x[3]] ∈ MathOptInterface.SOS1{Float64}([1.0, 2.0, 3.0])
```

You can optionally pass SOS1 a weight vector like

```
julia> @constraint(model, x in SOS1([0.2, 0.5, 0.3]))
[x[1], x[2], x[3]] ∈ MathOptInterface.SOS1{Float64}([0.2, 0.5, 0.3])
```

If the decision variables are related and have a physical ordering, then the weight vector, although not used directly in the constraint, can help the solver make a better decision in the solution process.

### Special Ordered Sets of Type 2

A Special Ordered Set of type 2 is a set of non-negative variables, of which at most two can be non-zero, and if two are non-zero these must be consecutive in their ordering.

```
julia> model = Model();

julia> @variable(model, x[1:3])
3-element Vector{VariableRef}:
x[1]
x[2]
x[3]

julia> @constraint(model, x in SOS2([3.0, 1.0, 2.0]))
[x[1], x[2], x[3]] ∈ MathOptInterface.SOS2{Float64}([3.0, 1.0, 2.0])
```

The ordering provided by the weight vector is more important in this case as the variables need to be consecutive according to the ordering. For example, in the above constraint, the possible pairs are:

- Consecutive

- $(x[1] \text{ and } x[3])$  as they correspond to 3 and 2 resp. and thus can be non-zero
- $(x[2] \text{ and } x[3])$  as they correspond to 1 and 2 resp. and thus can be non-zero
- Non-consecutive
  - $(x[1] \text{ and } x[2])$  as they correspond to 3 and 1 resp. and thus cannot be non-zero

### Piecewise linear approximations

SOSII constraints are most often used to form piecewise linear approximations of a function.

Given a set of points for x:

```
julia> x = -1:0.5:2
-1.0:0.5:2.0
```

and a set of corresponding points for y:

```
julia> y = x .^ 2
7-element Vector{Float64}:
 1.0
 0.25
 0.0
 0.25
 1.0
 2.25
 4.0
```

the piecewise linear approximation is constructed by representing x and y as convex combinations of  $\hat{x}$  and  $\hat{y}$ .

```
julia> N = length(x)
7

julia> model = Model();

julia> @variable(model, -1 <= x <= 2)
x

julia> @variable(model, y)
y

julia> @variable(model, 0 <= λ[1:N] <= 1)
7-element Vector{VariableRef}:
 λ[1]
 λ[2]
 λ[3]
 λ[4]
 λ[5]
 λ[6]
 λ[7]

julia> @objective(model, Max, y)
```

```

y

julia> @constraints(model, begin
           x == sum(ŷ[i] * λ[i] for i in 1:N)
           y == sum(ŷ[i] * λ[i] for i in 1:N)
           sum(λ) == 1
           λ in SOS2()
       end)
(x + λ[1] + 0.5 λ[2] - 0.5 λ[4] - λ[5] - 1.5 λ[6] - 2 λ[7] = 0, y - λ[1] - 0.25 λ[2] - 0.25 λ[4] -
→ λ[5] - 2.25 λ[6] - 4 λ[7] = 0, λ[1] + λ[2] + λ[3] + λ[4] + λ[5] + λ[6] + λ[7] = 1, [λ[1], λ[2],
→ λ[3], λ[4], λ[5], λ[6], λ[7]] ∈ MathOptInterface.SOS2{Float64}([1.0, 2.0, 3.0, 4.0, 5.0, 6.0,
→ 7.0]))

```

## 6.9 Approximating nonlinear functions

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

The purpose of this tutorial is to explain how to approximate nonlinear functions with a mixed-integer linear program.

This tutorial uses the following packages:

```

using JuMP
import HiGHS
import Plots

```

### Minimizing a convex function (outer approximation)

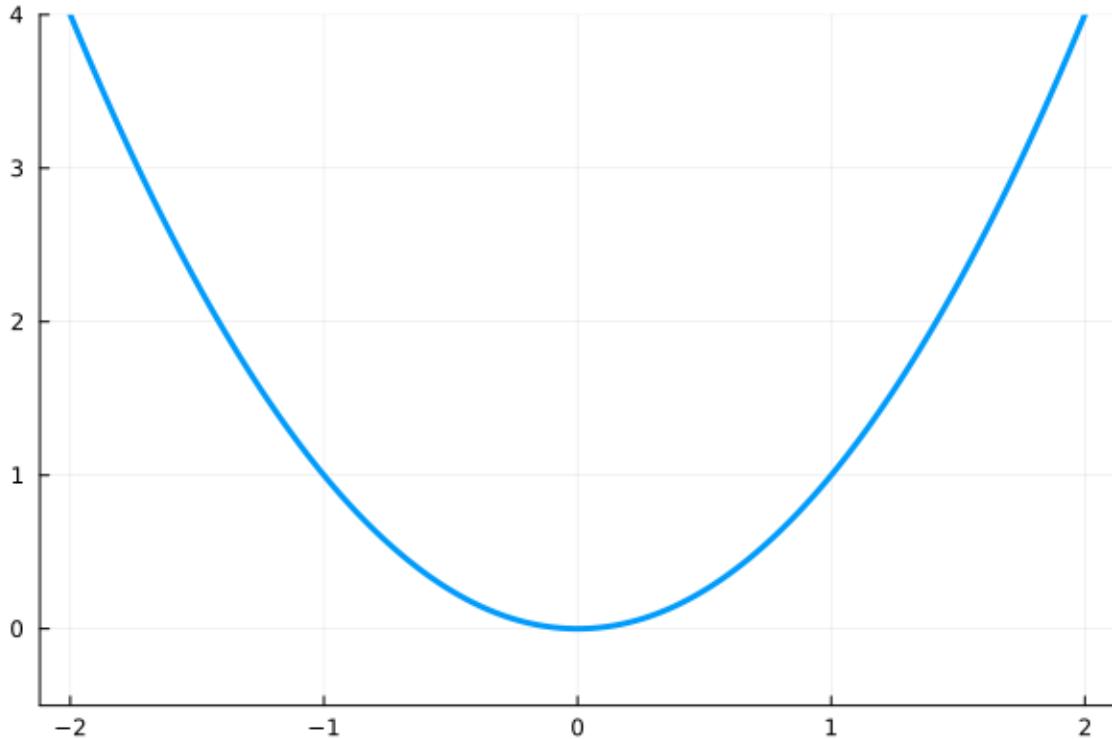
If the function you are approximating is convex, and you want to minimize "down" onto it, then you can use an outer approximation.

For example,  $f(x) = x^2$  is a convex function:

```

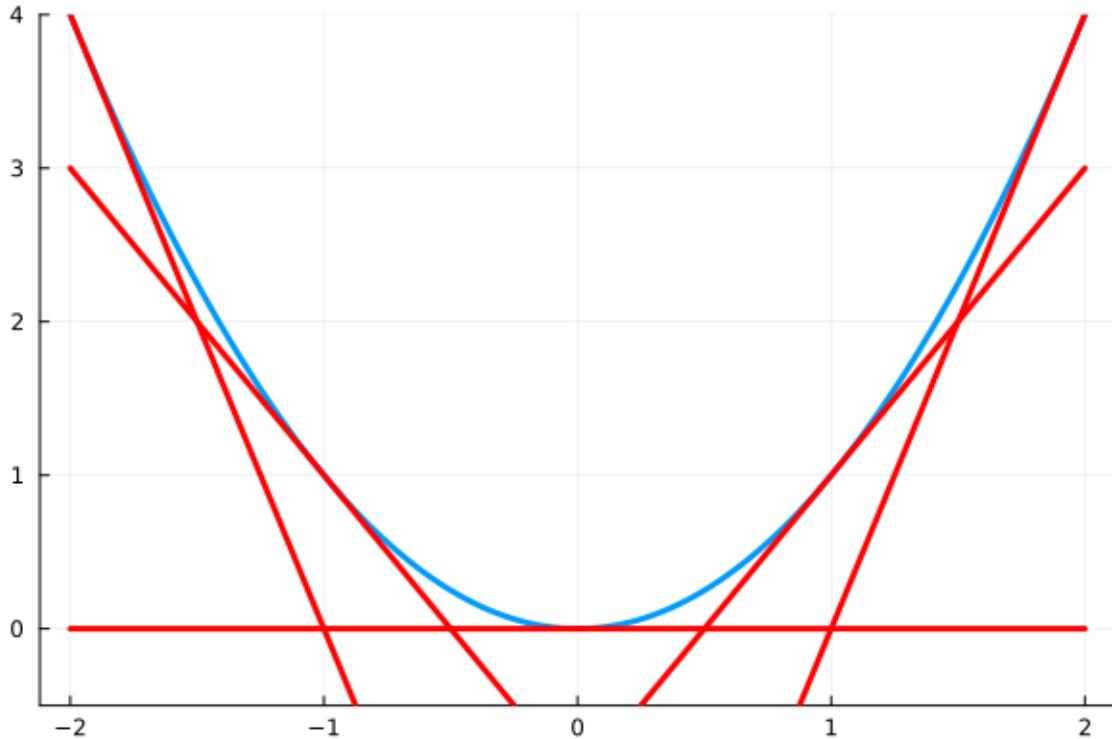
f(x) = x^2
∇f(x) = 2 * x
plot = Plots.plot(f, -2:0.01:2; ylims = (-0.5, 4), label = false, width = 3)

```



Because  $f$  is convex, we know that for any  $x_k$ , we have:  $f(x) \geq f(x_k) + \nabla f(x_k) \cdot (x - x_k)$

```
for x_k in -2:1:2 ## Tip: try changing the number of points x_k
    g = x -> f(x_k) + ∇f(x_k) * (x - x_k)
    Plots.plot!(plot, g, -2:0.01:2; color = :red, label = false, width = 3)
end
plot
```



We can use these *tangent planes* as constraints in our model to create an outer approximation of the function. As we add more planes, the error between the true function and the piecewise linear outer approximation decreases.

Here is the model in JuMP:

```
function outer_approximate_x_squared(x̄)
    f(x) = x^2
    ∇f(x) = 2x
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, -2 ≤ x ≤ 2)
    @variable(model, y)
    # Tip: try changing the number of points x_k
    @constraint(model, [x_k in -2:1:2], y ≥= f(x_k) + ∇f(x_k) * (x - x_k))
    @objective(model, Min, y)
    @constraint(model, x == x̄) # <-- a trivial constraint just for testing.
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value(y)
end
```

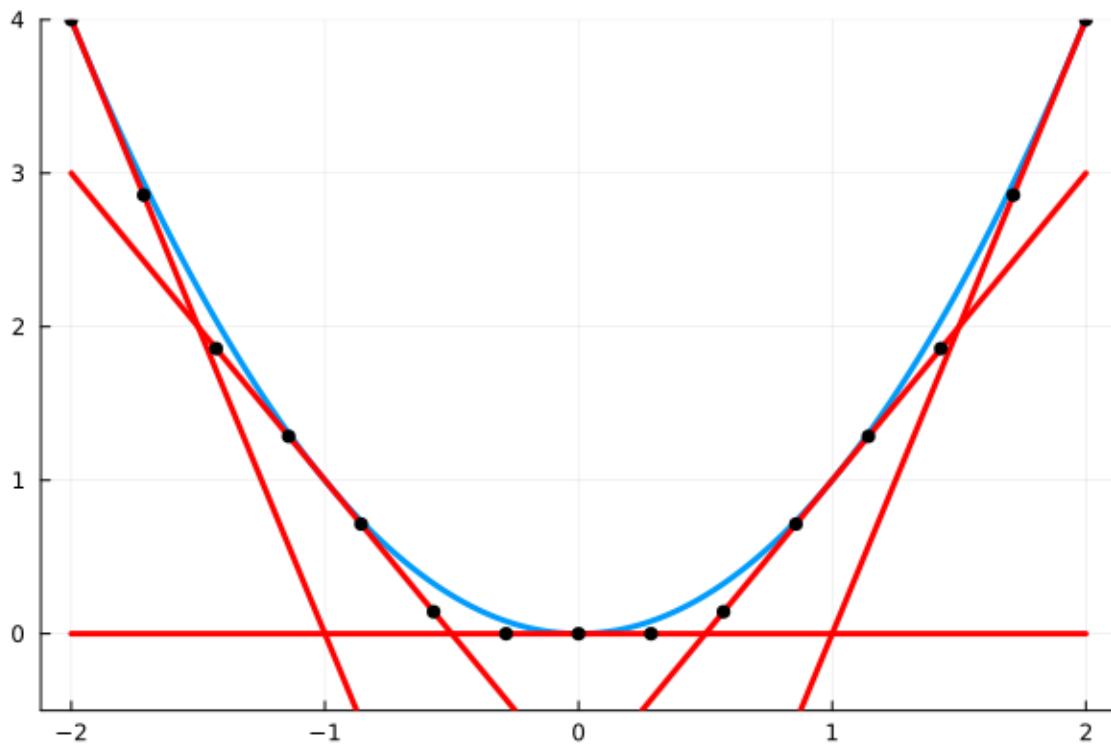
```
outer_approximate_x_squared (generic function with 1 method)
```

Here are a few values:

```

for x in range(; start = -2, stop = 2, length = 15)
    ŷ = outer_approximate_x_squared(x)
    Plots.scatter!(plot, [x], [ŷ]; label = false, color = :black)
end
plot

```

**Note**

This formulation does not work if we want to maximize y.

**Maximizing a concave function (outer approximation)**

The outer approximation also works if we want to maximize "up" into a concave function.

```

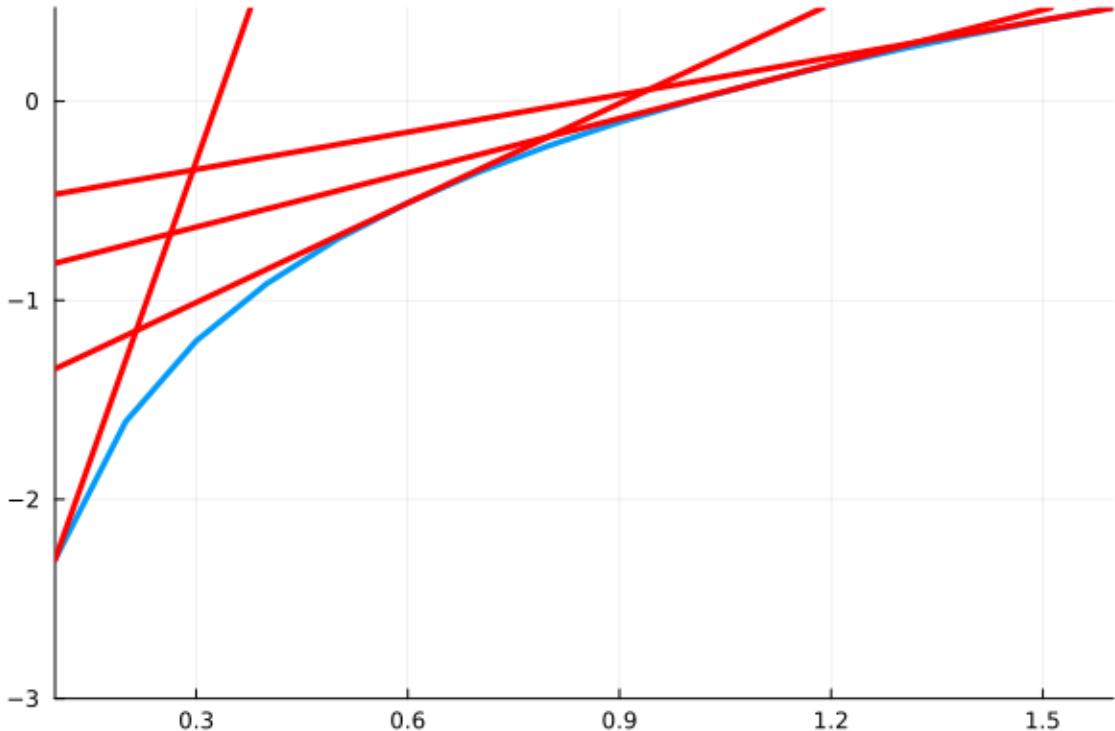
f(x) = log(x)
∇f(x) = 1 / x
X = 0.1:0.1:1.6
plot = Plots.plot(
    f,
    X;
    xlims = (0.1, 1.6),
    ylims = (-3, log(1.6)),
    label = false,
    width = 3,
)

```

```

for x_k in 0.1:0.5:1.6 ## Tip: try changing the number of points x_k
    g = x -> f(x_k) + ∇f(x_k) * (x - x_k)
    Plots.plot!(plot, g, X; color = :red, label = false, width = 3)
end
plot

```



Here is the model in JuMP:

```

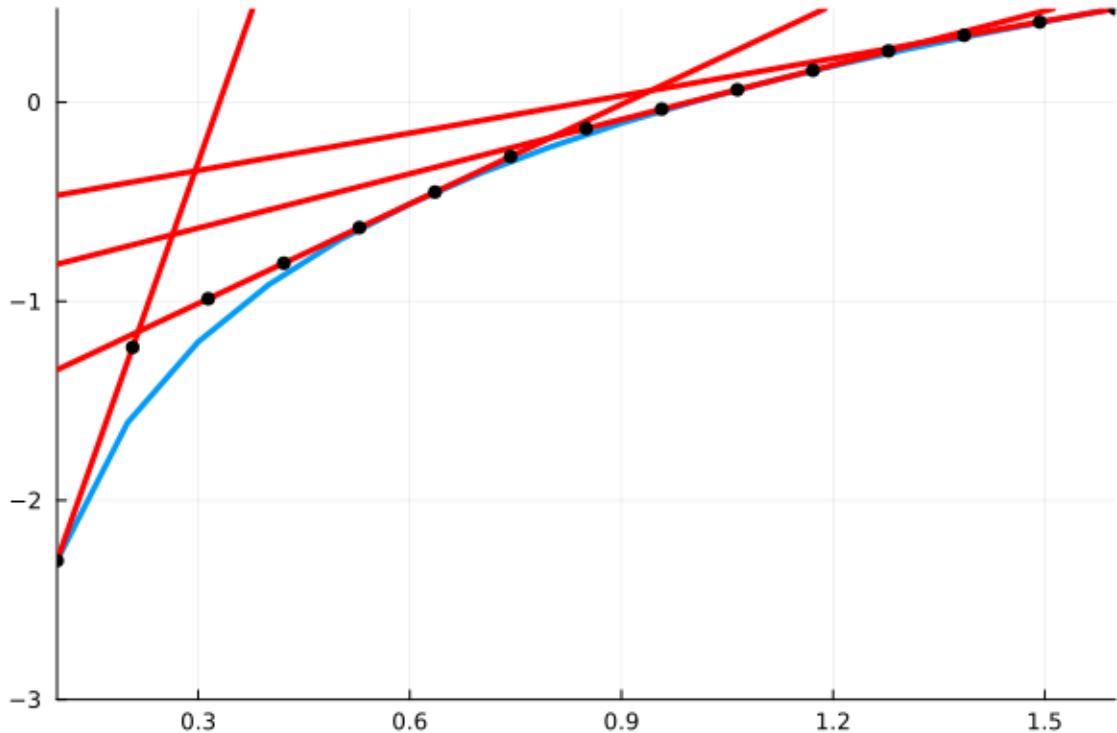
function outer_approximate_log(ȳ)
    f(x) = log(x)
    ∇f(x) = 1 / x
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, 0.1 <= x <= 1.6)
    @variable(model, y)
    # Tip: try changing the number of points x_k
    @constraint(model, [x_k in 0.1:0.5:2], y <= f(x_k) + ∇f(x_k) * (x - x_k))
    @objective(model, Max, y)
    @constraint(model, x == ȳ) # <- a trivial constraint just for testing.
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value(y)
end

```

```
outer_approximate_log (generic function with 1 method)
```

Here are a few values:

```
for x̄ in range(; start = 0.1, stop = 1.6, length = 15)
    ȳ = outer_approximate_log(x̄)
    Plots.scatter!(plot, [x̄], [ȳ]; label = false, color = :black)
end
plot
```



#### Note

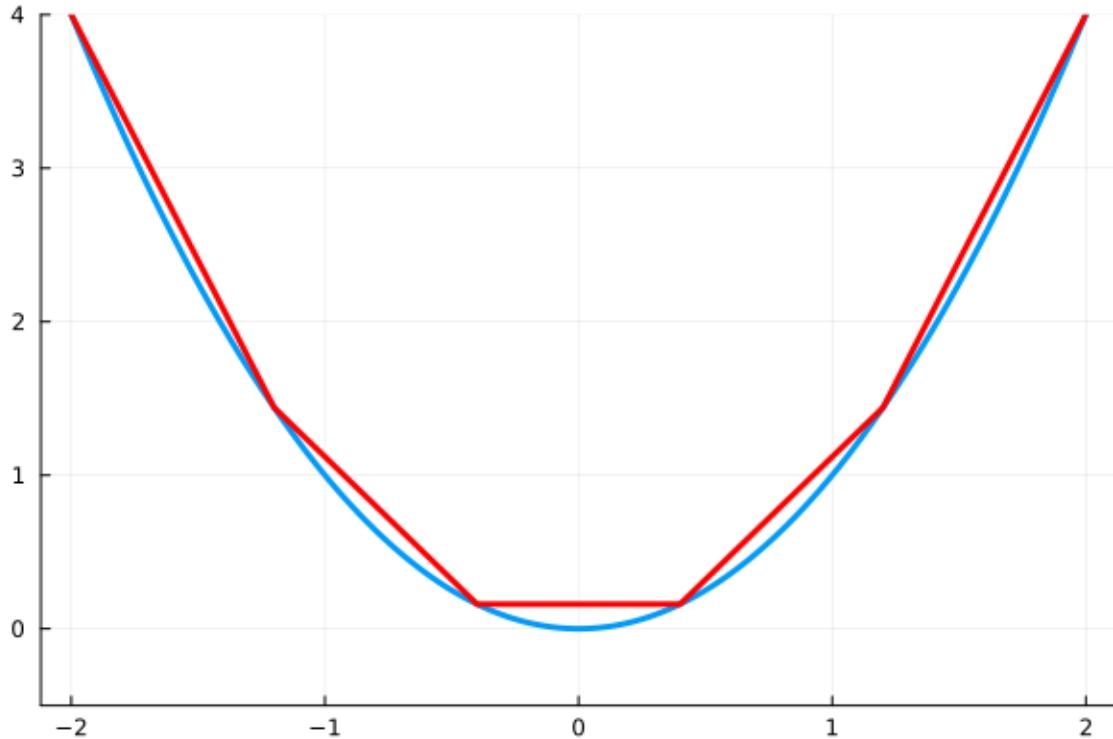
This formulation does not work if we want to minimize  $y$ .

### Minimizing a convex function (inner approximation)

Instead of creating an outer approximation, we can also create an inner approximation. For example, given  $f(x) = x^2$ , we may want to approximate the true function by the red piecewise linear function:

```
f(x) = x^2
x̄ = -2:0.8:2 ## Tip: try changing the number of points in x̄
plot = Plots.plot(f, -2:0.01:2; ylims = (-0.5, 4), label = false, linewidth = 3)
```

```
Plots.plot!(plot, f, x; label = false, color = :red, linewidth = 3)
plot
```

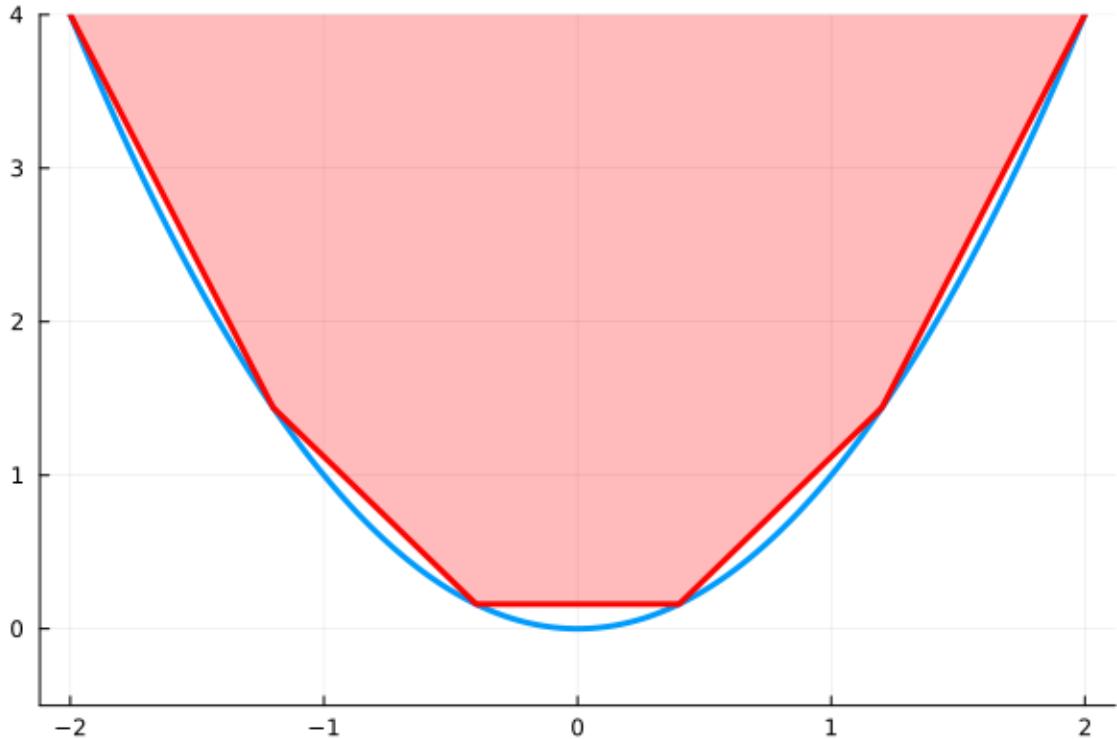


To do so, we represent the decision variables  $(x, y)$  by the convex combination of a set of discrete points  $\{x_k, y_k\}_{k=1}^K$ :

$$\begin{aligned} x &= \sum_{k=1}^K \lambda_k x_k \\ y &= \sum_{k=1}^K \lambda_k y_k \\ \sum_{k=1}^K \lambda_k &= 1 \\ \lambda_k &\geq 0, k = 1, \dots, K \end{aligned}$$

The feasible region of the convex combination actually allows any  $(x, y)$  point inside this shaded region:

```
I = [1, 2, 3, 4, 5, 6, 1]
Plots.plot!(x[I], f.(x[I])); fill = (0, 0, "#f004"), width = 0, label = false)
plot
```



Thus, this formulation does not work if we want to maximize  $y$ .

Here is the model in JuMP:

```

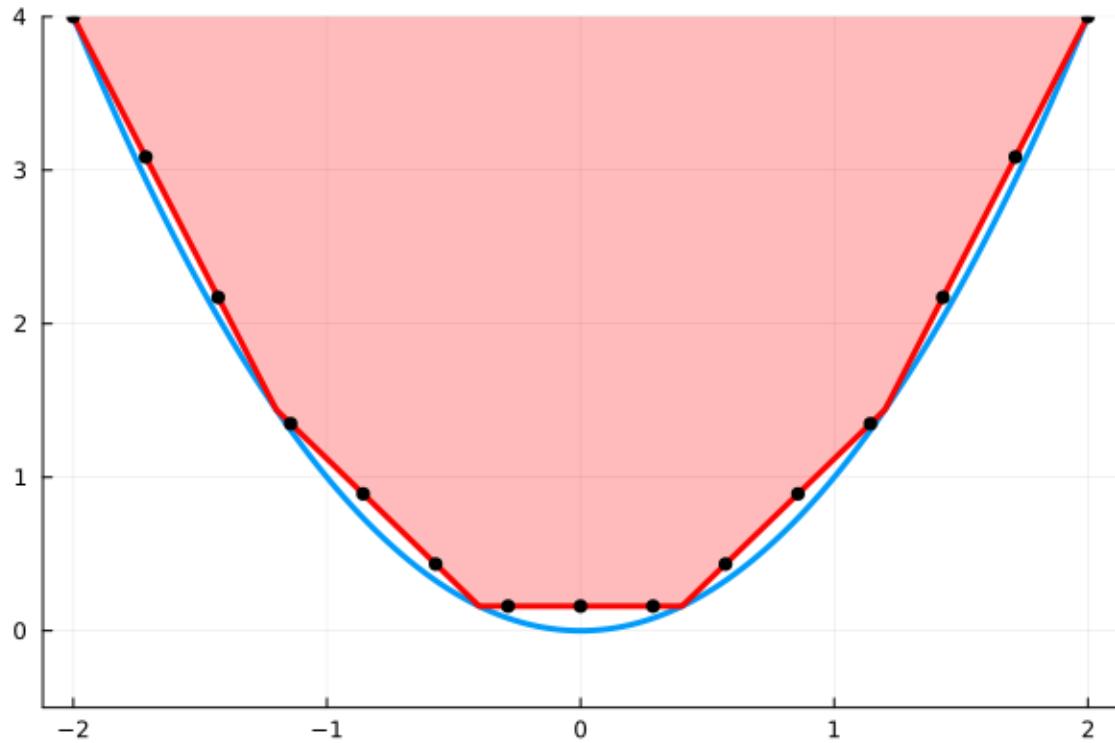
function inner_approximate_x_squared(x̄)
    f(x) = x^2
    ∇f(x) = 2x
    x̂ = -2:0.8:2 ## Tip: try changing the number of points in x̂
    ŷ = f.(x̂)
    n = length(x̂)
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, -2 <= x <= 2)
    @variable(model, y)
    @variable(model, 0 <= λ[1:n] <= 1)
    @constraint(model, x == sum(λ[i] * x̂[i] for i in 1:n))
    @constraint(model, y == sum(λ[i] * ŷ[i] for i in 1:n))
    @constraint(model, sum(λ) == 1)
    @objective(model, Min, y)
    @constraint(model, x == x̄) # <-- a trivial constraint just for testing.
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value(y)
end

```

```
inner_approximate_x_squared (generic function with 1 method)
```

Here are a few values:

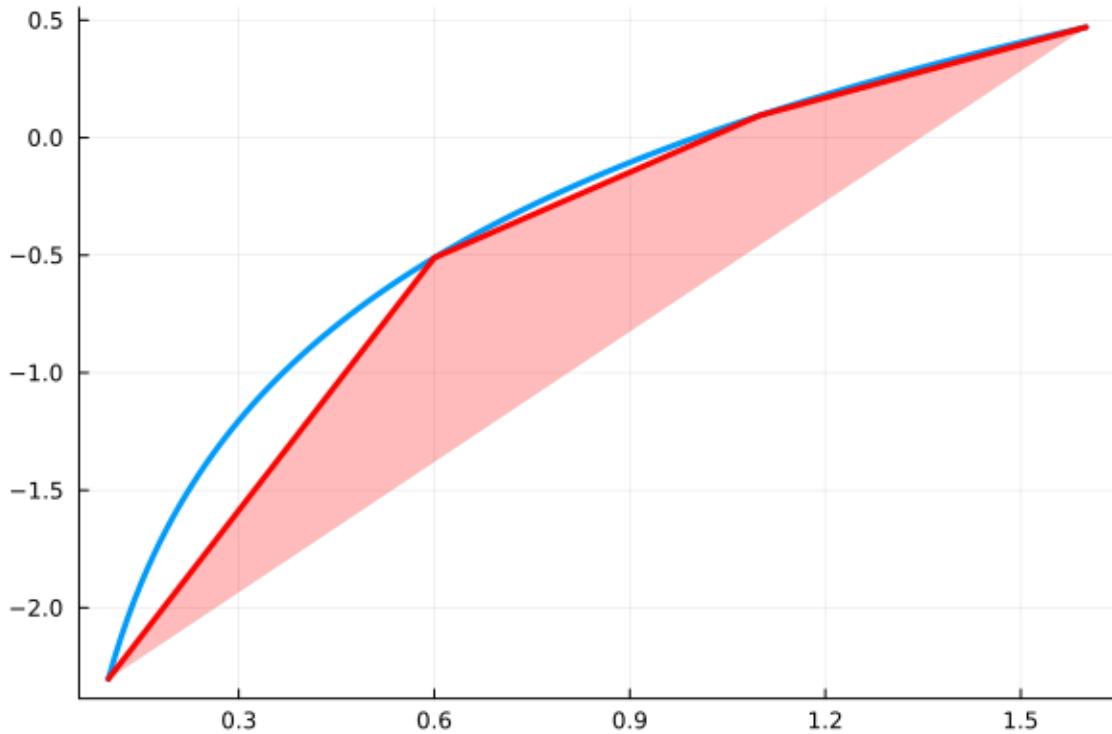
```
for x̄ in range(; start = -2, stop = 2, length = 15)
    ȳ = inner_approximate_x_squared(x̄)
    Plots.scatter!(plot, [x̄], [ȳ]; label = false, color = :black)
end
plot
```



### Maximizing a convex function (inner approximation)

The inner approximation also works if we want to maximize "up" into a concave function.

```
f(x) = log(x)
x̄ = 0.1:0.5:1.6 ## Tip: try changing the number of points in x̄
plot = Plots.plot(f, 0.1:0.01:1.6; label = false, linewidth = 3)
Plots.plot!(x̄, f.(x̄); linewidth = 3, color = :red, label = false)
I = [1, 2, 3, 4, 1]
Plots.plot!(x̄[I], f.(x̄[I])); fill = (0, 0, "#f004"), width = 0, label = false)
plot
```



Here is the model in JuMP:

```
function inner_approximate_log(x̄)
    f(x) = log(x)
    x̂ = 0.1:0.5:1.6 ## Tip: try changing the number of points in x̂
    ŷ = f.(x̂)
    n = length(x̂)
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, 0.1 <= x <= 1.6)
    @variable(model, y)
    @variable(model, 0 <= λ[1:n] <= 1)
    @constraint(model, sum(λ) == 1)
    @constraint(model, x == sum(λ[i] * x̂[i] for i in 1:n))
    @constraint(model, y == sum(λ[i] * ŷ[i] for i in 1:n))
    @objective(model, Max, y)
    @constraint(model, x == x̄) # <- a trivial constraint just for testing.
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value(y)
end
```

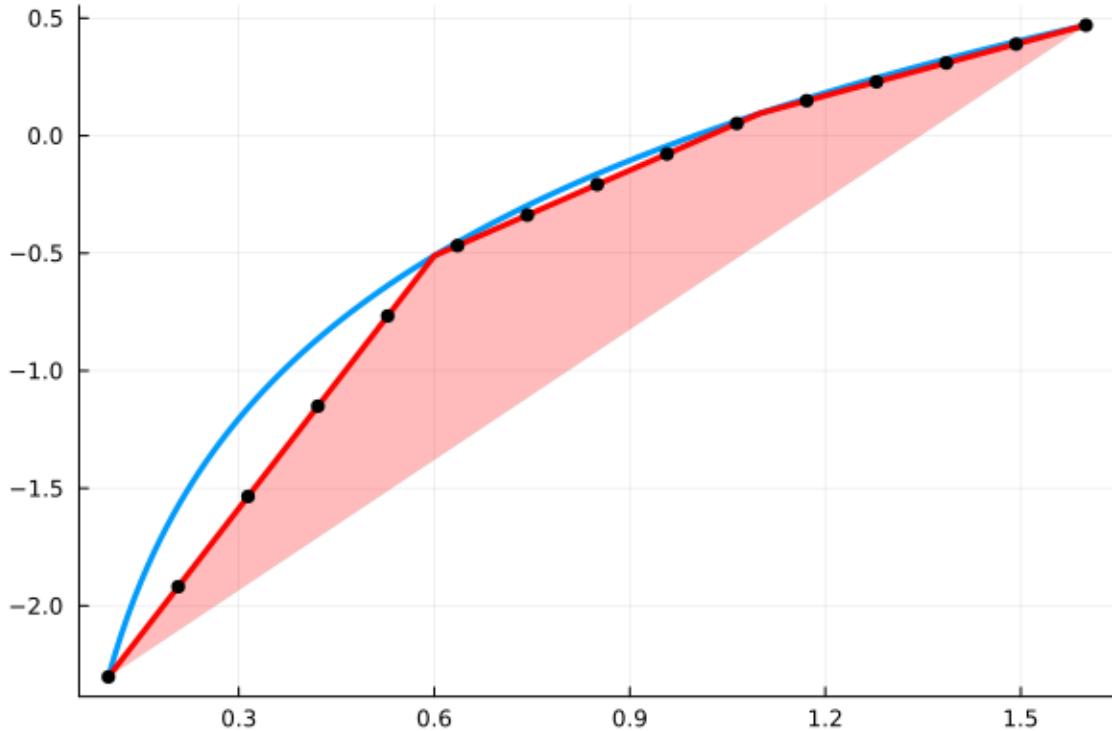
inner\_approximate\_log (generic function with 1 method)

Here are a few values:

```

for x in range(; start = 0.1, stop = 1.6, length = 15)
    y = inner_approximate_log(x)
    Plots.scatter!(plot, [x], [y]; label = false, color = :black)
end
plot

```



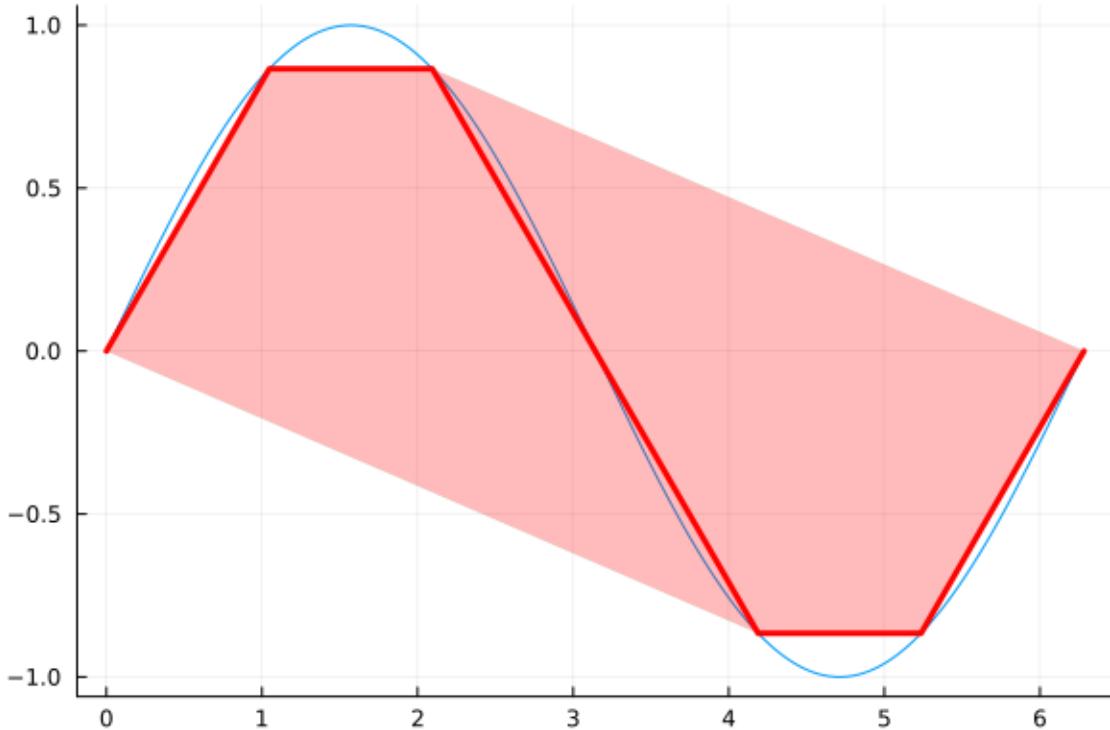
### Piecewise linear approximation

If the model is non-convex (or non-concave), then we cannot use an outer approximation, and the inner approximation allows a solution far from the true function. For example, for  $f(x) = \sin(x)$ , we have:

```

f(x) = sin(x)
plot = Plots.plot(f, 0:0.01:2π; label = false)
x = range(; start = 0, stop = 2π, length = 7)
Plots.plot!(x, f.(x); linewidth = 3, color = :red, label = false)
I = [1, 5, 6, 7, 3, 2, 1]
Plots.plot!(x[I], f.(x[I]); fill = (0, 0, "#f004"), width = 0, label = false)
plot

```



We can force the inner approximation to stay on the red line by adding the constraint  $\lambda$  in `SOS2()`. The `SOS2` set is a Special Ordered Set of Type 2, and it ensures that at most two elements of  $\lambda$  can be non-zero, and if they are, that they must be adjacent. This prevents the model from taking a convex combination of points 1 and 5 to end up on the lower boundary of the shaded red area.

Here is the model in JuMP:

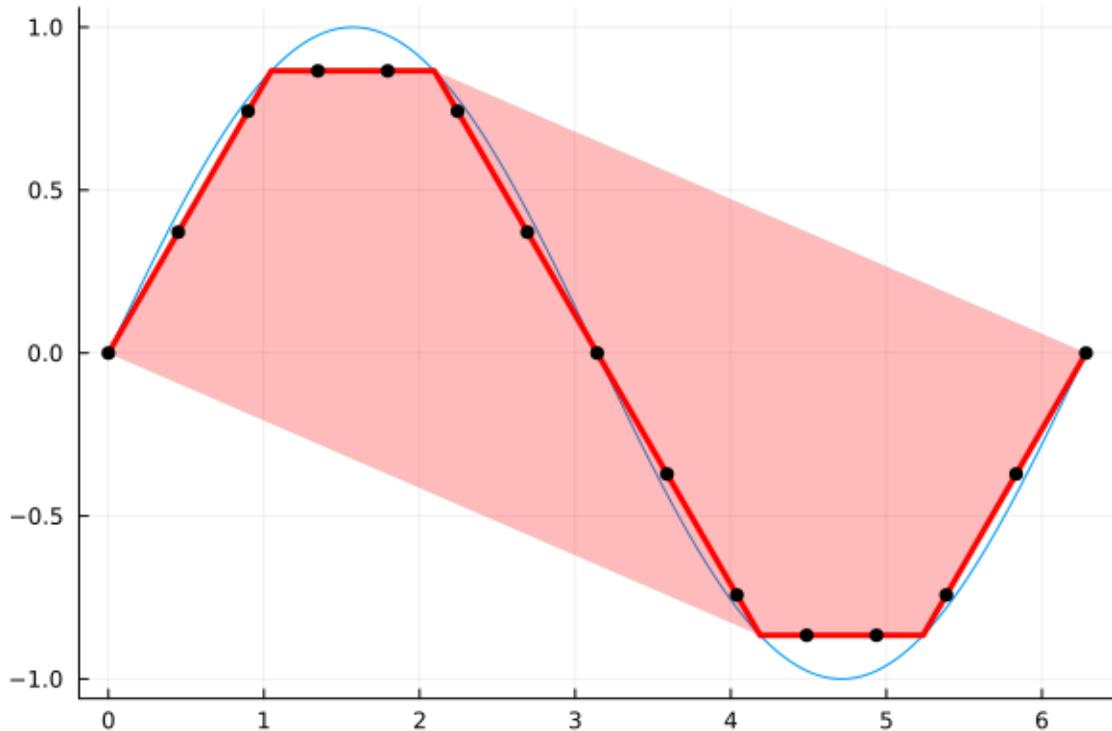
```
function piecewise_linear_sin(x)
    f(x) = sin(x)
    # Tip: try changing the number of points in x^
    x̂ = range(; start = 0, stop = 2π, length = 7)
    ŷ = f.(x̂)
    n = length(x̂)
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, 0 ≤ x ≤ 2π)
    @variable(model, y)
    @variable(model, 0 ≤ λ[1:n] ≤ 1)
    @constraints(model, begin
        x == sum(λ[i] * x̂[i] for i in 1:n)
        y == sum(λ[i] * ŷ[i] for i in 1:n)
        sum(λ) == 1
        λ in SOS2() # <-- this is new
    end)
    @constraint(model, x == x̂) # <-- a trivial constraint just for testing.
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value(y)
```

```
end
```

```
piecewise_linear_sin (generic function with 1 method)
```

Here are a few values:

```
for x in range(; start = 0, stop = 2π, length = 15)
    y = piecewise_linear_sin(x)
    Plots.scatter!(plot, [x], [y]; label = false, color = :black)
end
plot
```



## 6.10 The facility location problem

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

**This tutorial was originally contributed by Mathieu Tanneau and Alexis Montoison.**

### Required packages

This tutorial requires the following packages:

```
using JuMP
import HiGHS
import LinearAlgebra
import Plots
import Random
```

## Uncapacitated facility location

### Problem description

We are given

- A set  $M = \{1, \dots, m\}$  of clients
- A set  $N = \{1, \dots, n\}$  of sites where a facility can be built

**Decision variables** Decision variables are split into two categories:

- Binary variable  $y_j$  indicates whether facility  $j$  is built or not
- Binary variable  $x_{i,j}$  indicates whether client  $i$  is assigned to facility  $j$

**Objective** The objective is to minimize the total cost of serving all clients. This costs breaks down into two components:

- Fixed cost of building a facility.

In this example, this cost is  $f_j = 1, \forall j$ .

- Cost of serving clients from the assigned facility.

In this example, the cost  $c_{i,j}$  of serving client  $i$  from facility  $j$  is the Euclidean distance between the two.

### Constraints

- Each customer must be served by exactly one facility
- A facility cannot serve any client unless it is open

### MILP formulation

The problem can be formulated as the following MILP:

$$\begin{aligned} \min_{x,y} \quad & \sum_{i,j} c_{i,j} x_{i,j} + \sum_j f_j y_j \\ \text{s.t.} \quad & \sum_j x_{i,j} = 1, \quad \forall i \in M \\ & x_{i,j} \leq y_j, \quad \forall i \in M, j \in N \\ & x_{i,j}, y_j \in \{0, 1\}, \quad \forall i \in M, j \in N \end{aligned}$$

where the first set of constraints ensures that each client is served exactly once, and the second set of constraints ensures that no client is served from an unopened facility.

### Problem data

To ensure reproducibility, we set the random number seed:

```
Random.seed!(314)
```

```
Random.TaskLocalRNG()
```

Here's the data we need:

```
# Number of clients
m = 12
# Number of facility locations
n = 5

# Clients' locations
x_c, y_c = rand(m), rand(m)

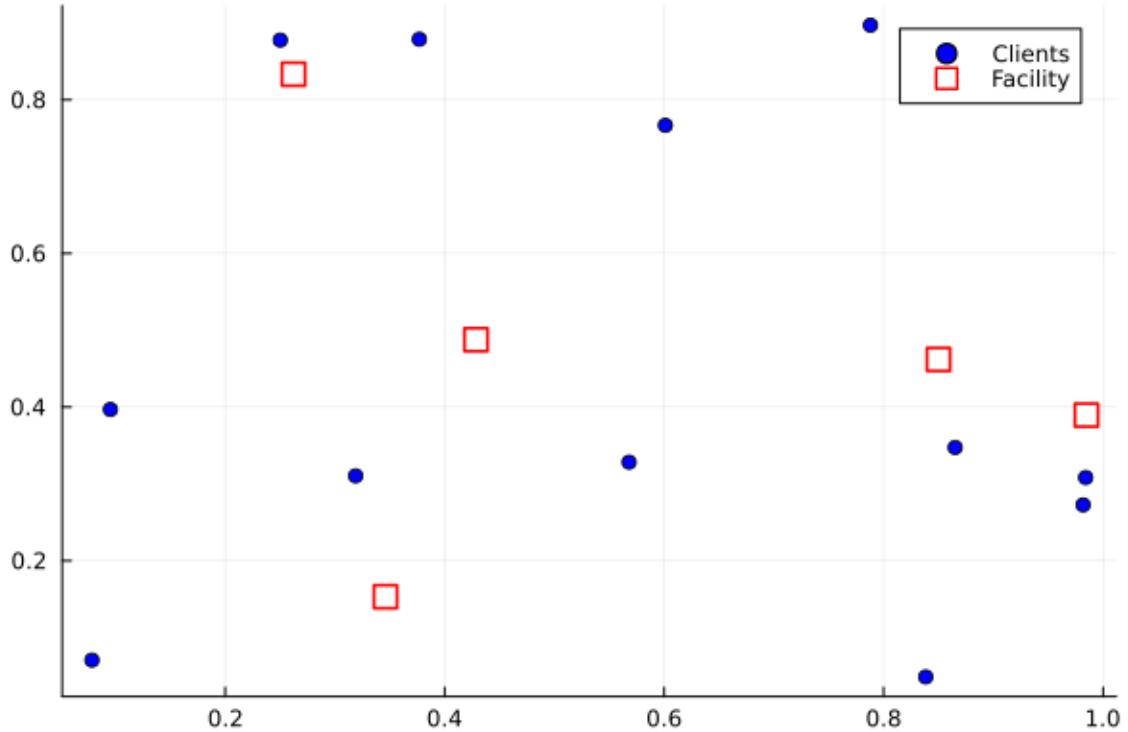
# Facilities' potential locations
x_f, y_f = rand(n), rand(n)

# Fixed costs
f = ones(n);

# Distance
c = zeros(m, n)
for i in 1:m
    for j in 1:n
        c[i, j] = LinearAlgebra.norm([x_c[i] - x_f[j], y_c[i] - y_f[j]], 2)
    end
end
```

Display the data

```
Plots.scatter(
    x_c,
    y_c;
    label = "Clients",
    markershape = :circle,
    markercolor = :blue,
)
Plots.scatter!(
    x_f,
    y_f;
    label = "Facility",
    markershape = :square,
    markercolor = :white,
    markersize = 6,
    markerstrokecolor = :red,
    markerstrokewidth = 2,
)
```



### JuMP implementation

Create a JuMP model

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, y[1:n], Bin);
@variable(model, x[1:m, 1:n], Bin);
# Each client is served exactly once
@constraint(model, client_service[i in 1:m], sum(x[i, j] for j in 1:n) == 1);
# A facility must be open to serve a client
@constraint(model, open_facility[i in 1:m, j in 1:n], x[i, j] <= y[j]);
@objective(model, Min, f' * y + sum(c .* x));
```

Solve the uncapacitated facility location problem with HiGHS

```
optimize!(model)
assert_is_solved_and_feasible(model)
println("Optimal value: ", objective_value(model))
```

Optimal value: 5.7018394545724185

**Visualizing the solution**

The threshold  $1e-5$  ensure that edges between clients and facilities are drawn when  $x[i, j] \approx 1$ .

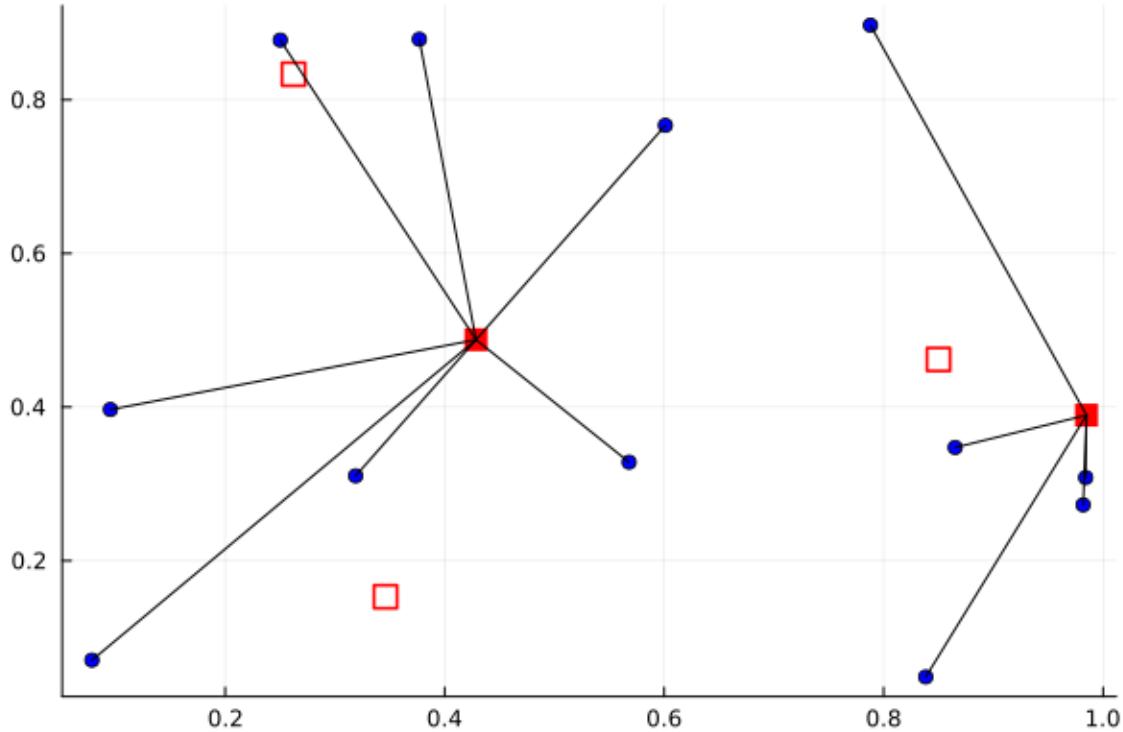
```
x_is_selected = isapprox.(value.(x), 1; atol = 1e-5);
y_is_selected = isapprox.(value.(y), 1; atol = 1e-5);

p = Plots.scatter(
    x_c,
    y_c;
    markershape = :circle,
    markercolor = :blue,
    label = nothing,
)

Plots.scatter!(
    x_f,
    y_f;
    markershape = :square,
    markercolor = [(y_is_selected[j] ? :red : :white) for j in 1:n],
    markersize = 6,
    markerstrokecolor = :red,
    markerstrokewidth = 2,
    label = nothing,
)

for i in 1:m, j in 1:n
    if x_is_selected[i, j]
        Plots.plot!(
            [x_c[i], x_f[j]],
            [y_c[i], y_f[j]];
            color = :black,
            label = nothing,
        )
    end
end

p
```



### Capacitated facility location

#### Problem formulation

The capacitated variant introduces a capacity constraint on each facility, that is, clients have a certain level of demand to be served, while each facility only has finite capacity which cannot be exceeded.

Specifically,

- The demand of client  $i$  is denoted by  $a_i \geq 0$
- The capacity of facility  $j$  is denoted by  $q_j \geq 0$

The capacity constraints then write

$$\sum_i a_i x_{i,j} \leq q_j y_j \quad \forall j \in N$$

Note that, if  $y_j$  is set to 0, the capacity constraint above automatically forces  $x_{i,j}$  to 0.

Thus, the capacitated facility location can be formulated as follows

$$\begin{aligned}
 & \min_{x,y} \sum_{i,j} c_{i,j} x_{i,j} + \sum_j f_j y_j \\
 & s.t. \sum_j x_{i,j} = 1, \quad \forall i \in M \\
 & \quad \sum_i a_i x_{i,j} \leq q_j y_j, \quad \forall j \in N \\
 & \quad x_{i,j}, y_j \in \{0, 1\}, \quad \forall i \in M, j \in N
 \end{aligned}$$

For simplicity, we will assume that there is enough capacity to serve the demand, that is, there exists at least one feasible solution.

We need some new data:

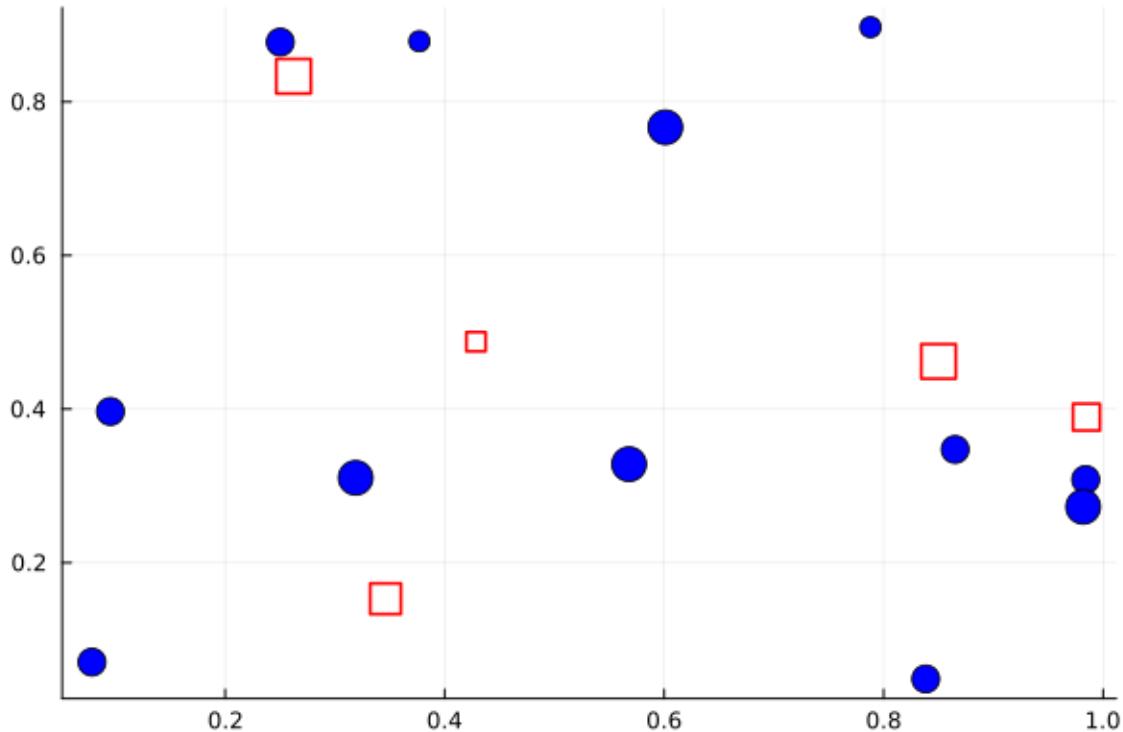
```
# Demands
a = rand(1:3, m);

# Capacities
q = rand(5:10, n);
```

Display the data

```
Plots.scatter(
    x_c,
    y_c;
    label = nothing,
    markershape = :circle,
    markercolor = :blue,
    markersize = 2 .* (2 .+ a),
)

Plots.scatter!(
    x_f,
    y_f;
    label = nothing,
    markershape = :rect,
    markercolor = :white,
    markersize = q,
    markerstrokecolor = :red,
    markerstrokewidth = 2,
```



### JuMP implementation

Create a JuMP model

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, y[1:n], Bin);
@variable(model, x[1:m, 1:n], Bin);
# Each client is served exactly once
@constraint(model, client_service[i in 1:m], sum(x[i, :]) == 1);
# Capacity constraint
@constraint(model, capacity, x' * a .≤= (q .* y));
# Objective
@objective(model, Min, f' * y + sum(c .* x));
```

Solve the problem

```
optimize!(model)
assert_is_solved_and_feasible(model)
println("Optimal value: ", objective_value(model))
```

Optimal value: 6.1980444155009975

### Visualizing the solution

The threshold  $1e-5$  ensure that edges between clients and facilities are drawn when  $x[i, j] \approx 1$ .

```
x_is_selected = isapprox.(value.(x), 1; atol = 1e-5);
y_is_selected = isapprox.(value.(y), 1; atol = 1e-5);
```

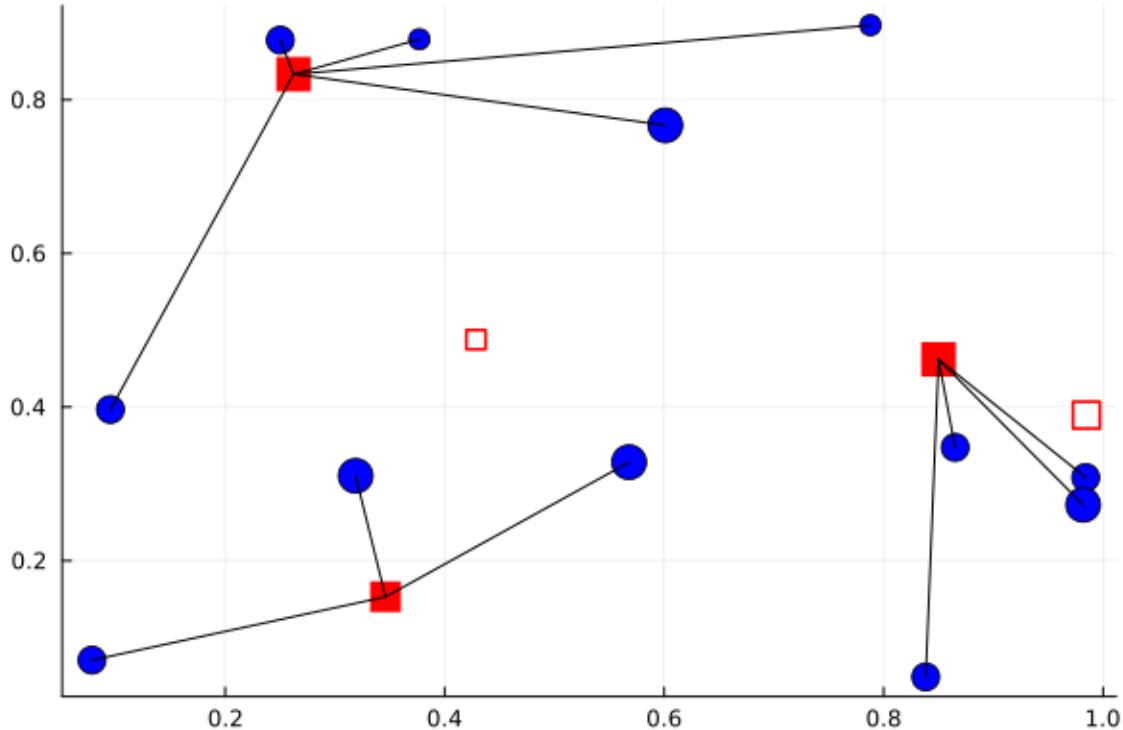
Display the solution

```
p = Plots.scatter(
    x_c,
    y_c;
    label = nothing,
    markershape = :circle,
    markercolor = :blue,
    markersize = 2 .* (2 .+ a),
)

Plots.scatter!(
    x_f,
    y_f;
    label = nothing,
    markershape = :rect,
    markercolor = [(y_is_selected[j] ? :red : :white) for j in 1:n],
    markersize = q,
    markerstrokecolor = :red,
    markerstrokewidth = 2,
)

for i in 1:m, j in 1:n
    if x_is_selected[i, j]
        Plots.plot!(
            [x_c[i], x_f[j]],
            [y_c[i], y_f[j]];
            color = :black,
            label = nothing,
        )
    end
end

p
```



## 6.11 Financial modeling problems

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

**This tutorial was originally contributed by Arpit Bhatia.**

Optimization models play an increasingly important role in financial decisions. Many computational finance problems can be solved efficiently using modern optimization techniques.

In this tutorial we will discuss two such examples taken from ([Cornuéjols et al., 2018](#)).

This tutorial uses the following packages

```
using JuMP
import HiGHS
```

### Short-term financing

Corporations routinely face the problem of financing short term cash commitments such as the following:

Month	Jan	Feb	Mar	Apr	May	Jun
Net Cash Flow	-150	-100	200	-200	50	300

Net cash flow requirements are given in thousands of dollars. The company has the following sources of funds:

- A line of credit of up to \$100K at an interest rate of 1% per month,

- In any one of the first three months, it can issue 90-day commercial paper bearing a total interest of 2% for the 3-month period,
- Excess funds can be invested at an interest rate of 0.3% per month.

Our task is to find out the most economical way to use these 3 sources such that we end up with the most amount of money at the end of June.

We model this problem in the following manner:

We will use the following decision variables:

- the amount  $u_i$  drawn from the line of credit in month  $i$
- the amount  $v_i$  of commercial paper issued in month  $i$
- the excess funds  $w_i$  in month  $i$

Here we have three types of constraints:

1. for every month, cash inflow = cash outflow for each month
2. upper bounds on  $u_i$
3. nonnegativity of the decision variables  $u_i$ ,  $v_i$  and  $w_i$ .

Our objective will be to simply maximize the company's wealth in June, which we represent with the variable  $m$ .

```

financing = Model(HiGHS.Optimizer)

@variables(financing, begin
    0 <= u[1:5] <= 100
    0 <= v[1:3]
    0 <= w[1:5]
    m
end)

@objective(financing, Max, m)

@constraints(
    financing,
    begin
        begin
            u[1] + v[1] - w[1] == 150 # January
            u[2] + v[2] - w[2] - 1.01u[1] + 1.003w[1] == 100 # February
            u[3] + v[3] - w[3] - 1.01u[2] + 1.003w[2] == -200 # March
            u[4] - w[4] - 1.02v[1] - 1.01u[3] + 1.003w[3] == 200 # April
            u[5] - w[5] - 1.02v[2] - 1.01u[4] + 1.003w[4] == -50 # May
            -m - 1.02v[3] - 1.01u[5] + 1.003w[5] == -300 # June
        end
    )
)

optimize!(financing)
assert_is_solved_and_feasible(financing)
objective_value(financing)

```

```
92.49694915254233
```

### Combinatorial auctions

In many auctions, the value that a bidder has for a set of items may not be the sum of the values that he has for individual items.

Examples are equity trading, electricity markets, pollution right auctions and auctions for airport landing slots.

To take this into account, combinatorial auctions allow the bidders to submit bids on combinations of items.

Let  $M = \{1, 2, \dots, m\}$  be the set of items that the auctioneer has to sell. A bid is a pair  $B_j = (S_j, p_j)$  where  $S_j \subseteq M$  is a nonempty set of items and  $p_j$  is the price offer for this set.

Suppose that the auctioneer has received  $n$  bids  $B_1, B_2, \dots, B_n$ . The goal of this problem is to help an auctioneer determine the winners in order to maximize his revenue.

We model this problem by taking a decision variable  $y_j$  for every bid. We add a constraint that each item  $i$  is sold at most once. This gives us the following model:

$$\begin{aligned} \max \quad & \sum_{i=1}^n p_j y_j \\ \text{s.t.} \quad & \sum_{j:i \in S_j} y_j \leq 1 \quad \forall i = \{1, 2 \dots m\} \\ & y_j \in \{0, 1\} \quad \forall j \in \{1, 2 \dots n\} \end{aligned}$$

```
bid_values = [6 3 12 12 8 16]
bid_items = [[1], [2], [3 4], [1 3], [2 4], [1 3 4]]

auction = Model(HiGHS.Optimizer)
@variable(auction, y[1:6], Bin)
@objective(auction, Max, sum(y' .* bid_values))
for i in 1:6
    @constraint(auction, sum(y[j] for j in 1:6 if i in bid_items[j]) <= 1)
end
optimize!(auction)
assert_is_solved_and_feasible(auction)
objective_value(auction)
```

```
21.0
```

```
value.(y)
```

```
6-element Vector{Float64}:
1.0
1.0
1.0
-0.0
-0.0
0.0
```

## 6.12 Geographical clustering

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

**This tutorial was originally contributed by Matthew Helm and Mathieu Tanneau.**

The goal of this exercise is to cluster  $n$  cities into  $k$  groups, minimizing the total pairwise distance between cities *and* ensuring that the variance in the total populations of each group is relatively small.

This tutorial uses the following packages:

```
using JuMP
import DataFrames
import HiGHS
import LinearAlgebra
```

For this example, we'll use the 20 most populous cities in the United States.

```
cities = DataFrames.DataFrame(
    Union{String,Float64}[
        "New York, NY" 8.405 40.7127 -74.0059
        "Los Angeles, CA" 3.884 34.0522 -118.2436
        "Chicago, IL" 2.718 41.8781 -87.6297
        "Houston, TX" 2.195 29.7604 -95.3698
        "Philadelphia, PA" 1.553 39.9525 -75.1652
        "Phoenix, AZ" 1.513 33.4483 -112.0740
        "San Antonio, TX" 1.409 29.4241 -98.4936
        "San Diego, CA" 1.355 32.7157 -117.1610
        "Dallas, TX" 1.257 32.7766 -96.7969
        "San Jose, CA" 0.998 37.3382 -121.8863
        "Austin, TX" 0.885 30.2671 -97.7430
        "Indianapolis, IN" 0.843 39.7684 -86.1580
        "Jacksonville, FL" 0.842 30.3321 -81.6556
        "San Francisco, CA" 0.837 37.7749 -122.4194
        "Columbus, OH" 0.822 39.9611 -82.9987
        "Charlotte, NC" 0.792 35.2270 -80.8431
        "Fort Worth, TX" 0.792 32.7554 -97.3307
        "Detroit, MI" 0.688 42.3314 -83.0457
        "El Paso, TX" 0.674 31.7775 -106.4424
        "Memphis, TN" 0.653 35.1495 -90.0489
    ],
    ["city", "population", "lat", "lon"],
)
```

	city	population	lat	lon
	Union...	Union...	Union...	Union...
1	New York, NY	8.405	40.7127	-74.0059
2	Los Angeles, CA	3.884	34.0522	-118.244
3	Chicago, IL	2.718	41.8781	-87.6297
4	Houston, TX	2.195	29.7604	-95.3698
5	Philadelphia, PA	1.553	39.9525	-75.1652
6	Phoenix, AZ	1.513	33.4483	-112.074
7	San Antonio, TX	1.409	29.4241	-98.4936
8	San Diego, CA	1.355	32.7157	-117.161
9	Dallas, TX	1.257	32.7766	-96.7969
10	San Jose, CA	0.998	37.3382	-121.886
11	Austin, TX	0.885	30.2671	-97.743
12	Indianapolis, IN	0.843	39.7684	-86.158
13	Jacksonville, FL	0.842	30.3321	-81.6556
14	San Francisco, CA	0.837	37.7749	-122.419
15	Columbus, OH	0.822	39.9611	-82.9987
16	Charlotte, NC	0.792	35.227	-80.8431
17	Fort Worth, TX	0.792	32.7554	-97.3307
18	Detroit, MI	0.688	42.3314	-83.0457
19	El Paso, TX	0.674	31.7775	-106.442
20	Memphis, TN	0.653	35.1495	-90.0489

### Model Specifics

We will cluster these 20 cities into 3 different groups and we will assume that the ideal or target population  $P$  for a group is simply the total population of the 20 cities divided by 3:

```
n = size(cities, 1)
k = 3
P = sum(cities.population) / k
```

11.03833333333334

### Obtaining the distances between each city

Let's compute the pairwise Haversine distance between each of the cities in our data set and store the result in a variable we'll call `dm`:

```
"""
haversine(lat1, long1, lat2, long2, r = 6372.8)

Compute the haversine distance between two points on a sphere of radius `r`,
where the points are given by the latitude/longitude pairs `lat1/long1` and
`lat2/long2` (in degrees).
"""

function haversine(lat1, long1, lat2, long2, r = 6372.8)
    lat1, long1 = deg2rad(lat1), deg2rad(long1)
    lat2, long2 = deg2rad(lat2), deg2rad(long2)
```

```

hav(a, b) = sin((b - a) / 2)^2
inner_term = hav(lat1, lat2) + cos(lat1) * cos(lat2) * hav(long1, long2)
d = 2 * r * asin(sqrt(inner_term))
# Round distance to nearest kilometer.
return round(Int, d)
end

```

Main.haversine

Our distance matrix is symmetric so we'll convert it to a `LowerTriangular` matrix so that we can better interpret the objective value of our model:

```

dm = LinearAlgebra.LowerTriangular([
    haversine(cities.lat[i], cities.lon[i], cities.lat[j], cities.lon[j])
    for i in 1:n, j in 1:n
])

```

0	.	.	.	.	.	.	.	.	..	.	.	.	.	.	.	.	.	.	.
3937	0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
1145	2805	0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
2282	2207	1516	0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
130	3845	1068	2157	0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
3445	574	2337	1633	3345	0	.	..	.	.	.	.	.	.	.	.	.	.	.	.
2546	1934	1695	304	2423	1363	0	.	.	.	.	.	.	.	.	.	.	.	.	.
3908	179	2787	2094	3812	481	1813	.	.	.	.	.	.	.	.	.	.	.	.	.
2206	1993	1295	362	2089	1424	406	.	.	.	.	.	.	.	.	.	.	.	.	.
4103	492	2958	2588	4023	989	2336	.	.	.	.	.	.	.	.	.	.	.	.	.
2432	1972	1577	235	2310	1398	118	..	.	.	.	.	.	.	.	.	.	.	.	.
1036	2907	265	1394	938	2409	1609	.	.	.	.	.	.	.	.	.	.	.	.	.
1345	3450	1391	1321	1221	2883	1626	.	.	.	.	.	.	.	.	.	.	.	.	.
4130	559	2986	2644	4052	1051	2394	.	.	.	.	.	.	.	.	.	.	.	.	.
767	3177	444	1598	668	2679	1834	0	.	.	.	.	.	.	.	.	.	.	.	.
855	3405	946	1490	725	2863	1777	..	560	0	.	.	.	.	.	.	.	.	.	.
2251	1944	1327	382	2134	1375	387	1511	1543	0	.	.	.	.	.	.	.	.	.	.
774	3186	382	1780	711	2716	1994	264	813	1646	0	.	.	.	.	.	.	.	.	.
3054	1130	2010	1081	2945	559	804	2292	2398	864	2374	0	.	.	.	.	.	.	.	.
1534	2576	777	780	1415	2028	1017	820	837	722	1003	1565	0	.	.	.	.	.	.	.

### Build the model

Now that we have the basics taken care of, we can set up our model, create decision variables, add constraints, and then solve.

First, we'll set up a model that leverages the Cbc solver. Next, we'll set up a binary variable  $x_{i,k}$  that takes the value 1 if city  $i$  is in group  $k$  and 0 otherwise. Each city must be in a group, so we'll add the constraint  $\sum_k x_{i,k} = 1$  for every  $i$ .

```

model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:n, 1:k], Bin)
@constraint(model, [i = 1:n], sum(x[i, :]) == 1);
# To reduce symmetry, we fix the first city to belong to the first group.
fix(x[1, 1], 1; force = true)

```

The total population of a group  $k$  is  $Q_k = \sum_i x_{i,k} q_i$  where  $q_i$  is simply the  $i$ -th value from the population column in our `cities` DataFrame. Let's add constraints so that  $\alpha \leq (Q_k - P) \leq \beta$ . We'll set  $\alpha$  equal to  $-3$  million and  $\beta$  equal to  $3$ . By adjusting these thresholds you'll find that there is a tradeoff between having relatively even populations between groups and having geographically close cities within each group. In other words, the larger the absolute values of  $\alpha$  and  $\beta$ , the closer together the cities in a group will be but the variance between the group populations will be higher.

```

@variable(model, -3 <= population_diff[1:k] <= 3)
@constraint(model, population_diff .== x' * cities.population .. P)

```

```

3-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.EqualTo{Float64}}, ScalarShape}}:
-8.405 x[1,1] - 3.884 x[2,1] - 2.718 x[3,1] - 2.195 x[4,1] - 1.553 x[5,1] - 1.513 x[6,1] - 1.409
    ↵ x[7,1] - 1.355 x[8,1] - 1.257 x[9,1] - 0.998 x[10,1] - 0.885 x[11,1] - 0.843 x[12,1] - 0.842
    ↵ x[13,1] - 0.837 x[14,1] - 0.822 x[15,1] - 0.792 x[16,1] - 0.792 x[17,1] - 0.688 x[18,1] -
    ↵ 0.674 x[19,1] - 0.653 x[20,1] + population_diff[1] = -11.038333333333334
-8.405 x[1,2] - 3.884 x[2,2] - 2.718 x[3,2] - 2.195 x[4,2] - 1.553 x[5,2] - 1.513 x[6,2] - 1.409
    ↵ x[7,2] - 1.355 x[8,2] - 1.257 x[9,2] - 0.998 x[10,2] - 0.885 x[11,2] - 0.843 x[12,2] - 0.842
    ↵ x[13,2] - 0.837 x[14,2] - 0.822 x[15,2] - 0.792 x[16,2] - 0.792 x[17,2] - 0.688 x[18,2] -
    ↵ 0.674 x[19,2] - 0.653 x[20,2] + population_diff[2] = -11.038333333333334
-8.405 x[1,3] - 3.884 x[2,3] - 2.718 x[3,3] - 2.195 x[4,3] - 1.553 x[5,3] - 1.513 x[6,3] - 1.409
    ↵ x[7,3] - 1.355 x[8,3] - 1.257 x[9,3] - 0.998 x[10,3] - 0.885 x[11,3] - 0.843 x[12,3] - 0.842
    ↵ x[13,3] - 0.837 x[14,3] - 0.822 x[15,3] - 0.792 x[16,3] - 0.792 x[17,3] - 0.688 x[18,3] -
    ↵ 0.674 x[19,3] - 0.653 x[20,3] + population_diff[3] = -11.038333333333334

```

Now we need to add one last binary variable  $z_{i,j}$  to our model that we'll use to compute the total distance between the cities in our groups, defined as  $\sum_{i,j} d_{i,j} z_{i,j}$ . Variable  $z_{i,j}$  will equal  $1$  if cities  $i$  and  $j$  are in the same group, and  $0$  if they are not in the same group.

To ensure that  $z_{i,j} = 1$  if and only if cities  $i$  and  $j$  are in the same group, we add the constraints  $z_{i,j} \geq x_{i,k} + x_{j,k} - 1$  for every pair  $i, j$  and every  $k$ :

```

@variable(model, z[i = 1:n, j = 1:i], Bin)
for k in 1:k, i in 1:n, j in 1:i
    @constraint(model, z[i, j] >= x[i, k] + x[j, k] - 1)
end

```

We can now add an objective to our model which will simply be to minimize the dot product of  $z$  and our distance matrix, `dm`.

```
@objective(model, Min, sum(dm[i, j] * z[i, j] for i in 1:n, j in 1:i));
```

We can then call `optimize!` and review the results.

```
optimize!(model)
assert_is_solved_and_feasible(model)
```

### Reviewing the Results

Now that we have results, we can add a column to our cities DataFrame for the group and then loop through our `x` variable to assign each city to its group. Once we have that, we can look at the total population for each group and also look at the cities in each group to verify that they are grouped by geographic proximity.

```
cities.group = zeros(n)

for i in 1:n, j in 1:k
    if round(Int, value(x[i, j])) == 1
        cities.group[i] = j
    end
end

for group in DataFrames.groupby(cities, :group)
    @show group
    println("")
    @show sum(group.population)
    println("")
end
```

group = 7x5 SubDataFrame					
Row	city	population	lat	lon	group
	Union...	Union...	Union...	Union...	Float64
1	New York, NY	8.405	40.7127	-74.0059	1.0
2	Philadelphia, PA	1.553	39.9525	-75.1652	1.0
3	Indianapolis, IN	0.843	39.7684	-86.158	1.0
4	Jacksonville, FL	0.842	30.3321	-81.6556	1.0
5	Columbus, OH	0.822	39.9611	-82.9987	1.0
6	Charlotte, NC	0.792	35.227	-80.8431	1.0
7	Detroit, MI	0.688	42.3314	-83.0457	1.0

sum(group.population) = 13.944999999999999					
Row	city	population	lat	lon	group
	Union...	Union...	Union...	Union...	Float64
1	Chicago, IL	2.718	41.8781	-87.6297	2.0
2	Houston, TX	2.195	29.7604	-95.3698	2.0
3	San Antonio, TX	1.409	29.4241	-98.4936	2.0
4	Dallas, TX	1.257	32.7766	-96.7969	2.0

```

5 | Austin, TX      0.885      30.2671 -97.743    2.0
6 | Fort Worth, TX 0.792      32.7554 -97.3307   2.0
7 | Memphis, TN    0.653      35.1495 -90.0489   2.0

sum(group.population) = 9.909

group = 6x5 SubDataFrame
  Row | city              population  lat        lon        group
       | Union...          Union...    Union...  Union...  Float64
  ---|---

  1 | Los Angeles, CA   3.884      34.0522 -118.244  3.0
  2 | Phoenix, AZ      1.513      33.4483 -112.074  3.0
  3 | San Diego, CA    1.355      32.7157 -117.161  3.0
  4 | San Jose, CA     0.998      37.3382 -121.886  3.0
  5 | San Francisco, CA 0.837      37.7749 -122.419  3.0
  6 | El Paso, TX      0.674      31.7775 -106.442  3.0

sum(group.population) = 9.261000000000001

```

## 6.13 Network flow problems

This tutorial was generated using [Literate.jl](#). Download the source as a [.jl file](#).

**This tutorial was originally contributed by Arpit Bhatia.**

In graph theory, a flow network (also known as a transportation network) is a directed graph where each edge has a capacity and each edge receives a flow. The amount of flow on an edge cannot exceed the capacity of the edge.

Often in operations research, a directed graph is called a network, the vertices are called nodes and the edges are called arcs.

A flow must satisfy the restriction that the amount of flow into a node equals the amount of flow out of it, unless it is a source, which has only outgoing flow, or sink, which has only incoming flow.

A network can be used to model traffic in a computer network, circulation with demands, fluids in pipes, currents in an electrical circuit, or anything similar in which something travels through a network of nodes.

This tutorial requires the following packages:

```
using JuMP  
import HiGHS
```

## The shortest path problem

Suppose that each arc  $(i, j)$  of a graph is assigned a scalar cost  $a_{i,j}$ , and suppose that we define the cost of a forward path to be the sum of the costs of its arcs.

Given a pair of nodes, the shortest path problem is to find a forward path that connects these nodes and has minimum cost.

$$\begin{aligned} \min \quad & \sum_{\forall e(i,j) \in E} a_{i,j} \times x_{i,j} \\ s.t. \quad & \sum_j x_{ij} - \sum_k x_{ki} = b_i \quad \forall i \\ & x_e \in \{0, 1\} \quad \forall e \in E \end{aligned}$$

where  $b_i$  is 1 if  $i$  is the starting node,  $-1$  if  $i$  is the ending node, and 0 otherwise.

```
G = [
    0 100 30 0 0
    0 0 20 0 0
    0 0 0 10 60
    0 15 0 0 50
    0 0 0 0 0
]
n = size(G)[1]
b = [1, -1, 0, 0, 0]
shortest_path = Model(HiGHS.Optimizer)
set_silent(shortest_path)
@variable(shortest_path, x[1:n, 1:n], Bin)
# Arcs with zero cost are not a part of the path as they do no exist
@constraint(shortest_path, [i = 1:n, j = 1:n; G[i, j] == 0], x[i, j] == 0)
# Flow conservation constraint
@constraint(shortest_path, [i = 1:n], sum(x[i, :]) - sum(x[:, i]) == b[i],)
@objective(shortest_path, Min, sum(G .* x))
optimize!(shortest_path)
assert_is_solved_and_feasible(shortest_path)
objective_value(shortest_path)
```

55.0

value.(x)

```
5×5 Matrix{Float64}:
 0.0  0.0  1.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  1.0  0.0
 0.0  1.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0
```

### The assignment problem

Suppose that there are  $n$  persons and  $n$  objects that we have to match on a one-to-one basis. There is a benefit or value  $a_{i,j}$  for matching person  $i$  with object  $j$ , and we want to assign persons to objects so as to maximize the total benefit.

There is also a restriction that person  $i$  can be assigned to object  $j$  only if  $(i, j)$  belongs to a given set of pairs  $A$ .

Mathematically, we want to find a set of person-object pairs  $(1, j_1), \dots, (n, j_n)$  from  $A$  such that the objects  $j_1, \dots, j_n$  are all distinct, and the total benefit  $\sum_{i=1}^y a_{ij_i}$  is maximized.

$$\begin{aligned} \max \quad & \sum_{(i,j) \in A} a_{i,j} \times y_{i,j} \\ \text{s.t.} \quad & \sum_{\{j | (i,j) \in A\}} y_{i,j} = 1 \quad \forall i = \{1, 2, \dots, n\} \\ & \sum_{\{i | (i,j) \in A\}} y_{i,j} = 1 \quad \forall j = \{1, 2, \dots, n\} \\ & y_{i,j} \in \{0, 1\} \quad \forall (i, j) \in \{1, 2, \dots, k\} \end{aligned}$$

```
G = [
    6 4 5 0
    0 3 6 0
    5 0 4 3
    7 5 5 5
]
n = size(G)[1]
assignment = Model(HiGHS.Optimizer)
set_silent(assignment)
@variable(assignment, y[1:n, 1:n], Bin)
# One person can only be assigned to one object
@constraint(assignment, [i = 1:n], sum(y[:, i]) == 1)
# One object can only be assigned to one person
@constraint(assignment, [j = 1:n], sum(y[j, :]) == 1)
@objective(assignment, Max, sum(G .* y))
optimize!(assignment)
assert_is_solved_and_feasible(assignment)
objective_value(assignment)
```

20.0

value.(y)

```
4x4 Matrix{Float64}:
 -0.0  1.0  -0.0   0.0
  0.0  0.0   1.0   0.0
  1.0  0.0   0.0  -0.0
 -0.0  0.0   0.0   1.0
```

### The max-flow problem

In the max-flow problem, we have a graph with two special nodes: the *source*, denoted by  $s$ , and the *sink*, denoted by  $t$ .

The objective is to move as much flow as possible from  $s$  into  $t$  while observing the capacity constraints.

$$\begin{aligned} \max \quad & \sum_{v:(s,v) \in E} f(s, v) \\ s.t. \quad & \sum_{u:(u,v) \in E} f(u, v) = \sum_{w:(v,w) \in E} f(v, w) \quad \forall v \in V - \{s, t\} \\ & f(u, v) \leq c(u, v) \quad \forall (u, v) \in E \\ & f(u, v) \geq 0 \quad \forall (u, v) \in E \end{aligned}$$

```
G = [
    0 3 2 2 0 0 0 0
    0 0 0 0 5 1 0 0
    0 0 0 0 1 3 1 0
    0 0 0 0 0 1 0 0
    0 0 0 0 0 0 0 4
    0 0 0 0 0 0 0 2
    0 0 0 0 0 0 0 4
    0 0 0 0 0 0 0 0
]
n = size(G)[1]
max_flow = Model(HiGHS.Optimizer)
@variable(max_flow, f[1:n, 1:n] >= 0)
# Capacity constraints
@constraint(max_flow, [i = 1:n, j = 1:n], f[i, j] <= G[i, j])
# Flow conservation constraints
@constraint(max_flow, [i = 1:n; i != 1 && i != 8], sum(f[i, :]) == sum(f[:, i]))
@objective(max_flow, Max, sum(f[1, :]))
optimize!(max_flow)
assert_is_solved_and_feasible(max_flow)
objective_value(max_flow)
```

6.0

value.(f)

```
8x8 Matrix{Float64}:
-0.0   3.0   2.0   1.0   -0.0   -0.0   -0.0   -0.0
 0.0   0.0   0.0   0.0    2.0    1.0    0.0    0.0
 0.0   0.0   0.0   0.0    1.0   -0.0    1.0    0.0
-0.0  -0.0  -0.0   0.0   -0.0    1.0   -0.0   -0.0
 0.0   0.0   0.0   0.0    0.0    0.0    0.0    3.0
 0.0   0.0   0.0   0.0    0.0    0.0    0.0    2.0
```

0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

## 6.14 The transportation problem

This tutorial was generated using [Literate.jl](#). Download the source as a [.jl file](#).

**This tutorial was originally contributed by Louis Luangkesorn.**

This tutorial is an adaptation of the transportation problem described in [AMPL: A Modeling Language for Mathematical Programming](#), by R. Fourer, D.M. Gay and B.W. Kernighan.

The purpose of this tutorial is to demonstrate how to create a JuMP model from an ad-hoc structured text file.

### Required packages

This tutorial uses the following packages:

```
using JuMP
import DelimitedFiles
import HiGHS
```

### Formulation

Suppose that we have a set of factories that produce [pogo sticks](#), and a set of retail stores in which to sell them. Each factory has a maximum number of pogo sticks that it can produce, and each retail store has a demand of pogo sticks that it can sell.

In the transportation problem, we want to choose the number of pogo sticks to make and ship from each factory to each retail store that minimizes the total shipping cost.

Mathematically, we represent our set of factories by a set of origins  $i \in O$  and our retail stores by a set of destinations  $j \in D$ . The maximum supply at each factory is  $s_i$  and the demand from each retail store is  $d_j$ . The cost of shipping one pogo stick from  $i$  to  $j$  is  $c_{i,j}$ .

With a little effort, we can model the transportation problem as the following linear program:

$$\begin{aligned} \min \quad & \sum_{i \in O, j \in D} c_{i,j} x_{i,j} \\ \text{s.t.} \quad & \sum_{j \in D} x_{i,j} \leq s_i \quad \forall i \in O \\ & \sum_{i \in O} x_{i,j} = d_j \quad \forall j \in D \\ & x_{i,j} \geq 0 \quad \forall i \in O, j \in D \end{aligned}$$

### Data

We assume our data is in the form of a text file that has the following form. In practice, we would obtain this text file from the user as input, but for the purpose of this tutorial we're going to create it from Julia.

```

open(joinpath($__DIR__, "transp.txt"), "w") do io
    print(
        io,
        """
            . FRA DET LAN WIN STL FRE LAF SUPPLY
            GARY 39 14 11 14 16 82 8 1400
            CLEV 27 . 12 . 26 95 17 2600
            PITT 24 14 17 13 28 99 20 2900
            DEMAND 900 1200 600 400 1700 1100 1000 0
            """
    )
    return
end

```

Here the rows are the origins, the columns are the destinations, and the values are the cost of shipping one pogo stick from the origin to the destination. If pogo stick cannot be transported from a source to a destination, then the value is .. The final row and final column are the demand and supply of each location respectively.

We didn't account for arcs which do not exist in our formulation, but we can make a small change and fix  $x_{i,j} = 0$  if  $c_{i,j} = \text{..}$ .

Our first step is to convert this text format into an appropriate Julia datastructure that we can work with. Since our data is tabular with named rows and columns, one option is JuMP's `Containers.DenseAxisArray` object:

```

function read_data(filename::String)
    data = DelimitedFiles.readdlm(filename)
    rows, columns = data[2:end, 1], data[1, 2:end]
    return Containers.DenseAxisArray(data[2:end, 2:end], rows, columns)
end

data = read_data(joinpath($__DIR__, "transp.txt"))

```

```

2-dimensional DenseAxisArray{Any,2,...} with index sets:
Dimension 1, Any["GARY", "CLEV", "PITT", "DEMAND"]
Dimension 2, Any["FRA", "DET", "LAN", "WIN", "STL", "FRE", "LAF", "SUPPLY"]
And data, a 4x8 Matrix{Any}:
39 14 11 14 16 82 8 1400
27 .. 12 .. 26 95 17 2600
24 14 17 13 28 99 20 2900
900 1200 600 400 1700 1100 1000 0

```

## JuMP formulation

Following [Design patterns for larger models](#), we code our JuMP model as a function which takes in an input. In this example, we print the output to stdout:

```

function solve_transportation_problem(data::Containers.DenseAxisArray)
    # Get the set of supplies and demands
    O, D = axes(data)
    # Drop the SUPPLY and DEMAND nodes from our sets
    O, D = setdiff(O, ["DEMAND"]), setdiff(D, ["SUPPLY"])

```

```

model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[o in 0, d in D] >= 0)
# Remove arcs with "." cost by fixing them to 0.0.
for o in 0, d in D
    if data[o, d] == "."
        fix(x[o, d], 0.0; force = true)
    end
end
@objective(
    model,
    Min,
    sum(data[o, d] * x[o, d] for o in 0, d in D if data[o, d] != "."),
)
@constraint(model, [o in 0], sum(x[o, :]) <= data[o, "SUPPLY"])
@constraint(model, [d in D], sum(x[:, d]) == data["DEMAND", d])
optimize!(model)
assert_is_solved_and_feasible(model)
# Pretty print the solution in the format of the input
print(" ", join(lpad.(D, 7, ' ')))
for o in 0
    print("\n", o)
    for d in D
        if isapprox(value(x[o, d]), 0.0; atol = 1e-6)
            print("      .")
        else
            print(" ", lpad(value(x[o, d]), 6, ' '))
        end
    end
end
return
end

```

solve\_transportation\_problem (generic function with 1 method)

## Solution

Let's solve and view the solution:

```
solve_transportation_problem(data)
```

	FRA	DET	LAN	WIN	STL	FRE	LAF
GARY	.	.	.	.	300.0	1100.0	.
CLEV	.	.	600.0	.	1000.0	.	1000.0
PITT	900.0	1200.0	.	400.0	400.0	.	.

## 6.15 Multi-objective knapsack

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to demonstrate how to create and solve a multi-objective linear program. In addition, it demonstrates how to work with solvers which return multiple solutions.

### Required packages

This tutorial requires the following packages:

```
using JuMP
import HiGHS
import MultiObjectiveAlgorithms as MOA
import Plots
```

`MultiObjectiveAlgorithms.jl` is a package which implements a variety of algorithms for solving multi-objective optimization problems. Because it is a long package name, we import it instead as `MOA`.

### Formulation

The [knapsack problem](#) is a classic problem in mixed-integer programming. Given a collection of items  $i \in I$ , each of which has an associated weight,  $w_i$ , and profit,  $p_i$ , the knapsack problem determines which profit-maximizing subset of items to pack into a knapsack such that the total weight is less than a capacity  $c$ . The mathematical formulation is:

$$\begin{aligned} & \max \sum_{i \in I} p_i x_i \\ \text{s.t. } & \sum_{i \in I} w_i x_i \leq c \\ & x_i \in \{0, 1\} \quad \forall i \in I \end{aligned}$$

where  $x_i$  is 1 if we pack item  $i$  into the knapsack and 0 otherwise.

For this tutorial, we extend the single-objective knapsack problem by adding another objective: given a desirability rating,  $r_i$ , we wish to maximize the total desirability of the items in our knapsack. Thus, our mathematical formulation is now:

$$\begin{aligned} & \max \sum_{i \in I} p_i x_i \\ & \sum_{i \in I} r_i x_i \\ \text{s.t. } & \sum_{i \in I} w_i x_i \leq c \\ & x_i \in \{0, 1\} \quad \forall i \in I \end{aligned}$$

### Data

The data for this example was taken from [vOptGeneric](#), and the original author was [@xgandibleux](#).

```
profit = [77, 94, 71, 63, 96, 82, 85, 75, 72, 91, 99, 63, 84, 87, 79, 94, 90]
desire = [65, 90, 90, 77, 95, 84, 70, 94, 66, 92, 74, 97, 60, 60, 65, 97, 93]
weight = [80, 87, 68, 72, 66, 77, 99, 85, 70, 93, 98, 72, 100, 89, 67, 86, 91]
capacity = 900
N = length(profit)
```

17

Comparing the capacity to the total weight of all the items:

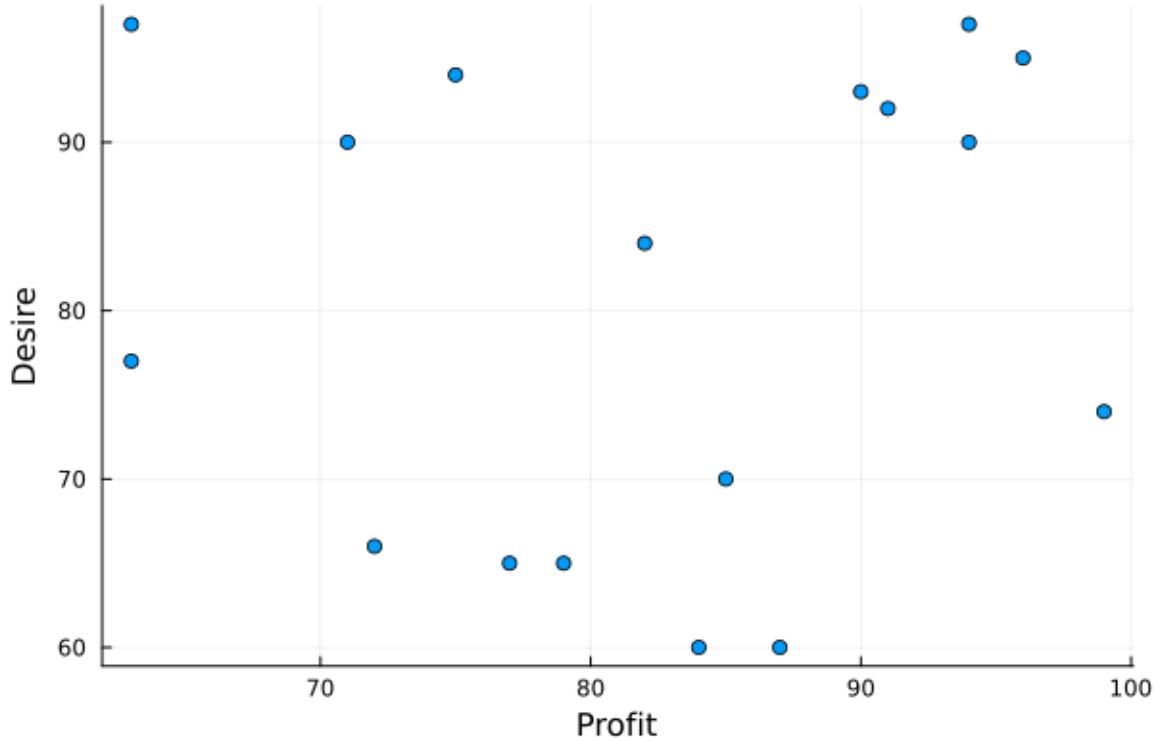
```
capacity / sum(weight)
```

0.6428571428571429

shows that we can take approximately 64% of the items.

Plotting the items, we see that there are a range of items with different profits and desirability. Some items have a high profit and a high desirability, others have a low profit and a high desirability (and vice versa).

```
Plots.scatter(
    profit,
    desire;
    xlabel = "Profit",
    ylabel = "Desire",
    legend = false,
)
```



The goal of the bi-objective knapsack problem is to choose a subset which maximizes both objectives.

### JuMP formulation

Our JuMP formulation is a direct translation of the mathematical formulation:

```
model = Model()
@variable(model, x[1:N], Bin)
@constraint(model, sum(weight[i] * x[i] for i in 1:N) <= capacity)
@expression(model, profit_expr, sum(profit[i] * x[i] for i in 1:N))
@expression(model, desire_expr, sum(desire[i] * x[i] for i in 1:N))
@objective(model, Max, [profit_expr, desire_expr])
```

```
2-element Vector{AffExpr}:
77 x[1] + 94 x[2] + 71 x[3] + 63 x[4] + 96 x[5] + 82 x[6] + 85 x[7] + 75 x[8] + 72 x[9] + 91 x[10]
    + 99 x[11] + 63 x[12] + 84 x[13] + 87 x[14] + 79 x[15] + 94 x[16] + 90 x[17]
65 x[1] + 90 x[2] + 90 x[3] + 77 x[4] + 95 x[5] + 84 x[6] + 70 x[7] + 94 x[8] + 66 x[9] + 92 x[10]
    + 74 x[11] + 97 x[12] + 60 x[13] + 60 x[14] + 65 x[15] + 97 x[16] + 93 x[17]
```

Note how we form a multi-objective program by passing a vector of scalar objective functions.

### Solution

To solve our model, we need an optimizer which supports multi-objective linear programs. One option is to use the [MultiObjectiveAlgorithms.jl](#) package.

```
set_optimizer(model, () -> MOA.Optimizer(HiGHS.Optimizer))
set_silent(model)
```

MultiObjectiveAlgorithms.jl supports many different algorithms for solving multiobjective optimization problems. One option is the epsilon-constraint method:

```
set_attribute(model, MOA.Algorithm(), MOA.EpsilonConstraint())
```

Let's solve the problem and see the solution

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : MOA[algorithm=MultiObjectiveAlgorithms.EpsilonConstraint, optimizer=HiGHS]

* Status
  Result count      : 9
  Termination status : OPTIMAL
  Message from the solver:
  "Solve complete. Found 9 solution(s)"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : NO_SOLUTION
  Objective value    : [9.18000e+02, 9.83000e+02]
  Objective bound    : [9.55000e+02, 9.83000e+02]

* Work counters
  Solve time (sec)   : 9.81781e-02
```

There are 9 solutions available. We can also use `result_count` to see how many solutions are available:

```
result_count(model)
```

```
9
```

### Accessing multiple solutions

Access the nine different solutions in the model using the `result` keyword to `solution_summary`, `value`, and `objective_value`:

```
solution_summary(model; result = 5)
```

```
* Solver : MOA[algorithm=MultiObjectiveAlgorithms.EpsilonConstraint, optimizer=HiGHS]
* Status
  Result count      : 9
  Termination status : OPTIMAL

* Candidate solution (result #5)
  Primal status      : FEASIBLE_POINT
  Dual status        : NO_SOLUTION
  Objective value    : [9.36000e+02, 9.42000e+02]
```

```
@assert primal_status(model; result = 5) == FEASIBLE_POINT
```

```
assert_is_solved_and_feasible(model; result = 5)
```

```
objective_value(model; result = 5)
```

```
2-element Vector{Float64}:
 936.0
 942.0
```

Note that because we set a vector of two objective functions, the objective value is a vector with two elements. We can also query the value of each objective separately:

```
value(profit_expr; result = 5)
```

```
936.0
```

## Visualizing objective space

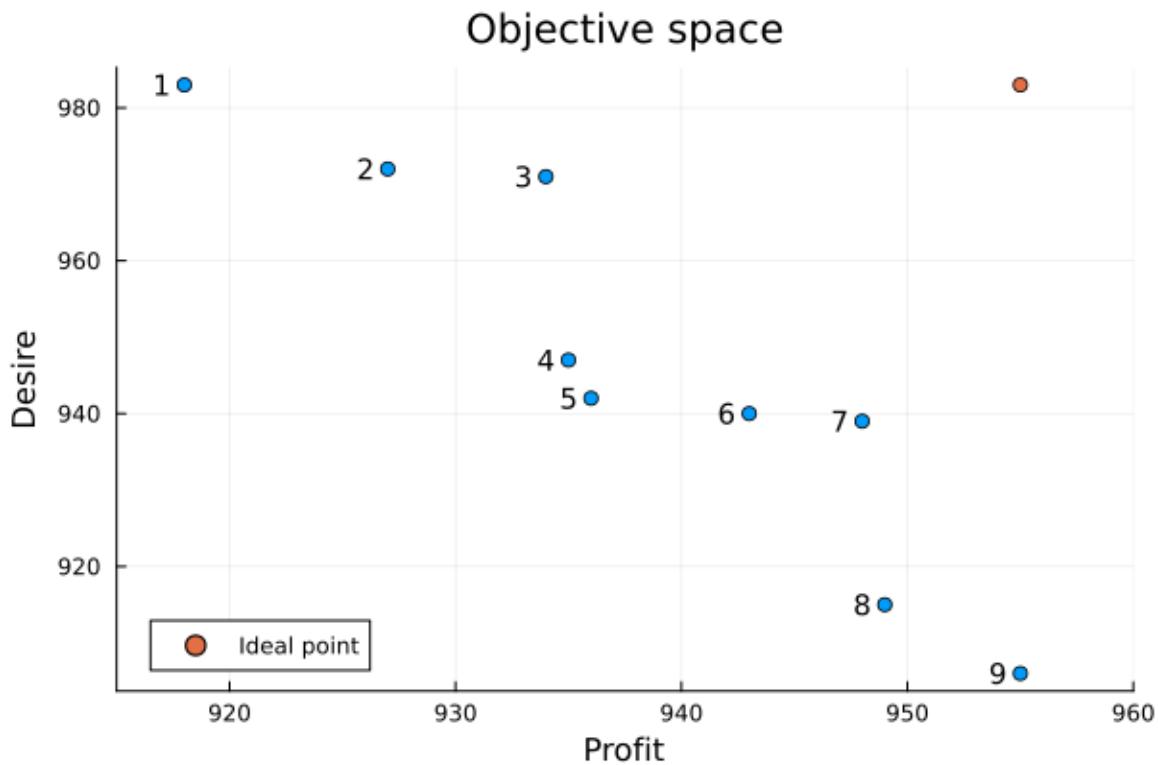
Unlike single-objective optimization problems, multi-objective optimization problems do not have a single optimal solution. Instead, the solutions returned represent possible trade-offs that the decision maker can choose between the two objectives. A common way to visualize this is by plotting the objective values of each of the solutions:

```
plot = Plots.scatter(
    [value(profit_expr; result = i) for i in 1:result_count(model)],
    [value(desire_expr; result = i) for i in 1:result_count(model)];
    xlabel = "Profit",
    ylabel = "Desire",
    title = "Objective space",
```

```

        label = "",
        xlims = (915, 960),
)
for i in 1:result_count(model)
    y = objective_value(model; result = i)
    Plots.annotate!(y[1] - 1, y[2], (i, 10))
end
ideal_point = objective_bound(model)
Plots.scatter!([ideal_point[1]], [ideal_point[2]]; label = "Ideal point")

```



Visualizing the objective space lets the decision maker choose a solution that suits their personal preferences. For example, result #7 is close to the maximum value of profit, but offers significantly higher desirability compared with solutions #8 and #9.

The set of items that are chosen in solution #7 are:

```
items_chosen = [i for i in 1:N if value(x[i]); result = 7) > 0.9]
```

```

11-element Vector{Int64}:
1
2
3
5
6

```

```
8
10
11
15
16
17
```

## Next steps

[MultiObjectiveAlgorithms.jl](#) implements a number of different algorithms. Try solving the same problem using `MOA.Dichotomy()`. Does it find the same solution?

## 6.16 Simple multi-objective examples

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

This tutorial contains a number of examples of multi-objective programs from the literature.

### Required packages

This tutorial requires the following packages:

```
using JuMP
import HiGHS
import MultiObjectiveAlgorithms as MOA
```

### Bi-objective linear problem

This example is taken from Example 6.3 (from Steuer, 1985), page 154 of Ehrgott, M. (2005). *Multicriteria Optimization*. Springer, Berlin. The code was adapted from an example in [vOptGeneric](#) by [@xgandibleux](#).

```
model = Model()
set_silent(model)
@variable(model, x1 >= 0)
@variable(model, 0 <= x2 <= 3)
@objective(model, Min, [3x1 + x2, -x1 - 2x2])
@constraint(model, 3x1 - x2 <= 6)
set_optimizer(model, () -> MOA.Optimizer(HiGHS.Optimizer))
set_attribute(model, MOA.Algorithm(), MOA.Lexicographic())
optimize!(model)
solution_summary(model)
```

```
* Solver : MOA[algorithm=MultiObjectiveAlgorithms.Lexicographic, optimizer=HiGHS]
* Status
Result count      : 2
Termination status : OPTIMAL
Message from the solver:
"Solve complete. Found 2 solution(s)"
```

```

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : NO_SOLUTION
Objective value   : [0.00000e+00,0.00000e+00]
Objective bound    : [0.00000e+00,-9.00000e+00]

* Work counters
Solve time (sec)   : 1.25313e-03

```

```

for i in 1:result_count(model)
    assert_is_solved_and_feasible(model; result = i)
    print(i, ": z = ", round.(Int, objective_value(model; result = i)), " | ")
    println("x = ", value.([x1, x2]; result = i))
end

```

```

1: z = [0, 0] | x = [0.0, -0.0]
2: z = [12, -9] | x = [3.0, 3.0]

```

### Bi-objective linear assignment problem

This example is taken from Example 9.38 (from Ulungu and Teghem, 1994), page 255 of Ehrgott, M. (2005). *Multicriteria Optimization*. Springer, Berlin. The code was adapted from an example in `vOptGeneric` by [@xgandibleux](#).

```

C1 = [5 1 4 7; 6 2 2 6; 2 8 4 4; 3 5 7 1]
C2 = [3 6 4 2; 1 3 8 3; 5 2 2 3; 4 2 3 5]
n = size(C2, 1)
model = Model()
set_silent(model)
@variable(model, x[1:n, 1:n], Bin)
@objective(model, Min, [sum(C1 .* x), sum(C2 .* x)])
@constraint(model, [i = 1:n], sum(x[i, :]) == 1)
@constraint(model, [j = 1:n], sum(x[:, j]) == 1)
set_optimizer(model, () -> MOA.Optimizer(HiGHS.Optimizer))
set_attribute(model, MOA.Algorithm(), MOA.EpsilonConstraint())
optimize!(model)
solution_summary(model)

```

```

* Solver : MOA[algorithm=MultiObjectiveAlgorithms.EpsilonConstraint, optimizer=HiGHS]

* Status
Result count      : 6
Termination status : OPTIMAL
Message from the solver:
"Solve complete. Found 6 solution(s)"

```

```

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : NO_SOLUTION
Objective value   : [6.00000e+00,2.40000e+01]
Objective bound    : [6.00000e+00,7.00000e+00]

* Work counters
Solve time (sec)   : 7.67899e-03

```

```

for i in 1:result_count(model)
    assert_is_solved_and_feasible(model; result = i)
    print(i, ": z = ", round.(Int, objective_value(model; result = i)), " | ")
    println("x = ", round.(Int, value.(x; result = i)))
end

```

```

1: z = [6, 24] | x = [0 1 0 0; 0 0 1 0; 1 0 0 0; 0 0 0 1]
2: z = [9, 17] | x = [0 0 1 0; 0 1 0 0; 1 0 0 0; 0 0 0 1]
3: z = [12, 13] | x = [1 0 0 0; 0 1 0 0; 0 0 1 0; 0 0 0 1]
4: z = [16, 11] | x = [0 0 0 1; 0 1 0 0; 0 0 1 0; 1 0 0 0]
5: z = [19, 10] | x = [0 0 1 0; 1 0 0 0; 0 0 0 1; 0 1 0 0]
6: z = [22, 7]  | x = [0 0 0 1; 1 0 0 0; 0 0 1 0; 0 1 0 0]

```

### Bi-objective shortest path problem

This example is taken from Exercise 9.5 page 269 of Ehrgott, M. (2005). *Multicriteria Optimization*. Springer, Berlin. The code was adapted from an example in `vOptGeneric` by `@xgandibleux`.

```

M = 50
C1 = [
    M 4 5 M M M
    M M 2 1 2 7
    M M M 5 2 M
    M M 5 M M 3
    M M M M M 4
    M M M M M M
]
C2 = [
    M 3 1 M M M
    M M 1 4 2 2
    M M M 1 7 M
    M M 1 M M 2
    M M M M M 2
    M M M M M M
]
n = size(C2, 1)
model = Model()
set_silent(model)

```

```

@variable(model, x[1:n, 1:n], Bin)
@objective(model, Min, [sum(C1 .* x), sum(C2 .* x)])
@constraint(model, sum(x[1, :]) == 1)
@constraint(model, sum(x[:, n]) == 1)
@constraint(model, [i = 2:n-1], sum(x[i, :]) - sum(x[:, i]) == 0)
set_optimizer(model, () -> MOA.Optimizer(HiGHS.Optimizer))
set_attribute(model, MOA.Algorithm(), MOA.EpsilonConstraint())
optimize!(model)
solution_summary(model)

```

```

* Solver : MOA[algorithm=MultiObjectiveAlgorithms.EpsilonConstraint, optimizer=HiGHS]

* Status
  Result count      : 4
  Termination status : OPTIMAL
  Message from the solver:
  "Solve complete. Found 4 solution(s)"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : NO_SOLUTION
  Objective value    : [8.00000e+00,9.00000e+00]
  Objective bound    : [8.00000e+00,4.00000e+00]

* Work counters
  Solve time (sec)   : 5.53799e-03

```

```

for i in 1:result_count(model)
    assert_is_solved_and_feasible(model; result = i)
    print(i, ": z = ", round.(Int, objective_value(model; result = i)), " | ")
    X = round.(Int, value.(x; result = i))
    print("Path:")
    for ind in findall(val -> val ≈ 1, X)
        i, j = ind.I
        print(" $i->$j")
    end
    println()
end

```

```

1: z = [8, 9] | Path: 1->2 2->4 4->6
2: z = [10, 7] | Path: 1->2 2->5 5->6
3: z = [11, 5] | Path: 1->2 2->6
4: z = [13, 4] | Path: 1->3 3->4 4->6

```

## 6.17 Sudoku

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4		8		3				1
7			2					6
	6				2	8		
		4	1	9				5
			8			7	9	

Figure 6.1: Partially solved Sudoku

**This tutorial was originally contributed by Iain Dunning.**

Sudoku is a popular number puzzle. The goal is to place the digits 1 to 9 on a nine-by-nine grid, with some of the digits already filled in. Your solution must satisfy the following rules:

- The numbers 1 to 9 must appear in each 3x3 square
- The numbers 1 to 9 must appear in each row
- The numbers 1 to 9 must appear in each column

Here is a partially solved Sudoku problem:

Solving a Sudoku isn't an optimization problem with an objective; it's actually a *feasibility* problem: we wish to find a feasible solution that satisfies these rules. You can think of it as an optimization problem with an objective of 0.

### Mixed-integer linear programming formulation

We can model this problem using 0-1 integer programming: a problem where all the decision variables are binary. We'll use JuMP to create the model, and then we can solve it with any integer programming solver.

```
using JuMP
using HiGHS
```

We will define a binary variable (a variable that is either 0 or 1) for each possible number in each possible cell. The meaning of each variable is as follows:  $x[i,j,k] = 1$  if and only if cell  $(i,j)$  has number  $k$ , where  $i$  is the row and  $j$  is the column.

Create a model

```
sudoku = Model(HiGHS.Optimizer)
set_silent(sudoku)
```

Create our variables

```
@variable(sudoku, x[i = 1:9, j = 1:9, k = 1:9], Bin);
```

Now we can begin to add our constraints. We'll actually start with something obvious to us as humans, but what we need to enforce: that there can be only one number per cell.

```
for i in 1:9 # For each row
    for j in 1:9 # and each column
        # Sum across all the possible digits. One and only one of the digits
        # can be in this cell, so the sum must be equal to one.
        @constraint(sudoku, sum(x[i, j, k] for k in 1:9) == 1)
    end
end
```

Next we'll add the constraints for the rows and the columns. These constraints are all very similar, so much so that we can actually add them at the same time.

```
for ind in 1:9 # Each row, OR each column
    for k in 1:9 # Each digit
        # Sum across columns (j) - row constraint
        @constraint(sudoku, sum(x[ind, j, k] for j in 1:9) == 1)
        # Sum across rows (i) - column constraint
        @constraint(sudoku, sum(x[i, ind, k] for i in 1:9) == 1)
    end
end
```

Finally, we have to enforce the constraint that each digit appears once in each of the nine 3x3 sub-grids. Our strategy will be to index over the top-left corners of each 3x3 square with for loops, then sum over the squares.

```

for i in 1:3:7
    for j in 1:3:7
        for k in 1:9
            # i is the top left row, j is the top left column.
            # We'll sum from i to i+2, for example, i=4, r=4, 5, 6.
            @constraint(
                sudoku,
                sum(x[r, c, k] for r in i:(i+2), c in j:(j+2)) == 1
            )
        end
    end
end

```

The final step is to add the initial solution as a set of constraints. We'll solve the problem that is in the picture at the start of the tutorial. We'll put a 0 if there is no digit in that location.

The given digits

```

init_sol = [
    5 3 0 0 7 0 0 0 0
    6 0 0 1 9 5 0 0 0
    0 9 8 0 0 0 0 6 0
    8 0 0 0 6 0 0 0 3
    4 0 0 8 0 3 0 0 1
    7 0 0 0 2 0 0 0 6
    0 6 0 0 0 0 2 8 0
    0 0 0 4 1 9 0 0 5
    0 0 0 0 8 0 0 7 9
]
for i in 1:9
    for j in 1:9
        # If the space isn't empty
        if init_sol[i, j] != 0
            # Then the corresponding variable for that digit and location must
            # be 1.
            fix(x[i, j, init_sol[i, j]], 1; force = true)
        end
    end
end

```

solve problem

```

optimize!(sudoku)
assert_is_solved_and_feasible(sudoku)

```

Extract the values of x

```
x_val = value.(x);
```

Create a matrix to store the solution

```

sol = zeros(Int, 9, 9) # 9x9 matrix of integers
for i in 1:9
    for j in 1:9
        for k in 1:9
            # Integer programs are solved as a series of linear programs so the
            # values might not be precisely 0 and 1. We can round them to
            # the nearest integer to make it easier.
            if round(Int, x_val[i, j, k]) == 1
                sol[i, j] = k
            end
        end
    end
end

```

Display the solution

```
sol
```

```

9x9 Matrix{Int64}:
5 3 4 6 7 8 9 1 2
6 7 2 1 9 5 3 4 8
1 9 8 3 4 2 5 6 7
8 5 9 7 6 1 4 2 3
4 2 6 8 5 3 7 9 1
7 1 3 9 2 4 8 5 6
9 6 1 5 3 7 2 8 4
2 8 7 4 1 9 6 3 5
3 4 5 2 8 6 1 7 9

```

Which is the correct solution:

### Constraint programming formulation

We can also model this problem using constraint programming and the all-different constraint, which says that no two elements of a vector can take the same value.

Because of the reformulation system in MathOptInterface, we can still solve this problem using HiGHS.

```

model = Model(HiGHS.Optimizer)
set_silent(model)
# HiGHS v1.2 has a bug in presolve which causes the problem to be classified as
# infeasible.
set_attribute(model, "presolve", "off")

```

Instead of the binary variables, we directly define a 9x9 grid of integer values between 1 and 9:

```
@variable(model, 1 <= x[1:9, 1:9] <= 9, Int);
```

Then, we enforce that the values in each row must be all-different:

5	3	4	6	7	8	9	1	2
6	7	2	1	9	5	3	4	8
1	9	8	3	4	2	5	6	7
8	5	9	7	6	1	4	2	3
4	2	6	8	5	3	7	9	1
7	1	3	9	2	4	8	5	6
9	6	1	5	3	7	2	8	4
2	8	7	4	1	9	6	3	5
3	4	5	2	8	6	1	7	9

Figure 6.2: Solved Sudoku

```
@constraint(model, [i = 1:9], x[i, :] in MOI.AllDifferent(9));
```

That the values in each column must be all-different:

```
@constraint(model, [j = 1:9], x[:, j] in MOI.AllDifferent(9));
```

And that the values in each 3x3 sub-grid must be all-different:

```
for i in (0, 3, 6), j in (0, 3, 6)
    @constraint(model, vec(x[i.+(1:3), j.+(1:3)]) in MOI.AllDifferent(9))
end
```

Finally, as before we set the initial solution and optimize:

```

for i in 1:9, j in 1:9
    if init_sol[i, j] != 0
        fix(x[i, j], init_sol[i, j]; force = true)
    end
end

optimize!(model)
assert_is_solved_and_feasible(model)

```

Display the solution

```
csp_sol = round.(Int, value.(x))
```

```

9x9 Matrix{Int64}:
 5  3  4  6  7  8  9  1  2
 6  7  2  1  9  5  3  4  8
 1  9  8  3  4  2  5  6  7
 8  5  9  7  6  1  4  2  3
 4  2  6  8  5  3  7  9  1
 7  1  3  9  2  4  8  5  6
 9  6  1  5  3  7  2  8  4
 2  8  7  4  1  9  6  3  5
 3  4  5  2  8  6  1  7  9

```

Which is the same as we found before:

```
sol == csp_sol
```

```
true
```

## 6.18 N-Queens

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

**This tutorial was originally contributed by Matthew Helm and Mathieu Tanneau.**

The N-Queens problem involves placing N queens on an N x N chessboard such that none of the queens attacks another. In chess, a queen can move vertically, horizontally, and diagonally so there cannot be more than one queen on any given row, column, or diagonal.

*Note that none of the queens above are able to attack any other as a result of their careful placement.*

```

using JuMP
import HiGHS
import LinearAlgebra

```

N-Queens

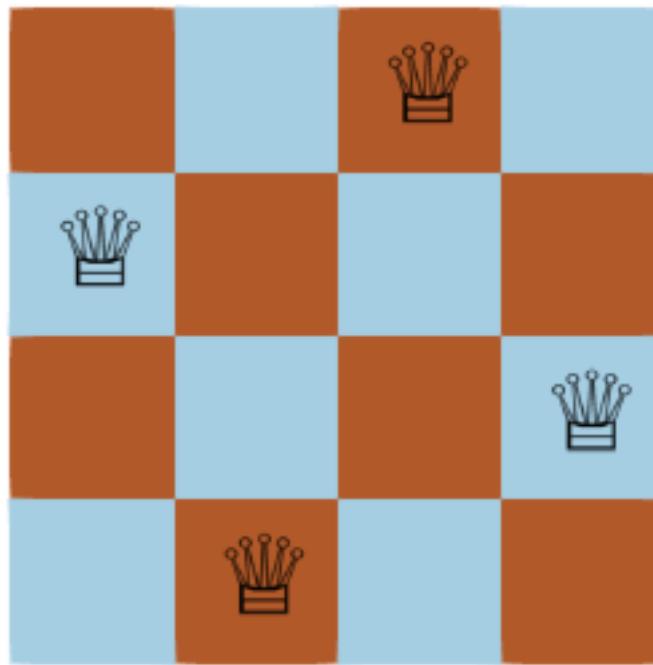


Figure 6.3: Four Queens

```
N = 8

model = Model(HiGHS.Optimizer)
set_silent(model)
```

Next, let's create an  $N \times N$  chessboard of binary values. 0 will represent an empty space on the board and 1 will represent a space occupied by one of our queens:

```
@variable(model, x[1:N, 1:N], Bin);
```

Now we can add our constraints:

There must be exactly one queen in a given row/column

```
for i in 1:N
    @constraint(model, sum(x[i, :]) == 1)
    @constraint(model, sum(x[:, i]) == 1)
end
```

There can only be one queen on any given diagonal

```
for i in -(N - 1):(N-1)
    @constraint(model, sum(LinearAlgebra.diag(x, i)) <= 1)
    @constraint(model, sum(LinearAlgebra.diag(reverse(x; dims = 1), i)) <= 1)
end
```

We are ready to put our model to work and see if it is able to find a feasible solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
```

We can now review the solution that our model found:

```
solution = round.(Int, value.(x))
```

```
8x8 Matrix{Int64}:
 0  0  0  0  1  0  0  0
 0  0  1  0  0  0  0  0
 0  0  0  0  0  0  0  1
 0  0  0  1  0  0  0  0
 0  0  0  0  0  0  1  0
 1  0  0  0  0  0  0  0
 0  0  0  0  1  0  0  0
 0  1  0  0  0  0  0  0
```

## 6.19 Constraint programming

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

JuMP supports a range of constraint-programming type constraints via the corresponding sets in MathOptInterface. For most constraints, there are reformulations built-in that convert the constraint programming constraint into a mixed-integer programming equivalent.

Because of this reformulation, all variables must be integer, and they must typically have finite bounds. An error will be thrown if the reformulation requires finiteness and you have a variable with non-finite bounds.

This tutorial uses the following packages:

```
using JuMP
import HiGHS
```

### AllDifferent

The `MOI.AllDifferent` set ensures that every element in a list takes a different integer value.

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, 1 <= x[1:4] <= 4, Int)
@constraint(model, x in MOI.AllDifferent(4))
optimize!(model)
assert_is_solved_and_feasible(model)
value.(x)
```

```
4-element Vector{Float64}:
1.0
4.0
3.0000000000000004
1.9999999999999996
```

## BinPacking

The `MOI.BinPacking` set can be used to divide up a set of items into different groups, such that the sum of their weights does not exceed the capacity of a bin.

```
weights, capacity = Float64[1, 1, 2, 2, 3], 3.0;
number_of_bins = 3
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, 1 <= x[1:length(weights)] <= number_of_bins, Int)
@constraint(model, x in MOI.BinPacking(capacity, weights))
optimize!(model)
assert_is_solved_and_feasible(model)
value.(x)
```

```
5-element Vector{Float64}:
2.0
1.0
2.0
1.0
3.0
```

Here, the value of `x[i]` is the bin that item `i` was placed into.

## Circuit

The `MOI.Circuit` set is used to construct a tour of a list of `N` variables. They will each be assigned an integer from 1 to `N`, that describes the successor to each variable in the list:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:4], Int)
@constraint(model, x in MOI.Circuit(4))
optimize!(model)
assert_is_solved_and_feasible(model)
```

Let's see what tour was found, starting at node number 1:

```
y = round.(Int, value.(x))
tour = Int[1]
while length(tour) < length(y)
    push!(tour, y[tour[end]])
```

```
end
tour
```

```
4-element Vector{Int64}:
1
4
3
2
```

### CountAtLeast

The `MOI.CountAtLeast` set is used to ensure that at least n elements in a set of variables belong to a set of values.

For example, here is a model with three variables, constrained between 0 and 5:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, 0 <= x[1:3] <= 5, Int)
```

```
3-element Vector{VariableRef}:
x[1]
x[2]
x[3]
```

If we want to ensure that at least one element of each set  $\{x[1], x[2]\}$  and  $\{x[2], x[3]\}$  is in the set  $\{3\}$ , then we create a list of variables by concatenating the sets together:

```
variables = [x[1], x[2], x[2], x[3]]
```

```
4-element Vector{VariableRef}:
x[1]
x[2]
x[2]
x[3]
```

Then we need a partition list that contains the number of elements in each set of variables:

```
partitions = [2, 2]
```

```
2-element Vector{Int64}:
2
2
```

Finally, we need a set of values that the elements must be a part of:

```
values = Set([3])
```

```
Set{Int64} with 1 element:  
3
```

And the number of elements that must be part of the set values:

```
n = 1
```

```
1
```

The constraint is:

```
@constraint(model, variables in MOI.CountAtLeast(n, partitions, values))
```

$$[x_1, x_2, x_2, x_3] \in \text{MathOptInterface.CountAtLeast}(1, [2, 2], \text{Set}([3]))$$

To ensure the uniqueness of the solution, we'll add a constraint that  $x[2]$  must be  $\leq 2$ . This ensures that the only feasible solution is for  $x[1]$  and  $x[3]$  to be 3:

```
@constraint(model, x[2] <= 2)
```

$$x_2 \leq 2$$

Let's check that we found a valid solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
value.(x)
```

```
3-element Vector{Float64}:
3.0
0.0
3.0
```

### CountBelongs

The `MOI.CountBelongs` set is used to count how many elements in a set of variables belong to a set of values.

For example, to count how many elements in a set of 4 variables belong to the set {2, 3}, do:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, 0 <= x[i = 1:4] <= i, Int)
@variable(model, n, Int)
@objective(model, Max, sum(x))
set = Set([2, 3])
@constraint(model, [n; x] in MOI.CountBelongs(1 + length(x), set))
optimize!(model)
assert_is_solved_and_feasible(model)
value(n), value.(x)
```

```
(2.0, [1.0, 2.0, 3.0, 4.0])
```

### CountDistinct

The `MOI.CountDistinct` set is used to count the number of distinct elements in a set of variables.

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, 0 <= x[i = 1:4] <= i, Int)
@variable(model, n, Int)
@objective(model, Max, sum(x))
@constraint(model, [n; x] in MOI.CountDistinct(1 + length(x)))
optimize!(model)
assert_is_solved_and_feasible(model)
value(n), value.(x)
```

```
(4.0, [1.0, 2.0, 3.0, 4.0])
```

### CountGreaterThan

The `MOI.CountGreaterThan` set is used to strictly upper-bound the number of distinct elements in a set of variables that have a value equal to another variable.

For example, to count the number  $n$  of times that  $y$  appears in the vector  $x$ , use:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, 0 <= x[i = 1:4] <= i, Int)
@variable(model, n, Int)
@variable(model, 3 <= y <= 4, Int)
@objective(model, Max, sum(x))
@constraint(model, [n; y; x] in MOI.CountGreaterThan(1 + 1 + length(x)))
```

```
optimize!(model)
assert_is_solved_and_feasible(model)
value(n), value(y), value.(x)
```

```
(2.0, 3.0, [1.0, 2.0, 3.0, 4.0])
```

Here  $n$  is strictly greater than the count, and there is no limit on how large  $n$  could be. For example,  $n = 100$  is also a feasible solution. The only constraint is that  $n$  cannot be equal to or smaller than the number of times that  $y$  appears.

### Table

The `MOI.Table` set is used to select a single row from a matrix of values.

For example, given a matrix:

```
table = Float64[1 1 0; 0 1 1; 1 0 1; 1 1 1]
```

```
4x3 Matrix{Float64}:
1.0  1.0  0.0
0.0  1.0  1.0
1.0  0.0  1.0
1.0  1.0  1.0
```

we can constraint a 3-element vector  $x$  to equal one of the rows in `table` via:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[i = 1:3], Int)
@constraint(model, x in MOI.Table(table))
optimize!(model)
assert_is_solved_and_feasible(model)
value.(x)
```

```
3-element Vector{Float64}:
1.0
1.0
0.0
```

## 6.20 Callbacks

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of the tutorial is to demonstrate the various solver-independent and solver-dependent callbacks that are supported by JuMP.

The tutorial uses the following packages:

```
using JuMP
import Gurobi
import Random
import Test
```

### Info

This tutorial uses the `MathOptInterface` API. By default, JuMP exports the `MOI` symbol as an alias for the `MathOptInterface.jl` package. We recommend making this more explicit in your code by adding the following lines:

```
import MathOptInterface as MOI
```

## Lazy constraints

An example using a lazy constraint callback.

```
function example_lazy_constraint()
    model = Model(Gurobi.Optimizer)
    set_silent(model)
    @variable(model, 0 <= x <= 2.5, Int)
    @variable(model, 0 <= y <= 2.5, Int)
    @objective(model, Max, y)
    lazy_called = false
    function my_callback_function(cb_data)
        lazy_called = true
        x_val = callback_value(cb_data, x)
        y_val = callback_value(cb_data, y)
        println("Called from (x, y) = ($x_val, $y_val)")
        status = callback_node_status(cb_data, model)
        if status == MOI.CALLBACK_NODE_STATUS_FRACTIONAL
            println(" - Solution is integer infeasible!")
        elseif status == MOI.CALLBACK_NODE_STATUS_INTEGER
            println(" - Solution is integer feasible!")
        else
            @assert status == MOI.CALLBACK_NODE_STATUS_UNKNOWN
            println(" - I don't know if the solution is integer feasible :(")
        end
        if y_val - x_val > 1 + 1e-6
            con = @build_constraint(y - x <= 1)
            println("Adding $(con)")
            MOI.submit(model, MOI.LazyConstraint(cb_data), con)
        elseif y_val + x_val > 3 + 1e-6
            con = @build_constraint(y + x <= 3)
            println("Adding $(con)")
            MOI.submit(model, MOI.LazyConstraint(cb_data), con)
        end
    end
    return
end
set_attribute(model, MOI.LazyConstraintCallback(), my_callback_function)
```

```

optimize!(model)
assert_is_solved_and_feasible(model)
Test.@test lazy_called
Test.@test value(x) == 1
Test.@test value(y) == 2
println("Optimal solution (x, y) = ($(value(x)), $(value(y)))")
return
end

example_lazy_constraint()

```

```

Set parameter WLSAccessID
Set parameter WLSSecret
Set parameter LicenseID to value 722777
Set parameter GURO_PAR_SPECIAL
WLS license 722777 - registered to JuMP Development
Called from (x, y) = (-0.0, 2.0)
- Solution is integer feasible!
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(y - x,
↪ MathOptInterface.LessThan{Float64}(1.0))
Called from (x, y) = (2.0, 2.0)
- Solution is integer feasible!
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(y + x,
↪ MathOptInterface.LessThan{Float64}(3.0))
Called from (x, y) = (2.0, 2.0)
- Solution is integer feasible!
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(y + x,
↪ MathOptInterface.LessThan{Float64}(3.0))
Called from (x, y) = (2.0, 2.0)
- Solution is integer feasible!
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(y + x,
↪ MathOptInterface.LessThan{Float64}(3.0))
Called from (x, y) = (-0.0, 2.0)
- Solution is integer feasible!
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(y - x,
↪ MathOptInterface.LessThan{Float64}(1.0))
Called from (x, y) = (1.0, 2.0)
- Solution is integer feasible!
Optimal solution (x, y) = (1.0, 2.0)

```

## User-cuts

An example using a user-cut callback.

```

function example_user_cut_constraint()
    Random.seed!(1)
    N = 30
    item_weights, item_values = rand(N), rand(N)
    model = Model(Gurobi.Optimizer)
    set_silent(model)
    # Turn off "Cuts" parameter so that our new one must be called. In real
    # models, you should leave "Cuts" turned on.

```

```

set_attribute(model, "Cuts", 0)
@variable(model, x[1:N], Bin)
@constraint(model, sum(item_weights[i] * x[i] for i in 1:N) <= 10)
@objective(model, Max, sum(item_values[i] * x[i] for i in 1:N))
callback_called = false
function my_callback_function(cb_data)
    callback_called = true
    x_vals = callback_value.(Ref(cb_data), x)
    accumulated = sum(item_weights[i] for i in 1:N if x_vals[i] > 1e-4)
    println("Called with accumulated = $(accumulated)")
    n_terms = sum(1 for i in 1:N if x_vals[i] > 1e-4)
    if accumulated > 10
        con = @build_constraint(
            sum(x[i] for i in 1:N if x_vals[i] > 0.5) <= n_terms - 1
        )
        println("Adding $(con)")
        MOI.submit(model, MOI.UserCut(cb_data), con)
    end
end
set_attribute(model, MOI.UserCutCallback(), my_callback_function)
optimize!(model)
assert_is_solved_and_feasible(model)
Test.@test callback_called
@show callback_called
return
end

example_user_cut_constraint()

```

```

Set parameter WLSSecret
Set parameter LicenseID to value 722777
Set parameter GURO_PAR_SPECIAL
WLS license 722777 - registered to JuMP Development
Called with accumulated = 10.37975831721494
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(x[1] + x[2] + x[3] + x[4] +
↪ x[5] + x[7] + x[8] + x[9] + x[10] + x[11] + x[12] + x[13] + x[14] + x[16] + x[17] + x[18] +
↪ x[20] + x[22] + x[23] + x[25] + x[26] + x[28] + x[29] + x[30],
↪ MathOptInterface.LessThan{Float64}(23.0))
Called with accumulated = 10.37975831721494
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(x[1] + x[2] + x[3] + x[4] +
↪ x[5] + x[7] + x[8] + x[9] + x[10] + x[12] + x[13] + x[14] + x[16] + x[17] + x[18] + x[20] +
↪ x[22] + x[23] + x[25] + x[26] + x[28] + x[29] + x[30],
↪ MathOptInterface.LessThan{Float64}(23.0))
Called with accumulated = 10.37975831721494
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(x[1] + x[2] + x[3] + x[4] +
↪ x[5] + x[7] + x[8] + x[9] + x[10] + x[11] + x[12] + x[13] + x[14] + x[16] + x[17] + x[18] +
↪ x[20] + x[22] + x[23] + x[25] + x[26] + x[29] + x[30],
↪ MathOptInterface.LessThan{Float64}(23.0))
Called with accumulated = 10.37975831721494
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(x[1] + x[2] + x[3] + x[4] +
↪ x[5] + x[7] + x[8] + x[9] + x[10] + x[12] + x[13] + x[14] + x[16] + x[17] + x[18] + x[20] +
↪ x[22] + x[23] + x[25] + x[26] + x[28] + x[29] + x[30],
↪ MathOptInterface.LessThan{Float64}(23.0))

```

```

Called with accumulated = 10.37975831721494
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(x[1] + x[2] + x[3] + x[4] +
↪ x[5] + x[7] + x[8] + x[9] + x[10] + x[12] + x[13] + x[14] + x[16] + x[17] + x[18] + x[20] +
↪ x[22] + x[23] + x[25] + x[26] + x[28] + x[29] + x[30],
↪ MathOptInterface.LessThan{Float64}(23.0))
Called with accumulated = 10.37975831721494
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(x[1] + x[2] + x[3] + x[4] +
↪ x[5] + x[7] + x[8] + x[9] + x[10] + x[12] + x[13] + x[14] + x[16] + x[17] + x[18] + x[20] +
↪ x[22] + x[23] + x[25] + x[26] + x[28] + x[29] + x[30],
↪ MathOptInterface.LessThan{Float64}(23.0))
Called with accumulated = 10.585271197221452
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(x[1] + x[2] + x[3] + x[4] +
↪ x[5] + x[7] + x[8] + x[9] + x[10] + x[11] + x[12] + x[13] + x[14] + x[16] + x[17] + x[18] +
↪ x[20] + x[22] + x[23] + x[25] + x[26] + x[28] + x[29] + x[30],
↪ MathOptInterface.LessThan{Float64}(23.0))
Called with accumulated = 10.37975831721494
Adding ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(x[1] + x[2] + x[3] + x[4] +
↪ x[5] + x[7] + x[8] + x[9] + x[10] + x[12] + x[13] + x[14] + x[16] + x[17] + x[18] + x[20] +
↪ x[22] + x[23] + x[25] + x[26] + x[28] + x[29] + x[30],
↪ MathOptInterface.LessThan{Float64}(23.0))
callback_called = true

```

## Heuristic solutions

An example using a heuristic solution callback.

```

function example_heuristic_solution()
    Random.seed!(1)
    N = 30
    item_weights, item_values = rand(N), rand(N)
    model = Model(Gurobi.Optimizer)
    set_silent(model)
    # Turn off "Heuristics" parameter so that our new one must be called. In
    # real models, you should leave "Heuristics" turned on.
    set_attribute(model, "Heuristics", 0)
    @variable(model, x[1:N], Bin)
    @constraint(model, sum(item_weights[i] * x[i] for i in 1:N) <= 10)
    @objective(model, Max, sum(item_values[i] * x[i] for i in 1:N))
    callback_called = false
    function my_callback_function(cb_data)
        callback_called = true
        x_vals = callback_value.(Ref(cb_data), x)
        ret =
            MOI.submit(model, MOI.HeuristicSolution(cb_data), x, floor.(x_vals))
        println("Heuristic solution status = $(ret)")
        Test.@test ret in (
            MOI.HEURISTIC_SOLUTION_ACCEPTED,
            MOI.HEURISTIC_SOLUTION_REJECTED,
        )
    end
    set_attribute(model, MOI.HeuristicCallback(), my_callback_function)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    Test.@test callback_called

```

```

    return
end

example_heuristic_solution()

```

```

Set parameter WLSSecret
Set parameter WLSSecret
Set parameter LicenseID to value 722777
Set parameter GURO_PAR_SPECIAL
WLS license 722777 - registered to JuMP Development
Heuristic solution status = HEURISTIC_SOLUTION_ACCEPTED
Heuristic solution status = HEURISTIC_SOLUTION_REJECTED

```

### Gurobi solver-dependent callback

An example using Gurobi's solver-dependent callback.

```

function example_solver_dependent_callback()
    model = direct_model(Gurobi.Optimizer())
    @variable(model, 0 <= x <= 2.5, Int)
    @variable(model, 0 <= y <= 2.5, Int)
    @objective(model, Max, y)
    cb_calls = Cint[]
    function my_callback_function(cb_data, cb_where::Cint)
        # You can reference variables outside the function as normal
        push!(cb_calls, cb_where)
        # You can select where the callback is run
        if cb_where == Gurobi.GRB_CB_MIPNODE
            # You can query a callback attribute using GRBcbget
            resultP = Ref{Cint}()
            Gurobi.GRBcbget(
                cb_data,
                cb_where,
                Gurobi.GRB_CB_MIPNODE_STATUS,
                resultP,
            )
            if resultP[] != Gurobi.GRB_OPTIMAL
                return # Solution is something other than optimal.
            end
        elseif cb_where != Gurobi.GRB_CB_MIPSOL
            return
        end
        # Before querying `callback_value`, you must call:
        Gurobi.load_callback_variable_primal(cb_data, cb_where)
        x_val = callback_value(cb_data, x)
        y_val = callback_value(cb_data, y)
        # You can submit solver-independent MathOptInterface attributes such as
        # lazy constraints, user-cuts, and heuristic solutions.
        if y_val - x_val > 1 + 1e-6
            con = @build_constraint(y - x <= 1)
            MOI.submit(model, MOI.LazyConstraint(cb_data), con)
        elseif y_val + x_val > 3 + 1e-6
    end

```

```

        con = @build_constraint(y + x <= 3)
        MOI.submit(model, MOI.LazyConstraint(cb_data), con)
    end
    # You can terminate the callback as follows:
    Gurobi.GRBterminate(backend(model))
    return
end
# You _must_ set this parameter if using lazy constraints.
set_attribute(model, "LazyConstraints", 1)
set_attribute(model, Gurobi.CallbackFunction(), my_callback_function)
optimize!(model)
Test.@test termination_status(model) == MOI.INTERRUPTED
return
end

example_solver_dependent_callback()

```

```

Set parameter WLSAccessID
Set parameter WLSSecret
Set parameter LicenseID to value 722777
Set parameter GURO_PAR_SPECIAL
WLS license 722777 - registered to JuMP Development
Set parameter LazyConstraints to value 1
Gurobi Optimizer version 12.0.0 build v12.0.0rc1 (linux64 - "Ubuntu 24.04.1 LTS")

CPU model: AMD EPYC 7763 64-Core Processor, instruction set [SSE2|AVX|AVX2]
Thread count: 2 physical cores, 4 logical processors, using up to 4 threads

Non-default parameters:
LazyConstraints 1

WLS license 722777 - registered to JuMP Development
Optimize a model with 0 rows, 2 columns and 0 nonzeros
Model fingerprint: 0x1cb4e750
Variable types: 0 continuous, 2 integer (0 binary)
Coefficient statistics:
    Matrix range      [0e+00, 0e+00]
    Objective range   [1e+00, 1e+00]
    Bounds range      [2e+00, 2e+00]
    RHS range         [0e+00, 0e+00]
Presolve time: 0.00s

Explored 0 nodes (0 simplex iterations) in 0.00 seconds (0.00 work units)
Thread count was 1 (of 4 available processors)

Solution count 0

Solve interrupted
Best objective -, best bound -, gap -

User-callback calls 31, time in user-callback 0.03 sec

```

## 6.21 Sensitivity analysis of a linear program

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

This tutorial explains how to use the `lp_sensitivity_report` function to create sensitivity reports like those that are produced by the Excel Solver. This is most often used in introductory classes to linear programming.

In brief, sensitivity analysis of a linear program is about asking two questions:

1. Given an optimal solution, how much can the objective coefficients change by before a different solution becomes optimal?
2. Given an optimal solution, how much can the right-hand side of a linear constraint change by before a different solution becomes optimal?

JuMP provides a function, `lp_sensitivity_report`, to help us compute these values, but this tutorial extends that to create more informative tables in the form of a `DataFrame`.

### Setup

This tutorial uses the following packages:

```
using JuMP
import HiGHS
import DataFrames
```

as well as this small linear program:

```
model = Model(HiGHS.Optimizer)
@variable(model, x >= 0)
@variable(model, 0 <= y <= 3)
@variable(model, z <= 1)
@objective(model, Min, 12x + 20y - z)
@constraint(model, c1, 6x + 8y >= 100)
@constraint(model, c2, 7x + 12y >= 120)
@constraint(model, c3, x + y <= 20)
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model; verbose = true)
```

```
* Solver : HiGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 2.04000e+02
```

```

Objective bound      : 2.04000e+02
Relative gap        : 0.00000e+00
Dual objective value : 2.04000e+02
Primal solution :
  x : 1.50000e+01
  y : 1.25000e+00
  z : 1.00000e+00
Dual solution :
  c1 : 2.50000e-01
  c2 : 1.50000e+00
  c3 : 0.00000e+00

* Work counters
  Solve time (sec)   : 2.26021e-04
  Simplex iterations : 2
  Barrier iterations : 0
  Node count         : -1

```

Can you identify:

- The objective coefficient of each variable?
- The right-hand side of each constraint?
- The optimal primal and dual solutions?

### Sensitivity reports

Now let's call `lp_sensitivity_report`:

```
report = lp_sensitivity_report(model)
```

```

SensitivityReport{Float64}(Dict{ConstraintRef, Tuple{Float64, Float64}}(c1 : 6 x + 8 y ≥ 100 =>
  ↳ (-4.0, 2.857142857142857), x ≥ 0 => (-Inf, 15.0), y ≤ 3 => (-1.75, Inf), c3 : x + y ≤ 20 =>
  ↳ (-3.75, Inf), c2 : 7 x + 12 y ≥ 120 => (-3.3333333333333335, 4.666666666666667), y ≥ 0 =>
  ↳ (-Inf, 1.25), z ≤ 1 => (-Inf, Inf)), Dict{VariableRef, Tuple{Float64, Float64}}(y => (-4.0,
  ↳ 0.5714285714285714), x => (-0.3333333333333333, 3.0), z => (-Inf, 1.0)))

```

It returns a `SensitivityReport` object, which maps:

- Every variable reference to a tuple `(d_lo, d_hi)::Tuple{Float64,Float64}`, explaining how much the objective coefficient of the corresponding variable can change by, such that the original basis remains optimal.
- Every constraint reference to a tuple `(d_lo, d_hi)::Tuple{Float64,Float64}`, explaining how much the right-hand side of the corresponding constraint can change by, such that the basis remains optimal.

Both tuples are relative, rather than absolute. So, given an objective coefficient of 1.0 and a tuple (-0.5, 0.5), the objective coefficient can range between 1.0 - 0.5 and 1.0 + 0.5.

For example:

```
report[x]
```

```
(-0.333333333333333, 3.0)
```

indicates that the objective coefficient on  $x$ , that is, 12, can decrease by -0.333 or increase by 3.0 and the primal solution (15, 1.25) will remain optimal. In addition:

```
report[c1]
```

```
(-4.0, 2.857142857142857)
```

means that the right-hand side of the  $c_1$  constraint (100), can decrease by 4 units, or increase by 2.85 units, and the primal solution (15, 1.25) will remain optimal.

### Variable sensitivity

By themselves, the tuples aren't informative. Let's put them in context by collating a range of other information about a variable:

```
function variable_report(xi)
    return (
        name = name(xi),
        lower_bound = has_lower_bound(xi) ? lower_bound(xi) : -Inf,
        value = value(xi),
        upper_bound = has_upper_bound(xi) ? upper_bound(xi) : Inf,
        reduced_cost = reduced_cost(xi),
        obj_coefficient = coefficient(objective_function(model), xi),
        allowed_decrease = report[xi][1],
        allowed_increase = report[xi][2],
    )
end
```

```
variable_report (generic function with 1 method)
```

Calling our function on  $x$ :

```
x_report = variable_report(x)
```

```
(name = "x", lower_bound = 0.0, value = 15.0, upper_bound = Inf, reduced_cost = 0.0,
↪ obj_coefficient = 12.0, allowed_decrease = -0.33333333333333, allowed_increase = 3.0)
```

That's a bit hard to read, so let's call this on every variable in the model and put things into a DataFrame:

```
variable_df =
    DataFrames.DataFrame(variable_report(xi) for xi in all_variables(model))
```

	name	lower_bound	value	upper_bound	reduced_cost	obj_coefficient	allowed_decrease	allowed_increase
	String	Float64	Float64	Float64	Float64	Float64	Float64	Float64
1	x	0.0	15.0	Inf	0.0	12.0	-0.333333	3.0
2	y	0.0	1.25	3.0	0.0	20.0	-4.0	0.571429
3	z	-Inf	1.0	1.0	-1.0	-1.0	-Inf	1.0

## Constraint sensitivity

We can do something similar with constraints:

```
function constraint_report(c::ConstraintRef)
    return (
        name = name(c),
        value = value(c),
        rhs = normalized_rhs(c),
        slack = normalized_rhs(c) - value(c),
        shadow_price = shadow_price(c),
        allowed_decrease = report[c][1],
        allowed_increase = report[c][2],
    )
end

c1_report = constraint_report(c1)
```

```
(name = "c1", value = 100.0, rhs = 100.0, slack = 0.0, shadow_price = -0.25, allowed_decrease =
↪ -4.0, allowed_increase = 2.857142857142857)
```

That's a bit hard to read, so let's call this on every constraint in the model and put things into a DataFrame:

```
constraint_df = DataFrames.DataFrame(
    constraint_report(ci) for (F, S) in list_of_constraint_types(model) for
    ci in all_constraints(model, F, S) if F == AffExpr
)
```

## Analysis questions

Now we can use these dataframes to ask questions of the solution.

For example, we can find basic variables by looking for variables with a reduced cost of 0:

	name	value	rhs	slack	shadow_price	allowed_decrease	allowed_increase
	String	Float64	Float64	Float64	Float64	Float64	Float64
1	c1	100.0	100.0	0.0	-0.25	-4.0	2.85714
2	c2	120.0	120.0	0.0	-1.5	-3.33333	4.66667
3	c3	16.25	20.0	3.75	0.0	-3.75	Inf

```
basic = filter(row -> iszero(row.reduced_cost), variable_df)
```

	name	lower_bound	value	upper_bound	reduced_cost	obj_coefficient	allowed_decrease	allowed_increase
	String	Float64	Float64	Float64	Float64	Float64	Float64	Float64
1	x	0.0	15.0	Inf	0.0	12.0	-0.333333	3.0
2	y	0.0	1.25	3.0	0.0	20.0	-4.0	0.571429

and non-basic variables by looking for non-zero reduced costs:

```
non_basic = filter(row -> !iszero(row.reduced_cost), variable_df)
```

	name	lower_bound	value	upper_bound	reduced_cost	obj_coefficient	allowed_decrease	allowed_increase
	String	Float64	Float64	Float64	Float64	Float64	Float64	Float64
1	z	-Inf	1.0	1.0	-1.0	-1.0	-Inf	1.0

we can also find constraints that are binding by looking for zero slacks:

```
binding = filter(row -> iszero(row.slack), constraint_df)
```

	name	value	rhs	slack	shadow_price	allowed_decrease	allowed_increase
	String	Float64	Float64	Float64	Float64	Float64	Float64
1	c1	100.0	100.0	0.0	-0.25	-4.0	2.85714
2	c2	120.0	120.0	0.0	-1.5	-3.33333	4.66667

or non-zero shadow prices:

```
binding2 = filter(row -> !iszero(row.shadow_price), constraint_df)
```

## 6.22 Basis matrices

This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.

This tutorial explains how to query the basis of a linear program.

### Setup

This tutorial uses the following packages:

```
using JuMP
import HiGHS
```

	name	value	rhs	slack	shadow_price	allowed_decrease	allowed_increase
	String	Float64	Float64	Float64	Float64	Float64	Float64
1	c1	100.0	100.0	0.0	-0.25	-4.0	2.85714
2	c2	120.0	120.0	0.0	-1.5	-3.33333	4.66667

### Standard form example

Consider the following example, which is from the Wikipedia article on [Basic feasible solutions](#):

$$\begin{aligned} & \max 0 \\ \text{s.t. } & 1x_1 + 5x_2 + 3x_3 + 4x_4 + 6x_5 = 14 \\ & 0x_1 + 1x_2 + 3x_3 + 5x_4 + 6x_5 = 7 \\ & x_i \geq 0, \forall i = 1, \dots, 5. \end{aligned}$$

The A matrix is:

```
A = [1 5 3 4 6; 0 1 3 5 6]
```

```
2×5 Matrix{Int64}:
1 5 3 4 6
0 1 3 5 6
```

and the right-hand side b vector is:

```
b = [14, 7]
```

```
2-element Vector{Int64}:
14
7
```

We can create and optimize the problem in the standard form:

```
n = size(A, 2)
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:n] >= 0)
@constraint(model, A * x == b)
optimize!(model)
assert_is_solved_and_feasible(model)
```

This has a solution:

```
value.(x)
```

```
5-element Vector{Float64}:
0.0
2.0
0.0
1.0
0.0
```

Query the basis status of a variable using `MOI.VariableBasisStatus`:

```
get_attribute(x[1], MOI.VariableBasisStatus())
```

```
NONBASIC_AT_LOWER::BasisStatusCode = 2
```

the result is a `MOI.BasisStatusCode`. Query all of the basis statuses with the broadcast `get_attribute.(:`

```
get_attribute.(x, MOI.VariableBasisStatus())
```

```
5-element Vector{MathOptInterface.BasisStatusCode}:
NONBASIC_AT_LOWER::BasisStatusCode = 2
BASIC::BasisStatusCode = 0
NONBASIC_AT_LOWER::BasisStatusCode = 2
BASIC::BasisStatusCode = 0
NONBASIC_AT_LOWER::BasisStatusCode = 2
```

For this problem, the values are either `MOI.NONBASIC_AT_LOWER` or `MOI.BASIC`. All of the `MOI.NONBASIC_AT_LOWER` variables have a value at their lower bound. The `MOI.BASIC` variables correspond to the columns of the optimal basis.

Get the columns using:

```
indices = get_attribute.(x, MOI.VariableBasisStatus()) .== MOI.BASIC
```

```
5-element BitVector:
0
1
0
1
0
```

Filter the basis matrix from A:

```
B = A[:, indices]
```

```
2x2 Matrix{Int64}:
5  4
1  5
```

Since the basis matrix is non-singular, solving the system  $Bx = b$  must yield the optimal primal solution of the basic variables:

```
B \ b
```

```
2-element Vector{Float64}:
2.0
0.9999999999999998
```

```
value.(x[indices])
```

```
2-element Vector{Float64}:
2.0
1.0
```

### A more complicated example

Often, you may want to work with the basis of a model that is not in a nice standard form. For example:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x >= 0)
@variable(model, 0 <= y <= 3)
@variable(model, z <= 1)
@objective(model, Min, 12x + 20y - z)
@constraint(model, c1, 6x + 8y >= 100)
@constraint(model, c2, 7x + 12y >= 120)
@constraint(model, c3, x + y <= 20)
optimize!(model)
assert_is_solved_and_feasible(model)
```

A common way to query the basis status of every variable is:

```
v_basis = Dict(
    xi => get_attribute(xi, MOI.VariableBasisStatus()) for
    xi in all_variables(model)
)
```

```
Dict{VariableRef, MathOptInterface.BasisStatusCode} with 3 entries:
z => NONBASIC_AT_UPPER
y => BASIC
x => BASIC
```

Despite the model having three constraints, there are only two basic variables. Since the basis matrix must be square, where is the other basic variable?

The answer is that solvers will reformulate inequality constraints:

$$Ax \leq b$$

into the system:

$$Ax + Is = b$$

Thus, for every inequality constraint there is a slack variable  $s$ .

Query the basis status of the slack variables associated with a constraint using `MOI.ConstraintBasisStatus`:

```
c_basis = Dict(
    ci => get_attribute(ci, MOI.ConstraintBasisStatus()) for ci in
    all_constraints(model; include_variable_in_set_constraints = false)
)
```

```
Dict{ConstraintRef{Model, C, ScalarShape} where C, MathOptInterface.BasisStatusCode} with 3
↪ entries:
c1 : 6 x + 8 y ≥ 100  => NONBASIC
c3 : x + y ≤ 20      => BASIC
c2 : 7 x + 12 y ≥ 120 => NONBASIC
```

Thus, the basis is formed by  $x$ ,  $y$ , and the slack associated with  $c3$ .

A simple way to get the  $A$  matrix of an unstructured linear program is with `lp_matrix_data`:

```
matrix = lp_matrix_data(model)
matrix.A
```

```
3×3 SparseArrays.SparseMatrixCSC{Float64, Int64} with 6 stored entries:
6.0  8.0  .
7.0  12.0 .
1.0  1.0  .
```

You can check the permutation of the rows and columns using

```
matrix.variables
```

```
3-element Vector{VariableRef}:
x
y
z
```

and

```
matrix.affine_constraints
```

```
3-element Vector{ConstraintRef}:
c1 : 6 x + 8 y ≥ 100
c2 : 7 x + 12 y ≥ 120
c3 : x + y ≤ 20
```

We can construct the slack column associated with c3 as:

```
s_column = zeros(size(matrix.A, 1))
s_column[3] = 1.0
```

```
1.0
```

The full basis matrix is therefore:

```
B = hcat(matrix.A[:, [1, 2]], s_column)
```

```
3x3 SparseArrays.SparseMatrixCSC{Float64, Int64} with 7 stored entries:
 6.0   8.0   ·
 7.0  12.0   ·
 1.0   1.0   1.0
```

`lp_matrix_data` returns separate vectors for the lower and upper row bounds. Convert to a single right-hand side vector by taking the finite elements:

```
b = ifelse.(isfinite.(matrix.b_lower), matrix.b_lower, matrix.b_upper)
```

```
3-element Vector{Float64}:
100.0
120.0
20.0
```

Solving the Basis system as before yields:

```
B \ b
```

```
3-element Vector{Float64}:
14.99999999999995
1.2500000000000004
3.75
```

which is the value of  $x$ ,  $y$ , and the slack associated with  $c_3$ .

### Identifying degenerate variables

Another common task is identifying degenerate variables. A degenerate variable is a basic variable that has an optimal value at its lower or upper bound.

Here is a function that computes whether a variable is degenerate:

```
function is_degenerate(x)
    if get_attribute(x, MOI.VariableBasisStatus()) == MOI.BASIC
        return (has_lower_bound(x) && ≈(value(x), lower_bound(x))) ||
               (has_upper_bound(x) && ≈(value(x), upper_bound(x)))
    end
    return false
end
```

```
is_degenerate (generic function with 1 method)
```

A simple example of a linear program with a degenerate solution is:

```
A, b, c = [1 1; 0 1], [1, 1], [1, 1]
model = Model(HiGHS.Optimizer);
set_silent(model)
@variable(model, x[1:2] >= 0)
@objective(model, Min, c' * x)
@constraint(model, A * x == b)
optimize!(model)
degenerate_variables = filter(is_degenerate, all_variables(model))
```

```
1-element Vector{VariableRef}:
x[1]
```

The solution is degenerate because:

```
value(x[1])
```

```
-0.0
```

and

```
get_attribute(x[1], MOI.VariableBasisStatus())
```

```
BASIC::BasisStatusCode = 0
```

## 6.23 Computing the duals of a mixed-integer program

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

This tutorial explains how to compute the duals of a mixed-integer linear program by fixing the discrete variables to their optimal solution and resolving as a linear program.

This tutorial uses the following packages:

```
using JuMP
import HiGHS
```

### The model

Our example model is the unit commitment example from [Unit commitment](#). The details are unimportant, other than to note that there are two types of continuous variables,  $g$  and  $w$ , representing the quantity of generation from thermal and wind plants, and a discrete variable  $dispatch$ , which is 1 if plant  $i$  is operating, and 0 if not.

We are interested in the "dual" of the `power_balance` constraint, because it represents the marginal price of electricity that consumers should pay for their consumption.

```
generators = [
    (min = 0.0, max = 1000.0, fixed_cost = 1000.0, variable_cost = 50.0),
    (min = 300.0, max = 1000.0, fixed_cost = 0.0, variable_cost = 100.0),
]
N = length(generators)
model = Model(HiGHS.Optimizer)
set_silent(model)
@variables(model, begin
    generators[i].min <= g[i = 1:N] <= generators[i].max
    0 <= w <= 200
    dispatch[i = 1:N], Bin
end)
@constraints(model, begin
    power_balance, sum(g[i] for i in 1:N) + w == 1500
)
```

```
[i = 1:N], g[i] <= generators[i].max * dispatch[i]
[i = 1:N], g[i] >= generators[i].min * dispatch[i]
end)
@objective(
    model,
    Min,
    sum(
        generators[i].fixed_cost * dispatch[i] +
        generators[i].variable_cost * g[i] for i in 1:N
    )
)
print(model)
```

```
Min 1000 dispatch[1] + 50 g[1] + 100 g[2]
Subject to
power_balance : g[1] + g[2] + w = 1500
g[1] ≥ 0
g[2] - 300 dispatch[2] ≥ 0
g[1] - 1000 dispatch[1] ≤ 0
g[2] - 1000 dispatch[2] ≤ 0
g[1] ≥ 0
g[2] ≥ 300
w ≥ 0
g[1] ≤ 1000
g[2] ≤ 1000
w ≤ 200
dispatch[1] binary
dispatch[2] binary
```

### Manually fix the variables

If we optimize this model, we obtain a `dual_status` of `NO_SOLUTION`:

```
optimize!(model)
assert_is_solved_and_feasible(model)
dual_status(model)
```

```
NO_SOLUTION::ResultStatusCode = 0
```

This is because HiGHS cannot compute the duals of a mixed-integer program. We can work around this problem by fixing the integer variables to their optimal solution, relaxing integrality, and re-solving as a linear program.

```
discrete_values = value.(dispatch)
fix.(dispatch, discrete_values; force = true)
unset_binary.(dispatch)
print(model)
```

```

Min 1000 dispatch[1] + 50 g[1] + 100 g[2]
Subject to
power_balance : g[1] + g[2] + w = 1500
g[1] ≥ 0
g[2] - 300 dispatch[2] ≥ 0
g[1] - 1000 dispatch[1] ≤ 0
g[2] - 1000 dispatch[2] ≤ 0
dispatch[1] = 1
dispatch[2] = 1
g[1] ≥ 0
g[2] ≥ 300
w ≥ 0
g[1] ≤ 1000
g[2] ≤ 1000
w ≤ 200

```

Now if we re-solve the problem, we obtain a [FEASIBLE\\_POINT](#) for the dual:

```

optimize!(model)
assert_is_solved_and_feasible(model)
dual_status(model)

```

```
FEASIBLE_POINT::ResultStatusCode = 1
```

and a marginal price of electricity of \$100/MWh:

```
dual(power_balance)
```

```
100.0
```

To reset the problem back to a mixed-integer linear program, we need to [unfix](#) and call [set\\_binary](#):

```

unfix.(dispatch)
set_binary.(dispatch)
print(model)

```

```

Min 1000 dispatch[1] + 50 g[1] + 100 g[2]
Subject to
power_balance : g[1] + g[2] + w = 1500
g[1] ≥ 0
g[2] - 300 dispatch[2] ≥ 0
g[1] - 1000 dispatch[1] ≤ 0
g[2] - 1000 dispatch[2] ≤ 0
g[1] ≥ 0

```

```

g[2] ≥ 300
w ≥ 0
g[1] ≤ 1000
g[2] ≤ 1000
w ≤ 200
dispatch[1] binary
dispatch[2] binary

```

### Use `fix_discrete_variables`

Manually choosing the variables to relax and fix works for our small example, but it becomes more difficult in problems with a larger number of binary and integer variables. To automate the process we just did manually, JuMP provides the `fix_discrete_variables` function:

```

optimize!(model)
assert_is_solved_and_feasible(model)
dual_status(model)

```

```
NO_SOLUTION::ResultStatusCode = 0
```

```
undo = fix_discrete_variables(model);
```

Here `undo` is a function that, when called with no arguments, returns the model to the original mixed-integer formulation.

#### Tip

After calling `fix_discrete_variables`, you can set a new solver with `set_optimizer` if your mixed-integer solver does not support computing a dual solution.

```
print(model)
```

```

Min 1000 dispatch[1] + 50 g[1] + 100 g[2]
Subject to
power_balance : g[1] + g[2] + w = 1500
g[1] ≥ 0
g[2] - 300 dispatch[2] ≥ 0
g[1] - 1000 dispatch[1] ≤ 0
g[2] - 1000 dispatch[2] ≤ 0
dispatch[1] = 1
dispatch[2] = 1
g[1] ≥ 0
g[2] ≥ 300
w ≥ 0
g[1] ≤ 1000

```

```
g[2] ≤ 1000
w ≤ 200
```

```
optimize!(model)
assert_is_solved_and_feasible(model)
dual_status(model)
```

```
FEASIBLE_POINT::ResultStatusCode = 1
```

```
dual(power_balance)
```

```
100.0
```

Finally, call undo to revert the reformulation

```
undo()
print(model)
```

```
Min 1000 dispatch[1] + 50 g[1] + 100 g[2]
Subject to
power_balance : g[1] + g[2] + w = 1500
g[1] ≥ 0
g[2] - 300 dispatch[2] ≥ 0
g[1] - 1000 dispatch[1] ≤ 0
g[2] - 1000 dispatch[2] ≤ 0
g[1] ≥ 0
g[2] ≥ 300
w ≥ 0
g[1] ≤ 1000
g[2] ≤ 1000
w ≤ 200
dispatch[1] binary
dispatch[2] binary
```

## 6.24 Finding multiple feasible solutions

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

*Author: James Foster (@jd-foster)*

This tutorial demonstrates how to formulate and solve a combinatorial problem with multiple feasible solutions. In fact, we will see how to find *all* feasible solutions to our problem. We will also see how to enforce an "all-different" constraint on a set of integer variables.

## Required packages

This tutorial uses the following packages:

```
using JuMP
import Gurobi
import Test
```

### Warning

This tutorial uses [Gurobi.jl](#) as the solver because it supports returning multiple feasible solutions, something that open-source MIP solvers such as HiGHS do not currently support. Gurobi is a commercial solver and requires a paid license. However, there are free licenses available for academic and student users. See [Gurobi.jl](#) for more details.

## Symmetric number squares

Symmetric [number squares](#) and their sums often arise in recreational mathematics. Here are a few examples:

$$\begin{array}{r} 1 \ 5 \ 2 \ 9 \\ 5 \ 8 \ 3 \ 7 \\ + \ 2 \ 3 \ 4 \ 0 \\ = \ 9 \ 7 \ 0 \ 6 \end{array} \quad \begin{array}{r} 2 \ 3 \ 1 \ 8 \\ 3 \ 7 \ 9 \ 0 \\ + 1 \ 9 \ 5 \ 6 \\ = 8 \ 0 \ 6 \ 4 \end{array} \quad \begin{array}{r} 5 \ 2 \ 1 \ 9 \\ 2 \ 3 \ 8 \ 4 \\ + 1 \ 8 \ 6 \ 7 \\ = 9 \ 4 \ 7 \ 0 \end{array}$$

Notice how all the digits 0 to 9 are used at least once, the first three rows sum to the last row, the columns in each are the same as the corresponding rows (forming a symmetric matrix), and 0 does not appear in the first column.

We will answer the question: how many such squares are there?

### JuMP model

We now encode the symmetric number square as a JuMP model. First, we need a symmetric matrix of decision variables between 0 and 9 to represent each number:

```
n = 4
optimizer = Gurobi.Optimizer
model = Model(optimizer)
set_silent(model)
@variable(model, 0 <= x_digits[row in 1:n, col in 1:n] <= 9, Int, Symmetric)
```

```
4x4 LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}:
x_digits[1,1]  x_digits[1,2]  x_digits[1,3]  x_digits[1,4]
x_digits[1,2]  x_digits[2,2]  x_digits[2,3]  x_digits[2,4]
x_digits[1,3]  x_digits[2,3]  x_digits[3,3]  x_digits[3,4]
x_digits[1,4]  x_digits[2,4]  x_digits[3,4]  x_digits[4,4]
```

We modify the lower bound to ensure that the first column cannot contain 0:

```
set_lower_bound.(x_digits[:, 1], 1)
```

```
4-element Vector{Nothing}:
nothing
nothing
nothing
nothing
```

Then, we need a constraint that the sum of the first three rows equals the last row:

```
@expression(model, x_base_10, x_digits * [1_000, 100, 10, 1]);
@constraint(model, sum(x_base_10[i] for i in 1:n-1) == x_base_10[n])
```

$$1000x_{digits_{1,1}} + 1100x_{digits_{1,2}} + 100x_{digits_{2,2}} + 1010x_{digits_{1,3}} + 110x_{digits_{2,3}} + 10x_{digits_{3,3}} - 999x_{digits_{1,4}} - 99x_{digits_{2,4}}$$

And we use `MOI.AllDifferent` to ensure that each digit is used exactly once in the upper triangle matrix of `x_digits`:

```
x_digits_upper = [x_digits[i, j] for j in 1:n for i in 1:j]
@constraint(model, x_digits_upper in MOI.AllDifferent(length(x_digits_upper)));
```

If we optimize this model, we find that Gurobi has returned one solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
Test.@test result_count(model) == 1
solution_summary(model)
```

```
* Solver : Gurobi

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "Model was solved to optimality (subject to tolerances), and an optimal solution is available."

* Candidate solution (result #1)
  Primal status       : FEASIBLE_POINT
  Dual status         : NO_SOLUTION
  Objective value     : 0.00000e+00
  Objective bound     : 0.00000e+00
  Relative gap        : 0.00000e+00
  Dual objective value : 0.00000e+00

* Work counters
```

```
Solve time (sec)    : 4.54578e-02
Simplex iterations : 1587
Barrier iterations : 0
Node count         : 255
```

To return multiple solutions, we need to set Gurobi-specific parameters to enable the [solution pool](#). Moreover, there is a bug in Gurobi that means the solution pool is not activated if we have already solved the model once. To work around the bug, we need to reset the optimizer. If you turn the solution pool options on before the first solve you do not need to reset the optimizer.

```
set_optimizer(model, optimizer)
```

```
Set parameter WLSAccessID
Set parameter WLSSecret
Set parameter LicenseID to value 722777
Set parameter GURO_PAR_SPECIAL
WLS license 722777 - registered to JuMP Development
```

The first option turns on the exhaustive search mode for multiple solutions:

```
set_attribute(model, "PoolSearchMode", 2)
```

The second option sets a limit for the number of solutions found:

```
set_attribute(model, "PoolSolutions", 100)
```

Here the value 100 is an "arbitrary but large enough" whole number for our particular model (and in general will depend on the application).

We can then call `optimize!` and view the results.

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : Gurobi

* Status
  Result count      : 20
  Termination status : OPTIMAL
  Message from the solver:
  "Model was solved to optimality (subject to tolerances), and an optimal solution is available."

* Candidate solution (result #1)
  Primal status     : FEASIBLE_POINT
```

```

Dual status      : NO_SOLUTION
Objective value  : 0.00000e+00
Objective bound   : 0.00000e+00
Relative gap     : 0.00000e+00
Dual objective value : 0.00000e+00

* Work counters
Solve time (sec)  : 3.78707e-01
Simplex iterations : 19526
Barrier iterations : 0
Node count        : 4661

```

Now Gurobi has found 20 solutions:

```
result_count(model)
```

```
20
```

## Viewing the Results

Access the various feasible solutions by using the `value` function with the `result` keyword:

```
solutions =
    [round.(Int, value.(x_digits; result = i)) for i in 1:result_count(model)];
```

Here we have converted the solution to an integer after rounding off very small numerical tolerances.

An example of one feasible solution is:

```
solutions[1]
```

```
4x4 Matrix{Int64}:
1 5 2 9
5 8 3 7
2 3 4 0
9 7 0 6
```

and we can nicely print out all the feasible solutions with

```
function solution_string(x::Matrix)
    header = [" ", " ", "+", "="]
    return join([join(vcat(header[i], x[i, :]), " ") for i in 1:4], "\n")
end
```

```
for i in 1:result_count(model)
    println("Solution $i: \n", solution_string(solutions[i]), "\n")
end
```

Solution 1:

```
1 5 2 9
5 8 3 7
+ 2 3 4 0
= 9 7 0 6
```

Solution 2:

```
1 5 2 9
5 7 4 6
+ 2 4 0 8
= 9 6 8 3
```

Solution 3:

```
1 3 2 7
3 6 5 4
+ 2 5 0 8
= 7 4 8 9
```

Solution 4:

```
2 3 1 7
3 5 6 4
+ 1 6 0 8
= 7 4 8 9
```

Solution 5:

```
2 1 4 8
1 9 6 7
+ 4 6 3 5
= 8 7 5 0
```

Solution 6:

```
3 2 1 7
2 9 4 5
+ 1 4 0 6
= 7 5 6 8
```

Solution 7:

```
1 2 3 7
2 9 6 8
+ 3 6 4 5
= 7 8 5 0
```

Solution 8:

```
2 3 1 8
3 7 9 0
+ 1 9 5 6
= 8 0 6 4
```

Solution 9:

```
5 1 3 9
```

$$\begin{array}{r} 1 \ 0 \ 4 \ 6 \\ + 3 \ 4 \ 8 \ 7 \\ = 9 \ 6 \ 7 \ 2 \end{array}$$

Solution 10:

$$\begin{array}{r} 5 \ 2 \ 1 \ 9 \\ 2 \ 6 \ 8 \ 7 \\ + 1 \ 8 \ 3 \ 4 \\ = 9 \ 7 \ 4 \ 0 \end{array}$$

Solution 11:

$$\begin{array}{r} 5 \ 2 \ 1 \ 9 \\ 2 \ 3 \ 8 \ 4 \\ + 1 \ 8 \ 6 \ 7 \\ = 9 \ 4 \ 7 \ 0 \end{array}$$

Solution 12:

$$\begin{array}{r} 2 \ 1 \ 6 \ 9 \\ 1 \ 3 \ 0 \ 5 \\ + 6 \ 0 \ 7 \ 4 \\ = 9 \ 5 \ 4 \ 8 \end{array}$$

Solution 13:

$$\begin{array}{r} 1 \ 2 \ 5 \ 9 \\ 2 \ 6 \ 4 \ 3 \\ + 5 \ 4 \ 7 \ 8 \\ = 9 \ 3 \ 8 \ 0 \end{array}$$

Solution 14:

$$\begin{array}{r} 1 \ 2 \ 5 \ 9 \\ 2 \ 4 \ 3 \ 0 \\ + 5 \ 3 \ 8 \ 7 \\ = 9 \ 0 \ 7 \ 6 \end{array}$$

Solution 15:

$$\begin{array}{r} 2 \ 1 \ 4 \ 8 \\ 1 \ 5 \ 6 \ 3 \\ + 4 \ 6 \ 7 \ 9 \\ = 8 \ 3 \ 9 \ 0 \end{array}$$

Solution 16:

$$\begin{array}{r} 5 \ 2 \ 1 \ 9 \\ 2 \ 7 \ 4 \ 3 \\ + 1 \ 4 \ 0 \ 6 \\ = 9 \ 3 \ 6 \ 8 \end{array}$$

Solution 17:

$$\begin{array}{r} 5 \ 1 \ 3 \ 9 \\ 1 \ 4 \ 0 \ 6 \\ + 3 \ 0 \ 8 \ 2 \\ = 9 \ 6 \ 2 \ 7 \end{array}$$

Solution 18:

$$\begin{array}{r} 1 \ 2 \ 3 \ 7 \\ 2 \ 5 \ 6 \ 4 \end{array}$$

$$\begin{array}{r} + 3 6 8 9 \\ = 7 4 9 0 \end{array}$$

Solution 19:

$$\begin{array}{r} 1 4 2 8 \\ 4 7 5 6 \\ + 2 5 0 9 \\ = 8 6 9 3 \end{array}$$

Solution 20:

$$\begin{array}{r} 3 2 1 6 \\ 2 0 4 7 \\ + 1 4 9 5 \\ = 6 7 5 8 \end{array}$$

The result is the full list of feasible solutions. So the answer to "how many such squares are there?" turns out to be 20.

## Chapter 7

# Nonlinear programs

### 7.1 Introduction

Nonlinear programs (NLPs) are a class of optimization problems in which some of the constraints or the objective function are nonlinear:

$$\min_{x \in \mathbb{R}^n} f_0(x) \quad (7.1)$$

$$\text{s.t. } l_j \leq f_j(x) \leq u_j \quad j = 1 \dots m \quad (7.2)$$

$$l_i \leq x_i \leq u_i \quad i = 1 \dots n. \quad (7.3)$$

Mixed-integer nonlinear linear programs (MINLPs) are extensions of nonlinear programs in which some (or all) of the decision variables take discrete values.

#### How to choose a solver

JuMP supports a range of nonlinear solvers; look for "NLP" in the list of [Supported solvers](#). However, very few solvers support mixed-integer nonlinear linear programs. Solvers supporting discrete variables start with "(MI)" in the list of [Supported solvers](#).

If the only nonlinearities in your model are quadratic terms (that is, multiplication between two decision variables), you can also use second-order cone solvers, which are indicated by "SOCP." In most cases, these solvers are restricted to convex quadratic problems and will error if you pass a nonconvex quadratic function; however, Gurobi has the ability to solve nonconvex quadratic terms.

#### How these tutorials are structured

Having a high-level overview of how this part of the documentation is structured will help you know where to look for certain things.

- The following tutorials are worked examples that present a problem in words, then formulate it in mathematics, and then solve it in JuMP. This usually involves some sort of visualization of the solution. Start here if you are new to JuMP.
  - [Example: nonlinear optimal control of a rocket](#)
  - [Example: optimal control for a Space Shuttle reentry trajectory](#)
  - [Example: portfolio optimization](#)

- The [Computing Hessians](#) is an advanced tutorial which explains how to compute the Hessian of the Lagrangian of a nonlinear program. This is useful only in particular cases.
- The remaining tutorials are less verbose and styled in the form of short code examples. These tutorials have less explanation, but may contain useful code snippets, particularly if they are similar to a problem you are trying to solve.

## 7.2 Simple examples

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

This tutorial is a collection of examples of small nonlinear programs.

### Required packages

This tutorial uses the following packages:

```
using JuMP
import Ipopt
import Random
import Statistics
import Test
```

### The Rosenbrock function

A nonlinear example of the classical [Rosenbrock function](#).

```
function example_rosenbrock()
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, x)
    @variable(model, y)
    @objective(model, Min, (1 - x)^2 + 100 * (y - x^2)^2)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    Test.@test objective_value(model) ≈ 0.0 atol = 1e-10
    Test.@test value(x) ≈ 1.0
    Test.@test value(y) ≈ 1.0
    return
end

example_rosenbrock()
```

### The cnlbeam problem

Based on an AMPL model by Hande Y. Benson

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Source:

H. Maurer and H.D. Mittelman, "The non-linear beam via optimal control with bound state variables," Optimal Control Applications and Methods 12, pp. 19-31, 1991.

```

function example_cnlbeam()
    N = 1000
    h = 1 / N
    alpha = 350
    model = Model(Ipopt.Optimizer)
    @variables(model, begin
        -1 <= t[1:(N+1)] <= 1
        -0.05 <= x[1:(N+1)] <= 0.05
        u[1:(N+1)])
    end)
    @objective(
        model,
        Min,
        sum(
            0.5 * h * (u[i+1]^2 + u[i]^2) +
            0.5 * alpha * h * (cos(t[i+1]) + cos(t[i])) for i in 1:N
        ),
    )
    @constraint(
        model,
        [i = 1:N],
        x[i+1] - x[i] - 0.5 * h * (sin(t[i+1]) + sin(t[i])) == 0,
    )
    @constraint(
        model,
        [i = 1:N],
        t[i+1] - t[i] - 0.5 * h * u[i+1] - 0.5 * h * u[i] == 0,
    )
    optimize!(model)
    println("""
        termination_status = $(termination_status(model))
        primal_status      = $(primal_status(model))
        objective_value    = $(objective_value(model))
    """)
    assert_is_solved_and_feasible(model)
    return
end

example_cnlbeam()

```

This is Ipopt version 3.14.17, running with linear solver MUMPS 5.7.3.

Number of nonzeros in equality constraint Jacobian...	8000
Number of nonzeros in inequality constraint Jacobian.:	0
Number of nonzeros in Lagrangian Hessian.....:	4002
Total number of variables.....:	3003
variables with only lower bounds:	0
variables with lower and upper bounds:	2002

```

variables with only upper bounds:          0
Total number of equality constraints.....: 2000
Total number of inequality constraints....: 0
    inequality constraints with only lower bounds: 0
    inequality constraints with lower and upper bounds: 0
    inequality constraints with only upper bounds: 0

iter   objective   inf_pr   inf_du lg(mu) ||d|| lg(rg) alpha_du alpha_pr ls
  0  3.500000e+02 0.00e+00 0.00e+00 -1.0 0.00e+00 - 0.00e+00 0.00e+00 0
  1  3.500000e+02 0.00e+00 0.00e+00 -1.7 0.00e+00 - 1.00e+00 1.00e+00 0
  2  3.500000e+02 0.00e+00 0.00e+00 -3.8 0.00e+00 -2.0 1.00e+00 1.00e+00T 0
  3  3.500000e+02 0.00e+00 0.00e+00 -5.7 0.00e+00 0.2 1.00e+00 1.00e+00T 0
  4  3.500000e+02 0.00e+00 0.00e+00 -8.6 0.00e+00 -0.2 1.00e+00 1.00e+00T 0

Number of Iterations....: 4

(scaled)                      (unscaled)
Objective.....: 3.5000000000000318e+02 3.5000000000000318e+02
Dual infeasibility.....: 0.00000000000000e+00 0.00000000000000e+00
Constraint violation....: 0.00000000000000e+00 0.00000000000000e+00
Variable bound violation: 0.00000000000000e+00 0.00000000000000e+00
Complementarity.....: 2.5059035596802450e-09 2.5059035596802450e-09
Overall NLP error.....: 2.5059035596802450e-09 2.5059035596802450e-09

Number of objective function evaluations = 5
Number of objective gradient evaluations = 5
Number of equality constraint evaluations = 5
Number of inequality constraint evaluations = 0
Number of equality constraint Jacobian evaluations = 5
Number of inequality constraint Jacobian evaluations = 0
Number of Lagrangian Hessian evaluations = 4
Total seconds in IPOPT = 0.030

EXIT: Optimal Solution Found.
termination_status = LOCALLY_SOLVED
primal_status      = FEASIBLE_POINT
objective_value    = 350.000000000032

```

## Maximum likelihood estimation

This example uses nonlinear optimization to compute the maximum likelihood estimate (MLE) of the parameters of a normal distribution, a.k.a., the sample mean and variance.

```

function example_mle()
  n = 1_000
  Random.seed!(1234)
  data = randn(n)
  model = Model(Ipopt.Optimizer)
  set_silent(model)
  @variable(model, μ, start = 0.0)
  @variable(model, σ >= 0.0, start = 1.0)
  @objective(

```

```

        model,
        Max,
        n / 2 * log(1 / (2 * π * σ^2)) -
        sum((data[i] - μ)^2 for i in 1:n) / (2 * σ^2)
    )
    optimize!(model)
    assert_is_solved_and_feasible(model)
    println("μ           = ", value(μ))
    println("mean(data)   = ", Statistics.mean(data))
    println("σ^2          = ", value(σ)^2)
    println("var(data)     = ", Statistics.var(data))
    println("MLE objective = ", objective_value(model))
    Test.@test value(μ) ≈ Statistics.mean(data) atol = 1e-3
    Test.@test value(σ)^2 ≈ Statistics.var(data) atol = 1e-2
    # You can even do constrained MLE!
    @constraint(model, μ == σ^2)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    Test.@test value(μ) ≈ value(σ)^2
    println()
    println("With constraint μ == σ^2:")
    println("μ           = ", value(μ))
    println("σ^2          = ", value(σ)^2)
    println("Constrained MLE objective = ", objective_value(model))
    return
end

example_mle()

```

```

μ           = -0.0215521734290741
mean(data)   = -0.021552173429074114
σ^2          = 1.100101397871862
var(data)     = 1.1012026004695599
MLE objective = -1466.6397109231782

With constraint μ == σ^2:
μ           = 0.6621385003734601
σ^2          = 0.66213850037346
Constrained MLE objective = -1896.4889420749978

```

## Quadratically constrained programs

A simple quadratically constrained program based on an [example from Gurobi](#).

```

function example_qcp()
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, x)
    @variable(model, y >= 0)
    @variable(model, z >= 0)
    @objective(model, Max, x)
    @constraint(model, x + y + z == 1)

```

```

@constraint(model, x * x + y * y - z * z <= 0)
@constraint(model, x * x - y * z <= 0)
optimize!(model)
assert_is_solved_and_feasible(model)
print(model)
println("Objective value: ", objective_value(model))
println("x = ", value(x))
println("y = ", value(y))
Test.@test objective_value(model) ≈ 0.32699 atol = 1e-5
Test.@test value(x) ≈ 0.32699 atol = 1e-5
Test.@test value(y) ≈ 0.25707 atol = 1e-5
return
end

example_qcp()

```

```

Max x
Subject to
x + y + z = 1
x^2 + y^2 - z^2 ≤ 0
x^2 - y*z ≤ 0
y ≥ 0
z ≥ 0
Objective value: 0.32699283491387243
x = 0.32699283491387243
y = 0.2570658388068964

```

### 7.3 User-defined operators with vector outputs

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to demonstrate how to write a user-defined operator with a vector-valued output.

#### Required packages

This tutorial uses the following packages:

```

using JuMP
import Ipopt
import Test

```

#### Motivation

A common situation is to have a user-defined operator like the following that returns multiple outputs (we define `function_calls` to keep track of how many times we call this method):

```

function_calls = 0
function foo(x, y)
    global function_calls += 1

```

```

common_term = x^2 + y^2
term_1 = sqrt(1 + common_term)
term_2 = common_term
return term_1, term_2
end

```

foo (generic function with 1 method)

For example, the first term might be used in the objective, and the second term might be used in a constraint, and often they share work that is expensive to evaluate.

This is a problem for JuMP, because it requires user-defined operators to return a single number. One option is to define two separate functions, the first returning the first argument, and the second returning the second argument.

```

foo_1(x, y) = foo(x, y)[1]
foo_2(x, y) = foo(x, y)[2]

```

foo\_2 (generic function with 1 method)

However, if the common term is expensive to compute, this approach is wasteful because it will evaluate the expensive term twice. Let's have a look at how many times we evaluate  $x^2 + y^2$  during a solve:

```

model = Model(Ipopt.Optimizer)
set_silent(model)
@variable(model, x[1:2] >= 0, start = 0.1)
@operator(model, op_foo_1, 2, foo_1)
@operator(model, op_foo_2, 2, foo_2)
@objective(model, Max, op_foo_1(x[1], x[2]))
@constraint(model, op_foo_2(x[1], x[2]) <= 2)
function_calls = 0
optimize!(model)
assert_is_solved_and_feasible(model)
Test.@test objective_value(model) ≈ √3 atol = 1e-4
Test.@test value.(x) ≈ [1.0, 1.0] atol = 1e-4
println("Naive approach: function calls = $(function_calls)")

```

Naive approach: function calls = 44

## Memoization

An alternative approach is to use *memoization*, which uses a cache to store the result of function evaluations. We can write a memoization function as follows:

```
"""
memoize(foo::Function, n_outputs::Int)

Take a function `foo` and return a vector of length `n_outputs`, where element
`i` is a function that returns the equivalent of `foo(x...)[i]`.

To avoid duplication of work, cache the most-recent evaluations of `foo`.
Because `foo_i` is auto-differentiated with ForwardDiff, our cache needs to
work when `x` is a `Float64` and a `ForwardDiff.Dual`.

"""

function memoize(foo::Function, n_outputs::Int)
    last_x, last_f = nothing, nothing
    last_dx, last_dfdx = nothing, nothing
    function foo_i(i, x::T...) where {T<:Real}
        if T == Float64
            if x !== last_x
                last_x, last_f = x, foo(x...)
            end
            return last_f[i]::T
        else
            if x !== last_dx
                last_dx, last_dfdx = x, foo(x...)
            end
            return last_dfdx[i]::T
        end
    end
    return [(x...) -> foo_i(i, x...) for i in 1:n_outputs]
end

```

Main.memoize

Let's see how it works. First, construct the memoized versions of `foo`:

```
memoized_foo = memoize(foo, 2)
```

```
2-element Vector{Main.var"#4#7"{Int64, Main.var"#foo_i#5"{typeof(Main.foo)}}}:
#4 (generic function with 1 method)
#4 (generic function with 1 method)
```

Now try evaluating the first element of `memoized_foo`.

```
function_calls = 0
memoized_foo[1](1.0, 1.0)
println("function_calls = ", function_calls)
```

```
function_calls = 1
```

As expected, this evaluated the function once. However, if we call the function again, we hit the cache instead of needing to re-compute `foo` and `function_calls` is still 1!

```
memoized_foo[1](1.0, 1.0)
println("function_calls = ", function_calls)
```

```
function_calls = 1
```

Now let's see how this works during a real solve:

```
model = Model(Ipopt.Optimizer)
set_silent(model)
@variable(model, x[1:2] >= 0, start = 0.1)
@operator(model, op_foo_1, 2, memoized_foo[1])
@operator(model, op_foo_2, 2, memoized_foo[2])
@objective(model, Max, op_foo_1(x[1], x[2]))
@constraint(model, op_foo_2(x[1], x[2]) <= 2)
function_calls = 0
optimize!(model)
assert_is_solved_and_feasible(model)
Test.@test objective_value(model) ≈ √3 atol = 1e-4
Test.@test value.(x) ≈ [1.0, 1.0] atol = 1e-4
println("Memoized approach: function_calls = $(function_calls)")
```

```
Memoized approach: function_calls = 22
```

Compared to the naive approach, the memoized approach requires half as many function evaluations.

## 7.4 Automatic differentiation of user-defined operators

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to demonstrate how to apply automatic differentiation to [User-defined operators](#).

### Tip

This tutorial is for advanced users. As an alternative, consider using [Function tracing](#) instead of creating an operator, and if an operator is necessary, consider using the default of `@operator(model, op_f, N, f)` instead of passing explicit [Gradients and Hessians](#).

## Required packages

This tutorial uses the following packages:

```
using JuMP
import DifferentiationInterface
import Enzyme
import ForwardDiff
import Ipopt
import Test
```

## Primal function

As a simple example, we consider the Rosenbrock function:

```
f(x::T...) where {T} = (1 - x[1])^2 + 100 * (x[2] - x[1]^2)^2
```

```
f (generic function with 1 method)
```

Here's the value at a random point:

```
x = rand(2)
```

```
2-element Vector{Float64}:
 0.8809678954777748
 0.5901641516460916
```

```
f(x...)
```

```
3.4715474597921627
```

## Analytic derivative

If expressions are simple enough, you can provide analytic functions for the gradient and Hessian.

### Gradient

The Rosenbrock function has the gradient vector:

```
function analytic_Vf(g::AbstractVector, x...)
    g[1] = 400 * x[1]^3 - 400 * x[1] * x[2] + 2 * x[1] - 2
    g[2] = 200 * (x[2] - x[1]^2)
    return
end
```

```
analytic_Vf (generic function with 1 method)
```

Let's evaluate it at the same vector  $x$ :

```
analytic_g = zeros(2)
analytic_Vf(analytic_g, x...)
analytic_g
```

```
2-element Vector{Float64}:
 65.28490308207542
 -37.18805624328958
```

## Hessian

The Hessian matrix is:

```
function analytic_V^2f(H::AbstractMatrix, x...)
    H[1, 1] = 1200 * x[1]^2 - 400 * x[2] + 2
    # H[1, 2] = -400 * x[1] <-- not needed because Hessian is symmetric
    H[2, 1] = -400 * x[1]
    H[2, 2] = 200.0
    return
end
```

```
analytic_V^2f (generic function with 1 method)
```

Note that because the Hessian is symmetric, JuMP requires that we fill in only the lower triangle.

```
analytic_H = zeros(2, 2)
analytic_V^2f(analytic_H, x...)
analytic_H
```

```
2x2 Matrix{Float64}:
 697.26      0.0
 -352.387   200.0
```

## JuMP example

Putting our analytic functions together, we get:

```

function analytic_rosenbrock()
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, x[1:2])
    @operator(model, op_rosenbrock, 2, f, analytic_∇f, analytic_∇²f)
    @objective(model, Min, op_rosenbrock(x[1], x[2]))
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(x)
end

analytic_rosenbrock()

```

```

2-element Vector{Float64}:
 0.999999999999655
 0.999999999999305

```

## ForwardDiff

Instead of analytic functions, you can use [ForwardDiff.jl](#) to compute derivatives.

### Info

If you do not specify a gradient or Hessian, JuMP will use ForwardDiff.jl to compute derivatives by default. We provide this section as a worked example of what is going on under the hood.

### Pros and cons

The main benefit of ForwardDiff is that it is simple, robust, and works with a broad range of Julia syntax.

The main downside is that  $f$  must be a function that accepts arguments of  $x::\text{Real}....$ . See [Common mistakes when writing a user-defined operator](#) for more details.

### Gradient

The gradient can be computed using `ForwardDiff.gradient!`. Note that `ForwardDiff` expects a single `Vector{T}` argument, but we receive  $x$  as a tuple, so we need  $y \rightarrow f(y\dots)$  and `collect(x)` to get things in the right format.

```

function fdiff_∇f(g::AbstractVector{T}, x::Vararg{T,N}) where {T,N}
    ForwardDiff.gradient!(g, y → f(y\dots), collect(x))
    return
end

```

```

fdiff_∇f (generic function with 1 method)

```

Let's check that we find the analytic solution:

```
fdiff_g = zeros(2)
fdiff_Vf(fdif_g, x...)
Test.@test ≈(analytic_g, fdif_g)
```

Test Passed

## Hessian

The Hessian is a bit more complicated, but code to implement it is:

```
function fdiff_V^2f(H::AbstractMatrix{T}, x::Vararg{T,N}) where {T,N}
    h = ForwardDiff.hessian(y -> f(y...), collect(x))
    for i in 1:N, j in 1:i
        H[i, j] = h[i, j]
    end
    return
end
```

fdiff\_V^2f (generic function with 1 method)

Let's check that we find the analytic solution:

```
fdiff_H = zeros(2, 2)
fdiff_V^2f(fdif_H, x...)
Test.@test ≈(analytic_H, fdif_H)
```

Test Passed

## JuMP example

The code for computing the gradient and Hessian using ForwardDiff can be re-used for many operators. Thus, it is helpful to encapsulate it into the function:

```
"""
    fdif_derivatives(f::Function) -> Tuple{Function, Function}

Return a tuple of functions that evaluate the gradient and Hessian of `f` using
ForwardDiff.jl.

"""

function fdif_derivatives(f::Function)
    function Vf(g::AbstractVector{T}, x::Vararg{T,N}) where {T,N}
        ForwardDiff.gradient!(g, y -> f(y...), collect(x))
        return
    end
end
```

```

function ∇²f(H::AbstractMatrix{T}, x::Vararg{T,N}) where {T,N}
    h = ForwardDiff.hessian(y -> f(y...), collect(x))
    for i in 1:N, j in 1:i
        H[i, j] = h[i, j]
    end
    return
end
return ∇f, ∇²f
end

```

Main.fdiff\_derivatives

Here's an example using `fdiff_derivatives`:

```

function fdfi_rosenbrock()
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, x[1:2])
    @operator(model, op_rosenbrock, 2, f, fdfi_derivatives(f)...)
    @objective(model, Min, op_rosenbrock(x[1], x[2]))
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(x)
end

fdfi_rosenbrock()

```

2-element Vector{Float64}:

```

0.999999999999899
0.999999999999792

```

## Enzyme

Another library for automatic differentiation in Julia is [Enzyme.jl](#).

### Pros and cons

The main benefit of Enzyme is that it can produce fast derivatives for functions with many input arguments.

The main downsides are that it may throw unusual errors if your code uses an unsupported feature of Julia and that it may have large compile times.

#### Warning

The JuMP developers cannot help you debug error messages related to Enzyme. If the operator works, it works. If not, we suggest you try a different automatic differentiation library. See [juliadiff.org](#) for details.

## Gradient

The gradient can be computed using Enzyme.autodiff with the Enzyme.Reverse mode. We need to wrap  $x$  in Enzyme.Active to indicate that we want to compute the derivatives with respect to these arguments.

```
function enzyme_Vf(g::AbstractVector{T}, x::Vararg{T,N}) where {T,N}
    g .= Enzyme.autodiff(Enzyme.Reverse, f, Enzyme.Active.(x)...)[1]
    return
end
```

```
enzyme_Vf (generic function with 1 method)
```

Let's check that we find the analytic solution:

```
enzyme_g = zeros(2)
enzyme_Vf(enzyme_g, x...)
Test.@test ≈(analytic_g, enzyme_g)
```

```
Test Passed
```

## Hessian

We can compute the Hessian in Enzyme using forward-over-reverse automatic differentiation.

The code to implement the Hessian in Enzyme is complicated, so we will not explain it in detail; see the [Enzyme documentation](#).

```
function enzyme_V2f(H::AbstractMatrix{T}, x::Vararg{T,N}) where {T,N}
    # direction(i) returns a tuple with a `1` in the `i``th entry and `0` 
    # otherwise
    direction(i) = ntuple(j -> Enzyme.Active(T(i == j)), N)
    # As the inner function, compute the gradient using Reverse mode
    Vf(x...) = Enzyme.autodiff(Enzyme.Reverse, f, Enzyme.Active, x...)[1]
    # For the outer autodiff, use Forward mode.
    hess = Enzyme.autodiff(
        Enzyme.Forward,
        Vf,
        # Compute multiple evaluations of Forward mode, each time using `x` but
        # initializing with a different direction.
        Enzyme.BatchDuplicated.(Enzyme.Active.(x), ntuple(direction, N))...,
    )[1]
    # Unpack Enzyme's `hess` data structure into the matrix `H` expected by
    # JuMP.
    for j in 1:N, i in 1:j
        H[j, i] = hess[j][i]
    end
    return
end
```

```
enzyme_∇²f (generic function with 1 method)
```

Let's check that we find the analytic solution:

```
enzyme_H = zeros(2, 2)
enzyme_∇²f(enzyme_H, x...)
Test.@test ≈(analytic_H, enzyme_H)
```

Test Passed

### JuMP example

The code for computing the gradient and Hessian using Enzyme can be re-used for many operators. Thus, it is helpful to encapsulate it into the function:

```
"""
enzyme_derivatives(f::Function) -> Tuple{Function,Function}

Return a tuple of functions that evaluate the gradient and Hessian of `f` using
Enzyme.jl.

"""

function enzyme_derivatives(f::Function)
    function ∇f(g::AbstractVector{T}, x::Vararg{T,N}) where {T,N}
        g .= Enzyme.autodiff(Enzyme.Reverse, f, Enzyme.Active.(x)...)[1]
        return
    end
    function ∇²f(H::AbstractMatrix{T}, x::Vararg{T,N}) where {T,N}
        direction(i) = ntuple(j -> Enzyme.Active(T(i == j)), N)
        ∇f(x...) = Enzyme.autodiff(Enzyme.Reverse, f, Enzyme.Active, x...)[1]
        hess = Enzyme.autodiff(
            Enzyme.Forward,
            ∇f,
            Enzyme.BatchDuplicated.(Enzyme.Active.(x), ntuple(direction, N))...,
        )[1]
        for j in 1:N, i in 1:j
            H[j, i] = hess[j][i]
        end
        return
    end
    return ∇f, ∇²f
end
```

Main.enzyme\_derivatives

Here's an example using `enzyme_derivatives`:

```
function enzyme_rosenbrock()
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, x[1:2])
    @operator(model, op_rosenbrock, 2, f, enzyme_derivatives(f)...)
    @objective(model, Min, op_rosenbrock(x[1], x[2]))
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(x)
end

enzyme_rosenbrock()
```

```
2-element Vector{Float64}:
 0.999999999999899
 0.999999999999792
```

## DifferentiationInterface

Julia offers many different autodiff packages. `DifferentiationInterface.jl` is a package that provides an abstraction layer across a few underlying autodiff libraries.

### Warning

The JuMP developers cannot help you debug error messages related to `DifferentiationInterface`. If the operator works, it works. If not, we suggest you directly try using a different automatic differentiation library rather than the DI wrapper. See [juliadiff.org](http://juliadiff.org) for details.

All the necessary information about your choice of underlying autodiff package is encoded in a "backend object" like this one:

```
DifferentiationInterface.AutoForwardDiff()
```

```
ADTypes.AutoForwardDiff()
```

This type comes from another package called `ADTypes.jl`, but `DifferentiationInterface` re-exports it. Other options include `AutoZygote()` and `AutoFiniteDiff()`.

## Gradient

Apart from providing the backend object, the syntax below remains very similar:

```
function di_vf(
    g::AbstractVector{T},
    x::Vararg{T,N};
    backend = DifferentiationInterface.AutoForwardDiff(),
) where {T,N}
```

```
DifferentiationInterface.gradient!(splat(f), g, backend, collect(x))
    return
end
```

```
di_Vf (generic function with 1 method)
```

Let's check that we find the analytic solution:

```
di_g = zeros(2)
di_Vf(di_g, x...)
Test.@test ≈(analytic_g, di_g)
```

```
Test Passed
```

## Hessian

The Hessian follows exactly the same logic, except we need only the lower triangle.

```
function di_V2f(
    H::AbstractMatrix{T},
    x::Vararg{T,N};
    backend = DifferentiationInterface.AutoForwardDiff(),
) where {T,N}
    H_dense = DifferentiationInterface.hessian(splat(f), backend, collect(x))
    for i in 1:N, j in 1:i
        H[i, j] = H_dense[i, j]
    end
    return
end
```

```
di_V2f (generic function with 1 method)
```

Let's check that we find the analytic solution:

```
di_H = zeros(2, 2)
di_V2f(di_H, x...)
Test.@test ≈(analytic_H, di_H)
```

```
Test Passed
```

### JuMP example

The code for computing the gradient and Hessian using DifferentiationInterface can be re-used for many operators. Thus, it is helpful to encapsulate it into the function:

```
"""
di_derivatives(f::Function; backend) -> Tuple{Function,Function}

Return a tuple of functions that evaluate the gradient and Hessian of `f` using
DifferentiationInterface.jl with any given `backend`.

"""

function di_derivatives(f::Function; backend)
    function ∇f(g::AbstractVector{T}, x::Vararg{N}) where {T,N}
        DifferentiationInterface.gradient!(splat(f), g, backend, collect(x))
        return
    end
    function ∇²f(H::AbstractMatrix{T}, x::Vararg{N}) where {T,N}
        H_dense =
            DifferentiationInterface.hessian(splat(f), backend, collect(x))
        for i in 1:N, j in 1:i
            H[i, j] = H_dense[i, j]
        end
        return
    end
    return ∇f, ∇²f
end
end
```

Main.di\_derivatives

Here's an example using di\_derivatives:

```
function di_rosenbrock(; backend)
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, x[1:2])
    @operator(model, op_rosenbrock, 2, f, di_derivatives(f; backend)... )
    @objective(model, Min, op_rosenbrock(x[1], x[2]))
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value.(x)
end

di_rosenbrock(; backend = DifferentiationInterface.AutoForwardDiff())
```

2-element Vector{Float64}:
0.999999999999899
0.999999999999792

## 7.5 User-defined Hessians

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

In this tutorial, we explain how to write a user-defined operator (see [User-defined operators](#)) with a Hessian matrix explicitly provided by the user.

For a more advanced example, see [Nested optimization problems](#).

### Required packages

This tutorial uses the following packages:

```
using JuMP
import Ipopt
```

### Rosenbrock example

As a simple example, we consider the Rosenbrock function:

```
rosenbrock(x...) = (1 - x[1])^2 + 100 * (x[2] - x[1]^2)^2
```

```
rosenbrock (generic function with 1 method)
```

which has the gradient vector:

```
function ∇rosenbrock(g::AbstractVector, x...)
    g[1] = 400 * x[1]^3 - 400 * x[1] * x[2] + 2 * x[1] - 2
    g[2] = 200 * (x[2] - x[1]^2)
    return
end
```

```
∇rosenbrock (generic function with 1 method)
```

and the Hessian matrix:

```
function ∇²rosenbrock(H::AbstractMatrix, x...)
    H[1, 1] = 1200 * x[1]^2 - 400 * x[2] + 2
    # H[1, 2] = -400 * x[1] <-- not needed because Hessian is symmetric
    H[2, 1] = -400 * x[1]
    H[2, 2] = 200.0
    return
end
```

```
∇²rosenbrock (generic function with 1 method)
```

You may assume the Hessian matrix  $H$  is initialized with zeros, and because it is symmetric you need only to fill in the non-zero of the lower-triangular terms.

The matrix type passed in as  $H$  depends on the automatic differentiation system, so make sure the first argument to the Hessian function supports an `AbstractMatrix` (it may be something other than `Matrix{Float64}`). However, you may assume only that  $H$  supports `size(H)` and `setindex!`.

Now that we have the function, its gradient, and its Hessian, we can construct a JuMP model, add the operator, and use it in a macro:

```
model = Model(Ipopt.Optimizer)
@variable(model, x[1:2])
@operator(model, op_rosenbrock, 2, rosenbrock, ∇rosenbrock, ∇²rosenbrock)
@objective(model, Min, op_rosenbrock(x[1], x[2]))
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model; verbose = true)
```

```
* Solver : Ipopt

* Status
  Result count      : 1
  Termination status : LOCALLY_SOLVED
  Message from the solver:
  "Solve_Succeeded"

* Candidate solution (result #1)
  Primal status       : FEASIBLE_POINT
  Dual status         : FEASIBLE_POINT
  Objective value    : 1.21190e-27
  Dual objective value : 0.00000e+00
  Primal solution :
    x[1] : 1.00000e+00
    x[2] : 1.00000e+00
  Dual solution :

* Work counters
  Solve time (sec)   : 3.76649e-02
  Barrier iterations : 14
```

## 7.6 Nested optimization problems

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

The purpose of this tutorial is to show how to solve a *nested* optimization problem, where an *upper* problem uses the results from the optimization of a *lower* subproblem.

To model the problem, we define a user-defined operator to handle the decomposition of the lower problem inside the upper one. Finally, we show how to improve the performance by using a cache that avoids resolving the lower problem.

For a simpler example of writing a user-defined operator, see the [User-defined Hessians](#) tutorial.

### Info

The JuMP extension `BilevelJuMP.jl` can also be used to model and solve bilevel optimization problems.

## Required packages

This tutorial uses the following packages:

```
using JuMP
import Ipopt
```

## Formulation

In the rest of this tutorial, our goal is to solve the bilevel optimization problem:

$$\begin{aligned} \min_{x,z} \quad & x_1^2 + x_2^2 + z \\ \text{s.t.} \quad & z = \max_y \quad x_1^2 y_1 + x_2^2 y_2 - x_1 y_1^4 - 2x_2 y_2^4 \\ & \quad \quad \quad (y_1 - 10)^2 + (y_2 - 10)^2 \leq 25 \\ & \quad \quad \quad x \geq 0. \end{aligned}$$

This bilevel optimization problem is composed of two nested optimization problems. An *upper level*, involving variables  $x$ , and a *lower level*, involving variables  $y$ . From the perspective of the lower-level problem, the values of  $x$  are fixed parameters, and so the model optimizes  $y$  given those fixed parameters. Simultaneously, the upper-level problem optimizes  $x$  and  $z$  given the response of  $y$ .

## Decomposition

There are a few ways to solve this problem, but we are going to use a nonlinear decomposition method. The first step is to write a function to compute the lower-level problem:

$$\begin{aligned} V(x_1, x_2) = \max_y \quad & x_1^2 y_1 + x_2^2 y_2 - x_1 y_1^4 - 2x_2 y_2^4 \\ \text{s.t.} \quad & (y_1 - 10)^2 + (y_2 - 10)^2 \leq 25 \end{aligned}$$

```
function solve_lower_level(x...)
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, y[1:2])
    @objective(
        model,
        Max,
        x[1]^2 * y[1] + x[2]^2 * y[2] - x[1] * y[1]^4 - 2 * x[2] * y[2]^4,
    )
    solve!(model)
    return value.(y)
end
```

```

)
@constraint(model, (y[1] - 10)^2 + (y[2] - 10)^2 <= 25)
optimize!(model)
assert_is_solved_and_feasible(model)
return objective_value(model), value.(y)
end

```

solve\_lower\_level (generic function with 1 method)

The next function takes a value of  $x$  and returns the optimal lower-level objective-value and the optimal response  $y$ . The reason why we need both the objective and the optimal  $y$  will be made clear shortly, but for now let us define:

```

function V(x...)
    f, _ = solve_lower_level(x...)
    return f
end

```

V (generic function with 1 method)

Then, we can substitute  $V$  into our full problem to create:

$$\begin{aligned} \min_x \quad & x_1^2 + x_2^2 + V(x_1, x_2) \\ \text{s.t.} \quad & x \geq 0. \end{aligned}$$

This looks like a nonlinear optimization problem with a user-defined operator  $V$ ! However, because  $V$  solves an optimization problem internally, we can't use automatic differentiation to compute the first and second derivatives. Instead, we can use JuMP's ability to pass callback functions for the gradient and Hessian instead.

First up, we need to define the gradient of  $V$  with respect to  $x$ . In general, this may be difficult to compute, but because  $x$  appears only in the objective, we can just differentiate the objective function with respect to  $x$ , giving:

```

function ∇V(g::AbstractVector, x...)
    _, y = solve_lower_level(x...)
    g[1] = 2 * x[1] * y[1] - y[1]^4
    g[2] = 2 * x[2] * y[2] - 2 * y[2]^4
    return
end

```

∇V (generic function with 1 method)

Second, we need to define the Hessian of  $V$  with respect to  $x$ . This is a symmetric matrix, but in our example only the diagonal elements are non-zero:

```
function  $\nabla^2 V(H::\text{AbstractMatrix}, x\dots)$ 
     $_y = \text{solve\_lower\_level}(x\dots)$ 
     $H[1, 1] = 2 * y[1]$ 
     $H[2, 2] = 2 * y[2]$ 
    return
end
```

$\nabla^2 V$  (generic function with 1 method)

### Info

Providing an explicit Hessian function is optional if first derivatives are already available.

We now have enough to define our bilevel optimization problem:

```
model = Model(Ipopt.Optimizer)
@variable(model, x[1:2] >= 0)
@operator(model, op_V, 2, V,  $\nabla V$ ,  $\nabla^2 V$ )
@objective(model, Min,  $x[1]^2 + x[2]^2 + op_V(x[1], x[2])$ )
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : Ipopt

* Status
  Result count      : 1
  Termination status : LOCALLY_SOLVED
  Message from the solver:
  "Solve_Succeeded"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value   : -4.18983e+05
  Dual objective value : 0.00000e+00

* Work counters
  Solve time (sec)   : 5.03003e-01
  Barrier iterations : 32
```

The optimal objective value is:

```
objective_value(model)
```

```
-418983.48680640775
```

and the optimal upper-level decision variables  $x$  are:

```
value.(x)
```

```
2-element Vector{Float64}:
154.97862337234338
180.0096143098799
```

To compute the optimal lower-level decision variables, we need to call `solve_lower_level` with the optimal upper-level decision variables:

```
_, y = solve_lower_level(value.(x)...)  
y
```

```
2-element Vector{Float64}:
7.072593961143734
5.94656989283847
```

## Improving performance

Our solution approach works, but it has a performance problem: every time we need to compute the value, gradient, or Hessian of  $V$ , we have to re-solve the lower-level optimization problem. This is wasteful, because we will often call the gradient and Hessian at the same point, and so solving the problem twice with the same input repeats work unnecessarily.

We can work around this by using a cache:

```
mutable struct Cache  
    x::Any  
    f::Float64  
    y::Vector{Float64}  
end
```

with a function to update the cache if needed:

```
function _update_if_needed(cache::Cache, x...)  
    if cache.x !== x  
        cache.f, cache.y = solve_lower_level(x...)  
        cache.x = x  
    end  
    return  
end
```

```
_update_if_needed (generic function with 1 method)
```

Then, we define cached versions of our three functions which call `_updated_if_needed` and return values from the cache.

```
function cached_f(cache::Cache, x...)
    _update_if_needed(cache, x...)
    return cache.f
end

function cached_Vf(cache::Cache, g::AbstractVector, x...)
    _update_if_needed(cache, x...)
    g[1] = 2 * x[1] * cache.y[1] - cache.y[1]^4
    g[2] = 2 * x[2] * cache.y[2] - 2 * cache.y[2]^4
    return
end

function cached_V2f(cache::Cache, H::AbstractMatrix, x...)
    _update_if_needed(cache, x...)
    H[1, 1] = 2 * cache.y[1]
    H[2, 2] = 2 * cache.y[2]
    return
end
```

```
cached_V2f (generic function with 1 method)
```

Now we're ready to setup and solve the upper level optimization problem:

```
model = Model(Ipopt.Optimizer)
@variable(model, x[1:2] >= 0)
cache = Cache(Float64[], NaN, Float64[])
@operator(
    model,
    op_cached_f,
    2,
    (x...) -> cached_f(cache, x...),
    (g, x...) -> cached_Vf(cache, g, x...),
    (H, x...) -> cached_V2f(cache, H, x...),
)
@objective(model, Min, x[1]^2 + x[2]^2 + op_cached_f(x[1], x[2]))
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : Ipopt
```

```
* Status
  Result count      : 1
```

```

Termination status : LOCALLY_SOLVED
Message from the solver:
"Solve_Succeeded"

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : FEASIBLE_POINT
Objective value   : -4.18983e+05
Dual objective value : 0.00000e+00

* Work counters
Solve time (sec)   : 2.11612e-01
Barrier iterations : 32

```

and we can check we get the same objective value:

```
objective_value(model)
```

```
-418983.48680640775
```

and upper-level decision variable  $x$ :

```
value.(x)
```

```

2-element Vector{Float64}:
154.97862337234338
180.0096143098799

```

## 7.7 Computing Hessians

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to demonstrate how to compute the Hessian of the Lagrangian of a nonlinear program.

### Warning

This is an advanced tutorial that interacts with the low-level nonlinear interface of MathOptInterface.

By default, JuMP exports the MOI symbol as an alias for the MathOptInterface.jl package. We recommend making this more explicit in your code by adding the following lines:

```
import MathOptInterface as MOI
```

Given a nonlinear program:

$$\min_{x \in \mathbb{R}^n} f(x) \quad (7.4)$$

$$\text{s.t.} \quad l \leq g_i(x) \leq u \quad (7.5)$$

the Hessian of the Lagrangian is computed as:

$$H(x, \sigma, \mu) = \sigma \nabla^2 f(x) + \sum_{i=1}^m \mu_i \nabla^2 g_i(x)$$

where  $x$  is a primal point,  $\sigma$  is a scalar (typically 1), and  $\mu$  is a vector of weights corresponding to the Lagrangian dual of the constraints.

## Required packages

This tutorial uses the following packages:

```
using JuMP
import Ipopt
import LinearAlgebra
import Random
import SparseArrays
```

## The basic model

To demonstrate how to interact with the lower-level nonlinear interface, we need an example model. The exact model isn't important; we use the model from [The Rosenbrock function](#) tutorial, with some additional constraints to demonstrate various features of the lower-level interface.

```
model = Model(Ipopt.Optimizer)
set_silent(model)
@variable(model, x[i = 1:2], start = -i)
@constraint(model, g_1, x[1]^2 <= 1)
@constraint(model, g_2, (x[1] + x[2])^2 <= 2)
@objective(model, Min, (1 - x[1])^2 + 100 * (x[2] - x[1]^2)^2)
optimize!(model)
assert_is_solved_and_feasible(model)
```

## The analytic solution

With a little work, it is possible to analytically derive the correct hessian:

```
function analytic_hessian(x, σ, μ)
    g_1_H = [2.0 0.0; 0.0 0.0]
    g_2_H = [2.0 2.0; 2.0 2.0]
    f_H = zeros(2, 2)
    f_H[1, 1] = 2.0 + 1200.0 * x[1]^2 - 400.0 * x[2]
```

```

f_H[1, 2] = f_H[2, 1] = -400.0 * x[1]
f_H[2, 2] = 200.0
return σ * f_H + μ' * [g_1_H, g_2_H]
end

```

```
analytic_hessian (generic function with 1 method)
```

Here are various points:

```
analytic_hessian([1, 1], 0, [0, 0])
```

```

2x2 Matrix{Float64}:
 0.0  0.0
 0.0  0.0

```

```
analytic_hessian([1, 1], 0, [1, 0])
```

```

2x2 Matrix{Float64}:
 2.0  0.0
 0.0  0.0

```

```
analytic_hessian([1, 1], 0, [0, 1])
```

```

2x2 Matrix{Float64}:
 2.0  2.0
 2.0  2.0

```

```
analytic_hessian([1, 1], 1, [0, 0])
```

```

2x2 Matrix{Float64}:
 802.0  -400.0
 -400.0   200.0

```

### Create a nonlinear model

JuMP delegates automatic differentiation to the `MOI.Nonlinear` submodule. Therefore, to compute the Hessian of the Lagrangian, we need to create a `MOI.Nonlinear.Model` object:

```

rows = Any[]
nlp = MOI.Nonlinear.Model()
for (F, S) in list_of_constraint_types(model)
    if F <: VariableRef
        continue # Skip variable bounds
    end
    for ci in all_constraints(model, F, S)
        push!(rows, ci)
        object = constraint_object(ci)
        MOI.Nonlinear.add_constraint(nlp, object.func, object.set)
    end
end
MOI.Nonlinear.set_objective(nlp, objective_function(model))
nlp

```

A Nonlinear.Model with:  
 1 objective  
 0 parameters  
 0 expressions  
 2 constraints

It is important that we save the constraint indices in a vector `rows`, so that we know the order of the constraints in the nonlinear model.

Next, we need to convert our model into an `MOI.Nonlinear.Evaluator`, specifying an automatic differentiation backend. In this case, we use `MOI.Nonlinear.SparseReverseMode`:

```

evaluator = MOI.Nonlinear.Evaluator(
    nlp,
    MOI.Nonlinear.SparseReverseMode(),
    index.(all_variables(model)),
)

```

Nonlinear.Evaluator with available features:  
 \* :Grad  
 \* :Jac  
 \* :JacVec  
 \* :Hess  
 \* :HessVec  
 \* :ExprGraph

Before computing anything with the evaluator, we need to initialize it. Use `MOI.features_available` to see what we can query:

```
MOI.features_available(evaluator)
```

```
6-element Vector{Symbol}:
:Grad
:Jac
:JacVec
:Hess
:HessVec
:ExprGraph
```

Consult the MOI documentation for specifics, but to obtain the Hessian matrix, we need to initialize :Hess:

```
MOI.initialize(evaluator, [:Hess])
```

MOI represents the Hessian as a sparse matrix. Get the sparsity pattern as follows:

```
hessian_sparsity = MOI.hessian_lagrangian_structure(evaluator)
```

```
7-element Vector{Tuple{Int64, Int64}}:
(1, 1)
(2, 2)
(2, 1)
(1, 1)
(1, 1)
(2, 2)
(2, 1)
```

The sparsity pattern has a few properties of interest:

- Each element  $(i, j)$  indicates a structural non-zero in row  $i$  and column  $j$
- The list may contain duplicates, in which case we should add the values together
- The list does not need to be sorted
- The list may contain any mix of lower- or upper-triangular indices

This format matches Julia's sparse-triplet form of a SparseArray, so we can convert from the sparse Hessian representation to a Julia SparseArray as follows:

```
I = [i for (i, _) in hessian_sparsity]
J = [j for (_, j) in hessian_sparsity]
V = zeros(length(hessian_sparsity))
n = num_variables(model)
H = SparseArrays.sparse(I, J, V, n, n)
```

```
2×2 SparseArrays.SparseMatrixCSC{Float64, Int64} with 3 stored entries:
 0.0   .
 0.0  0.0
```

Of course, knowing where the zeros are isn't very interesting. We really want to compute the value of the Hessian matrix at a point.

```
MOI.eval_hessian_lagrangian(evaluator, V, ones(n), 1.0, ones(length(rows)))
H = SparseArrays.sparse(I, J, V, n, n)
```

```
2x2 SparseArrays.SparseMatrixCSC{Float64, Int64} with 3 stored entries:
 806.0      .
 -398.0  202.0
```

In practice, we often want to compute the value of the hessian at the optimal solution.

First, we compute the primal solution. To do so, we need a vector of the variables in the order that they were passed to the solver:

```
x = all_variables(model)
```

```
2-element Vector{VariableRef}:
 x[1]
 x[2]
```

Here `x[1]` is the variable that corresponds to column 1, and so on. Here's the optimal primal solution:

```
x_optimal = value.(x)
```

```
2-element Vector{Float64}:
 0.7903587565231842
 0.6238546272155127
```

Next, we need the optimal dual solution associated with the nonlinear constraints (this is where it is important to record the order of the constraints as we added them to `nlp`):

```
y_optimal = dual.(rows)
```

```
2-element Vector{Float64}:
 -8.038451738599348e-8
 -0.05744089305771262
```

Now we can compute the Hessian at the optimal primal-dual point:

```
MOI.eval_hessian_lagrangian(evaluator, V, x_optimal, 1.0, y_optimal)
H = SparseArrays.sparse(I, J, V, n, n)
```

```
2×2 SparseArrays.SparseMatrixCSC{Float64, Int64} with 3 stored entries:
 501.944  .
 -316.258  199.885
```

However, this Hessian isn't quite right because it isn't symmetric. We can fix this by filling in the appropriate off-diagonal terms:

```
function fill_off_diagonal(H)
    ret = H + H'
    row_vals = SparseArrays.rowvals(ret)
    non_zeros = SparseArrays.nonzeros(ret)
    for col in 1:size(ret, 2)
        for i in SparseArrays.nzrange(ret, col)
            if col == row_vals[i]
                non_zeros[i] /= 2
            end
        end
    end
    return ret
end

fill_off_diagonal(H)
```

```
2×2 SparseArrays.SparseMatrixCSC{Float64, Int64} with 4 stored entries:
 501.944  -316.258
 -316.258   199.885
```

Putting everything together:

```
function compute_optimal_hessian(model::Model)
    rows = Any[]
    nlp = MOI.Nonlinear.Model()
    for (F, S) in list_of_constraint_types(model)
        for ci in all_constraints(model, F, S)
            push!(rows, ci)
            object = constraint_object(ci)
            MOI.Nonlinear.add_constraint(nlp, object.func, object.set)
        end
    end
    MOI.Nonlinear.set_objective(nlp, objective_function(model))
    x = all_variables(model)
    backend = MOI.Nonlinear.SparseReverseMode()
    evaluator = MOI.Nonlinear.Evaluator(nlp, backend, index.(x))
    MOI.initialize(evaluator, [:Hess])
    hessian_sparsity = MOI.hessian_lagrangian_structure(evaluator)
```

```

I = [i for (i, _) in hessian_sparsity]
J = [j for (_, j) in hessian_sparsity]
V = zeros(length(hessian_sparsity))
MOI.eval_hessian_lagrangian(evaluator, V, value.(x), 1.0, dual.(rows))
H = SparseArrays.sparse(I, J, V, length(x), length(x))
return Matrix(fill_off_diagonal(H))
end

H_star = compute_optimal_hessian(model)

```

```

2×2 Matrix{Float64}:
 501.944 -316.258
 -316.258  199.885

```

If we compare our solution against the analytical solution:

```
analytic_hessian(value.(x), 1.0, dual.([g_1, g_2]))
```

```

2×2 Matrix{Float64}:
 501.944 -316.258
 -316.258  199.885

```

If we look at the eigenvalues of the Hessian:

```
LinearAlgebra.eigvals(H_star)
```

```

2-element Vector{Float64}:
 0.4443995924983142
 701.3843426037456

```

we see that they are all positive. Therefore, the Hessian is positive definite, and so the solution found by Ipopt is a local minimizer.

## Jacobians

In addition to the Hessian, it is also possible to query other parts of the nonlinear model. For example, the Jacobian of the constraints can be queried using `MOI.jacobian_structure` and `MOI.eval_constraint_jacobian`.

```

function compute_optimal_jacobian(model::Model)
    rows = Any[]
    nlp = MOI.Nonlinear.Model()
    for (F, S) in list_of_constraint_types(model)
        for ci in all_constraints(model, F, S)
            if !(F <: VariableRef)

```

```

        push!(rows, ci)
        object = constraint_object(ci)
        MOI.Nonlinear.add_constraint(nlp, object.func, object.set)
    end
end
end
MOI.Nonlinear.set_objective(nlp, objective_function(model))
x = all_variables(model)
backend = MOI.Nonlinear.SparseReverseMode()
evaluator = MOI.Nonlinear.Evaluator(nlp, backend, index.(x))
# Initialize the Jacobian
MOI.initialize(evaluator, [:Jac])
# Query the Jacobian structure
sparsity = MOI.jacobian_structure(evaluator)
I, J, V = first.(sparsity), last.(sparsity), zeros(length(sparsity))
# Query the Jacobian values
MOI.eval_constraint_jacobian(evaluator, V, value.(x))
return SparseArrays.sparse(I, J, V, length(rows), length(x))
end

compute_optimal_jacobian(model)

```

```

2×2 SparseArrays.SparseMatrixCSC{Float64, Int64} with 3 stored entries:
1.58072  .
2.82843  2.82843

```

Compare that to the analytic solution:

```

y = value.(x)
[2y[1] 0; 2y[1]+2y[2] 2y[1]+2y[2]]

```

```

2×2 Matrix{Float64}:
1.58072  0.0
2.82843  2.82843

```

## 7.8 Example: mixed complementarity problems

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

The purpose of this tutorial is to provide a collection of mixed complementarity programs.

### Required packages

This tutorial uses the following packages:

```

using JuMP
import PATHSolver

```

## Background

A mixed complementarity problem has the form:

$$F_i(x) \perp x_i \quad i = 1 \dots n \quad (7.6)$$

$$l_i \leq x_i \leq u_i \quad i = 1 \dots n. \quad (7.7)$$

where the  $\perp$  constraint enforces the following relations:

- If  $l_i < x_i < u_i$ , then  $F_i(x) = 0$
- If  $l_i = x_i$ , then  $F_i(x) \geq 0$
- If  $x_i = u_i$ , then  $F_i(x) \leq 0$

You may have seen a complementarity problem written as  $0 \leq F(x) \perp x \geq 0$ . This is a special case of a mixed complementarity problem in which  $l_i = 0$  and  $u_i = \infty$ .

Importantly, a mixed complementarity problem does not have an objective, and no other constraint types are present.

## Linear complementarity

Form a mixed complementarity problem using the perp symbol  $\perp$  (type `\perp` in the REPL).

```
M = [0 0 -1 -1; 0 0 1 -2; 1 -1 2 -2; 1 2 -2 4]
q = [2, 2, -2, -6]
model = Model(PATHSolver.Optimizer)
set_silent(model)
@variable(model, 0 <= x[1:4] <= 10, start = 0)
@constraint(model, M * x + q ⊥ x)
optimize!(model)
assert_is_solved_and_feasible(model)
value.(x)
```

```
4-element Vector{Float64}:
 2.8
 0.0
 0.8
 1.2
```

## Other ways of writing linear complementarity problems

You do not need to use a single vector of variables, and the complementarity constraints can be given in any order. In addition, you can use the perp symbol, the complements( $F$ ,  $x$ ) syntax, or the [MOI.Complements](#) set.

```

model = Model(PATHSolver.Optimizer)
set_silent(model)
@variable(model, 0 <= w <= 10, start = 0)
@variable(model, 0 <= x <= 10, start = 0)
@variable(model, 0 <= y <= 10, start = 0)
@variable(model, 0 <= z <= 10, start = 0)
@constraint(model, complements(y - 2z + 2, x))
@constraint(model, [-y - z + 2, w] in MOI.Complements(2))
@constraint(model, w + 2x - 2y + 4z - 6 ⊥ z)
@constraint(model, w - x + 2y - 2z - 2 ⊥ y)
optimize!(model)
assert_is_solved_and_feasible(model)
value.([w, x, y, z])

```

```

4-element Vector{Float64}:
2.8
0.0
0.8
1.2

```

## Transportation

This example is a reformulation of the transportation problem from Chapter 3.3 of Dantzig, G.B. (1963). *Linear Programming and Extensions*. Princeton University Press, Princeton, New Jersey. It is based on the GAMS model `gamslib_transmcp`.

```

capacity = Dict("seattle" => 350, "san-diego" => 600)
demand = Dict("new-york" => 325, "chicago" => 300, "topeka" => 275)
cost = Dict(
    ("seattle" => "new-york") => 90 * 2.5 / 1_000,
    ("seattle" => "chicago") => 90 * 1.7 / 1_000,
    ("seattle" => "topeka") => 90 * 1.8 / 1_000,
    ("san-diego" => "new-york") => 90 * 2.5 / 1_000,
    ("san-diego" => "chicago") => 90 * 1.8 / 1_000,
    ("san-diego" => "topeka") => 90 * 1.4 / 1_000,
)
plants, markets = keys(capacity), keys(demand)
model = Model(PATHSolver.Optimizer)
set_silent(model)
@variable(model, w[i in plants] >= 0)
@variable(model, p[j in markets] >= 0)
@variable(model, x[i in plants, j in markets] >= 0)
@constraints(
    model,
    begin
        [i in plants, j in markets], w[i] + cost[i=>j] - p[j] ⊥ x[i, j]
        [i in plants], capacity[i] - sum(x[i, :]) ⊥ w[i]
        [j in markets], sum(x[:, j]) - demand[j] ⊥ p[j]
    end
)
optimize!(model)

```

```
assert_is_solved_and_feasible(model)
value.(p)
```

```
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
Dimension 1, ["new-york", "chicago", "topeka"]
And data, a 3-element Vector{Float64}:
0.22500000000033224
0.15299999994933886
0.126
```

### Expected utility of insurance

This example is taken from a lecture of the course AAE706, given by Thomas F. Rutherford at the University of Wisconsin, Madison. It models the expected coverage of insurance K that a rational actor would obtain to insure a risk that occurs with probability  $\pi$  and results in a loss of  $L$ .

```
pi = 0.01 # Probability of a bad outcome
L = 0.5 # Loss with a bad outcome
γ = 0.02 # Premium for coverage
σ = 0.5 # Elasticity
ρ = -1 # Risk exponent
U(C) = C^ρ / ρ
MU(C) = C^(ρ - 1)
model = Model(PATHSolver.Optimizer)
set_silent(model)
@variable(model, EU, start = 1) # Expected utility
@variable(model, EV, start = 1) # Equivalent variation in income
@variable(model, C_G, start = 1) # Consumption on a good day
@variable(model, C_B, start = 1) # Consumption on a bad day
@variable(model, K, start = 1) # Coverage
@constraints(
    model,
    begin
        (1 - pi) * U(C_G) + pi * U(C_B) - EU ⊥ EU
        100 * (((1 - pi) * C_G^ρ + pi * C_B^ρ)^(1 / ρ) - 1) - EV ⊥ EV
        1 - γ * K - C_G ⊥ C_G
        1 - L + (1 - γ) * K - C_B ⊥ C_B
        γ * ((1 - pi) * MU(C_G) + pi * MU(C_B)) - pi * MU(C_B) ⊥ K
    end
)
optimize!(model)
assert_is_solved_and_feasible(model)
value(K)
```

```
0.20474003534537774
```

## Electricity consumption

This example is a mixed complementarity formulation of Example 3.3.1 from (D'Aertrycke et al., 2017).

This example models a risk neutral competitive equilibrium between a producer and a consumer of electricity.

In our example, we assume a producer is looking to invest in a new power plant with capacity  $x$  [MW]. This plant has an annualized capital cost of  $I$  [€/MW] and an operating cost of  $C$  [€/MWh]. There are 8760 hours in a year.

After making the capital investment, there are five possible consumption scenarios,  $\omega$ , which occur with probability  $\theta_\omega$ . In each scenario, the producer makes  $Y$  MW of electricity.

There is one consumer in the model, who has a quadratic utility function,  $U(Q) = AQ + \frac{BQ^2}{2}$ .

We now build and solve the mixed complementarity problem with a few brief comments. The economic justification for the model would require a larger tutorial than the space available here. Consult (D'Aertrycke et al., 2017) for details.

```

I = 90_000           # Annualized capital cost
C = 60              # Operation cost per MWh
tau = 8_760          # Hours per year
theta = [0.2, 0.2, 0.2, 0.2, 0.2] # Scenario probabilities
A = [300, 350, 400, 450, 500] # Utility function coefficients
B = 1                # Utility function coefficients

model = Model(PATHSolver.Optimizer)
set_silent(model)

@variable(model, x >= 0, start = 1)           # Installed capacity
@variable(model, Q[w = 1:5] >= 0, start = 1)   # Consumption
@variable(model, Y[w = 1:5] >= 0, start = 1)   # Production
@variable(model, P[w = 1:5], start = 1)        # Electricity price
@variable(model, mu[w = 1:5] >= 0, start = 1)  # Capital scarcity margin
# Unit investment cost equals annualized scarcity profit or investment is 0
@constraint(model, I - tau * theta * mu ⊥ x)
# Difference between price and scarcity margin is equal to operation cost
@constraint(model, [w = 1:5], C - (P[w] - mu[w]) ⊥ Y[w])
# Price is equal to consumer's marginal utility
@constraint(model, [w = 1:5], P[w] - (A[w] - B * Q[w]) ⊥ Q[w])
# Production is equal to consumption
@constraint(model, [w = 1:5], Y[w] - Q[w] ⊥ P[w])
# Production does not exceed capacity
@constraint(model, [w = 1:5], x - Y[w] ⊥ mu[w])
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)

```

```

* Solver : Path 5.0.03

* Status
Result count      : 1
Termination status : LOCALLY_SOLVED
Message from the solver:
"The problem was solved"

* Candidate solution (result #1)
Primal status     : FEASIBLE_POINT

```

```

Dual status      : NO_SOLUTION
Objective value : 0.00000e+00

* Work counters
  Solve time (sec) : 1.45000e-04

```

An equilibrium solution is to build 389 MW:

```
value(x)
```

```
389.31506849315065
```

The production in each scenario is:

```
value.(Q)
```

```

5-element Vector{Float64}:
240.0000000000001
289.9999999999999
340.0
389.31506849315065
389.31506849315065

```

The price in each scenario is:

```
value.(P)
```

```

5-element Vector{Float64}:
59.99999999999886
60.0
59.9999999999994
60.68493150684928
110.68493150684935

```

## 7.9 Example: classification problems

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

The purpose of this tutorial is to show how JuMP can be used to formulate classification problems.

Classification problems deal with constructing functions, called *classifiers*, that can efficiently classify data into two or more distinct sets. A common application is classifying previously unseen data points after training a classifier on known data.

The theory and models in this tutorial come from Section 9.4 of ([Ferris et al., 2007](#)).

## Required packages

This tutorial uses the following packages:

```
using JuMP
import DelimitedFiles
import Ipopt
import LinearAlgebra
import Plots
import Random
import Test
```

## Data and visualisation

To start, let's generate some points to test with. The argument  $m$  is the number of 2-dimensional points:

```
function generate_test_points(m; random_seed = 1)
    rng = Random.MersenneTwister(random_seed)
    return 2.0 .* rand(rng, Float64, m, 2)
end
```

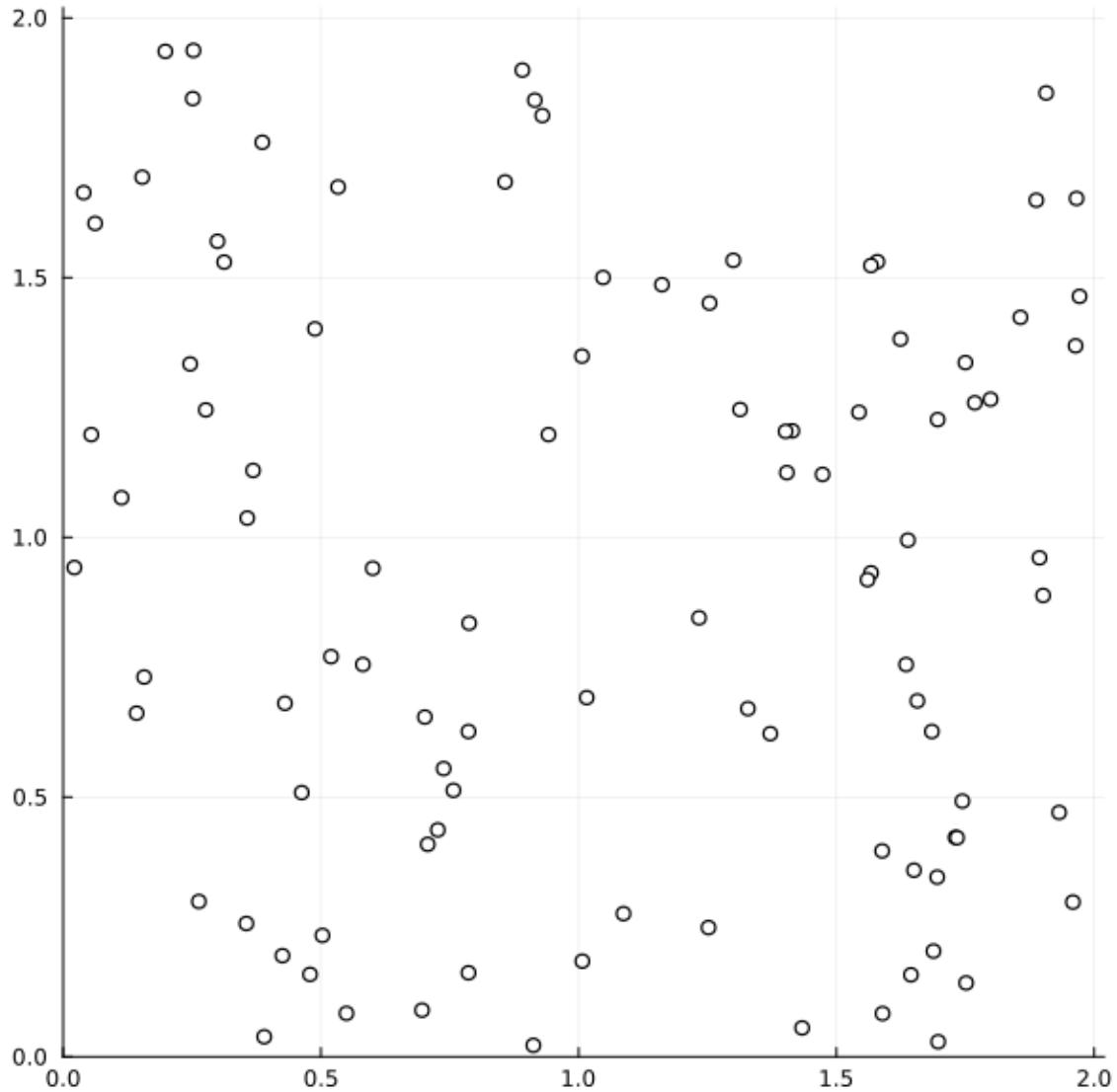
```
generate_test_points (generic function with 1 method)
```

For the sake of the example, let's take  $m = 100$ :

```
P = generate_test_points(100);
```

The points are represented row-wise in the matrix  $P$ . Let's visualise the points using the `Plots` package:

```
plot = Plots.scatter(
    P[:, 1],
    P[:, 2];
    xlim = (0, 2.02),
    ylim = (0, 2.02),
    color = :white,
    size = (600, 600),
    legend = false,
)
```



We want to split the points into two distinct sets on either side of a dividing line. We'll then label each point depending on which side of the line it happens to fall. Based on the labels of the point, we'll show how to create a classifier using a JuMP model. We can then test how well our classifier reproduces the original labels and the boundary between them.

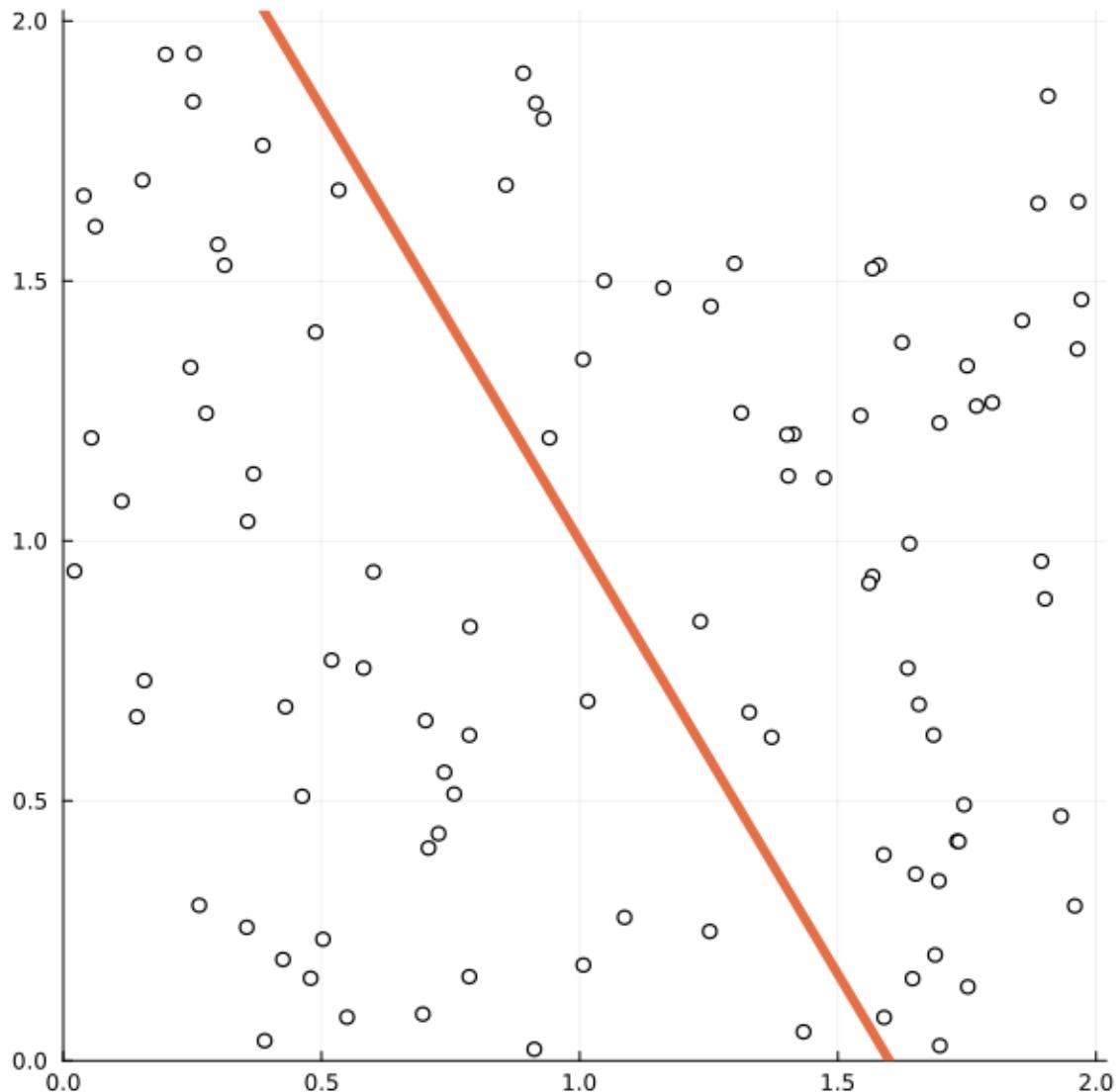
Let's make a line to divide the points into two sets by defining a gradient and a constant:

```
w_0, g_0 = [5, 3], 8
line(v::AbstractArray; w = w_0, g = g_0) = w' * v - g
line(x::Real; w = w_0, g = g_0) = -(w[1] * x - g) / w[2];
```

Julia's multiple dispatch feature allows us to define the vector and single-variable form of the `line` function under the same name.

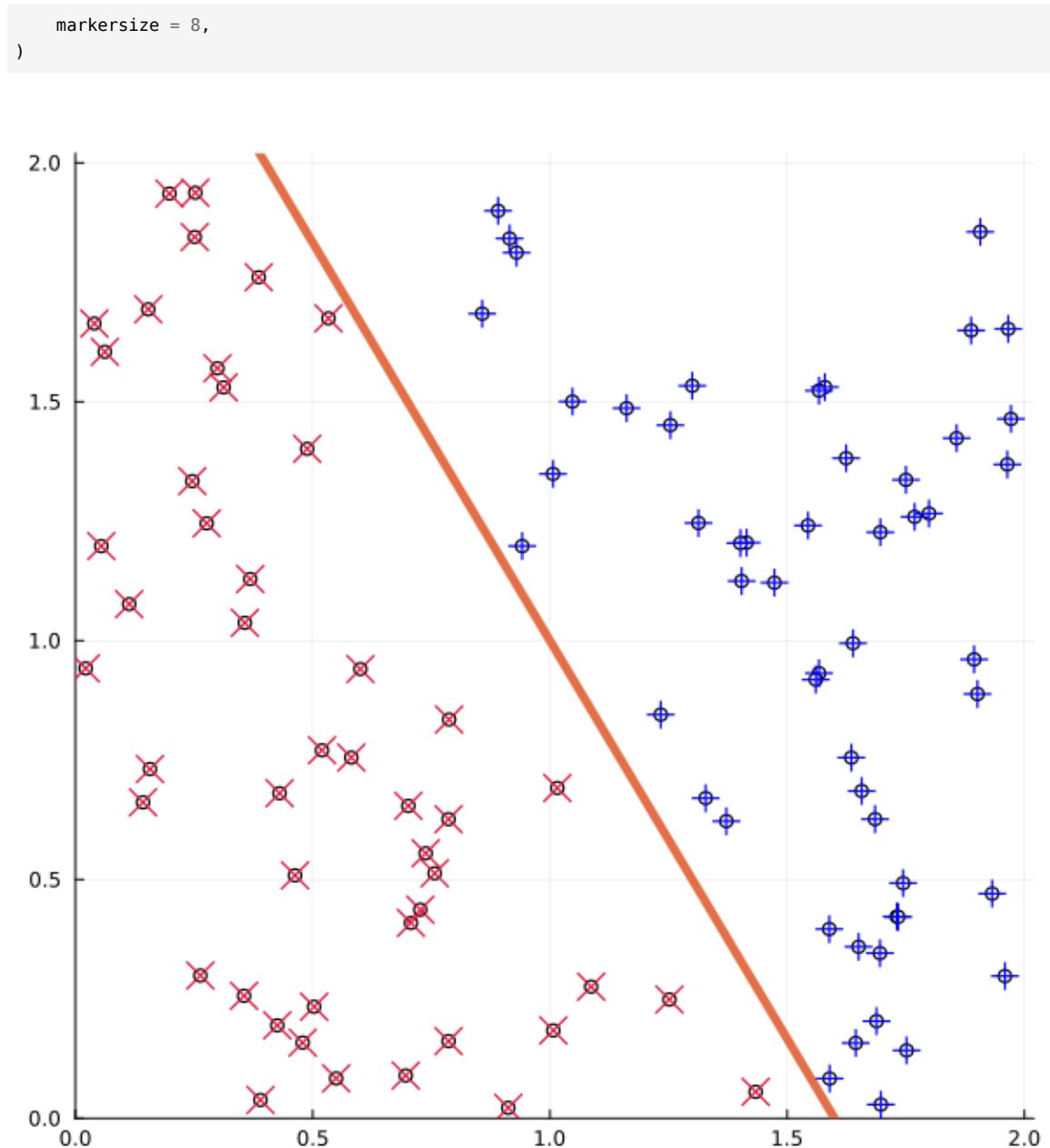
Let's add this to the plot:

```
Plots.plot!(plot, line; linewidth = 5)
```



Now we label the points relative to which side of the line they are. It is numerically useful to have the labels +1 and -1 for the upcoming JuMP formulation.

```
labels = ifelse.(line.(eachrow(P)) .>= 0, 1, -1)
Plots.scatter!(
    plot,
    P[:, 1],
    P[:, 2];
    shape = ifelse.(labels .== 1, :cross, :xcross),
    markercolor = ifelse.(labels .== 1, :blue, :crimson),
```



Our goal is to show we can reconstruct the line from *just* the points and the labels.

### Formulation: linear support vector machine

A classifier known as the linear *support vector machine* (SVM) looks for the affine function  $L(p) = w^\top p - g$  that satisfies  $L(p) < 0$  for all points  $p$  with a label -1 and  $L(p) \geq 0$  for all points  $p$  with a label +1.

The linearly constrained quadratic program that implements this is:

$$\begin{aligned}
 & \min_{w \in \mathbb{R}^n, g \in \mathbb{R}, y \in \mathbb{R}^m} \frac{1}{2} w^\top w + C \sum_{i=1}^m y_i \\
 \text{subject to} \quad & D \cdot (Pw - g) + y \geq \mathbf{1} \\
 & y \geq 0.
 \end{aligned}$$

where  $D$  is a diagonal matrix of the labels.

We need a default value for the positive penalty parameter  $C$ :

```
C_0 = 100.0;
```

### JuMP formulation

Here is the JuMP model:

```

function solve_SVM_classifier(P::Matrix, labels::Vector; C::Float64 = C_0)
    m, n = size(P)
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, w[1:n])
    @variable(model, g)
    @variable(model, y[1:m] >= 0)
    @objective(model, Min, 1 / 2 * w' * w + C * sum(y))
    D = LinearAlgebra.Diagonal(labels)
    @constraint(model, D * (P * w .- g) .+ y .>= 1)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    slack = extrema(value.(y))
    println("Minimum slack: ", slack[1], "\nMaximum slack: ", slack[2])
    classifier(x) = line(x; w = value.(w), g = value(g))
    return model, classifier
end

```

```
solve_SVM_classifier (generic function with 1 method)
```

### Results

Let's recover the values that define the classifier by solving the model:

```
_ , classifier = solve_SVM_classifier(P, labels)
```

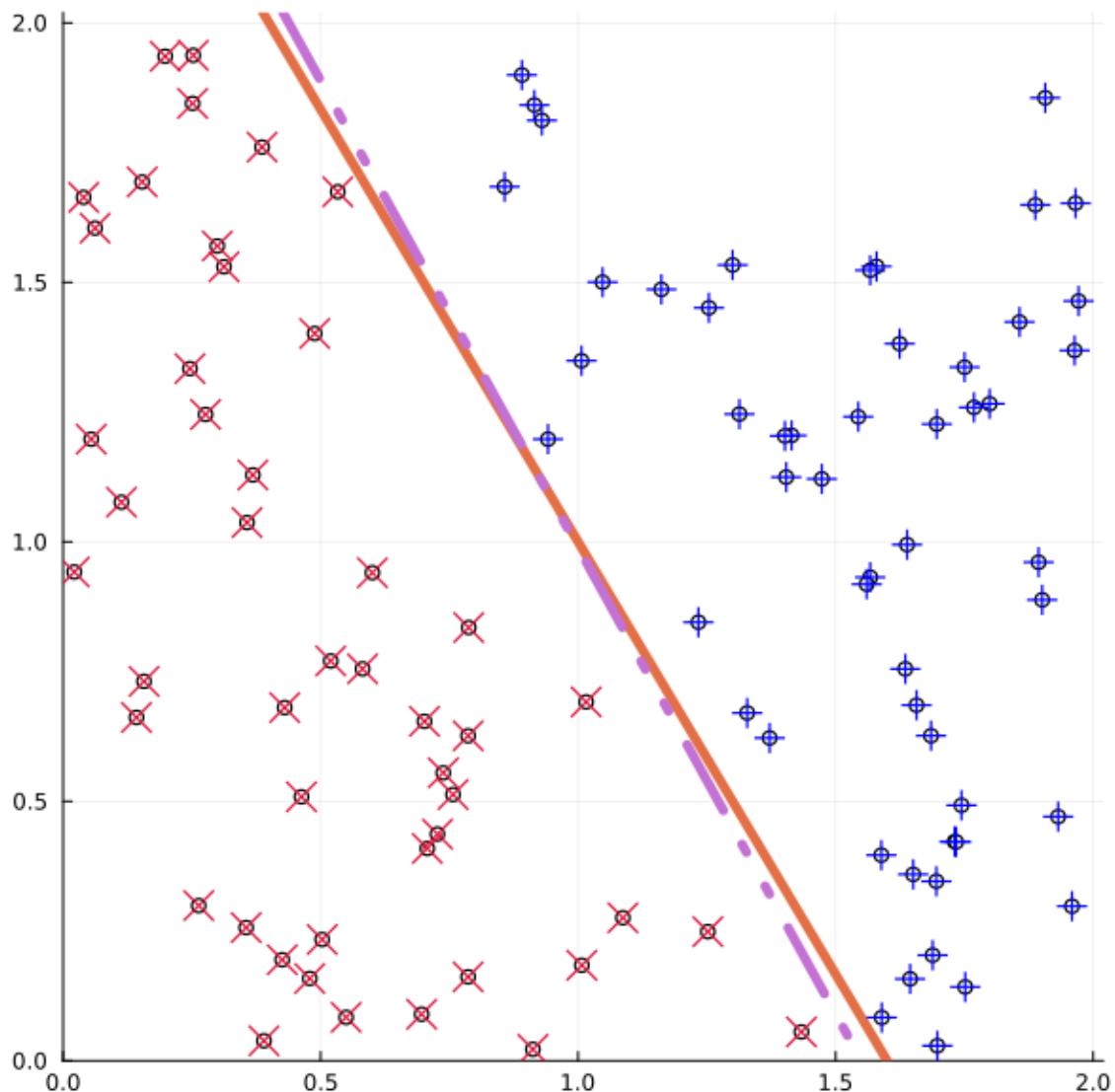
```
(A JuMP Model
| solver: Ipopt
| objective_sense: MIN_SENSE
| | objective_function_type: QuadExpr
```

```
|+ num_variables: 103
|+ num_constraints: 200
| |+ AffExpr in MOI.GreaterThan{Float64}: 100
| | |+ VariableRef in MOI.GreaterThan{Float64}: 100
|+ Names registered in the model
| |+ :g, :w, :y, Main.classifier)
```

With the solution, we can ask: was the value of the penalty constant "sufficiently large" for this data set? This can be judged in part by the range of the slack variables. If the slack is too large, then we need to increase the penalty constant.

Let's plot the solution and check how we did:

```
Plots.plot!(plot, classifier; linewidth = 5, linestyle = :dashdotdot)
```



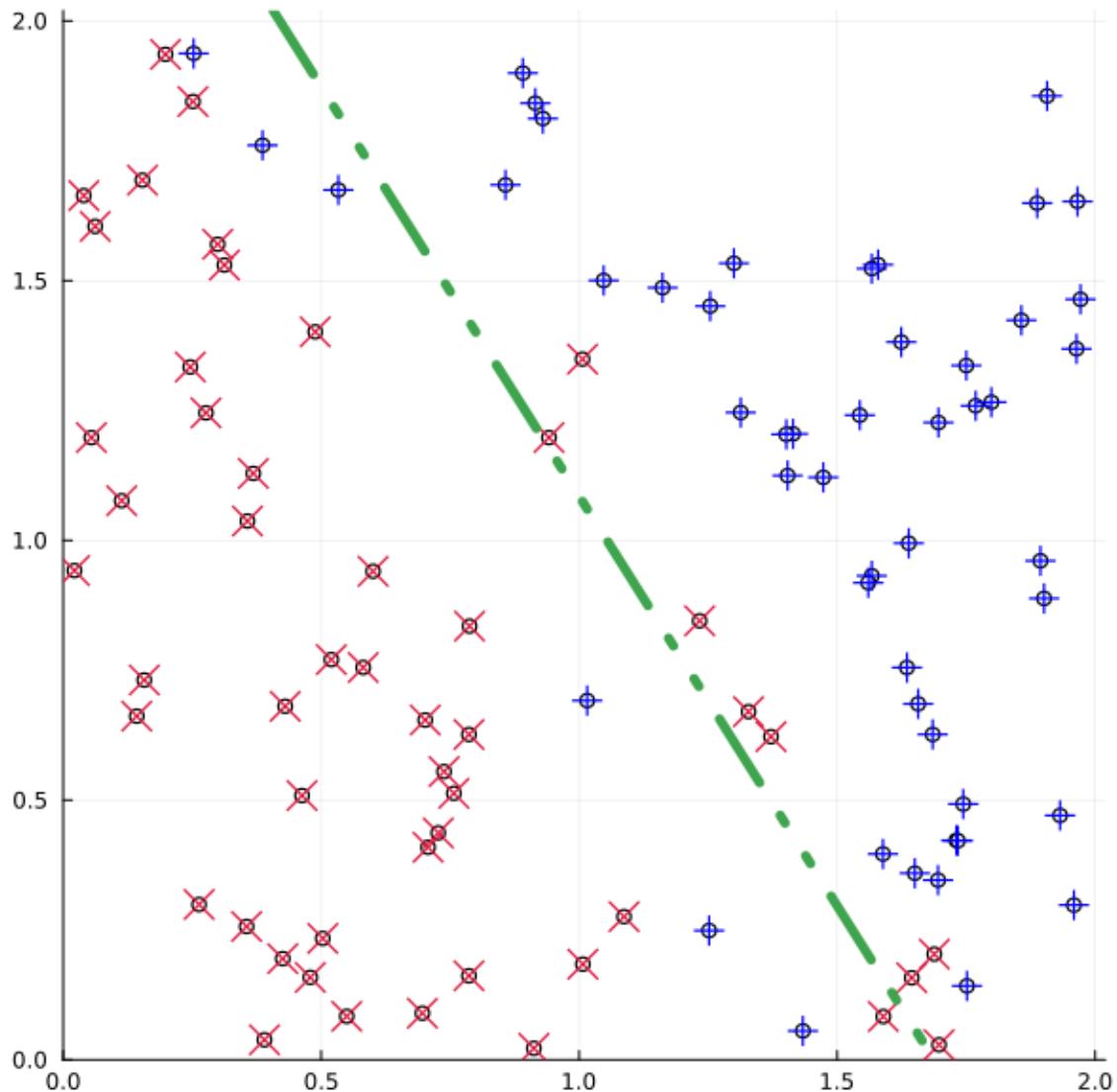
We find that we have recovered the dividing line from just the information of the points and their labels.

### Nonseparable classes of points

Now, what if the point sets are not cleanly separable by a line (or a hyperplane in higher dimensions)? Does this still work? Let's repeat the process, but this time we will simulate nonseparable classes of points by intermingling a few nearby points across the previously used line.

```
nearby_indices = abs.(line.(eachrow(P))) .< 1.1
labels_new = ifelse.(nearby_indices, -labels, labels)
model, classifier = solve_SVM_classifier(P, labels_new)
plot = Plots.scatter(
    P[:, 1],
    P[:, 2];
    xlim = (0, 2.02),
```

```
    ylim = (0, 2.02),
    color = :white,
    size = (600, 600),
    legend = false,
)
Plots.scatter!(
    plot,
    P[:, 1],
    P[:, 2];
    shape = ifelse.(labels_new .== 1, :cross, :xcross),
    markercolor = ifelse.(labels_new .== 1, :blue, :crimson),
    markersize = 8,
)
Plots.plot!(plot, classifier; linewidth = 5, linestyle = :dashdotdot)
```



So our JuMP formulation still produces a classifier, but it mis-classifies some of the nonseparable points.

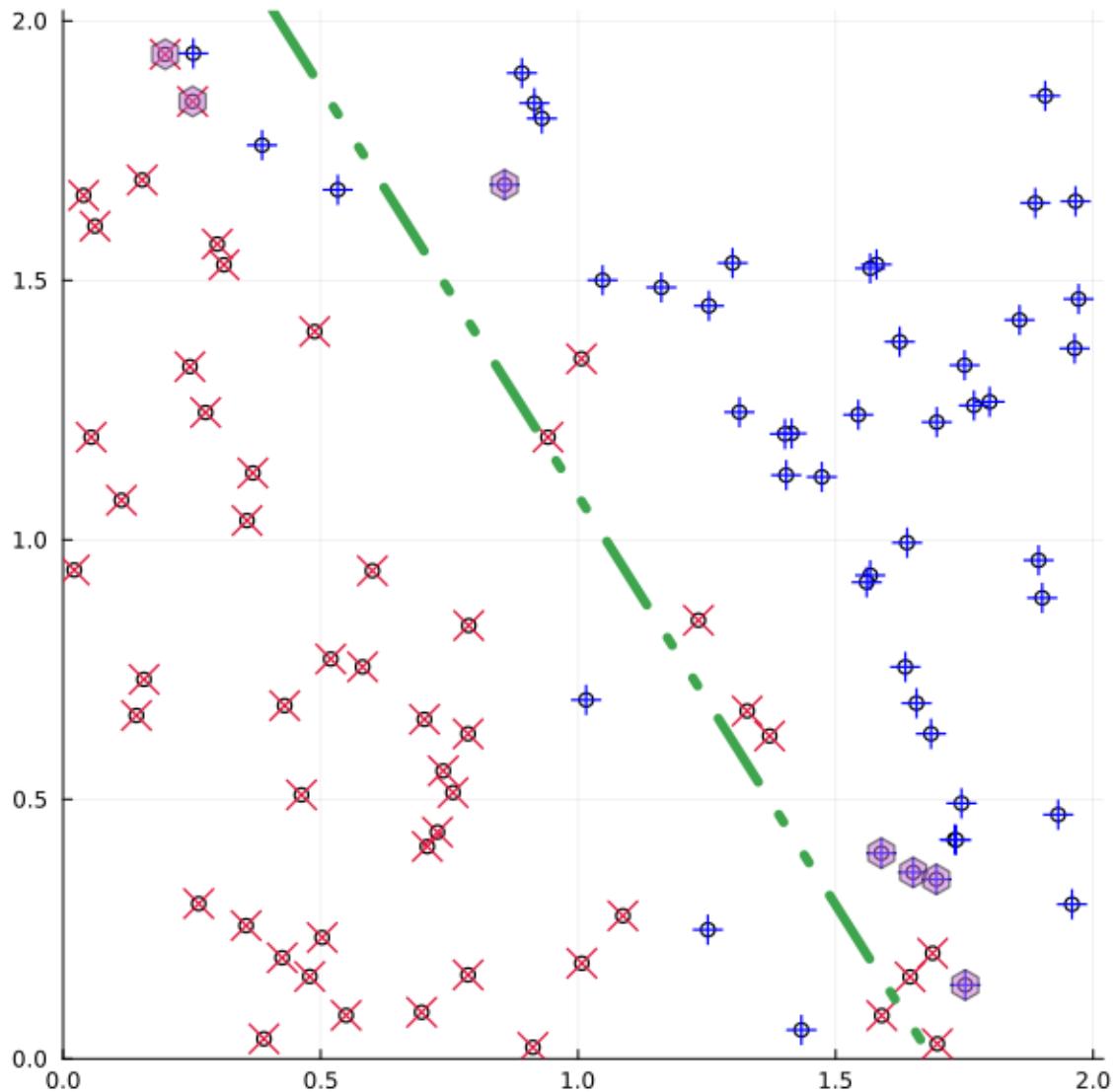
We can find out which points are contributing to the shape of the line by looking at the dual values of the affine constraints and comparing them to the penalty constant  $C$ :

```
affine_cons = all_constraints(model, AffExpr, MOI.GreaterThan{Float64})
active_cons = findall(isapprox.(dual.(affine_cons), C_0; atol = 0.001))
findall(nearby_indices) ⊆ active_cons
```

```
true
```

The last statement tells us that our nonseparable points are actively contributing to how the classifier is defined. The remaining points are of interest and are highlighted:

```
P_active = P[setdiff(active_cons, findall(nearby_indices)), :]
Plots.scatter!(
    plot,
    P_active[:, 1],
    P_active[:, 2];
    shape = :hexagon,
    markersize = 8,
    markeropacity = 0.5,
)
```



### Advanced: duality and the kernel method

We now consider an alternative formulation for a linear SVM by solving the dual problem.

#### The dual program

The dual of the linear SVM program is also a linearly constrained quadratic program:

$$\begin{aligned} \min_{u \in \mathbb{R}^m} \quad & \frac{1}{2} u^\top D P P^\top D u - \mathbf{1}^\top u \\ \text{subject to} \quad & \mathbf{1}^\top D u = 0 \\ & 0 \leq u \leq C \mathbf{1}. \end{aligned}$$

This is the JuMP model:

```

function solve_dual_SVM_classifier(P::Matrix, labels::Vector; C::Float64 = C_0)
    m, n = size(P)
    model = Model(Ipopt.Optimizer)
    set_silent(model)
    @variable(model, 0 <= u[1:m] <= C)
    D = LinearAlgebra.Diagonal(labels)
    @objective(model, Min, 1 / 2 * u' * D * P * P' * D * u - sum(u))
    @constraint(model, con, sum(D * u) == 0)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    w = P' * D * value.(u)
    g = dual(con)
    classifier(x) = line(x; w = w, g = g)
    return classifier
end

```

```
solve_dual_SVM_classifier (generic function with 1 method)
```

We recover the line gradient vector  $w$  through setting  $w = P^\top Du$ , and the line constant  $g$  as the dual value of the single affine constraint.

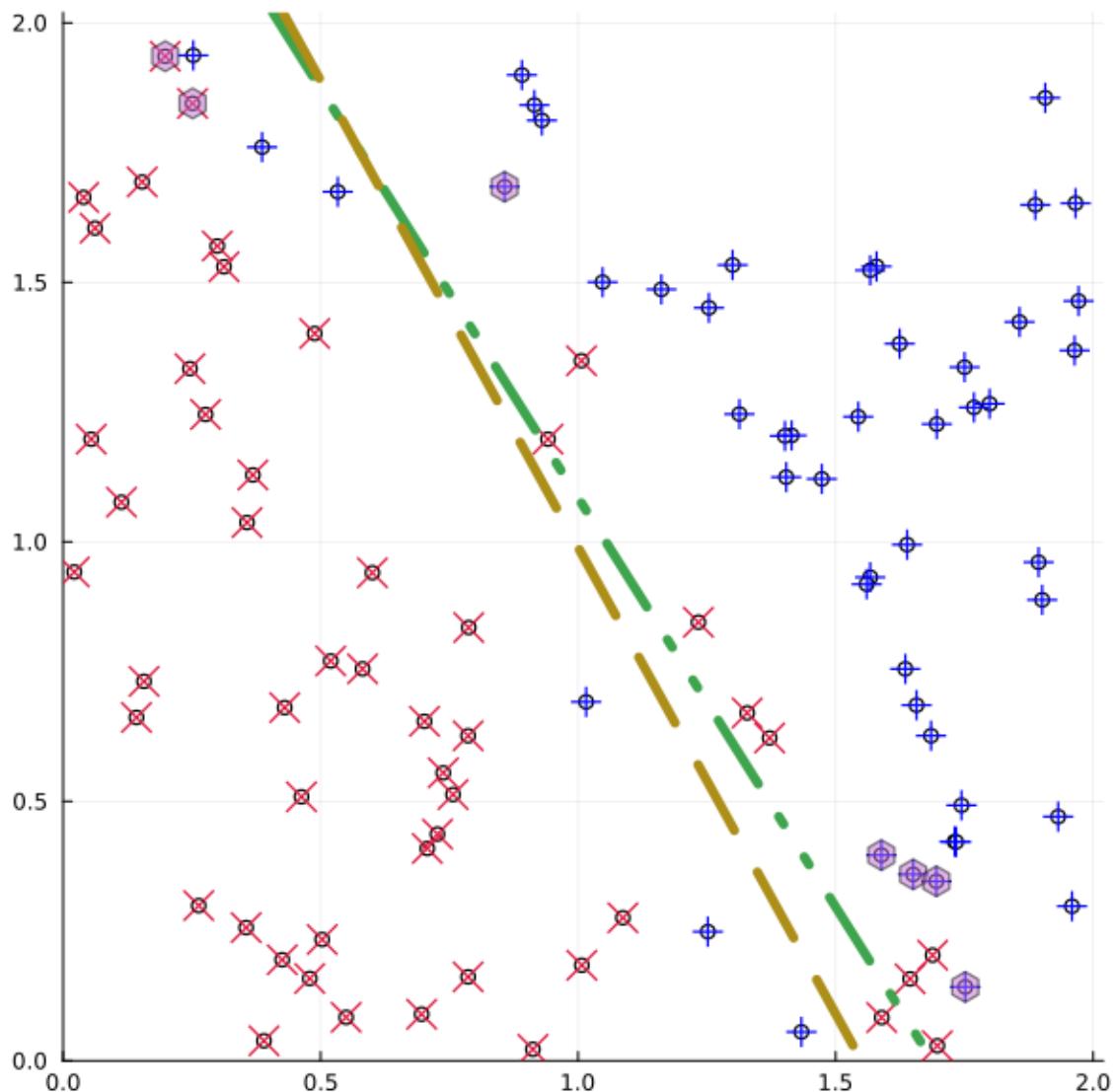
The dual problem has fewer variables and fewer constraints, so in many cases it may be simpler to solve the dual form.

We can check that the dual form has recovered a classifier:

```

classifier = solve_dual_SVM_classifier(P, labels)
Plots.plot!(plot, classifier; linewidth = 5, linestyle = :dash)

```



### The kernel method

Linear SVM techniques are not limited to finding separating hyperplanes in the original space of the dataset. One could first transform the training data under a nonlinear mapping, apply our method, then map the hyperplane back into original space.

The actual data describing the point set is held in a matrix  $P$ , but looking at the dual program we see that what actually matters is the Gram matrix  $PP^\top$ , expressing a pairwise comparison (an inner-product) between each point vector. It follows that any mapping of the point set only needs to be defined at the level of *pairwise* maps between points. Such maps are known as *kernel functions*:

$$k : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}, \quad (s, t) \mapsto \langle \Phi(s), \Phi(t) \rangle$$

where the right-hand side applies some transformation  $\Phi : \mathbb{R}^n \rightarrow \mathbb{R}^{n'}$  followed by an inner-product in that image space.

In practice, we can avoid having  $\Phi$  explicitly given but instead define a kernel function directly between pairs of vectors. This change to using a kernel function without knowing the map is called the *kernel method* (or sometimes, the *kernel trick*).

### Classifier using a Gaussian kernel

We will demonstrate the application of a *Gaussian* or *radial basis function* kernel:

$$k(s, t) = \exp(-\mu \|s - t\|_2^2)$$

for some positive parameter  $\mu$ .

```
k_gauss(s::Vector, t::Vector; μ = 0.5) = exp(-μ * LinearAlgebra.norm(s - t)^2)
```

`k_gauss` (generic function with 1 method)

Given a matrix of points expressed row-wise and a kernel, the next function returns the transformed matrix  $K$  that replaces  $PP^\top$ :

```
function pairwise_transform(kernel::Function, P::Matrix{T}) where {T}
    m, n = size(P)
    K = zeros(T, m, m)
    for j in 1:m, i in 1:j
        K[i, j] = K[j, i] = kernel(P[i, :], P[j, :])
    end
    return LinearAlgebra.Symmetric(K)
end
```

`pairwise_transform` (generic function with 1 method)

Now we're ready to define our optimization problem. We need to provide the kernel function to be used in the problem. Note that any extra keyword arguments here (like parameter values) are passed through to the kernel.

```
function solve_kernel_SVM_classifier(
    kernel::Function,
    P::Matrix,
    labels::Vector;
    C::Float64 = C_0,
    kwargs...,
)
    m, n = size(P)
    K = pairwise_transform(kernel, P)
```

```

model = Model(Ipopt.Optimizer)
set_silent(model)
@variable(model, 0 <= u[1:m] <= C)
D = LinearAlgebra.Diagonal(labels)
con = @constraint(model, sum(D * u) == 0)
@objective(model, Min, 1 / 2 * u' * D * K * D * u - sum(u))
optimize!(model)
assert_is_solved_and_feasible(model)
u_sol, g_sol = value.(u), dual(con)
function classifier(v::Vector)
    return sum(
        D[i, i] * u_sol[i] * kernel(P[i, :], v; kwargs...) for i in 1:m
    ) - g_sol
end
return classifier
end

```

```
solve_kernel_SVM_classifier (generic function with 1 method)
```

This time, we don't recover the line gradient vector  $w$  directly. Instead, we compute the classifier  $f$  using the function:

$$f(v) = \sum_{i=1}^m D_{ii} u_i k(p_i, v) - g$$

where  $p_i$  is row vector  $i$  of  $P$ .

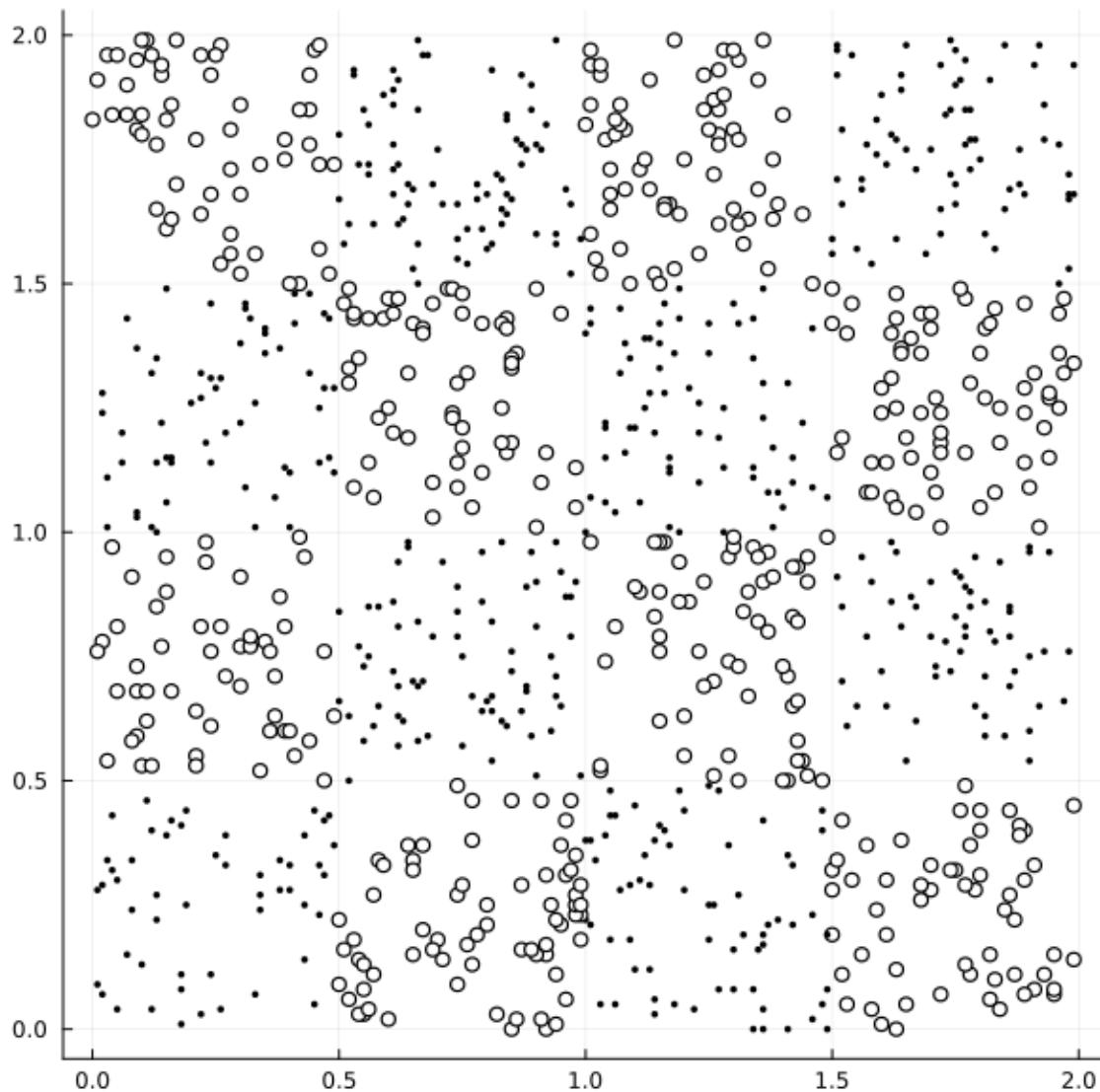
### Checkerboard dataset

To demonstrate this nonlinear technique, we'll use the [checkerboard dataset](#).

```

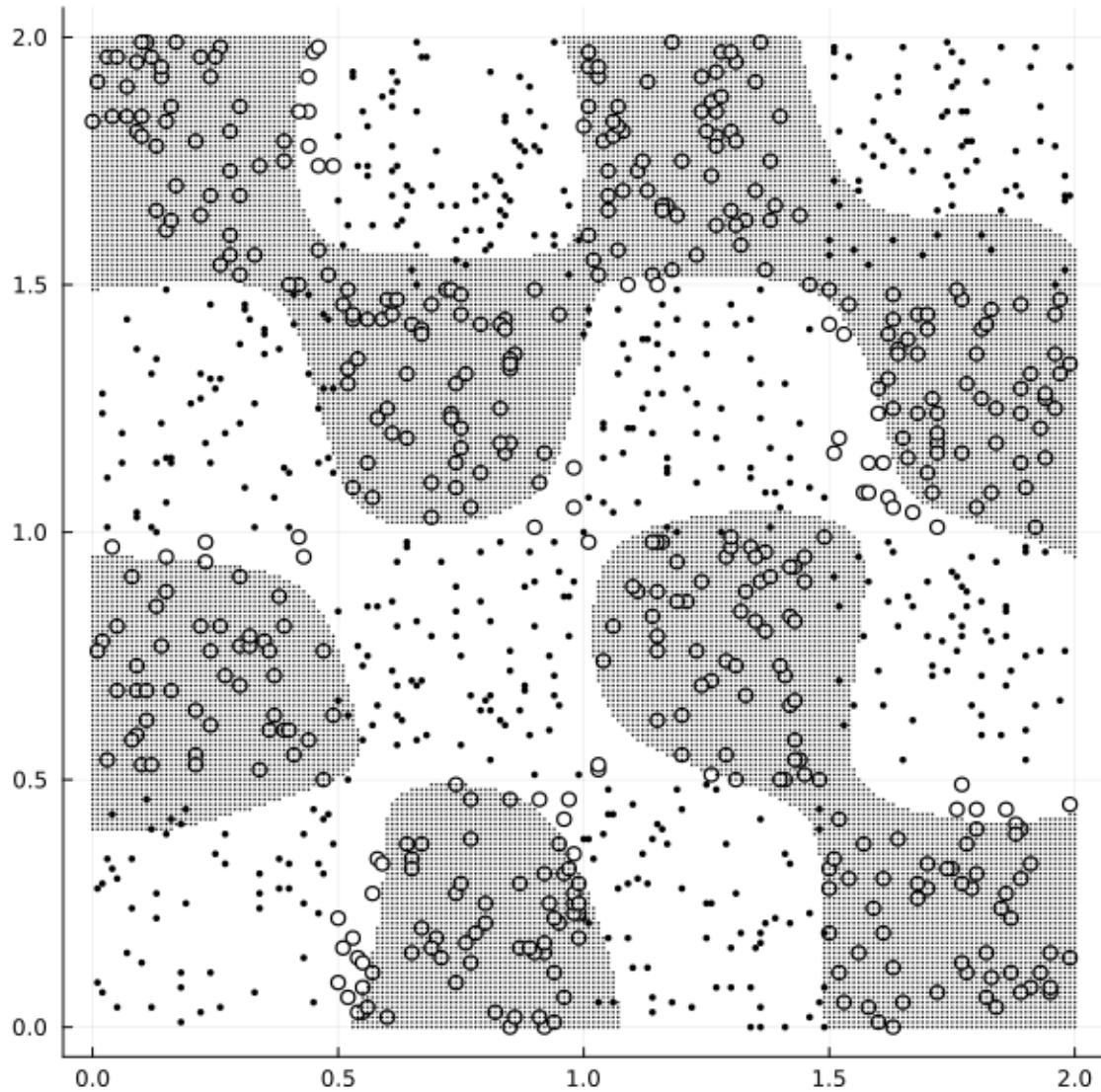
filename = joinpath(@__DIR__, "data", "checker", "checker.txt")
checkerboard = DelimitedFiles.readdlm(filename, ' ', Int)
labels = ifelse.(iszero.(checkerboard[:, 1]), -1, 1)
B = checkerboard[:, 2:3] ./ 100.0 # rescale to [0,2] x [0,2] square.
plot = Plots.scatter(
    B[:, 1],
    B[:, 2];
    color = ifelse.(labels .== 1, :white, :black),
    markersize = ifelse.(labels .== 1, 4, 2),
    size = (600, 600),
    legend = false,
)

```



Is the technique capable of generating a distinctly nonlinear surface? Let's solve the Gaussian kernel based quadratic problem with these parameters:

```
classifier = solve_kernel_SVM_classifier(k_gauss, B, labels; C = 1e5, μ = 10.0)
grid = [[x, y] for x in 0:0.01:2, y in 0:0.01:2]
grid_pos = [Tuple(g) for g in grid if classifier(g) >= 0]
Plots.scatter!(plot, grid_pos; markersize = 0.2)
```



We find that the kernel method can perform well as a nonlinear classifier.

The result has a fairly strong dependence on the choice of parameters, with larger values of  $\mu$  allowing for a more complex boundary while smaller values lead to a smoother boundary for the classifier. Determining a better performing kernel function and choice of parameters is covered by the process of *cross-validation* with respect to the dataset, where different testing, training and tuning sets are used to validate the best choice of parameters against a statistical measure of error.

## 7.10 Example: portfolio optimization

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

**This tutorial was originally contributed by Arpit Bhatia.**

Optimization models play an increasingly important role in financial decisions. Many computational finance problems can be solved efficiently using modern optimization techniques.

This tutorial solves the famous Markowitz Portfolio Optimization problem with data from [lecture notes from a course taught at Georgia Tech by Shabbir Ahmed](#).

## Required packages

This tutorial uses the following packages:

```
using JuMP
import DataFrames
import Ipopt
import MultiObjectiveAlgorithms as MOA
import Plots
import Statistics
import StatsPlots
```

## Formulation

Suppose we are considering investing 1000 dollars in three non-dividend paying stocks, IBM (IBM), Walmart (WMT), and Southern Electric (SEHI), for a one-month period.

We will use the initial money to buy shares of the three stocks at the current market prices, hold these for one month, and sell the shares off at the prevailing market prices at the end of the month.

As a rational investor, we hope to make some profit out of this endeavor, that is, the return on our investment should be positive.

Suppose we bought a stock at  $p$  dollars per share in the beginning of the month, and sold it off at  $s$  dollars per share at the end of the month. Then the one-month return on a share of the stock is  $\frac{s-p}{p}$ .

Since the stock prices are quite uncertain, so is the end-of-month return on our investment. Our goal is to invest in such a way that the expected end-of-month return is at least \$50 or 5%. Furthermore, we want to make sure that the “risk” of not achieving our desired return is minimum.

Note that we are solving the problem under the following assumptions:

1. We can trade any continuum of shares.
2. No short-selling is allowed.
3. There are no transaction costs.

We model this problem by taking decision variables  $x_i, i = 1, 2, 3$ , denoting the dollars invested in each of the 3 stocks.

Let us denote by  $\tilde{r}_i$  the random variable corresponding to the monthly return (increase in the stock price) per dollar for stock  $i$ .

Then, the return (or profit) on  $x_i$  dollars invested in stock  $i$  is  $\tilde{r}_i x_i$ , and the total (random) return on our investment is  $\sum_{i=1}^3 \tilde{r}_i x_i$ . The expected return on our investment is then  $\mathbb{E} \left[ \sum_{i=1}^3 \tilde{r}_i x_i \right] = \sum_{i=1}^3 \bar{r}_i x_i$ , where  $\bar{r}_i$  is the expected value of the  $\tilde{r}_i$ .

Now we need to quantify the notion of “risk” in our investment.

Markowitz, in his Nobel prize winning work, showed that a rational investor’s notion of minimizing risk can be closely approximated by minimizing the variance of the return of the investment portfolio. This variance is given by:

$$\text{Var} \left[ \sum_{i=1}^3 \tilde{r}_i x_i \right] = \sum_{i=1}^3 \sum_{j=1}^3 x_i x_j \sigma_{ij}$$

where  $\sigma_{ij}$  is the covariance of the return of stock  $i$  with stock  $j$ .

Note that the right hand side of the equation is the most reduced form of the expression and we have not shown the intermediate steps involved in getting to this form. We can also write this equation as:

$$\text{Var} \left[ \sum_{i=1}^3 \tilde{r}_i x_i \right] = x^\top Q x$$

Where  $Q$  is the covariance matrix for the random vector  $\tilde{r}$ .

Finally, we can write the model as:

$$\begin{aligned} & \min x^\top Q x \\ \text{s.t. } & \sum_{i=1}^3 x_i \leq 1000 \\ & \bar{r}^\top x \geq 50 \\ & x \geq 0 \end{aligned}$$

## Data

For the data in our problem, we use the stock prices given below, in monthly values from November 2000, through November 2001.

```
df = DataFrames.DataFrame(
    [
        93.043 51.826 1.063
        84.585 52.823 0.938
        111.453 56.477 1.000
        99.525 49.805 0.938
        95.819 50.287 1.438
        114.708 51.521 1.700
        111.515 51.531 2.540
        113.211 48.664 2.390
        104.942 55.744 3.120
        99.827 47.916 2.980
        91.607 49.438 1.900
        107.937 51.336 1.750
        115.590 55.081 1.800
    ],
    [:IBM, :WMT, :SEHI],
)
```

Next, we compute the percentage return for the stock in each month:

	IBM	WMT	SEH1
	Float64	Float64	Float64
1	93.043	51.826	1.063
2	84.585	52.823	0.938
3	111.453	56.477	1.0
4	99.525	49.805	0.938
5	95.819	50.287	1.438
6	114.708	51.521	1.7
7	111.515	51.531	2.54
8	113.211	48.664	2.39
9	104.942	55.744	3.12
10	99.827	47.916	2.98
11	91.607	49.438	1.9
12	107.937	51.336	1.75
13	115.59	55.081	1.8

```
returns = diff(Matrix(df); dims = 1) ./ Matrix(df[1:end-1, :])
```

```
12x3 Matrix{Float64}:
-0.0909042   0.0192374   -0.117592
 0.317645    0.0691744   0.0660981
-0.107023   -0.118137   -0.062
-0.0372369   0.00967774   0.533049
 0.197132    0.0245391   0.182197
-0.0278359   0.000194096  0.494118
 0.0152087   -0.0556364  -0.0590551
-0.0730406   0.145487    0.305439
-0.0487412   -0.140428  -0.0448718
-0.0823425   0.0317639  -0.362416
 0.178261    0.0383915  -0.0789474
 0.0709025   0.0729508   0.0285714
```

The expected monthly return is:

```
r = vec(Statistics.mean(returns; dims = 1))
```

```
3-element Vector{Float64}:
 0.026002150277777348
 0.008101316405671459
 0.07371590949198982
```

and the covariance matrix is:

```
Q = Statistics.cov(returns)
```

```
3x3 Matrix{Float64}:
 0.018641  0.00359853  0.00130976
 0.00359853  0.00643694  0.00488727
 0.00130976  0.00488727  0.0686828
```

### JuMP formulation

```
model = Model(Ipopt.Optimizer)
set_silent(model)
@variable(model, x[1:3] >= 0)
@objective(model, Min, x' * Q * x)
@constraint(model, sum(x) <= 1000)
@constraint(model, r' * x >= 50)
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : Ipopt

* Status
  Result count      : 1
  Termination status : LOCALLY_SOLVED
  Message from the solver:
  "Solve_Succeeded"

* Candidate solution (result #1)
  Primal status       : FEASIBLE_POINT
  Dual status         : FEASIBLE_POINT
  Objective value    : 2.26344e+04
  Dual objective value : 4.52688e+04

* Work counters
  Solve time (sec)   : 3.13497e-03
  Barrier iterations : 11
```

The optimal allocation of our assets is:

```
value.(x)
```

```
3-element Vector{Float64}:
 497.045529849864
 -9.670578501816873e-9
 502.9544801594809
```

So we spend \$497 on IBM, and \$503 on SEHI. This results in a variance of:

```
scalar_variance = value(x' * Q * x)
```

```
22634.417849884147
```

and an expected return of:

```
scalar_return = value(r' * x)
```

```
49.99999500002374
```

### Multi-objective portfolio optimization

The previous model returned a single solution that minimized the variance, ensuring that our expected return was at least \$50. In practice, we might be willing to accept a slightly higher variance if it meant a much increased expected return. To explore this problem space, we can instead formulate our portfolio optimization problem with two objectives:

1. to minimize the variance
2. to maximize the expected return

The solution to this bi-objective problem is the [efficient frontier](#) of modern portfolio theory, and each point in the solution is a point with the best return for a fixed level of risk.

```
model = Model(() -> MOA.Optimizer(Ipopt.Optimizer))
set_silent(model)
```

We also need to choose a solution algorithm for MOA. For our problem, the efficient frontier will have an infinite number of solutions. Since we cannot find all of the solutions, we choose an approximation algorithm and limit the number of solution points that are returned:

```
set_optimizer_attribute(model, MOA.Algorithm(), MOA.EpsilonConstraint())
set_optimizer_attribute(model, MOA.SolutionLimit(), 50)
```

Now we can define the rest of the model:

```
@variable(model, x[1:3] >= 0)
@constraint(model, sum(x) <= 1000)
@expression(model, variance, x' * Q * x)
@expression(model, expected_return, r' * x)
# We want to minimize variance and maximize expected return, but we must pick
# a single objective sense `Min`, and negate any `Max` objectives:
@objective(model, Min, [variance, -expected_return])
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : MOA[algorithm=MultiObjectiveAlgorithms.EpsilonConstraint, optimizer=Ipopt]

* Status
  Result count      : 50
  Termination status : OPTIMAL
  Message from the solver:
  "Solve complete. Found 50 solution(s)"

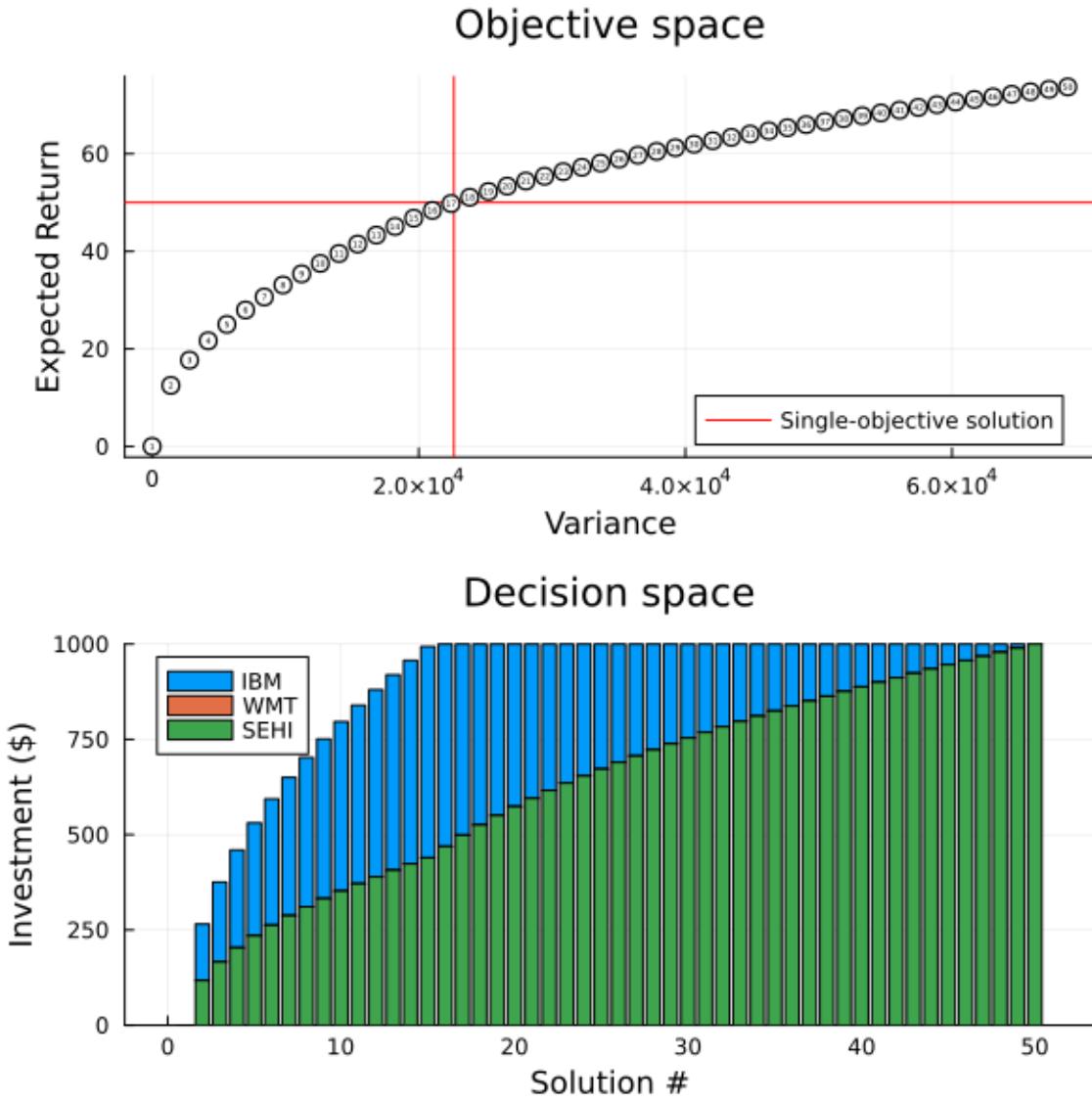
* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : NO_SOLUTION
  Objective value    : [2.58170e-08, -5.36777e-05]
  Objective bound    : [5.78303e-09, -7.37159e+01]

* Work counters
  Solve time (sec)   : 2.26656e-01
```

The algorithm found 50 different solutions. Let's plot them to see how they differ:

```
objective_space = Plots.hline(
    [scalar_return];
    label = "Single-objective solution",
    linecolor = :red,
)
Plots.vline!(objective_space, [scalar_variance]; label = "", linecolor = :red)
Plots.scatter!(
    objective_space,
    [value(variance; result = i) for i in 1:result_count(model)],
    [value(expected_return; result = i) for i in 1:result_count(model)];
    xlabel = "Variance",
    ylabel = "Expected Return",
    label = "",
    title = "Objective space",
    markercolor = "white",
    markersize = 5,
    legend = :bottomright,
)
for i in 1:result_count(model)
    y = objective_value(model; result = i)
    Plots.annotate!(objective_space, y[1], -y[2], (i, 3))
end

decision_space = StatsPlots.groupedbar(
    vcat([value.(x; result = i)' for i in 1:result_count(model)]...);
    bar_position = :stack,
    label = ["IBM" "WMT" "SEHI"],
    xlabel = "Solution #",
    ylabel = "Investment (\$)",
    title = "Decision space",
)
Plots.plot(objective_space, decision_space; layout = (2, 1), size = (600, 600))
```



Perhaps our trade-off wasn't so bad after all. Our original solution corresponded to picking a solution #17. If we buy more SEHI, we can increase the return, but the variance also increases. If we buy less SEHI, such as a solution like #5 or #6, then we can achieve the corresponding return without deploying all of our capital. We should also note that at no point should we buy WMT.

### 7.11 Example: nonlinear optimal control of a rocket

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

**This tutorial was originally contributed by Iain Dunning.**

The purpose of this tutorial is to demonstrate how to setup and solve a nonlinear optimization problem.

The example is an optimal control problem of a nonlinear rocket.

**Info**

The JuMP extension [InfiniteOpt.jl](#) can also be used to model and solve optimal control problems.

**Required packages**

This tutorial uses the following packages:

```
using JuMP
import Ipopt
import Plots
```

**Overview**

Our goal is to maximize the final altitude of a vertically launched rocket.

We can control the thrust of the rocket, and must take account of the rocket mass, fuel consumption rate, gravity, and aerodynamic drag.

Let us consider the basic description of the model (for the full description, including parameters for the rocket, see [COPS3](#)).

There are three state variables in our model:

- Velocity:  $x_v(t)$
- Altitude:  $x_h(t)$
- Mass of rocket and remaining fuel,  $x_m(t)$

and a single control variable:

- Thrust:  $u_t(t)$ .

There are three equations that control the dynamics of the rocket:

- Rate of ascent:  $\frac{dx_h}{dt} = x_v$
- Acceleration:  $\frac{dx_v}{dt} = \frac{u_t - D(x_h, x_v)}{x_m} - g(x_h)$
- Rate of mass loss:  $\frac{dx_m}{dt} = -\frac{u_t}{c}$

where drag  $D(x_h, x_v)$  is a function of altitude and velocity, gravity  $g(x_h)$  is a function of altitude, and  $c$  is a constant.

These forces are defined as:

$$D(x_h, x_v) = D_c \cdot x_v^2 \cdot e^{-h_c \left( \frac{x_h - x_{h(0)}}{x_{h(0)}} \right)}$$

$$\text{and } g(x_h) = g_0 \cdot \left( \frac{x_h(0)}{x_h} \right)^2$$

We use a discretized model of time, with a fixed number of time steps,  $T$ .

Our goal is thus to maximize  $x_h(T)$ .

## Data

All parameters in this model have been normalized to be dimensionless, and they are taken from [COPS3](#).

```

h_0 = 1                      # Initial height
v_0 = 0                      # Initial velocity
m_0 = 1.0                     # Initial mass
m_T = 0.6                     # Final mass
g_0 = 1                       # Gravity at the surface
h_c = 500                     # Used for drag
c = 0.5 * sqrt(g_0 * h_0)     # Thrust-to-fuel mass
D_c = 0.5 * 620 * m_0 / g_0   # Drag scaling
u_t_max = 3.5 * g_0 * m_0     # Maximum thrust
T_max = 0.2                   # Number of seconds
T = 1_000                     # Number of time steps
Δt = 0.2 / T;                 # Time per discretized step

```

## JuMP formulation

First, we create a model and choose an optimizer. Since this is a nonlinear program, we need to use a nonlinear solver like Ipopt. We cannot use a linear solver like HiGHS.

```

model = Model(Ipopt.Optimizer)
set_silent(model)

```

Next, we create our state and control variables, which are each indexed by t. It is good practice for nonlinear programs to always provide a starting solution for each variable.

```

@variable(model, x_v[1:T] >= 0, start = v_0)           # Velocity
@variable(model, x_h[1:T] >= 0, start = h_0)           # Height
@variable(model, x_m[1:T] >= m_T, start = m_0)         # Mass
@variable(model, 0 <= u_t[1:T] <= u_t_max, start = 0); # Thrust

```

We implement boundary conditions by fixing variables to values.

```

fix(x_v[1], v_0; force = true)
fix(x_h[1], h_0; force = true)
fix(x_m[1], m_0; force = true)
fix(u_t[T], 0.0; force = true)

```

The objective is to maximize altitude at end of time of flight.

```

@objective(model, Max, x_h[T])

```

$x_h_{1000}$

Forces are defined as functions:

```
D(x_h, x_v) = D_c * x_v^2 * exp(-h_c * (x_h - h_0) / h_0)
g(x_h) = g_0 * (h_0 / x_h)^2
```

```
g (generic function with 1 method)
```

The dynamical equations are implemented as constraints.

```
ddt(x::Vector, t::Int) = (x[t] - x[t-1]) / Δt
@constraint(model, [t in 2:T], ddt(x_h, t) == x_v[t-1])
@constraint(
    model,
    [t in 2:T],
    ddt(x_v, t) == (u_t[t-1] - D(x_h[t-1], x_v[t-1])) / x_m[t-1] - g(x_h[t-1]),
)
@constraint(model, [t in 2:T], ddt(x_m, t) == -u_t[t-1] / c);
```

Now we optimize the model and check that we found a solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : Ipopt

* Status
Result count      : 1
Termination status : LOCALLY_SOLVED
Message from the solver:
"Solve_Succeeded"

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : FEASIBLE_POINT
Objective value   : 1.01278e+00
Dual objective value : 4.66547e+00

* Work counters
Solve time (sec)   : 1.93004e-01
Barrier iterations : 24
```

Finally, we plot the solution:

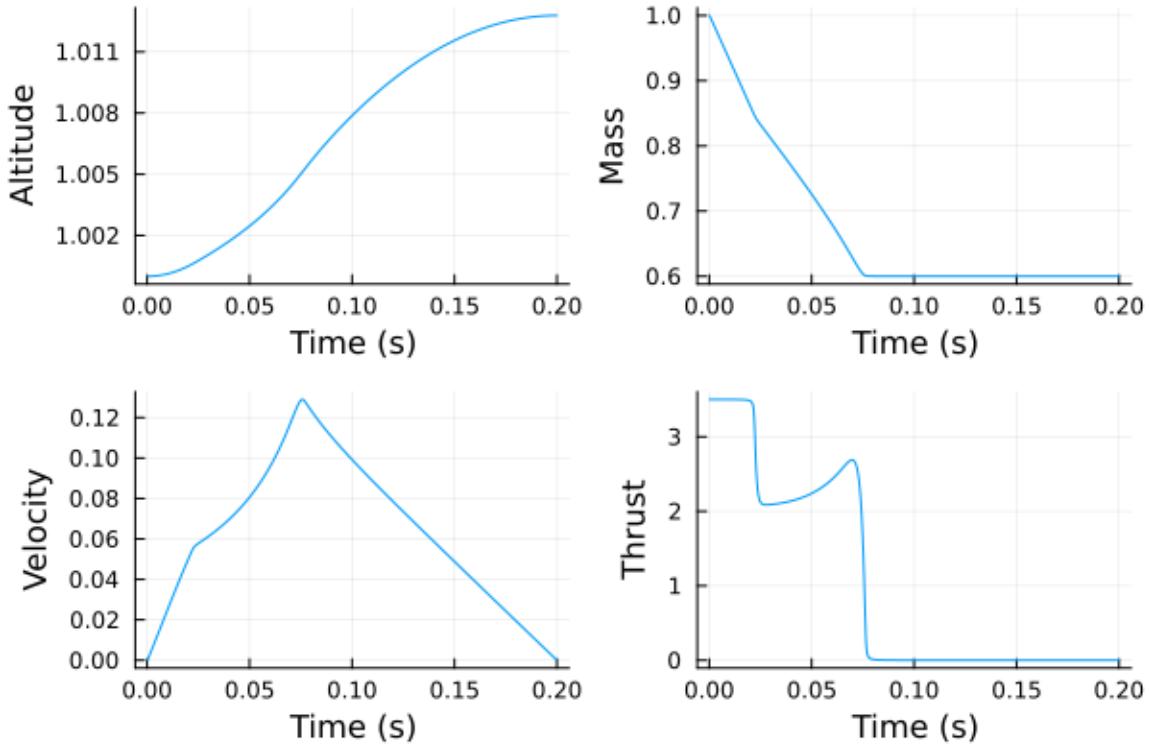
```
function plot_trajectory(y; kwargs...)
    return Plots.plot(
        (1:T) * Δt,
        value.(y);
```

```

        xlabel = "Time (s)",
        legend = false,
        kwargs...,
    )
end

Plots.plot(
    plot_trajectory(x_h; ylabel = "Altitude"),
    plot_trajectory(x_m; ylabel = "Mass"),
    plot_trajectory(x_v; ylabel = "Velocity"),
    plot_trajectory(u_t; ylabel = "Thrust");
    layout = (2, 2),
)

```



### Next steps

- Experiment with different values for the constants. How does the solution change? In particular, what happens if you change  $T_{\max}$ ?
- The dynamical equations use rectangular integration for the right-hand side terms. Modify the equations to use the [Trapezoidal rule](#) instead. (As an example,  $x_v[t-1]$  would become  $0.5 * (x_v[t-1] + x_v[t])$ .) Is there a difference?

## 7.12 Example: optimal control for a Space Shuttle reentry trajectory

This tutorial was generated using [Literate.jl](#). Download the source as a [.jl file](#).

**This tutorial was originally contributed by Henrique Ferrolho.**

This tutorial demonstrates how to compute a reentry trajectory for the [Space Shuttle](#), by formulating and solving a nonlinear programming problem. The problem was drawn from Chapter 6 of ([Betts, 2010](#)).

### Info

The JuMP extension [InfiniteOpt.jl](#) can also be used to model and solve optimal control problems.

### Tip

This tutorial is a more-complicated version of the [Example: nonlinear optimal control of a rocket](#) tutorial. If you are new to solving nonlinear programs in JuMP, you may want to start there instead.

## Required packages

This tutorial uses the following packages:

```
using JuMP
import Interpolations
import Ipopt
```

## Formulation

The motion of the vehicle is defined by the following set of DAEs:

$$\begin{aligned}\dot{h} &= v \sin \gamma, \\ \dot{\phi} &= \frac{v}{r} \cos \gamma \sin \psi / \cos \theta, \\ \dot{\theta} &= \frac{v}{r} \cos \gamma \cos \psi, \\ \dot{v} &= -\frac{D}{m} - g \sin \gamma, \\ \dot{\gamma} &= \frac{L}{mv} \cos(\beta) + \cos \gamma \left( \frac{v}{r} - \frac{g}{v} \right), \\ \dot{\psi} &= \frac{1}{mv \cos \gamma} L \sin(\beta) + \frac{v}{r \cos \theta} \cos \gamma \sin \psi \sin \theta, \\ q &\leq q_U,\end{aligned}$$

where the aerodynamic heating on the vehicle wing leading edge is  $q = q_a q_r$  and the dynamic variables are

$h$	altitude (ft),	$\gamma$	flight path angle (rad),
$\phi$	longitude (rad),	$\psi$	azimuth (rad),
$\theta$	latitude (rad),	$\alpha$	angle of attack (rad),
$v$	velocity (ft/sec),	$\beta$	bank angle (rad).

The aerodynamic and atmospheric forces on the vehicle are specified by the following quantities (English units):

$$\begin{aligned}
D &= \frac{1}{2} c_D S \rho v^2, & a_0 &= -0.20704, \\
L &= \frac{1}{2} c_L S \rho v^2, & a_1 &= 0.029244, \\
g &= \mu/r^2, & \mu &= 0.14076539 \times 10^{17}, \\
r &= R_e + h, & b_0 &= 0.07854, \\
\rho &= \rho_0 \exp[-h/h_r], & b_1 &= -0.61592 \times 10^{-2}, \\
\rho_0 &= 0.002378, & b_2 &= 0.621408 \times 10^{-3}, \\
h_r &= 23800, & q_r &= 17700\sqrt{\rho}(0.0001v)^{3.07}, \\
c_L &= a_0 + a_1\hat{\alpha}, & q_a &= c_0 + c_1\hat{\alpha} + c_2\hat{\alpha}^2 + c_3\hat{\alpha}^3, \\
c_D &= b_0 + b_1\hat{\alpha} + b_2\hat{\alpha}^2, & c_0 &= 1.0672181, \\
\hat{\alpha} &= 180\alpha/\pi, & c_1 &= -0.19213774 \times 10^{-1}, \\
R_e &= 20902900, & c_2 &= 0.21286289 \times 10^{-3}, \\
S &= 2690, & c_3 &= -0.10117249 \times 10^{-5}.
\end{aligned}$$

The reentry trajectory begins at an altitude where the aerodynamic forces are quite small with a weight of  $w = 203000$  (lb) and mass  $m = w/g_0$  (slug), where  $g_0 = 32.174$  (ft/sec $^2$ ). The initial conditions are as follows:

$$\begin{aligned}
h &= 260000 \text{ ft}, & v &= 25600 \text{ ft/sec}, \\
\phi &= 0 \text{ deg}, & \gamma &= -1 \text{ deg}, \\
\theta &= 0 \text{ deg}, & \psi &= 90 \text{ deg}.
\end{aligned}$$

The final point on the reentry trajectory occurs at the unknown (free) time  $t_F$ , at the so-called terminal area energy management (TAEM) interface, which is defined by the conditions

$$h = 80000 \text{ ft}, \quad v = 2500 \text{ ft/sec}, \quad \gamma = -5 \text{ deg}.$$

As explained in the book, our goal is to maximize the final cross-range, which is equivalent to maximizing the final latitude of the vehicle, that is,  $J = \theta(t_F)$ .

### Approach

We will use a discretized model of time, with a fixed number of discretized points,  $n$ . The decision variables at each point are going to be the state of the vehicle and the controls commanded to it. In addition, we will also make each time step size  $\Delta t$  a decision variable; that way, we can either fix the time step size easily, or allow the solver to fine-tune the duration between each adjacent pair of points. Finally, in order to approximate the derivatives of the problem dynamics, we will use either rectangular or trapezoidal integration.

#### Warning

Do not try to actually land a Space Shuttle using this notebook. There's no mesh refinement going on, which can lead to unrealistic trajectories having position and velocity errors with orders of magnitude  $10^4$  ft and  $10^2$  ft/sec, respectively.

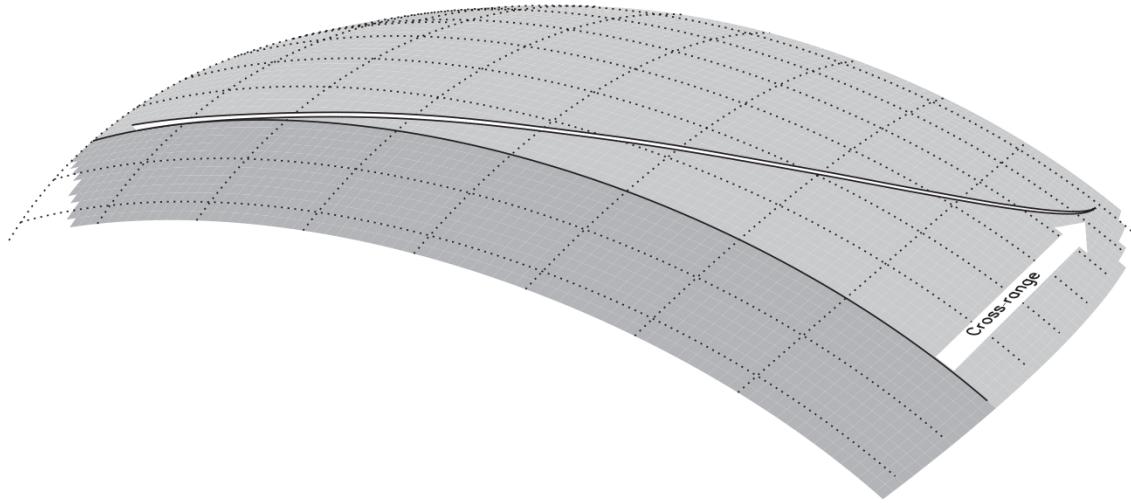


Figure 7.1: Max cross-range shuttle reentry

```

# Global variables
const w = 203000.0    # weight (lb)
const g_0 = 32.174     # acceleration (ft/sec^2)
const m = w / g_0      # mass (slug)

# Aerodynamic and atmospheric forces on the vehicle
const rho_0 = 0.002378
const h_r = 23800.0
const R_e = 20902900.0
const mu = 0.14076539e17
const S = 2690.0
const a_0 = -0.20704
const a_1 = 0.029244
const b_0 = 0.07854
const b_1 = -0.61592e-2
const b_2 = 0.621408e-3
const c_0 = 1.0672181
const c_1 = -0.19213774e-1
const c_2 = 0.21286289e-3
const c_3 = -0.10117249e-5

# Initial conditions
const h_s = 2.6          # altitude (ft) / 1e5
const phi_s = deg2rad(0)  # longitude (rad)
const theta_s = deg2rad(0) # latitude (rad)
const v_s = 2.56         # velocity (ft/sec) / 1e4
const gamma_s = deg2rad(-1) # flight path angle (rad)
const psi_s = deg2rad(90) # azimuth (rad)
const alpha_s = deg2rad(0) # angle of attack (rad)
const beta_s = deg2rad(0) # bank angle (rad)
const t_s = 1.00          # time step (sec)

# Final conditions, the so-called Terminal Area Energy Management (TAEM)

```

```

const h_t = 0.8           # altitude (ft) / 1e5
const v_t = 0.25          # velocity (ft/sec) / 1e4
const γ_t = deg2rad(-5)   # flight path angle (rad)

# Number of mesh points (knots) to be used
const n = 503

# Integration scheme to be used for the dynamics
const integration_rule = "rectangular"

```

### Choose a good linear solver

Picking a good linear solver is **extremely important** to maximize the performance of nonlinear solvers. For the best results, it is advised to experiment different linear solvers.

For example, the linear solver MA27 is outdated and can be quite slow. MA57 is a much better alternative, especially for highly sparse problems (such as trajectory optimization problems).

```

# Uncomment the lines below to pass user options to the solver
user_options = (
    # "mu_strategy" => "monotone",
    # "linear_solver" => "ma27",
)

# Create JuMP model, using Ipopt as the solver
model = Model(optimizer_with_attributes(Ipopt.Optimizer, user_options...))

@variables(model, begin
    0 ≤ scaled_h[1:n]                      # altitude (ft) / 1e5
    φ[1:n]                                # longitude (rad)
    deg2rad(-89) ≤ θ[1:n] ≤ deg2rad(89)    # latitude (rad)
    1e-4 ≤ scaled_v[1:n]                     # velocity (ft/sec) / 1e4
    deg2rad(-89) ≤ γ[1:n] ≤ deg2rad(89)    # flight path angle (rad)
    ψ[1:n]                                # azimuth (rad)
    deg2rad(-90) ≤ α[1:n] ≤ deg2rad(90)    # angle of attack (rad)
    deg2rad(-89) ≤ β[1:n] ≤ deg2rad(1)     # bank angle (rad)
    #      3.5 ≤ Δt[1:n] ≤ 4.5            # time step (sec)
    Δt[1:n] == 4.0                          # time step (sec)
)
end;

```

**Info**

Above you can find two alternatives for the  $\Delta t$  variables.

The first one,  $3.5 \leq \Delta t[1:n] \leq 4.5$  (currently commented), allows some wiggle room for the solver to adjust the time step size between pairs of mesh points. This is neat because it allows the solver to figure out which parts of the flight require more dense discretization than others. (Remember, the number of discretized points is fixed, and this example does not implement mesh refinement.) However, this makes the problem more complex to solve, and therefore leads to a longer computation time.

The second line,  $\Delta t[1:n] == 4.0$ , fixes the duration of every time step to exactly 4.0 seconds. This allows the problem to be solved faster. However, to do this we need to know beforehand that the close-to-optimal total duration of the flight is  $\sim 2009$  seconds. Therefore, if we split the total duration in slices of 4.0 seconds, we know that we require  $n = 503$  knots to discretize the whole trajectory.

```
# Fix initial conditions
fix(scaled_h[1], h_s; force = true)
fix(phi[1], phi_s; force = true)
fix(theta[1], theta_s; force = true)
fix(scaled_v[1], v_s; force = true)
fix(y[1], y_s; force = true)
fix(psi[1], psi_s; force = true)

# Fix final conditions
fix(scaled_h[n], h_t; force = true)
fix(scaled_v[n], v_t; force = true)
fix(y[n], y_t; force = true)

# Initial guess: linear interpolation between boundary conditions
x_s = [h_s, phi_s, theta_s, v_s, y_s, psi_s, alpha_s, beta_s, t_s]
x_t = [h_t, phi_s, theta_s, v_t, y_t, psi_s, alpha_s, beta_s, t_s]
interp_linear = Interpolations.LinearInterpolation([1, n], [x_s, x_t])
initial_guess = mapreduce(transpose, vcat, interp_linear.(1:n))
set_start_value.(all_variables(model), vec(initial_guess))

# Functions to restore `h` and `v` to their true scale
@expression(model, h[j = 1:n], scaled_h[j] * 1e5)
@expression(model, v[j = 1:n], scaled_v[j] * 1e4)

# Helper functions
@expression(model, c_L[j = 1:n], a_0 + a_1 * rad2deg(alpha[j]))
@expression(model, c_D[j = 1:n], b_0 + b_1 * rad2deg(alpha[j]) + b_2 * rad2deg(alpha[j])^2)
@expression(model, p[j = 1:n], p_0 * exp(-h[j] / h_r))
@expression(model, D[j = 1:n], 0.5 * c_D[j] * S * p[j] * v[j]^2)
@expression(model, L[j = 1:n], 0.5 * c_L[j] * S * p[j] * v[j]^2)
@expression(model, r[j = 1:n], R_e + h[j])
@expression(model, g[j = 1:n], mu / r[j]^2)

# Motion of the vehicle as a differential-algebraic system of equations (DAEs)
@expression(model, 6h[j = 1:n], v[j] * sin(y[j]))
@expression(
    model,
    6phi[j = 1:n],
    (v[j] / r[j]) * cos(y[j]) * sin(psi[j]) / cos(theta[j])
)
```

```

@expression(model, δθ[j = 1:n], (v[j] / r[j]) * cos(γ[j]) * cos(ψ[j]))
@expression(model, δv[j = 1:n], -(D[j] / m) - g[j] * sin(γ[j]))
@expression(
    model,
    δγ[j = 1:n],
    (L[j] / (m * v[j])) * cos(β[j]) +
    cos(γ[j]) * ((v[j] / r[j]) - (g[j] / v[j]))
)
@expression(
    model,
    δψ[j = 1:n],
    (1 / (m * v[j] * cos(γ[j]))) * L[j] * sin(β[j]) +
    (v[j] / (r[j] * cos(θ[j]))) * cos(γ[j]) * sin(ψ[j]) * sin(θ[j])
)

# System dynamics
for j in 2:n
    i = j - 1 # index of previous knot

    if integration_rule == "rectangular"
        # Rectangular integration
        @constraint(model, h[j] == h[i] + Δt[i] * δh[i])
        @constraint(model, φ[j] == φ[i] + Δt[i] * δφ[i])
        @constraint(model, θ[j] == θ[i] + Δt[i] * δθ[i])
        @constraint(model, v[j] == v[i] + Δt[i] * δv[i])
        @constraint(model, γ[j] == γ[i] + Δt[i] * δγ[i])
        @constraint(model, ψ[j] == ψ[i] + Δt[i] * δψ[i])
    elseif integration_rule == "trapezoidal"
        # Trapezoidal integration
        @constraint(model, h[j] == h[i] + 0.5 * Δt[i] * (δh[j] + δh[i]))
        @constraint(model, φ[j] == φ[i] + 0.5 * Δt[i] * (δφ[j] + δφ[i]))
        @constraint(model, θ[j] == θ[i] + 0.5 * Δt[i] * (δθ[j] + δθ[i]))
        @constraint(model, v[j] == v[i] + 0.5 * Δt[i] * (δv[j] + δv[i]))
        @constraint(model, γ[j] == γ[i] + 0.5 * Δt[i] * (δγ[j] + δγ[i]))
        @constraint(model, ψ[j] == ψ[i] + 0.5 * Δt[i] * (δψ[j] + δψ[i]))
    else
        @error "Unexpected integration rule '$(integration_rule)'"
    end
end

# Objective: Maximize cross-range
@objective(model, Max, θ[n])

set_silent(model) # Hide solver's verbose output
optimize!(model) # Solve for the control and state
assert_is_solved_and_feasible(model)

# Show final cross-range of the solution
println(
    "Final latitude θ = ",
    round(objective_value(model) |> rad2deg; digits = 2),
    "°",
)

```

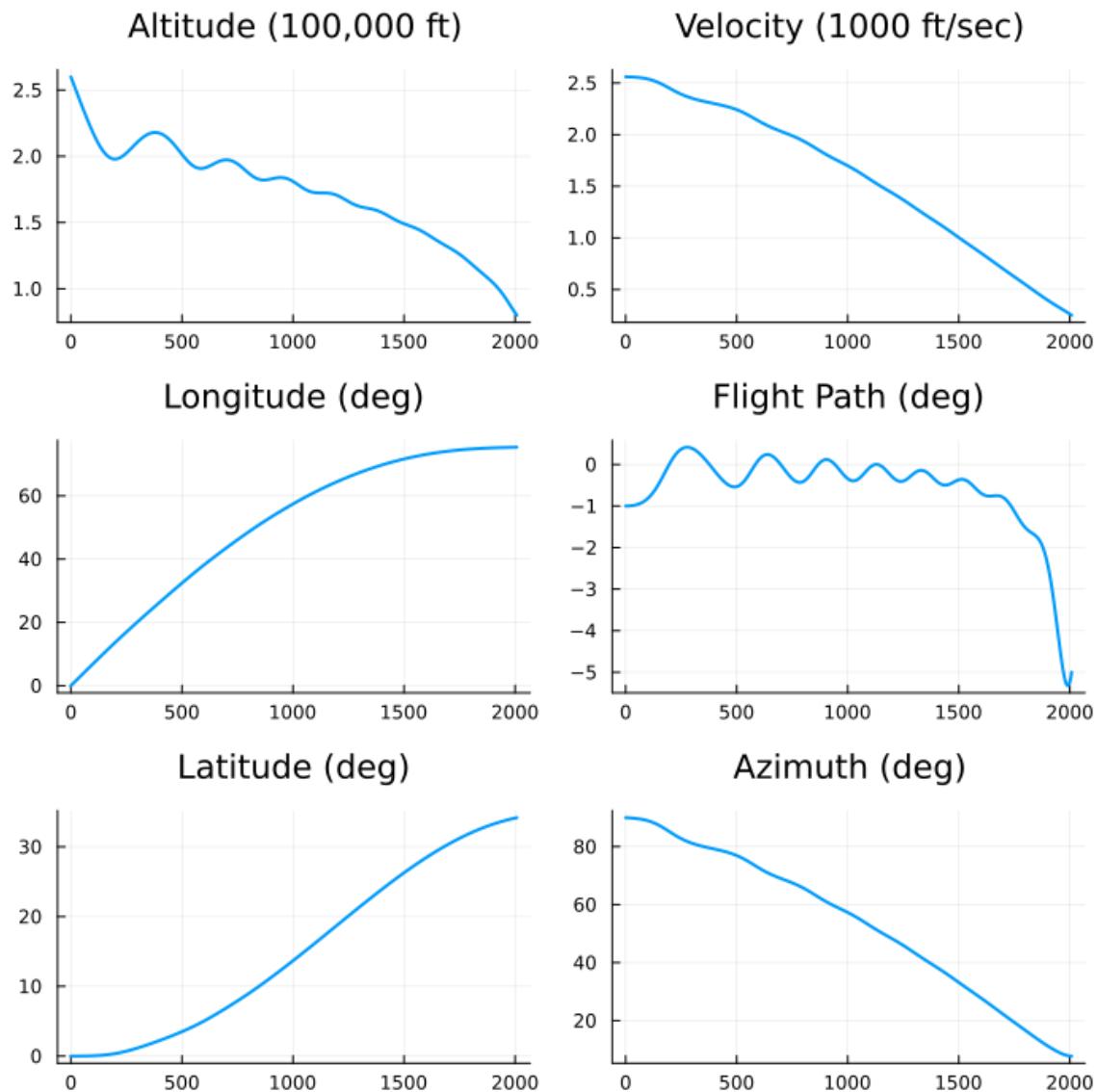
```
Final latitude θ = 34.18°
```

### Plotting the results

Let's plot the results to visualize the optimal trajectory:

```
using Plots
ts = cumsum([0; value.(Δt)]')[1:end-1]
plt_altitude = plot(
    ts,
    value.(scaled_h);
    legend = nothing,
    title = "Altitude (100,000 ft)",
)
plt_longitude =
    plot(ts, rad2deg.(value.(ϕ)); legend = nothing, title = "Longitude (deg)")
plt_latitude =
    plot(ts, rad2deg.(value.(θ)); legend = nothing, title = "Latitude (deg)")
plt_velocity = plot(
    ts,
    value.(scaled_v);
    legend = nothing,
    title = "Velocity (1000 ft/sec)",
)
plt_flight_path =
    plot(ts, rad2deg.(value.(γ)); legend = nothing, title = "Flight Path (deg)")
plt_azimuth =
    plot(ts, rad2deg.(value.(ψ)); legend = nothing, title = "Azimuth (deg)")

plot(
    plt_altitude,
    plt_velocity,
    plt_longitude,
    plt_flight_path,
    plt_latitude,
    plt_azimuth;
    layout = grid(3, 2),
    linewidth = 2,
    size = (700, 700),
)
```



```

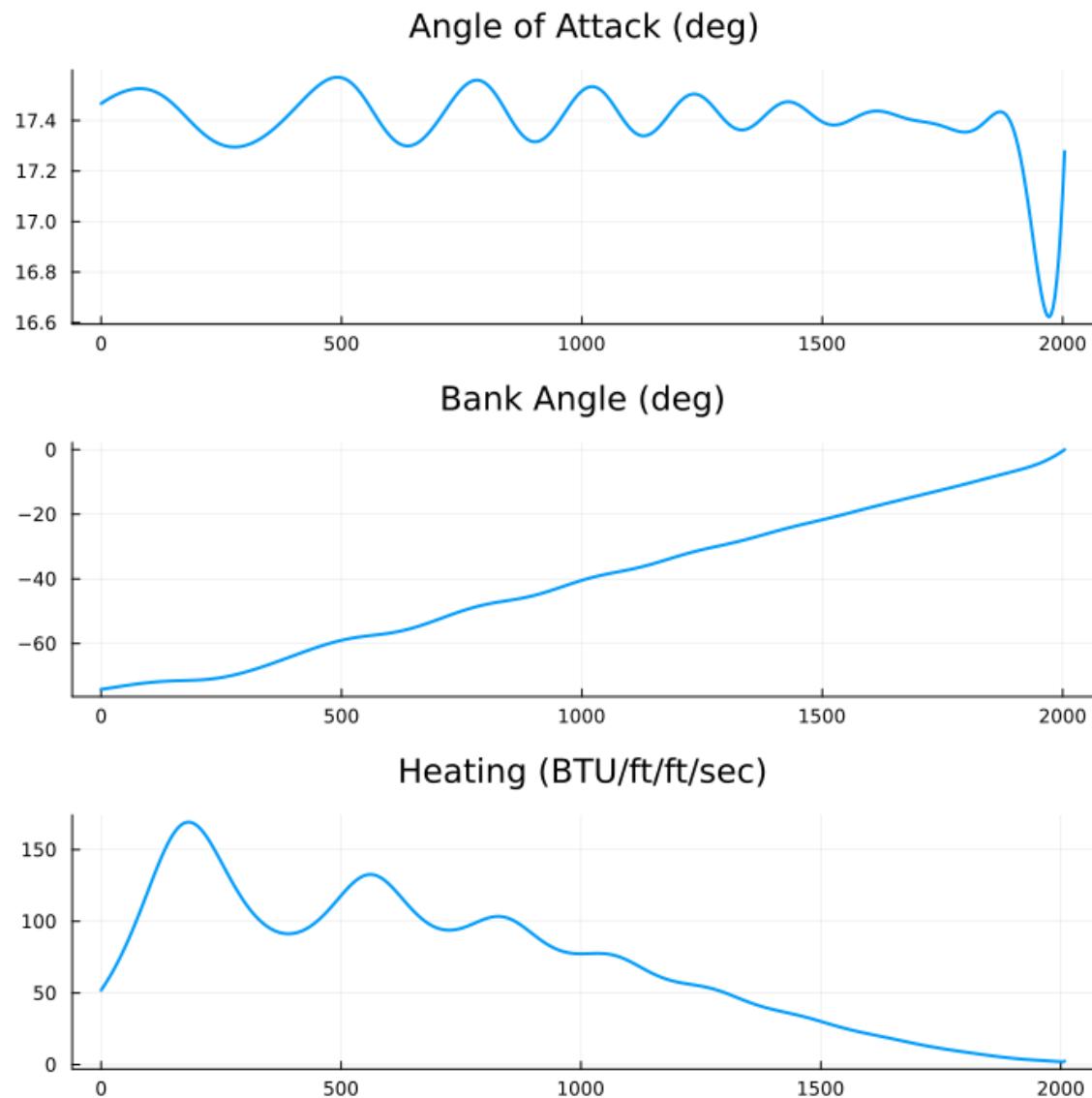
function q(h, v, a)
    p(h) = p0 * exp(-h / hr)
    qr(h, v) = 17700 * sqrt(p(h)) * (0.0001 * v)^3.07
    qa(a) = c0 + c1 * rad2deg(a) + c2 * rad2deg(a)^2 + c3 * rad2deg(a)^3
    # Aerodynamic heating on the vehicle wing leading edge
    return qa(a) * qr(h, v)
end

plt_attack_angle = plot(
    ts[1:end-1],
    rad2deg.(value.(α)[1:end-1]);
    legend = nothing,
    title = "Angle of Attack (deg)",
)

```

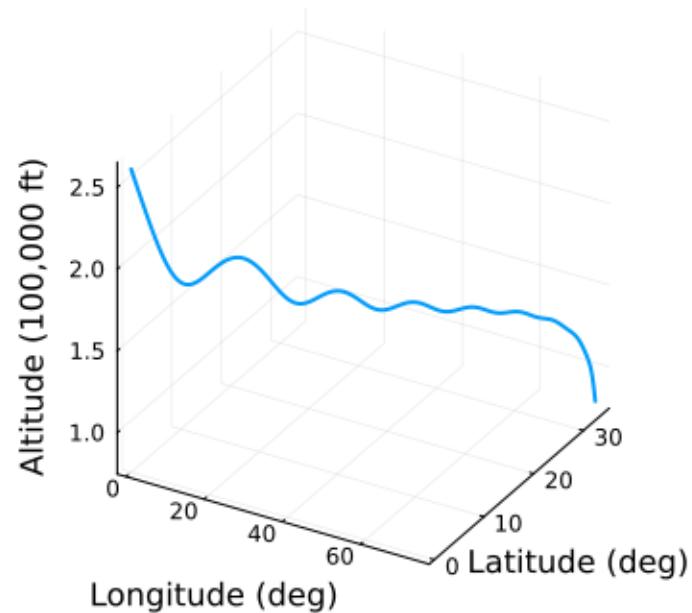
```
plt_bank_angle = plot(
    ts[1:end-1],
    rad2deg.(value.(β)[1:end-1]);
    legend = nothing,
    title = "Bank Angle (deg)",
)
plt_heating = plot(
    ts,
    q.(value.(scaled_h) * 1e5, value.(scaled_v) * 1e4, value.(α));
    legend = nothing,
    title = "Heating (BTU/ft/ft/sec)",
)

plot(
    plt_attack_angle,
    plt_bank_angle,
    plt_heating;
    layout = grid(3, 1),
    linewidth = 2,
    size = (700, 700),
)
```



```
plot(
  rad2deg.(value.(ϕ)),
  rad2deg.(value.(θ)),
  value.(scaled_h);
  linewidth = 2,
  legend = nothing,
  title = "Space Shuttle Reentry Trajectory",
  xlabel = "Longitude (deg)",
  ylabel = "Latitude (deg)",
  zlabel = "Altitude (100,000 ft)",
)
```

## Space Shuttle Reentry Trajectory



# Chapter 8

## Conic programs

### 8.1 Introduction

Conic programs are a class of convex nonlinear optimization problems which use cones to represent the nonlinearities. They have the form:

$$\min_{x \in \mathbb{R}^n} f_0(x) \quad (8.1)$$

$$\text{s.t.} \quad f_j(x) \in \mathcal{S}_j \quad j = 1 \dots m \quad (8.2)$$

Mixed-integer conic programs (MICPs) are extensions of conic programs in which some (or all) of the decision variables take discrete values.

#### How to choose a solver

JuMP supports a range of conic solvers, although support differs on what types of cones each solver supports. In the list of [Supported solvers](#), "SOCP" denotes solvers supporting second-order cones and "SDP" denotes solvers supporting semidefinite cones. In addition, solvers such as SCS and Mosek have support for the exponential cone. Moreover, due to the bridging system in MathOptInterface, many of these solvers support a much wider range of exotic cones than they natively support. Solvers supporting discrete variables start with "(MI)" in the list of [Supported solvers](#).

#### Tip

Duality plays a large role in solving conic optimization models. Depending on the solver, it can be more efficient to solve the dual instead of the primal. If performance is an issue, see the [Dualization](#) tutorial for more details.

#### How these tutorials are structured

Having a high-level overview of how this part of the documentation is structured will help you know where to look for certain things.

- The following tutorials are worked examples that present a problem in words, then formulate it in mathematics, and then solve it in JuMP. This usually involves some sort of visualization of the solution. Start here if you are new to JuMP.

- [Example: experiment design](#)
- [Example: logistic regression](#)
- The [Modeling with cones](#) tutorial contains a number of helpful reformulations and tricks you can use when modeling conic programs. Look here if you are stuck trying to formulate a problem as a conic program.
- The remaining tutorials are less verbose and styled in the form of short code examples. These tutorials have less explanation, but may contain useful code snippets, particularly if they are similar to a problem you are trying to solve.

## 8.2 Modeling with cones

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

**This tutorial was originally contributed by Arpit Bhatia.**

The purpose of this tutorial is to show how you can model various common problems using conic optimization.

### Tip

A good resource for learning more about functions which can be modeled using cones is the [MOSEK Modeling Cookbook](#).

### Required packages

This tutorial uses the following packages:

```
using JuMP
import LinearAlgebra
import MathOptInterface as MOI
import SCS
```

### Background theory

A subset  $C$  of a vector space  $V$  is a cone if  $\forall x \in C$  and positive scalars  $\lambda > 0$ , the product  $\lambda x \in C$ .

A cone  $C$  is a convex cone if  $\lambda x + (1 - \lambda)y \in C$ , for any  $\lambda \in [0, 1]$ , and any  $x, y \in C$ .

Conic programming problems are convex optimization problems in which a convex function is minimized over the intersection of an affine subspace and a convex cone. An example of a conic-form minimization problems, in the primal form is:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & a_0^T x + b_0 \\ \text{s.t.} \quad & A_i x + b_i \in \mathcal{C}_i \quad i = 1 \dots m \end{aligned}$$

The corresponding dual problem is:

$$\begin{aligned}
 & \max_{y_1, \dots, y_m} - \sum_{i=1}^m b_i^T y_i + b_0 \\
 \text{s.t.} \quad & a_0 - \sum_{i=1}^m A_i^T y_i = 0 \\
 & y_i \in \mathcal{C}_i^* \quad i = 1 \dots m
 \end{aligned}$$

where each  $\mathcal{C}_i$  is a closed convex cone and  $\mathcal{C}_i^*$  is its dual cone.

### Second-Order Cone

The [SecondOrderCone](#) (or Lorentz Cone) of dimension  $n$  is a cone of the form:

$$K_{soc} = \{(t, x) \in \mathbb{R}^n : t \geq \|x\|_2\}$$

It is most commonly used to represent the L2-norm of the vector  $x$ :

```

model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, x[1:3])
@variable(model, t)
@constraint(model, sum(x) == 1)
@constraint(model, [t; x] in SecondOrderCone())
@objective(model, Min, t)
optimize!(model)
assert_is_solved_and_feasible(model)
value(t), value.(x)

```

$(0.5773503148525415, [0.3333333333638126, 0.3333333333638124, 0.3333333333638124])$

### Rotated Second-Order Cone

A Second-Order Cone rotated by  $\pi/4$  in the  $(x_1, x_2)$  plane is called a [RotatedSecondOrderCone](#). It is a cone of the form:

$$K_{rsoc} = \{(t, u, x) \in \mathbb{R}^n : 2tu \geq \|x\|_2^2, t, u \geq 0\}$$

When  $u = 0.5$ , it represents the sum of squares of a vector  $x$ :

```

data = [1.0, 2.0, 3.0, 4.0]
target = [0.45, 1.04, 1.51, 1.97]
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, θ)

```

```

@variable(model, t)
@expression(model, residuals, θ * data .- target)
@constraint(model, [t; 0.5; residuals] in RotatedSecondOrderCone())
@objective(model, Min, t)
optimize!(model)
assert_is_solved_and_feasible(model)
value(θ), value(t)

```

(0.4980000000000544, 0.004979422159618532)

## Exponential Cone

The `MOI.ExponentialCone` is a set of the form:

$$K_{exp} = \{(x, y, z) \in \mathbb{R}^3 : y \exp(x/y) \leq z, y > 0\}$$

It can be used to model problems involving `log` and `exp`.

## Exponential

To model  $\exp(x) \leq z$ , use `(x, 1, z)`:

```

model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, x == 1.5)
@variable(model, z)
@objective(model, Min, z)
@constraint(model, [x, 1, z] in MOI.ExponentialCone())
optimize!(model)
assert_is_solved_and_feasible(model)
value(z), exp(1.5)

```

(4.481654619603659, 4.4816890703380645)

## Logarithm

To model  $x \leq \log(z)$ , use `(x, 1, z)`:

```

model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, x)
@variable(model, z == 1.5)
@objective(model, Max, x)
@constraint(model, [x, 1, z] in MOI.ExponentialCone())
optimize!(model)
assert_is_solved_and_feasible(model)
value(x), log(1.5)

```

$(0.4055956586655673, 0.4054651081081644)$

### Log-sum-exp

To model  $t \geq \log(\sum e^{x_i})$ , use:

```
N = 3
x0 = rand(N)
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, x[i = 1:N] == x0[i])
@variable(model, t)
@objective(model, Min, t)
@variable(model, u[1:N])
@constraint(model, sum(u) <= 1)
@constraint(model, [i = 1:N], [x[i] - t, 1, u[i]] in MOI.ExponentialCone())
optimize!(model)
value(t), log(sum(exp.(x0)))
```

$(1.4726849472138905, 1.472772274699489)$

### Entropy

The entropy maximization problem consists of maximizing the entropy function,  $H(x) = -x \log x$  subject to linear inequality constraints.

$$\begin{aligned} \max \quad & -\sum_{i=1}^n x_i \log x_i \\ \text{s.t.} \quad & \mathbf{1}^\top x = 1 \\ & Ax \leq b \end{aligned}$$

We can model this problem using an exponential cone by using the following transformation:

$$t \leq -x \log x \iff t \leq x \log(1/x) \iff (t, x, 1) \in K_{exp}$$

Thus, our problem becomes,

$$\begin{aligned} \max \quad & \mathbf{1}^\top t \\ \text{s.t.} \quad & Ax \leq b \\ & \mathbf{1}^\top x = 1 \\ & (t_i, x_i, 1) \in K_{exp} \quad \forall i = 1 \dots n \end{aligned}$$

```
m, n = 10, 15
A, b = randn(m, n), rand(m, 1)
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t[1:n])
@variable(model, x[1:n])
@objective(model, Max, sum(t))
@constraint(model, sum(x) == 1)
@constraint(model, A * x .<= b)
@constraint(model, [i = 1:n], [t[i], x[i], 1] in MOI.ExponentialCone())
optimize!(model)
assert_is_solved_and_feasible(model)
objective_value(model)
```

2.6632061721520914

The [MOI.ExponentialCone](#) has a dual, the [MOI.DualExponentialCone](#), that offers an alternative formulation that can be more efficient for some formulations.

There is also the [MOI.RelativeEntropyCone](#) for explicitly encoding the relative entropy function

```
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@variable(model, x[1:n])
@objective(model, Max, -t)
@constraint(model, sum(x) == 1)
@constraint(model, A * x .<= b)
@constraint(model, [t; ones(n); x] in MOI.RelativeEntropyCone(2n + 1))
optimize!(model)
assert_is_solved_and_feasible(model)
objective_value(model)
```

2.663173643175568

## PowerCone

The [MOI.PowerCone](#) is a three-dimensional set parameterized by a scalar value  $\alpha$ . It has the form:

$$K_p = \{(x, y, z) \in \mathbb{R}^3 : x^\alpha y^{1-\alpha} \geq |z|, x \geq 0, y \geq 0\}$$

The power cone permits a number of reformulations. For example, when  $p > 1$ , we can model  $t \geq x^p$  using the power cone  $(t, 1, x)$  with  $\alpha = 1/p$ . Thus, to model  $t \geq x^3$  with  $x \geq 0$

```

model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@variable(model, x >= 1.5)
@constraint(model, [t, 1, x] in MOI.PowerCone(1 / 3))
@objective(model, Min, t)
optimize!(model)
assert_is_solved_and_feasible(model)
value(t), value(x)

```

(3.3747548357745307, 1.49995522631546)

The `MOI.PowerCone` has a dual, the `MOI.DualPowerCone`, that offers an alternative formulation that can be more efficient for some formulations.

### P-Norm

The p-norm  $\|x\|_p = \left(\sum_i |x_i|^p\right)^{\frac{1}{p}}$  can be modeled using `MOI.PowerCones`. See the [Mosek Modeling Cookbook](#) for the derivation.

```

function p_norm(x::Vector, p)
    N = length(x)
    model = Model(SCS.Optimizer)
    set_silent(model)
    @variable(model, r[1:N])
    @variable(model, t)
    @constraint(model, [i = 1:N], [r[i], t, x[i]] in MOI.PowerCone(1 / p))
    @constraint(model, sum(r) == t)
    @objective(model, Min, t)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return value(t)
end

x = rand(5);
LinearAlgebra.norm(x, 4), p_norm(x, 4)

```

(0.9316922467512209, 0.9316875994951573)

### Positive Semidefinite Cone

The set of positive semidefinite matrices (PSD) of dimension  $n$  form a cone in  $\mathbb{R}^n$ . We write this set mathematically as:

$$\mathcal{S}_+^n = \{X \in \mathcal{S}^n \mid z^T X z \geq 0, \forall z \in \mathbb{R}^n\}.$$

A PSD cone is represented in JuMP using the MOI sets `PositiveSemidefiniteConeTriangle` (for upper triangle of a PSD matrix) and `PositiveSemidefiniteConeSquare` (for a complete PSD matrix). However, it is preferable to use the `PSDCone` shortcut as illustrated below.

#### Example: largest eigenvalue of a symmetric matrix

Suppose  $A$  has eigenvalues  $\lambda_1 \geq \lambda_2 \dots \geq \lambda_n$ . Then the matrix  $tI - A$  has eigenvalues  $t - \lambda_1, t - \lambda_2, \dots, t - \lambda_n$ . Note that  $tI - A$  is PSD exactly when all these eigenvalues are non-negative, and this happens for values  $t \geq \lambda_1$ . Thus, we can model the problem of finding the largest eigenvalue of a symmetric matrix as:

$$\begin{aligned}\lambda_1 &= \min t \\ \text{s.t. } tI - A &\succeq 0\end{aligned}$$

```
A = [3 2 4; 2 0 2; 4 2 3]
I = Matrix{Float64}(LinearAlgebra.I, 3, 3)
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@objective(model, Min, t)
@constraint(model, t .* I - A in PSDCone())
optimize!(model)
assert_is_solved_and_feasible(model)
objective_value(model)
```

8.000003377698677

#### GeometricMeanCone

The `MOI.GeometricMeanCone` is a cone of the form:

$$K_{geo} = \{(t, x) \in \mathbb{R}^n : x \geq 0, t \leq \sqrt[n-1]{x_1 x_2 \cdots x_{n-1}}\}$$

```
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, x[1:4])
@variable(model, t)
@constraint(model, sum(x) == 1)
@constraint(model, [t; x] in MOI.GeometricMeanCone(5))
optimize!(model)
value(t), value.(x)
```

(0.0, [0.2500000110304893, 0.25000001103052, 0.2500000110305065, 0.250000011030498])

### RootDetCone

The `MOI.RootDetConeSquare` is a cone of the form:

$$K = \{(t, X) \in \mathbb{R}^{1+d^2} : t \leq \det(X)^{\frac{1}{d}}\}$$

```
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@variable(model, X[1:2, 1:2])
@objective(model, Max, t)
@constraint(model, [t; vec(X)] in MOI.RootDetConeSquare(2))
@constraint(model, X .== [2 1; 1 3])
optimize!(model)
assert_is_solved_and_feasible(model)
value(t), sqrt(LinearAlgebra.det(value.(X)))
```

(2.236116364743875, 2.236067957402722)

If  $X$  is symmetric, then you can use `MOI.RootDetConeTriangle` instead. This can be more efficient because the solver does not need to add additional constraints to ensure  $X$  is symmetric.

When forming the function, use `triangle_vec` to obtain the column-wise upper triangle of the matrix as a vector in the order that JuMP requires.

```
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@variable(model, X[1:2, 1:2], Symmetric)
@objective(model, Max, t)
@constraint(model, [t; triangle_vec(X)] in MOI.RootDetConeTriangle(2))
@constraint(model, X .== [2 1; 1 3])
optimize!(model)
value(t), sqrt(LinearAlgebra.det(value.(X)))
```

(2.2361792479821516, 2.2360679863316997)

### LogDetCone

The `MOI.LogDetConeSquare` is a cone of the form:

$$K = \{(t, u, X) \in \mathbb{R}^{2+d^2} : t \leq u \log(\det(X/u))\}$$

```
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@variable(model, u)
@variable(model, X[1:2, 1:2])
@objective(model, Max, t)
@constraint(model, [t; u; vec(X)] in MOI.LogDetConeSquare(2))
@constraint(model, X .== [2 1; 1 3])
@constraint(model, u == 0.5)
optimize!(model)
assert_is_solved_and_feasible(model)
value(t), 0.5 * log(LinearAlgebra.det(value.(X) ./ 0.5))
```

(1.4979204458220756, 1.4978661006407135)

If  $X$  is symmetric, then you can use `MOI.LogDetConeTriangle` instead. This can be more efficient because the solver does not need to add additional constraints to ensure  $X$  is symmetric.

When forming the function, use `triangle_vec` to obtain the column-wise upper triangle of the matrix as a vector in the order that JuMP requires.

```
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@variable(model, u)
@variable(model, X[1:2, 1:2], Symmetric)
@objective(model, Max, t)
@constraint(model, [t; u; triangle_vec(X)] in MOI.LogDetConeTriangle(2))
@constraint(model, X .== [2 1; 1 3])
@constraint(model, u == 0.5)
optimize!(model)
assert_is_solved_and_feasible(model)
value(t), 0.5 * log(LinearAlgebra.det(value.(X) ./ 0.5))
```

(1.4979204481049098, 1.4978661010981238)

## NormNuclearCone

The `MOI.NormNuclearCone` is a cone of the form:

$$K = \{(t, X) \in \mathbb{R}^{1+m \cdot n} : t \geq \sum_i \sigma_i(X)\}$$

where  $\sigma_i$  is the  $i$  singular value of  $X$ .

```
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@variable(model, X[1:2, 1:3])
@objective(model, Min, t)
@constraint(model, [t; vec(X)] in MOI.NormNuclearCone(2, 3))
@constraint(model, X .== [1 2 3; 4 5 6])
optimize!(model)
assert_is_solved_and_feasible(model)
value(t), sum(LinearAlgebra.svdvals(value.(X)))
```

```
(10.28101138868147, 10.28090174727455)
```

### NormSpectralCone

The [MOI.NormSpectralCone](#) is a cone of the form:

$$K = \{(t, X) \in \mathbb{R}^{1+m \cdot n} : t \geq \max_i \sigma_i(X)\}$$

where  $\sigma_i$  is the  $i$  singular value of  $X$ .

```
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, t)
@variable(model, X[1:2, 1:3])
@objective(model, Min, t)
@constraint(model, [t; vec(X)] in MOI.NormSpectralCone(2, 3))
@constraint(model, X .== [1 2 3; 4 5 6])
optimize!(model)
assert_is_solved_and_feasible(model)
value(t), maximum(LinearAlgebra.svdvals(value.(X)))
```

```
(9.506936927003698, 9.508031076396836)
```

### Other Cones and Functions

For other cones supported by JuMP, check out the [MathOptInterface Manual](#).

## 8.3 Dualization

*This tutorial was generated using [Literate.jl](#). Download the source as a [.jl file](#).*

The purpose of this tutorial is to explain how to use [Dualization.jl](#) to improve the performance of some conic optimization models.

There are two important takeaways:

1. JuMP reformulates problems to meet the input requirements of the solver, potentially increasing the problem size by adding slack variables and constraints.
2. Solving the dual of a conic model can be more efficient than solving the primal.

[Dualization.jl](#) is a package which fixes these problems, allowing you to solve the dual instead of the primal with a one-line change to your code.

### Required packages

This tutorial uses the following packages:

```
using JuMP
import Dualization
import SCS
```

### Background

Conic optimization solvers typically accept one of two input formulations.

The first is the *standard* conic form:

$$\min_{x \in \mathbb{R}^n} c^\top x \quad (8.3)$$

$$\text{s.t. } Ax = b \quad (8.4)$$

$$x \in \mathcal{K} \quad (8.5)$$

in which we have a set of linear equality constraints  $Ax = b$  and the variables belong to a cone  $\mathcal{K}$ .

The second is the *geometric* conic form:

$$\min_{x \in \mathbb{R}^n} c^\top x \quad (8.6)$$

$$\text{s.t. } Ax - b \in \mathcal{K} \quad (8.7)$$

in which an affine function  $Ax - b$  belongs to a cone  $\mathcal{K}$  and the variables are free.

It is trivial to convert between these two representations, for example, to go from the geometric conic form to the standard conic form we introduce slack variables  $y$ :

$$\min_{x \in \mathbb{R}^n} c^\top x \quad (8.8)$$

$$\text{s.t. } [A \quad -I] \begin{bmatrix} x \\ y \end{bmatrix} = b \quad (8.9)$$

$$\begin{bmatrix} x \\ y \end{bmatrix} \in \mathbb{R}^n \times \mathcal{K} \quad (8.10)$$

and to go from the standard conic form to the geometric conic form, we can rewrite the equality constraint as a function belonging to the  $\{0\}$  cone:

$$\min_{x \in \mathbb{R}^n} c^\top x \quad (8.11)$$

$$\text{s.t. } \begin{bmatrix} A \\ I \end{bmatrix} x - \begin{bmatrix} b \\ 0 \end{bmatrix} \in \{0\} \times \mathcal{K} \quad (8.12)$$

From a theoretical perspective, the two formulations are equivalent, and if you implement a model in the standard conic form and pass it to a geometric conic form solver (or vice versa), then JuMP will automatically reformulate the problem into the correct formulation.

From a practical perspective though, the reformulations are problematic because the additional slack variables and constraints can make the problem much larger and therefore harder to solve.

You should also note many problems contain a mix of conic constraints and variables, and so they do not neatly fall into one of the two formulations. In these cases, JuMP reformulates only the variables and constraints as necessary to convert the problem into the desired form.

### Primal and dual formulations

Duality plays a large role in conic optimization. For a detailed description of conic duality, see [Duality](#).

A useful observation is that if the primal problem is in standard conic form, then the dual problem is in geometric conic form, and vice versa. Moreover, the primal and dual may have a different number of variables and constraints, although which one is smaller depends on the problem. Therefore, instead of reformulating the problem from one form to the other, it can be more efficient to solve the dual instead of the primal.

To demonstrate, we use a variation of the [Maximum cut via SDP](#) example.

The primal formulation (in standard conic form) is:

```
model_primal = Model()
@variable(model_primal, X[1:2, 1:2], PSD)
@objective(model_primal, Max, sum([-1, 1] .* X))
@constraint(model_primal, primal_c[i = 1:2], 1 - X[i, i] == 0)
print(model_primal)
```

```
Max X[1,1] - 2 X[1,2] + X[2,2]
Subject to
primal_c[1] : -X[1,1] = -1
primal_c[2] : -X[2,2] = -1
[X[1,1], X[1,2], X[2,2]] ∈ MathOptInterface.PositiveSemidefiniteConeTriangle(2)
```

This problem has three scalar decision variables (the matrix  $X$  is symmetric), two scalar equality constraints, and a constraint that  $X$  is positive semidefinite.

The dual of `model_primal` is:

```
model_dual = Model()
@variable(model_dual, y[1:2])
@objective(model_dual, Min, sum(y))
@constraint(model_dual, dual_c, [y[1]-1 1; 1 y[2]-1] in PSDCone())
print(model_dual)
```

```

Min y[1] + y[2]
Subject to
dual_c : [y[1] - 1 1
           1       y[2] - 1] ∈ PSDCone()

```

This problem has two scalar decision variables, and a 2x2 positive semidefinite matrix constraint.

### Tip

If you haven't seen conic duality before, try deriving the dual problem based on the description in [Duality](#). You'll need to know that the dual cone of `PSDCone` is the `PSDCone`.

When we solve `model_primal` with `SCS.Optimizer`, SCS reports three variables (variables `n: 3`), five rows in the constraint matrix (constraints `m: 5`), and five non-zeros in the matrix (`nnz(A): 5`):

```

set_optimizer(model_primal, SCS.Optimizer)
optimize!(model_primal)
assert_is_solved_and_feasible(model_primal; dual = true)

```

```

-----
^I      SCS v3.2.7 - Splitting Conic Solver
^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
problem: variables n: 3, constraints m: 5
cones: ^I z: primal zero / dual free vars: 2
^I s: psd vars: 3, ssize: 1
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^I acceleration_lookback: 10, acceleration_interval: 10
^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^I nnz(A): 5, nnz(P): 0
-----
iter | pri res | dua res |   gap   |    obj    | scale | time (s)
-----
 0| 1.65e+01  1.60e-01  5.09e+01 -2.91e+01  1.00e-01  1.08e-04
 50| 1.74e-08  2.70e-10  4.88e-08 -4.00e+00  1.00e-01  1.84e-04
-----
status: solved
timings: total: 1.85e-04s = setup: 4.60e-05s + solve: 1.39e-04s
^I lin-sys: 1.12e-05s, cones: 5.70e-05s, accel: 2.64e-06s
-----
objective = -4.000000
-----
```

(There are five rows in the constraint matrix because SCS expects problems in geometric conic form, and so JuMP has reformulated the `X`, `PSD` variable constraint into the affine constraint `X .+ 0` in `PSDCone()`.)

The solution we obtain is:

```
value.(X)
```

```
2x2 Matrix{Float64}:
 1.0  -1.0
 -1.0   1.0
```

```
dual.(primal_c)
```

```
2-element Vector{Float64}:
 1.999999997299085
 1.999999997299085
```

```
objective_value(model_primal)
```

```
3.999999506359716
```

When we solve `model_dual` with `SCS.Optimizer`, SCS reports two variables (variables `n`: 2), three rows in the constraint matrix (constraints `m`: 3), and two non-zeros in the matrix (`nnz(A)`: 2):

```
set_optimizer(model_dual, SCS.Optimizer)
optimize!(model_dual)
assert_is_solved_and_feasible(model_dual; dual = true)
```

```
-----
^I      SCS v3.2.7 - Splitting Conic Solver
^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
problem: variables n: 2, constraints m: 3
cones: ^I s: psd vars: 3, ssize: 1
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^I acceleration_lookback: 10, acceleration_interval: 10
^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^I nnz(A): 2, nnz(P): 0
-----
iter | pri res | dua res |   gap   |    obj    | scale | time (s)
-----
 0| 1.23e+01  1.00e+00  2.73e+01 -9.03e+00  1.00e-01  6.93e-05
 50| 1.13e-07  1.05e-09  3.23e-07  4.00e+00  1.00e-01  1.44e-04
-----
```

```

status: solved
timings: total: 1.45e-04s = setup: 3.16e-05s + solve: 1.13e-04s
^^I lin-sys: 8.55e-06s, cones: 4.88e-05s, accel: 2.57e-06s
-----
objective = 4.000000
-----
```

and the solution we obtain is:

```
dual.(dual_c)
```

```

2x2 Matrix{Float64}:
 1.0  -1.0
 -1.0   1.0
```

```
value.(y)
```

```

2-element Vector{Float64}:
 2.00000159272681
 2.00000159272681
```

```
objective_value(model_dual)
```

```
4.000000318545362
```

This particular problem is small enough that it isn't meaningful to compare the solve times, but in general, we should expect `model_dual` to solve faster than `model_primal` because it contains fewer variables and constraints. The difference is particularly noticeable on large-scale optimization problems.

### **dual\_optimizer**

Manually deriving the conic dual is difficult and error-prone. The package `Dualization.jl` provides the `Dualization.dual_optimizer` meta-solver, which wraps any `MathOptInterface`-compatible solver in an interface that automatically formulates and solves the dual of an input problem.

To demonstrate, we use `Dualization.dual_optimizer` to solve `model_primal`:

```

set_optimizer(model_primal, Dualization.dual_optimizer(SCS.Optimizer))
optimize!(model_primal)
assert_is_solved_and_feasible(model_primal; dual = true)
```

```
-----
^I      SCS v3.2.7 - Splitting Conic Solver
^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
problem: variables n: 2, constraints m: 3
cones: ^I s: psd vars: 3, ssize: 1
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^I acceleration_lookback: 10, acceleration_interval: 10
^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^I nnz(A): 2, nnz(P): 0
-----
iter | pri res | dua res |   gap   |   obj   | scale | time (s)
-----
 0| 1.23e+01  1.00e+00  2.73e+01 -9.03e+00  1.00e-01  8.57e-05
 50| 1.13e-07  1.05e-09  3.23e-07  4.00e+00  1.00e-01  1.60e-04
-----
status: solved
timings: total: 1.61e-04s = setup: 3.02e-05s + solve: 1.31e-04s
^I lin-sys: 8.76e-06s, cones: 4.85e-05s, accel: 2.56e-06s
-----
objective = 4.000000
-----
```

The performance is the same as if we solved `model_dual`, and the correct solution is returned to `X`:

```
value.(X)
```

```
2x2 Matrix{Float64}:
 1.0  -1.0
 -1.0   1.0
```

```
dual.(primal_c)
```

```
2-element Vector{Float64}:
 2.00000159272681
 2.00000159272681
```

Moreover, if we use `dual_optimizer` on `model_dual`, then we get the same performance as if we had solved `model_primal`:

```
set_optimizer(model_dual, Dualization.dual_optimizer(SCS.Optimizer))
optimize!(model_dual)
assert_is_solved_and_feasible(model_dual; dual = true)
```

```

-----
^I      SCS v3.2.7 - Splitting Conic Solver
^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
problem: variables n: 3, constraints m: 5
cones: ^I z: primal zero / dual free vars: 2
^I s: psd vars: 3, ssize: 1
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^I acceleration_lookback: 10, acceleration_interval: 10
^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^I nnz(A): 5, nnz(P): 0
-----
iter | pri res | dua res |   gap   |   obj   | scale | time (s)
-----
 0| 1.65e+01  1.60e-01  5.09e+01 -2.91e+01  1.00e-01  1.06e-04
 50| 1.74e-08  2.70e-10  4.88e-08 -4.00e+00  1.00e-01  1.82e-04
-----
status: solved
timings: total: 1.83e-04s = setup: 5.12e-05s + solve: 1.32e-04s
^I lin-sys: 1.10e-05s, cones: 5.80e-05s, accel: 2.69e-06s
-----
objective = -4.000000
-----
```

dual.(dual\_c)

```

2x2 Matrix{Float64}:
 1.0  -1.0
 -1.0   1.0
```

value.(y)

```

2-element Vector{Float64}:
 1.999999997299085
 1.999999997299085
```

### A mixed example

The [Maximum cut via SDP](#) example is nicely defined because the primal is in standard conic form and the dual is in geometric conic form. However, many practical models contain a mix of the two formulations. One example is [The minimum distortion problem](#):

```

D = [0 1 1 1; 1 0 2 2; 1 2 0 2; 1 2 2 0]
model = Model()
@variable(model, c²)
@variable(model, Q[1:4, 1:4], PSD)
@objective(model, Min, c²)
for i in 1:4, j in (i+1):4
    @constraint(model, D[i, j]^2 <= Q[i, i] + Q[j, j] - 2 * Q[i, j])
    @constraint(model, Q[i, i] + Q[j, j] - 2 * Q[i, j] <= c² * D[i, j]^2)
end
@constraint(model, Q[1, 1] == 0)
@constraint(model, c² >= 1)

```

$$c^2 \geq 1$$

In this formulation, the  $Q$  variable is of the form  $x \in \mathcal{K}$ , but there is also a free variable,  $c^2$ , a linear equality constraint,  $Q[1, 1] == 0$ , and some linear inequality constraints. Rather than attempting to derive the formulation that JuMP would pass to SCS and its dual, the simplest solution is to try solving the problem with and without `dual_optimizer` to see which formulation is most efficient.

```

set_optimizer(model, SCS.Optimizer)
optimize!(model)

```

```

-----
^I      SCS v3.2.7 - Splitting Conic Solver
^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
problem: variables n: 11, constraints m: 24
cones: ^I z: primal zero / dual free vars: 1
^I l: linear vars: 13
^I s: psd vars: 10, ssize: 1
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^I acceleration_lookback: 10, acceleration_interval: 10
^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^I nnz(A): 54, nnz(P): 0
-----
iter | pri res | dua res |   gap   |   obj   | scale | time (s)
-----
 0| 4.73e+00  1.00e+00  2.92e+00  1.23e+00  1.00e-01  1.53e-04
 150| 1.01e-04  3.07e-05  6.08e-05  1.33e+00  1.00e-01  7.23e-04
-----
status: solved
timings: total: 7.25e-04s = setup: 8.70e-05s + solve: 6.38e-04s
^I lin-sys: 1.01e-04s, cones: 3.90e-04s, accel: 3.62e-05s
-----
objective = 1.333363
-----
```

```
set_optimizer(model, Dualization.dual_optimizer(SCS.Optimizer))
optimize!(model)
```

```
-----
^I      SCS v3.2.7 - Splitting Conic Solver
^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
problem: variables n: 14, constraints m: 24
cones: ^I z: primal zero / dual free vars: 1
^I l: linear vars: 13
^I s: psd vars: 10, ssize: 1
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^I acceleration_lookback: 10, acceleration_interval: 10
^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^I nnz(A): 57, nnz(P): 0
-----
iter | pri res | dua res |   gap   |   obj   |   scale   | time (s)
-----
0| 3.71e+01  1.48e+00  2.23e+02 -1.13e+02  1.00e-01  9.42e-05
150| 1.57e-04  2.28e-05  2.08e-04 -1.33e+00  1.00e-01  6.97e-04
-----
status: solved
timings: total: 6.98e-04s = setup: 7.17e-05s + solve: 6.27e-04s
^I lin-sys: 1.06e-04s, cones: 4.16e-04s, accel: 2.17e-05s
-----
objective = -1.333460
-----
```

For this problem, SCS reports that the primal has variables n: 11, constraints m: 24 and that the dual has variables n: 14, constraints m: 24. Therefore, we should probably use the primal formulation because it has fewer variables and the same number of constraints.

### **When to use dual\_optimizer**

Because it can make the problem larger or smaller, depending on the problem and the choice of solver, there is no definitive rule on when you should use `dual_optimizer`. However, you should try `dual_optimizer` if your conic optimization problem takes a long time to solve, or if you need to repeatedly solve similarly structured problems with different data. In some cases solving the dual instead of the primal can make a large difference.

## **8.4 Arbitrary precision arithmetic**

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

The purpose of this tutorial is to explain how to use a solver which supports arithmetic using a number type other than `Float64`.

### **Required packages**

This tutorial uses the following packages:

```
using JuMP
import CDDLib
import Clarabel
```

## Higher-precision arithmetic

To create a model with a number type other than `Float64`, use `GenericModel` with an optimizer which supports the same number type:

```
model = GenericModel{BigFloat}(Clarabel.Optimizer{BigFloat})
```

```
A JuMP Model
└ value_type: BigFloat
└ solver: Clarabel
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none
```

The syntax for adding decision variables is the same as a normal JuMP model, except that values are converted to `BigFloat`:

```
@variable(model, -1 <= x[1:2] <= sqrt(big"2"))
```

```
2-element Vector{GenericVariableRef{BigFloat}}:
x[1]
x[2]
```

Note that each `x` is now a `GenericVariableRef{BigFloat}`, which means that the value of `x` in a solution will be a `BigFloat`.

The lower and upper bounds of the decision variables are also `BigFloat`:

```
lower_bound(x[1])
```

```
-1.0
```

```
typeof(lower_bound(x[1]))
```

```
BigFloat
```

```
upper_bound(x[2])
```

```
1.414213562373095048801688724209698078569671875376948073176679737990732478462102
```

```
typeof(upper_bound(x[2]))
```

```
BigFloat
```

The syntax for adding constraints is the same as a normal JuMP model, except that coefficients are converted to BigFloat:

```
@constraint(model, c, x[1] == big"2" * x[2])
```

$$x_1 - 2.0x_2 = 0.0$$

The function is a `GenericAffExpr` with BigFloat for the coefficient and variable types;

```
constraint = constraint_object(c)
typeof(constraint.func)
```

```
GenericAffExpr{BigFloat, GenericVariableRef{BigFloat}}
```

and the set is a `MOI.EqualTo{BigFloat}`:

```
typeof(constraint.set)
```

```
MathOptInterface.EqualTo{BigFloat}
```

The syntax for adding and objective is the same as a normal JuMP model, except that coefficients are converted to BigFloat:

```
@objective(model, Min, 3x[1]^2 + 2x[2]^2 - x[1] - big"4" * x[2])
```

$$3.0x_1^2 + 2.0x_2^2 - x_1 - 4.0x_2$$

```
typeof(objective_function(model))
```

```
GenericQuadExpr{BigFloat, GenericVariableRef{BigFloat}}
```

Here's the model we have built:

```
print(model)
```

```
Min 3.0 x[1]^2 + 2.0 x[2]^2 - x[1] - 4.0 x[2]
Subject to
c : x[1] - 2.0 x[2] = 0.0
x[1] ≥ -1.0
x[2] ≥ -1.0
x[1] ≤ 1.414213562373095048801688724209698078569671875376948073176679737990732478462102
x[2] ≤ 1.414213562373095048801688724209698078569671875376948073176679737990732478462102
```

Let's solve and inspect the solution:

```
optimize!(model)
assert_is_solved_and_feasible(model; dual = true)
solution_summary(model)
```

```
* Solver : Clarabel

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "SOLVED"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : -6.42857e-01
  Dual objective value : -6.42857e-01

* Work counters
  Solve time (sec)   : 1.54951e-03
  Barrier iterations : 5
```

The value of each decision variable is a `BigFloat`:

```
value.(x)
```

```
2-element Vector{BigFloat}:
0.4285714246558161076147072906813123533593766450416896337912086518811186790735189
0.2142857123279078924828007272730108809297577877991360649674411645247653239673801
```

as well as other solution attributes like the objective value:

```
objective_value(model)
```

```
-0.6428571428571422964607590389935242587959291815638830868454759876473734138856053
```

and dual solution:

```
dual(c)
```

```
1.571428571977140845343978069015092190548250919787945065022059071052557047888032
```

This problem has an analytic solution of  $x = [3//7, 3//14]$ . Currently, our solution has an error of approximately  $1e-9$ :

```
value.(x) .- [3 // 7, 3 // 14]
```

```
2-element Vector{BigFloat}:
-3.915612463813864137890116218069194783529738937637362776690309892355053792476207e-09
-1.957806393231484987012703404784527926486578220746844549760948961746906215408591e-09
```

But by reducing the tolerances, we can obtain a more accurate solution:

```
set_attribute(model, "tol_gap_abs", 1e-32)
set_attribute(model, "tol_gap_rel", 1e-32)
optimize!(model)
assert_is_solved_and_feasible(model)
value.(x) .- [3 // 7, 3 // 14]
```

```
2-element Vector{BigFloat}:
-4.120732596246374574619292889406407106157605546563218305172773512099467866195165e-32
-7.14664661078267765915230143608842323590025278021105798625136798113062355333357e-32
```

### Rational arithmetic

In addition to higher-precision floating point number types like `BigFloat`, JuMP also supports solvers with exact rational arithmetic. One example is `CDDLib.jl`, which supports the `Rational{BigInt}` number type:

```
model = GenericModel{Rational{BigInt}}(CDDLib.Optimizer{Rational{BigInt}})
```

```
A JuMP Model
├ value_type: Rational{BigInt}
├ solver: CDD
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none
```

As before, we can create variables using rational bounds:

```
@variable(model, 1 // 7 <= x[1:2] <= 2 // 3)
```

```
2-element Vector{GenericVariableRef{Rational{BigInt}}}:
x[1]
x[2]
```

```
lower_bound(x[1])
```

```
1//7
```

```
typeof(lower_bound(x[1]))
```

```
Rational{BigInt}
```

As well as constraints:

```
@constraint(model, c1, (2 // 1) * x[1] + x[2] <= 1)
```

$$2//1x_1 + x_2 \leq 1//1$$

```
@constraint(model, c2, x[1] + 3x[2] <= 9 // 4)
```

$$x_1 + 3/1x_2 \leq 9//4$$

and objective functions:

```
@objective(model, Max, sum(x))
```

$$x_1 + x_2$$

Here's the model we have built:

```
print(model)
```

```
Max x[1] + x[2]
Subject to
c1 : 2//1 x[1] + x[2] ≤ 1//1
c2 : x[1] + 3//1 x[2] ≤ 9//4
x[1] ≥ 1//7
x[2] ≥ 1//7
x[1] ≤ 2//3
x[2] ≤ 2//3
```

Let's solve and inspect the solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : CDD
* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "Optimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : NO_SOLUTION
  Objective value    : 5//6

* Work counters
```

The optimal values are given in exact rational arithmetic:

```
value.(x)
```

```
2-element Vector{Rational{BigInt}}:  
1//6  
2//3
```

```
objective_value(model)
```

```
5//6
```

```
value(c2)
```

```
13//6
```

## 8.5 Primal and dual warm-starts

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

Some conic solvers have the ability to set warm-starts for the primal and dual solution. This can improve performance, particularly if you are repeatedly solving a sequence of related problems.

The purpose of this tutorial is to demonstrate how to write a function that sets the primal and dual starts as the optimal solution stored in a model. It is intended to be a starting point for which you can modify if you want to do something similar in your own code.

### Tip

See `set_start_values` for a generic implementation of this function that was added to JuMP after this tutorial was written.

### Required packages

This tutorial uses the following packages:

```
using JuMP  
import SCS
```

### A basic function

The main component of this tutorial is the following function. The most important observation is that we cache all of the solution values first, and then we modify the model second. (Alternating between querying a value and modifying the model is not allowed in JuMP.)

```
function set_optimal_start_values(model::Model)
    # Store a mapping of the variable primal solution
    variable_primal = Dict(x => value(x) for x in all_variables(model))
    # In the following, we loop through every constraint and store a mapping
    # from the constraint index to a tuple containing the primal and dual
    # solutions.
    constraint_solution = Dict()
    for (F, S) in list_of_constraint_types(model)
        # We add a try-catch here because some constraint types might not
        # support getting the primal or dual solution.
        try
            for ci in all_constraints(model, F, S)
                constraint_solution[ci] = (value(ci), dual(ci))
            end
        catch
            @info("Something went wrong getting $F-in-$S. Skipping")
        end
    end
    # Now we can loop through our cached solutions and set the starting values.
    for (x, primal_start) in variable_primal
        set_start_value(x, primal_start)
    end
    for (ci, (primal_start, dual_start)) in constraint_solution
        set_start_value(ci, primal_start)
        set_dual_start_value(ci, dual_start)
    end
    return
end
```

```
set_optimal_start_values (generic function with 1 method)
```

### Testing the function

To test our function, we use the following linear program:

```
model = Model(SCS.Optimizer)
@variable(model, x[1:3] >= 0)
@constraint(model, sum(x) <= 1)
@objective(model, Max, sum(i * x[i] for i in 1:3))
optimize!(model)
assert_is_solved_and_feasible(model)
```

```
-----  
^I      SCS v3.2.7 - Splitting Conic Solver
```

```

^^I(c) Brendan O'Donoghue, Stanford University, 2012
-----
problem: variables n: 3, constraints m: 4
cones: ^^I l: linear vars: 4
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^^I acceleration_lookback: 10, acceleration_interval: 10
^^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^^I nnz(A): 6, nnz(P): 0
-----
iter | pri res | dua res |   gap   |   obj   |   scale   | time (s)
-----
 0| 4.42e+01  1.00e+00  1.28e+02 -6.64e+01  1.00e-01  8.89e-05
 75| 5.30e-07  2.63e-06  3.15e-07 -3.00e+00  1.00e-01  1.37e-04
-----
status: solved
timings: total: 1.38e-04s = setup: 4.11e-05s + solve: 9.65e-05s
^^I lin-sys: 1.37e-05s, cones: 6.73e-06s, accel: 3.67e-06s
-----
objective = -2.999998
-----
```

By looking at the log, we can see that SCS took 75 iterations to find the optimal solution. Now we set the optimal solution as our starting point:

```
set_optimal_start_values(model)
```

and we re-optimize:

```
optimize!(model)
```

```

-----  

^^I      SCS v3.2.7 - Splitting Conic Solver  

^^I(c) Brendan O'Donoghue, Stanford University, 2012  

-----  

problem: variables n: 3, constraints m: 4
cones: ^^I l: linear vars: 4
settings: eps_abs: 1.0e-04, eps_rel: 1.0e-04, eps_infeas: 1.0e-07
^^I alpha: 1.50, scale: 1.00e-01, adaptive_scale: 1
^^I max_iters: 100000, normalize: 1, rho_x: 1.00e-06
^^I acceleration_lookback: 10, acceleration_interval: 10
^^I compiled with openmp parallelization enabled
lin-sys: sparse-direct-amd-qdldl
^^I nnz(A): 6, nnz(P): 0
-----
iter | pri res | dua res |   gap   |   obj   |   scale   | time (s)
-----
 0| 1.90e-05  1.56e-06  9.14e-05 -3.00e+00  1.00e-01  8.67e-05
-----
```

```

status: solved
timings: total: 8.76e-05s = setup: 4.23e-05s + solve: 4.53e-05s
^^I lin-sys: 7.72e-07s, cones: 1.53e-06s, accel: 3.00e-08s
-----
objective = -3.000044
-----
```

Now the optimization terminates after 0 iterations because our starting point is already optimal.

### Caveats

Some solvers do not support setting some parts of the starting solution, for example, they may support only `set_start_value` for variables.

If you encounter an `UnsupportedSupported` attribute error for `MOI.VariablePrimalStart`, `MOI.ConstraintPrimalStart`, or `MOI.ConstraintDualStart`, comment out the corresponding part of the `set_optimal_start_values` function.

## 8.6 Simple semidefinite programming examples

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to provide a collection of examples of small conic programs from the field of [semidefinite programming \(SDP\)](#).

### Required packages

This tutorial uses the following packages:

```

using JuMP
import LinearAlgebra
import Plots
import Random
import SCS
import Test
```

### Maximum cut via SDP

The [maximum cut problem](#) is a classical example in graph theory, where we seek to partition a graph into two complementary sets, such that the weight of edges between the two sets is maximized. This problem is NP-hard, but it is possible to obtain an approximate solution using the semidefinite programming relaxation:

$$\begin{aligned} \max \quad & 0.25L \bullet X \\ \text{s.t.} \quad & \text{diag}(X) = e \\ & X \succeq 0 \end{aligned}$$

where  $L$  is the weighted graph Laplacian and  $e$  is a vector of ones. For more details, see ([Goemans and Williamson, 1995](#)).

```

"""
svd_cholesky(X::AbstractMatrix, rtol)

Return the matrix `U` of the Cholesky decomposition of `X` as `U' * U`.
Note that we do not use the `LinearAlgebra.cholesky` function because it
requires the matrix to be positive definite while `X` may be only
positive *semi*definite.

We use the convention `U' * U` instead of `U * U'` to be consistent with
`LinearAlgebra.cholesky`.

"""

function svd_cholesky(X::AbstractMatrix)
    F = LinearAlgebra.svd(X)
    # We now have `X ≈ F.U * D² * F.U'` where:
    D = LinearAlgebra.Diagonal(sqrt.(F.S))
    # So `X ≈ U' * U` where `U` is:
    return (F.U * D)'
end

function solve_max_cut_sdp(weights)
    N = size(weights, 1)
    # Calculate the (weighted) Laplacian of the graph: L = D - W.
    L = LinearAlgebra.diagm(0 => weights * ones(N)) - weights
    model = Model(SCS.Optimizer)
    set_silent(model)
    @variable(model, X[1:N, 1:N], PSD)
    for i in 1:N
        set_start_value(X[i, i], 1.0)
    end
    @objective(model, Max, 0.25 * LinearAlgebra.dot(L, X))
    @constraint(model, LinearAlgebra.diag(X) .== 1)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    V = svd_cholesky(value(X))
    Random.seed!(N)
    r = rand(N)
    r /= LinearAlgebra.norm(r)
    cut = [LinearAlgebra.dot(r, V[:, i]) > 0 for i in 1:N]
    S = findall(cut)
    T = findall(.!cut)
    println("Solution:")
    println(" (S, T) = (", join(S, ", "), ", ", join(T, ", "), ")")
    return S, T
end

```

```
solve_max_cut_sdp (generic function with 1 method)
```

Given the graph

```
[1] --- 5 --- [2]
```

The solution is (S, T) = ({1}, {2})

```
S, T = solve_max_cut_sdp([0 5; 5 0])
```

```
([2], [1])
```

Given the graph

```
[1] --- 5 --- [2]
|   \
|   \
7     6     1
|       \
|       \
[3] --- 1 --- [4]
```

The solution is  $(S, T) = (\{1\}, \{2, 3, 4\})$

```
S, T = solve_max_cut_sdp([0 5 7 6; 5 0 0 1; 7 0 0 1; 6 1 1 0])
```

```
([1], [2, 3, 4])
```

Given the graph

```
[1] --- 1 --- [2]
|
|
5     9
|
|
[3] --- 2 --- [4]
```

The solution is  $(S, T) = (\{1, 4\}, \{2, 3\})$

```
S, T = solve_max_cut_sdp([0 1 5 0; 1 0 0 9; 5 0 0 2; 0 9 2 0])
```

```
([1, 4], [2, 3])
```

### Low-rank matrix completion

The matrix completion problem seeks to find the missing entries of a matrix with a given (possibly random) subset of fixed entries, such that the completed matrix has the lowest attainable rank.

For more details, see ([Recht et al., 2010](#)).

```

function example_matrix_completion(; svdtol = 1e-6)
    rng = Random.MersenneTwister(1234)
    n = 20
    mask = rand(rng, 1:25, n, n) .== 1
    B = randn(rng, n, n)
    model = Model(SCS.Optimizer)
    @variable(model, X[1:n, 1:n])
    @constraint(model, X[mask] .== B[mask])
    @variable(model, t)
    @constraint(model, [t; vec(X)] in MOI.NormNuclearCone(n, n))
    @objective(model, Min, t)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    # Return the approximate rank of the completed matrix to a given tolerance:
    return sum(LinearAlgebra.svdvals(value.(X)) .> svdtol)
end

example_matrix_completion()

```

9

## K-means clustering via SDP

Given a set of points  $a_1, \dots, a_m$  in  $\mathbb{R}^n$ , allocate them to  $k$  clusters.

For more details, see ([Peng and Wei, 2007](#)).

```

function example_k_means_clustering()
    a = [[2.0, 2.0], [2.5, 2.1], [7.0, 7.0], [2.2, 2.3], [6.8, 7.0], [7.2, 7.5]]
    m = length(a)
    num_clusters = 2
    W = zeros(m, m)
    for i in 1:m, j in i+1:m
        W[i, j] = W[j, i] = exp(-LinearAlgebra.norm(a[i] - a[j]) / 1.0)
    end
    model = Model(SCS.Optimizer)
    set_silent(model)
    @variable(model, Z[1:m, 1:m] >= 0, PSD)
    @objective(model, Min, LinearAlgebra.tr(W * (LinearAlgebra.I - Z)))
    @constraint(model, [i = 1:m], sum(Z[i, :]) .== 1)
    @constraint(model, LinearAlgebra.tr(Z) == num_clusters)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    Z_val = value.(Z)
    current_cluster, visited = 0, Set{Int}()
    for i in 1:m
        if !(i in visited)
            current_cluster += 1
            println("Cluster $current_cluster")
            for j in i:m
                if isapprox(Z_val[i, i], Z_val[i, j]; atol = 1e-3)
                    println(a[j])

```

```

        push!(visited, j)
    end
end
end
return
end

example_k_means_clustering()

```

```

Cluster 1
[2.0, 2.0]
[2.5, 2.1]
[2.2, 2.3]
Cluster 2
[7.0, 7.0]
[6.8, 7.0]
[7.2, 7.5]

```

### The correlation problem

Given three random variables  $A$ ,  $B$ , and  $C$ , and given bounds on two of the three correlation coefficients:

$$\begin{aligned} -0.2 &\leq AB \leq -0.1 \\ 0.4 &\leq BC \leq 0.5 \end{aligned}$$

our problem is to determine upper and lower bounds on other correlation coefficient  $AC$ .

We solve an SDP to make use of the following positive semidefinite property of the correlation matrix:

$$\begin{bmatrix} 1 & AB & AC \\ AB & 1 & BC \\ AC & BC & 1 \end{bmatrix} \succeq 0$$

```

function example_correlation_problem()
    model = Model(SCS.Optimizer)
    set_silent(model)
    @variable(model, X[1:3, 1:3], PSD)
    S = ["A", "B", "C"]
    ρ = Containers.DenseAxisArray(X, S, S)
    @constraint(model, [i in S], ρ[i, i] == 1)
    @constraint(model, -0.2 <= ρ["A", "B"] <= -0.1)
    @constraint(model, 0.4 <= ρ["B", "C"] <= 0.5)
    @objective(model, Max, ρ["A", "C"])
    optimize!(model)
    assert_is_solved_and_feasible(model)
    println("An upper bound for ρ_AC is $(value(ρ["A", "C"]))")
    @objective(model, Min, ρ["A", "C"])

```

```

optimize!(model)
assert_is_solved_and_feasible(model)
println("A lower bound for ρ_AC is $(value(ρ["A", "C"]))")
return
end

example_correlation_problem()

```

```

An upper bound for ρ_AC is 0.8719220303115133
A lower bound for ρ_AC is -0.9779989594188935

```

### The minimum distortion problem

This example arises from computational geometry, in particular the problem of embedding a general finite metric space into a Euclidean space.

It is known that the 4-point metric space defined by the star graph

```

[1]
 \
 1
 \
 [0] -- 1 -- [2]
 /
 1
 /
[3]

```

cannot be exactly embedded into a Euclidean space of any dimension, where distances are computed by length of the shortest path between vertices. A distance-preserving embedding would require the three leaf nodes to form an equilateral triangle of side length 2, with the centre node (0) mapped to an equidistant point at distance 1; this is impossible since the [triangle inequality](#) in Euclidean space implies all points would need to be simultaneously [collinear](#).

Here we will formulate and solve an SDP to compute the best possible embedding, that is, the embedding  $f$  assigning each vertex  $v$  to a vector  $f(v)$  that minimizes the distortion  $c$  such that

$$D[a, b] \leq \|f(a) - f(b)\| \leq c D[a, b]$$

for all edges  $(a, b)$  in the graph, where  $D[a, b]$  is the distance in the graph metric space.

Any embedding  $f$  can be characterized by a Gram matrix  $Q$ , which is PSD and such that

$$\|f(a) - f(b)\|^2 = Q[a, a] + Q[b, b] - 2Q[a, b]$$

The matrix entry  $Q[a, b]$  represents the inner product of  $f(a)$  with  $f(b)$ .

We therefore impose the constraint

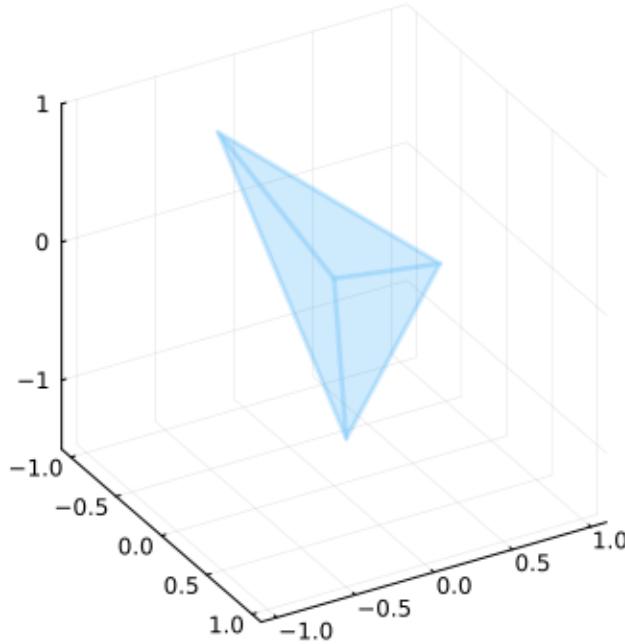
$$D[a, b]^2 \leq Q[a, a] + Q[b, b] - 2Q[a, b] \leq c^2 D[a, b]^2$$

for all edges  $(a, b)$  in the graph and minimize  $c^2$ , which gives us the SDP formulation below. Since we may choose any point to be the origin, we fix the first vertex at 0.

For more details, see ([Matoušek, 2013](#); [Linial, 2002](#)).

```
function example_minimum_distortion()
    model = Model(SCS.Optimizer)
    set_silent(model)
    D = [
        0.0 1.0 1.0 1.0
        1.0 0.0 2.0 2.0
        1.0 2.0 0.0 2.0
        1.0 2.0 2.0 0.0
    ]
    @variable(model, c² >= 1.0)
    @variable(model, Q[1:4, 1:4], PSD)
    for i in 1:4, j in (i+1):4
        @constraint(model, D[i, j]² <= Q[i, i] + Q[j, j] - 2 * Q[i, j])
        @constraint(model, Q[i, i] + Q[j, j] - 2 * Q[i, j] <= c² * D[i, j]²)
    end
    fix(Q[1, 1], 0)
    @objective(model, Min, c²)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    Test.@test objective_value(model) ≈ 4 / 3 atol = 1e-4
    # Recover the minimal distorted embedding:
    X = [zeros(3) sqrt(value.(Q)[2:end, 2:end])]
    return Plots.plot(
        X[1, :],
        X[2, :],
        X[3, :];
        seriestype = :mesh3d,
        connections = ([0, 0, 0, 1], [1, 2, 3, 2], [2, 3, 1, 3]),
        legend = false,
        fillalpha = 0.1,
        lw = 3,
        ratio = :equal,
        xlim = (-1.1, 1.1),
        ylim = (-1.1, 1.1),
        zlim = (-1.5, 1.0),
        zticks = -1:1,
        camera = (60, 30),
    )
end

example_minimum_distortion()
```



### Lovász numbers

The Lovász number of a graph, also known as Lovász's theta-function, is a number that lies between two important and related numbers that are computationally hard to determine, namely the chromatic and clique numbers of the graph. It is possible however to efficiently compute the Lovász number as the optimal value of a semidefinite program.

Consider the pentagon graph:

```
[5]
/
/   \
/     \
[1]   [4]
|       |
|       |
[2] --- [3]
```

with five vertices and edges. Its Lovász number is known to be precisely  $\sqrt{5} \approx 2.236$ , lying between 2 (the largest clique size) and 3 (the smallest number needed for a vertex coloring).

Let  $i, j$  be integers such that  $1 \leq i < j \leq 5$ . We define  $A^{ij}$  to be the  $5 \times 5$  symmetric matrix with entries  $(i, j)$  and  $(j, i)$  equal to 1, with all other entries 0. Let  $E$  be the graph's edge set; in this example,  $E$  contains  $(1,2), (2,3), (3,4), (4,5), (5,1)$  and their transposes. The Lovász number can be computed from the program

$$\max J \bullet X \quad (8.13)$$

$$\text{s.t. } A^{ij} \bullet X = 0 \text{ for all } (i, j) \notin E \quad (8.14)$$

$$I \bullet X = 1 \quad (8.15)$$

$$X \succeq 0 \quad (8.16)$$

where  $J$  is the matrix filled with ones, and  $I$  is the identity matrix.

For more details, see ([Barvinok, 2002](#); [Knuth, 1994](#)).

```
function example_theta_problem()
    model = Model(SCS.Optimizer)
    set_silent(model)
    E = [(1, 2), (2, 3), (3, 4), (4, 5), (5, 1)]
    @variable(model, X[1:5, 1:5], PSD)
    for i in 1:5
        for j in (i+1):5
            if !((i, j) in E || (j, i) in E)
                A = zeros(Int, 5, 5)
                A[i, j] = 1
                A[j, i] = 1
                @constraint(model, LinearAlgebra.dot(A, X) == 0)
            end
        end
    end
    @constraint(model, LinearAlgebra.tr(LinearAlgebra.I * X) == 1)
    J = ones(Int, 5, 5)
    @objective(model, Max, LinearAlgebra.dot(J, X))
    optimize!(model)
    assert_is_solved_and_feasible(model)
    Test.@test objective_value(model) ≈ sqrt(5) rtol = 1e-4
    println("The Lovász number is: $(objective_value(model))")
    return
end

example_theta_problem()
```

The Lovász number is: 2.2360678617950036

## Robust uncertainty sets

This example computes the Value at Risk for a data-driven uncertainty set. Closed-form expressions for the optimal value are available. For more details, see ([Bertsimas et al., 2018](#)).

```
function example_robust_uncertainty_sets()
    R, d, [], ε = 1, 3, 0.05, 0.05
    N = ceil((2 + 2 * log(2 / ε))^2) + 1
    c, μhat, M = randn(d), rand(d), rand(d, d)
    Σhat = 1 / (d - 1) * (M - ones(d) * μhat')' * (M - ones(d) * μhat')
    Γ1([], N) = R / sqrt(N) * (2 + sqrt(2 * log(1 / ε)))
```

```

Γ2(0, N) = 2 * R^2 / sqrt(N) * (2 + sqrt(2 * log(2 / 0)))
model = Model(SCS.Optimizer)
set_silent(model)
@variable(model, Σ[1:d, 1:d], PSD)
@variable(model, u[1:d])
@variable(model, μ[1:d])
@constraint(model, [Γ1(0 / 2, N); μ - μhat] in SecondOrderCone())
@constraint(model, [Γ2(0 / 2, N); vec(Σ - Σhat)] in SecondOrderCone())
@constraint(model, [(1-ε)/ε] (u - μ)' · (u - μ) Σ >= 0, PSDCone())
@objective(model, Max, c' * u)
optimize!(model)
assert_is_solved_and_feasible(model)
exact =
    μhat' * c +
    Γ1(0 / 2, N) * LinearAlgebra.norm(c) +
    sqrt((1 - ε) / ε) *
    sqrt(c' * (Σhat + Γ2(0 / 2, N) * LinearAlgebra.I) * c)
Test.@test objective_value(model) ≈ exact atol = 1e-2
return
end

example_robust_uncertainty_sets()

```

## 8.7 Example: logistic regression

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

**This tutorial was originally contributed by François Pacaud.**

This tutorial shows how to solve a logistic regression problem with JuMP. Logistic regression is a well known method in machine learning, useful when we want to classify binary variables with the help of a given set of features. To this goal, we find the optimal combination of features maximizing the (log)-likelihood onto a training set.

### Required packages

This tutorial uses the following packages:

```

using JuMP
import MathOptInterface as MOI
import Random
import SCS

Random.seed!(2713);

```

### Formulating the logistic regression problem

Suppose we have a set of training data-point  $i = 1, \dots, n$ , where for each  $i$  we have a vector of features  $x_i \in \mathbb{R}^p$  and a categorical observation  $y_i \in \{-1, 1\}$ .

The log-likelihood is given by

$$l(\theta) = \sum_{i=1}^n \log\left(\frac{1}{1 + \exp(-y_i \theta^\top x_i)}\right)$$

and the optimal  $\theta$  minimizes the logistic loss function:

$$\min_{\theta} \sum_{i=1}^n \log(1 + \exp(-y_i \theta^\top x_i)).$$

Most of the time, instead of solving directly the previous optimization problem, we prefer to add a regularization term:

$$\min_{\theta} \sum_{i=1}^n \log(1 + \exp(-y_i \theta^\top x_i)) + \lambda \|\theta\|$$

with  $\lambda \in \mathbb{R}_+$  a penalty and  $\|\cdot\|$  a norm function. By adding such a regularization term, we avoid overfitting on the training set and usually achieve a greater score in cross-validation.

### Reformulation as a conic optimization problem

By introducing auxiliary variables  $t_1, \dots, t_n$  and  $r$ , the optimization problem is equivalent to

$$\begin{aligned} & \min_{t, r, \theta} \sum_{i=1}^n t_i + \lambda r \\ \text{subject to } & t_i \geq \log(1 + \exp(-y_i \theta^\top x_i)) \\ & r \geq \|\theta\| \end{aligned}$$

Now, the trick is to reformulate the constraints  $t_i \geq \log(1 + \exp(-y_i \theta^\top x_i))$  with the help of the *exponential cone*

$$K_{\text{exp}} = \{(x, y, z) \in \mathbb{R}^3 : y \exp(x/y) \leq z\}.$$

Indeed, by passing to the exponential, we see that for all  $i = 1, \dots, n$ , the constraint  $t_i \geq \log(1 + \exp(-y_i \theta^\top x_i))$  is equivalent to

$$\exp(-t_i) + \exp(u_i - t_i) \leq 1$$

with  $u_i = -y_i \theta^\top x_i$ . Then, by adding two auxiliary variables  $z_{i1}$  and  $z_{i2}$  such that  $z_{i1} \geq \exp(u_i - t_i)$  and  $z_{i2} \geq \exp(-t_i)$ , we get the equivalent formulation

$$\begin{cases} (u_i - t_i, 1, z_{i1}) \in K_{exp} \\ (-t_i, 1, z_{i2}) \in K_{exp} \\ z_{i1} + z_{i2} \leq 1 \end{cases}$$

In this setting, the conic version of the logistic regression problems writes out

$$\begin{aligned} & \min_{t, z, r, \theta} \sum_{i=1}^n t_i + \lambda r \\ \text{subject to } & (u_i - t_i, 1, z_{i1}) \in K_{exp} \\ & (-t_i, 1, z_{i2}) \in K_{exp} \\ & z_{i1} + z_{i2} \leq 1 \\ & u_i = -y_i x_i^\top \theta \\ & r \geq \|\theta\| \end{aligned}$$

and thus encompasses  $3n + p + 1$  variables and  $3n + 1$  constraints ( $u_i = -y_i \theta^\top x_i$  is only a virtual constraint used to clarify the notation). Thus, if  $n \gg 1$ , we get a large number of variables and constraints.

### Fitting logistic regression with a conic solver

We start by implementing a function to generate a fake dataset, and where we could tune the correlation between the feature variables. The function is a direct transcription of the one used in [this blog post](#).

```
function generate_dataset(n_samples = 100, n_features = 10; shift = 0.0)
    X = randn(n_samples, n_features)
    w = randn(n_features)
    y = sign.(X * w)
    X .+= 0.8 * randn(n_samples, n_features) # add noise
    X .+= shift # shift the points in the feature space
    X = hcat(X, ones(n_samples, 1))
    return X, y
end
```

```
generate_dataset (generic function with 3 methods)
```

We write a `softplus` function to formulate each constraint  $t \geq \log(1 + \exp(u))$  with two exponential cones.

```
function softplus(model, t, u)
    z = @variable(model, [1:2], lower_bound = 0.0)
    @constraint(model, sum(z) <= 1.0)
    @constraint(model, [u - t, 1, z[1]] in MOI.ExponentialCone())
    @constraint(model, [-t, 1, z[2]] in MOI.ExponentialCone())
end
```

```
softplus (generic function with 1 method)
```

### $\ell_2$ regularized logistic regression

Then, with the help of the `softplus` function, we could write our optimization model. In the  $\ell_2$  regularization case, the constraint  $r \geq \|\theta\|_2$  rewrites as a second order cone constraint.

```
function build_logit_model(X, y, λ)
    n, p = size(X)
    model = Model()
    @variable(model, θ[1:p])
    @variable(model, t[1:n])
    for i in 1:n
        u = -(X[i, :]' * θ) * y[i]
        softplus(model, t[i], u)
    end
    # Add ℓ2 regularization
    @variable(model, 0.0 <= reg)
    @constraint(model, [reg; θ] in SecondOrderCone())
    # Define objective
    @objective(model, Min, sum(t) + λ * reg)
    return model
end
```

```
build_logit_model (generic function with 1 method)
```

We generate the dataset.

#### Warning

Be careful here, for large n and p SCS could fail to converge.

```
n, p = 200, 10
X, y = generate_dataset(n, p; shift = 10.0);

# We could now solve the logistic regression problem
λ = 10.0
model = build_logit_model(X, y, λ)
set_optimizer(model, SCS.Optimizer)
set_silent(model)
optimize!(model)
assert_is_solved_and_feasible(model)
```

```
θ̂ = value.(model[:θ])
```

```
11-element Vector{Float64}:
0.020413203134136172
0.16139903246564635
0.35700771838417933
-0.307880821875803
-0.3939184218208195
-0.059140401509885365
0.34717365911626014
-0.881212323544203
0.20125660911983811
0.5409398851900536
0.0809041969978851
```

It appears that the speed of convergence is not that impacted by the correlation of the dataset, nor by the penalty  $\lambda$ .

### $\ell_1$ regularized logistic regression

We now formulate the logistic problem with a  $\ell_1$  regularization term. The  $\ell_1$  regularization ensures sparsity in the optimal solution of the resulting optimization problem. Luckily, the  $\ell_1$  norm is implemented as a set in `MathOptInterface`. Thus, we could formulate the sparse logistic regression problem with the help of a `MOI.NormOneCone` set.

```
function build_sparse_logit_model(X, y, λ)
    n, p = size(X)
    model = Model()
    @variable(model, θ[1:p])
    @variable(model, t[1:n])
    for i in 1:n
        u = -(X[i, :]' * θ) * y[i]
        softplus(model, t[i], u)
    end
    # Add ℓ1 regularization
    @variable(model, 0.0 <= reg)
    @constraint(model, [reg; θ] in MOI.NormOneCone(p + 1))
    # Define objective
    @objective(model, Min, sum(t) + λ * reg)
    return model
end

# Auxiliary function to count non-null components:
count_nonzero(v::Vector; tol = 1e-6) = sum(abs.(v) .>= tol)

# We solve the sparse logistic regression problem on the same dataset as before.
λ = 10.0
sparse_model = build_sparse_logit_model(X, y, λ)
set_optimizer(sparse_model, SCS.Optimizer)
set_silent(sparse_model)
optimize!(sparse_model)
assert_is_solved_and_feasible(sparse_model)
```

```

θ# = value.(sparse_model[:θ])
println(
    "Number of non-zero components: ",
    count_nonzero(θ#),
    " (out of ",
    p,
    " features)",
)

```

Number of non-zero components: 8 (out of 10 features)

### Extensions

A direct extension would be to consider the sparse logistic regression with *hard* thresholding, which, on contrary to the *soft* version using a  $\ell_1$  regularization, adds an explicit cardinality constraint in its formulation:

$$\begin{aligned} \min_{\theta} \quad & \sum_{i=1}^n \log(1 + \exp(-y_i \theta^\top x_i)) + \lambda \|\theta\|_2^2 \\ \text{subject to} \quad & \|\theta\|_0 \leq k \end{aligned}$$

where  $k$  is the maximum number of non-zero components in the vector  $\theta$ , and  $\|\cdot\|_0$  is the  $\ell_0$  pseudo-norm:

$$\|x\|_0 = \#\{i : x_i \neq 0\}$$

The cardinality constraint  $\|\theta\|_0 \leq k$  could be reformulated with binary variables. Thus the hard sparse regression problem could be solved by any solver supporting mixed integer conic problems.

## 8.8 Example: experiment design

*This tutorial was generated using [Literate.jl](#). Download the source as a [.jl file](#).*

**This tutorial was originally contributed by Arpit Bhatia and Chris Coey.**

This tutorial covers experiment design examples (D-optimal, A-optimal, and E-optimal) from section 7.5 of ([Boyd and Vandenberghe, 2004](#)).

### Required packages

This tutorial uses the following packages:

```

using JuMP
import SCS
import LinearAlgebra
import MathOptInterface as MOI
import Random

```

We set a seed so the random numbers are repeatable:

```
Random.seed!(1234)
```

```
Random.TaskLocalRNG()
```

### The relaxed experiment design problem

The basic experiment design problem is as follows.

Given the menu of possible choices for experiments,  $v_1, \dots, v_p$ , and the total number  $m$  of experiments to be carried out, choose the numbers of each type of experiment, that is,  $m_1, \dots, m_p$  to make the error covariance  $E$  small (in some sense).

The variables  $m_1, \dots, m_p$  must, of course, be integers and sum to  $m$  the given total number of experiments. This leads to the optimization problem:

$$\begin{aligned} \min_{\text{w.r.t. } \mathbf{S}_+^n} (w.r.t. \mathbf{S}_+^n) E &= \left( \sum_{j=1}^p m_j v_j v_j^T \right)^{-1} \\ \text{subject to } m_i &\geq 0 \\ \sum_{i=1}^p m_i &= m \\ m_i &\in \mathbb{Z}, \quad i = 1, \dots, p \end{aligned}$$

The basic experiment design problem can be a hard combinatorial problem when  $m$ , the total number of experiments, is comparable to  $n$ , since in this case the  $m_i$  are all small integers.

In the case when  $m$  is large compared to  $n$ , however, a good approximate solution can be found by ignoring, or relaxing, the constraint that the  $m_i$  are integers.

Let  $\lambda_i = m_i/m$ , which is the fraction of the total number of experiments for which  $a_j = v_i$ , or the relative frequency of experiment  $i$ . We can express the error covariance in terms of  $\lambda_i$  as:

$$E = \frac{1}{m} \left( \sum_{i=1}^p \lambda_i v_i v_i^T \right)^{-1}$$

The vector  $\lambda \in \mathbf{R}^p$  satisfies  $\lambda \succeq 0$ ,  $\mathbf{1}^T \lambda = 1$ , and also, each  $\lambda_i$  is an integer multiple of  $1/m$ . By ignoring this last constraint, we arrive at the problem:

$$\begin{aligned} \min_{\text{w.r.t. } \mathbf{S}_+^n} (w.r.t. \mathbf{S}_+^n) E &= (1/m) \left( \sum_{i=1}^p \lambda_i v_i v_i^T \right)^{-1} \\ \text{subject to: } \lambda &\succeq 0 \\ \mathbf{1}^T \lambda &= 1 \end{aligned}$$

Several scalarizations have been proposed for the experiment design problem, which is a vector optimization problem over the positive semidefinite cone.

```
q = 4 # dimension of estimate space
p = 8 # number of experimental vectors
n_max = 3 # upper bound on lambda
n = 12

V = randn(q, p)

eye = Matrix{Float64}(LinearAlgebra.I, q, q);
```

### A-optimal design

In A-optimal experiment design, we minimize  $\text{tr } E$ , the trace of the covariance matrix. This objective is simply the mean of the norm of the error squared:

$$\mathbf{E}\|e\|_2^2 = \mathbf{E} \text{tr}(ee^T) = \text{tr } E$$

The A-optimal experiment design problem in SDP form is

$$\begin{aligned} & \min \mathbf{1}^T u \\ \text{subject to} \quad & \left[ \begin{array}{c} \sum_{i=1}^p \lambda_i v_i v_i^T e_k \\ e_k^T u_k \end{array} \right] \succeq 0, \quad k = 1, \dots, n \\ & \lambda \succeq 0 \\ & \mathbf{1}^T \lambda = 1 \end{aligned}$$

```
a0pt = Model(SCS.Optimizer)
set_silent(a0pt)
@variable(a0pt, np[1:p], lower_bound = 0, upper_bound = n_max)
@variable(a0pt, u[1:q], lower_bound = 0)
@constraint(a0pt, sum(np) <= n)
for i in 1:q
    matrix = [
        V*LinearAlgebra.diagm(0 => np ./ n)*V' eye[:, i]
        eye[i, :]' u[i]
    ]
    @constraint(a0pt, matrix >= 0, PSDCone())
end
@objective(a0pt, Min, sum(u))
optimize!(a0pt)
assert_is_solved_and_feasible(a0pt)
objective_value(a0pt)
```

```
5.103223362935127
```

```
value.(np)
```

```
8-element Vector{Float64}:
2.9495211350240993
1.7790921964770618
8.104871341338243e-6
4.706163785716405e-6
2.108266984184275
1.6983463798099494
1.2635010842547665
2.201229233017492
```

### E-optimal design

In  $E$ -optimal design, we minimize the norm of the error covariance matrix, that is, the maximum eigenvalue of  $E$ .

Since the diameter (twice the longest semi-axis) of the confidence ellipsoid  $\mathcal{E}$  is proportional to  $\|E\|_2^{1/2}$ , minimizing  $\|E\|_2$  can be interpreted geometrically as minimizing the diameter of the confidence ellipsoid.

E-optimal design can also be interpreted as minimizing the maximum variance of  $q^T e$ , over all  $q$  with  $\|q\|_2 = 1$ . The E-optimal experiment design problem in SDP form is:

$$\begin{aligned} & \text{min}_{t} \\ & \text{subject to } \sum_{i=1}^p \lambda_i v_i v_i^T \succeq tI \\ & \quad \lambda \succeq 0 \\ & \quad \mathbf{1}^T \lambda = 1 \end{aligned}$$

```
e0pt = Model(SCS.Optimizer)
set_silent(e0pt)
@variable(e0pt, 0 <= np[1:p] <= n_max)
@variable(e0pt, t)
@constraint(
    e0pt,
    V * LinearAlgebra.diagm(0 => np ./ n) * V' - (t .* eye) >= 0,
    PSDCone(),
)
@constraint(e0pt, sum(np) <= n)
@objective(e0pt, Max, t)
optimize!(e0pt)
assert_is_solved_and_feasible(e0pt)
objective_value(e0pt)
```

```
0.43538638563660814
```

```
value.(np)
```

```
8-element Vector{Float64}:
2.9999986784944226
2.75281016389529
-3.6095749146944787e-7
-1.487244304015834e-6
2.181846279181994
2.325263546495149
0.21896764657670037
1.5211163050178793
```

### D-optimal design

The most widely used scalarization is called  $D$ -optimal design, in which we minimize the determinant of the error covariance matrix  $E$ . This corresponds to designing the experiment to minimize the volume of the resulting confidence ellipsoid (for a fixed confidence level). Ignoring the constant factor  $1/m$  in  $E$ , and taking the logarithm of the objective, we can pose this problem as convex optimization problem:

$$\begin{aligned} \min \log \det \left( \sum_{i=1}^p \lambda_i v_i v_i^T \right)^{-1} \\ \text{subject to } \lambda \succeq 0 \\ \mathbf{1}^T \lambda = 1 \end{aligned}$$

```
d0pt = Model(SCS.Optimizer)
set_silent(d0pt)
@variable(d0pt, np[1:p], lower_bound = 0, upper_bound = n_max)
@variable(d0pt, t)
@objective(d0pt, Max, t)
@constraint(d0pt, sum(np) <= n)
E = V * LinearAlgebra.diagm(0 => np ./ n) * V'
@constraint(d0pt, [t; 1; triangle_vec(E)] in MOI.LogDetConeTriangle(q))
optimize!(d0pt)
assert_is_solved_and_feasible(d0pt)
objective_value(d0pt)
```

```
0.30845393467249815
```

```
value.(np)
```

```
8-element Vector{Float64}:
0.42758242662215623
2.9100163168940334
2.9168724590080685e-6
2.629197980393792e-6
2.9157806299837166
2.67337566459234
2.735395012219622
0.3378388086258122
```

## 8.9 Example: minimal ellipses

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

This example comes from section 8.4.1 of the book *Convex Optimization* by [Boyd and Vandenberghe \(2004\)](#).

### Formulation

Given a set of  $m$  ellipses of the form:

$$E(A, b, c) = \{x : x^\top Ax + 2b^\top x + c \leq 0\},$$

the minimal ellipse problem finds an ellipse with the minimum area that encloses the given ellipses.

It is convenient to parameterize the minimal enclosing ellipse as

$$\{x : \|Px + q\| \leq 1\}.$$

Then the optimal  $P$  and  $q$  are given by the convex semidefinite program;

$$\begin{aligned} & \text{maximize} && \log(\det(P)) \\ & \text{subject to} && \tau_i \geq 0, \quad i = 1, \dots, m \\ & && \begin{bmatrix} P^2 - \tau_i A_i & Pq - \tau_i b_i & 0 \\ (Pq - \tau_i b_i)^\top & -1 - \tau_i c_i & (Pq)^\top \\ 0 & (Pq) & -P^2 \end{bmatrix} \preceq 0 \text{ (PSD)} \quad i = 1, \dots, m \end{aligned}$$

with helper variables  $\tau$ .

### Required packages

This tutorial uses the following packages:

```
using JuMP
import LinearAlgebra
import Plots
import SCS
import Test
```

## Data

First, define the  $m$  input ellipses (here  $m = 6$ ), parameterized as  $x^T A_i x + 2b_i^T x + c \leq 0$ :

```
struct Ellipse
    A::Matrix{Float64}
    b::Vector{Float64}
    c::Float64
end

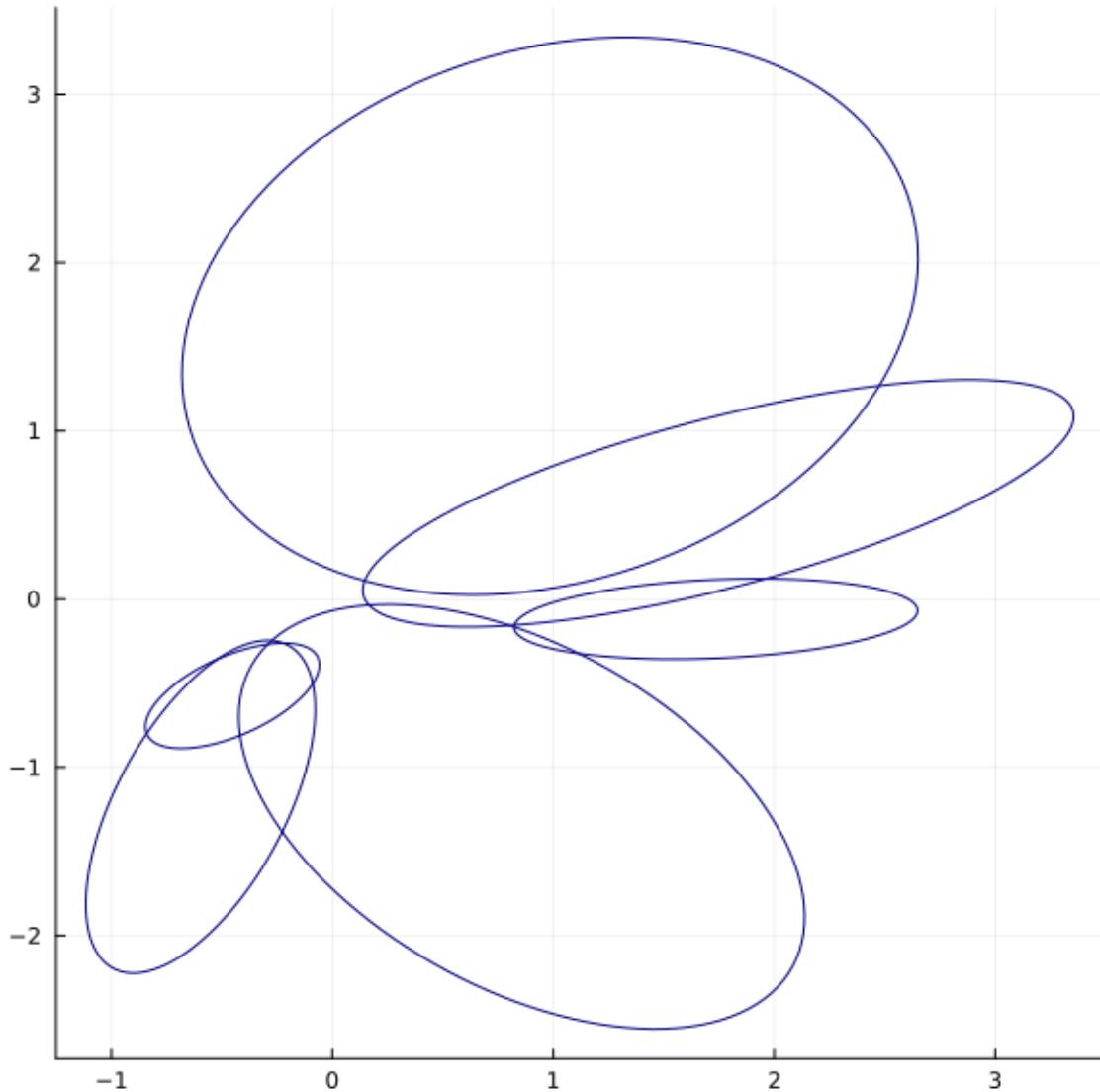
function Ellipse(A::Matrix{Float64}, b::Vector{Float64}, c::Float64)
    @assert isreal(A) && LinearAlgebra.issymmetric(A)
    return new(A, b, c)
end

ellipses = [
    Ellipse([1.2576 -0.3873; -0.3873 0.3467], [0.2722, 0.1969], 0.1831),
    Ellipse([1.4125 -2.1777; -2.1777 6.7775], [-1.228, -0.0521], 0.3295),
    Ellipse([1.7018 0.8141; 0.8141 1.7538], [-0.4049, 1.5713], 0.2077),
    Ellipse([0.9742 -0.7202; -0.7202 1.5444], [0.0265, 0.5623], 0.2362),
    Ellipse([0.6798 -0.1424; -0.1424 0.6871], [-0.4301, -1.0157], 0.3284),
    Ellipse([0.1796 -0.1423; -0.1423 2.6181], [-0.3286, 0.557], 0.4931),
];
```

We visualise the ellipses using the Plots package:

```
function plot_ellipse(plot, ellipse::Ellipse)
    A, b, c = ellipse.A, ellipse.b, ellipse.c
    θ = range(0, 2π + 0.05; step = 0.05)
    # Some linear algebra to convert θ into (x,y) coordinates.
    x_y = √A \ (√(b' * (A \ b) - c) .* hcat(cos.(θ), sin.(θ)) .. -(√A \ b)')'
    Plots.plot!(plot, x_y[1, :], x_y[2, :]; label = nothing, c = :navy)
    return
end

plot = Plots.plot(; size = (600, 600))
for ellipse in ellipses
    plot_ellipse(plot, ellipse)
end
plot
```



### Build the model

Now let's build the model, using the change-of-variables  $P^2 = P^2$  and  $P_q = Pg$ . We'll recover the true value of  $P$  and  $q$  after the solve.

```
model = Model(SCS.Optimizer)
# We need to use a tighter tolerance for this example, otherwise the bounding
# ellipse won't actually be bounding...
set_attribute(model, "eps_rel", 1e-6)
set_silent(model)
m, n = length(ellipses), size(first(ellipses).A, 1)
@variable(model, τ[1:m] >= 0)
@variable(model, P²[1:n, 1:n], PSD)
@variable(model, P_q[1:n])
```

```

for (i, ellipse) in enumerate(ellipses)
    A, b, c = ellipse.A, ellipse.b, ellipse.c
    X = [
        #! format: off
        (P² - τ[i] * A)  (P_q - τ[i] * b) zeros(n, n)
        (P_q - τ[i] * b)' (-1 - τ[i] * c) P_q'
        zeros(n, n)      P_q                -P²
        #! format: on
    ]
    @constraint(model, LinearAlgebra.Symmetric(X) <= 0, PSDCone())
end

```

We cannot directly represent the objective  $\log(\det(P))$ , so we introduce the conic reformulation:

```

@variable(model, log_det_P)
@constraint(model, [log_det_P; 1; vec(P²)] in MOI.LogDetConeSquare(n))
@objective(model, Max, log_det_P)

```

*log\_det\_P*

Now, solve the program:

```

optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)

```

```

* Solver : SCS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "solved"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value   : -4.04358e+00
  Dual objective value : -4.04364e+00

* Work counters
  Solve time (sec)   : 2.22253e-01

```

## Results

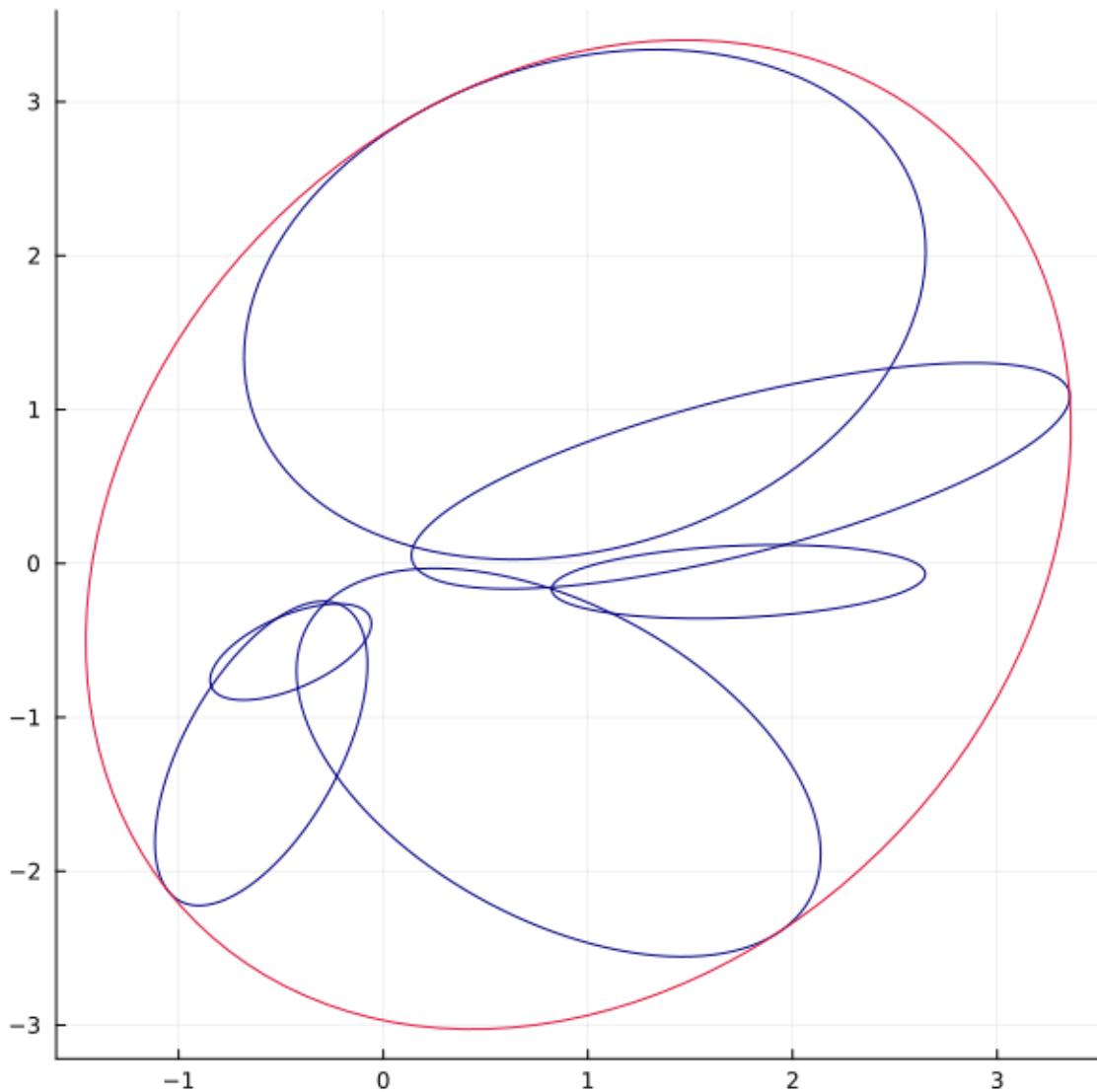
After solving the model to optimality we can recover the solution in terms of  $P$  and  $q$ :

```
P = sqrt(value.(P2))
q = P \ value.(P_q)
```

```
2-element Vector{Float64}:
-0.3964217693227084
-0.02139417862146734
```

Finally, overlaying the solution in the plot we see the minimal area enclosing ellipsoid:

```
Plots.plot!(
    plot,
    [tuple(P \ [cos(θ) - q[1], sin(θ) - q[2]]...) for θ in 0:0.05:(2pi+0.05)];
    c = :crimson,
    label = nothing,
)
```



## 8.10 Example: ellipsoid approximation

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

This tutorial considers the problem of computing *extremal ellipsoids*: finding ellipsoids that best approximate a given set. As an extension, we show how to use JuMP to inspect the bridges that were used, and how to explore alternative formulations.

The model comes from Section 4.9 of ([Ben-Tal and Nemirovski, 2001](#)).

For a related example, see also the [Example: minimal ellipses](#) tutorial.

### Required packages

This tutorial uses the following packages:

```
using JuMP
import LinearAlgebra
import Plots
import Random
import SCS
import Test
```

### Problem formulation

Suppose that we are given a set  $\mathcal{S}$  consisting of  $m$  points in  $n$ -dimensional space:

$$\mathcal{S} = \{x_1, \dots, x_m\} \subset \mathbb{R}^n$$

Our goal is to determine an optimal vector  $c \in \mathbb{R}^n$  and an optimal  $n \times n$  real symmetric matrix  $D$  such that the ellipse:

$$E(D, c) = \{x : (x - c)^\top D(x - c) \leq 1\},$$

contains  $\mathcal{S}$  and has the smallest possible volume.

The optimal  $D$  and  $c$  are given by the optimization problem:

$$\begin{aligned} & \max \quad t \\ \text{s.t.} \quad & Z \succeq 0 \\ & \begin{bmatrix} s & z^\top \\ z & Z \end{bmatrix} \succeq 0 \\ & x_i^\top Z x_i - 2x_i^\top z + s \leq 1 \quad i = 1, \dots, m \\ & t \leq \sqrt[n]{\det(Z)}, \end{aligned}$$

where  $D = Z_*$  and  $c = Z_*^{-1}z_*$ .

### Data

We first need to generate some points to work with.

```
function generate_point_cloud(
    m;           # number of 2-dimensional points
    a = 10,      # scaling in x direction
    b = 2,       # scaling in y direction
    rho = π / 6, # rotation of points around origin
    random_seed = 1,
)
    rng = Random.MersenneTwister(random_seed)
    P = randn(rng, Float64, m, 2)
    Phi = [a*cos(rho) a*sin(rho); -b*sin(rho) b*cos(rho)]
    S = P * Phi
    return S
end
```

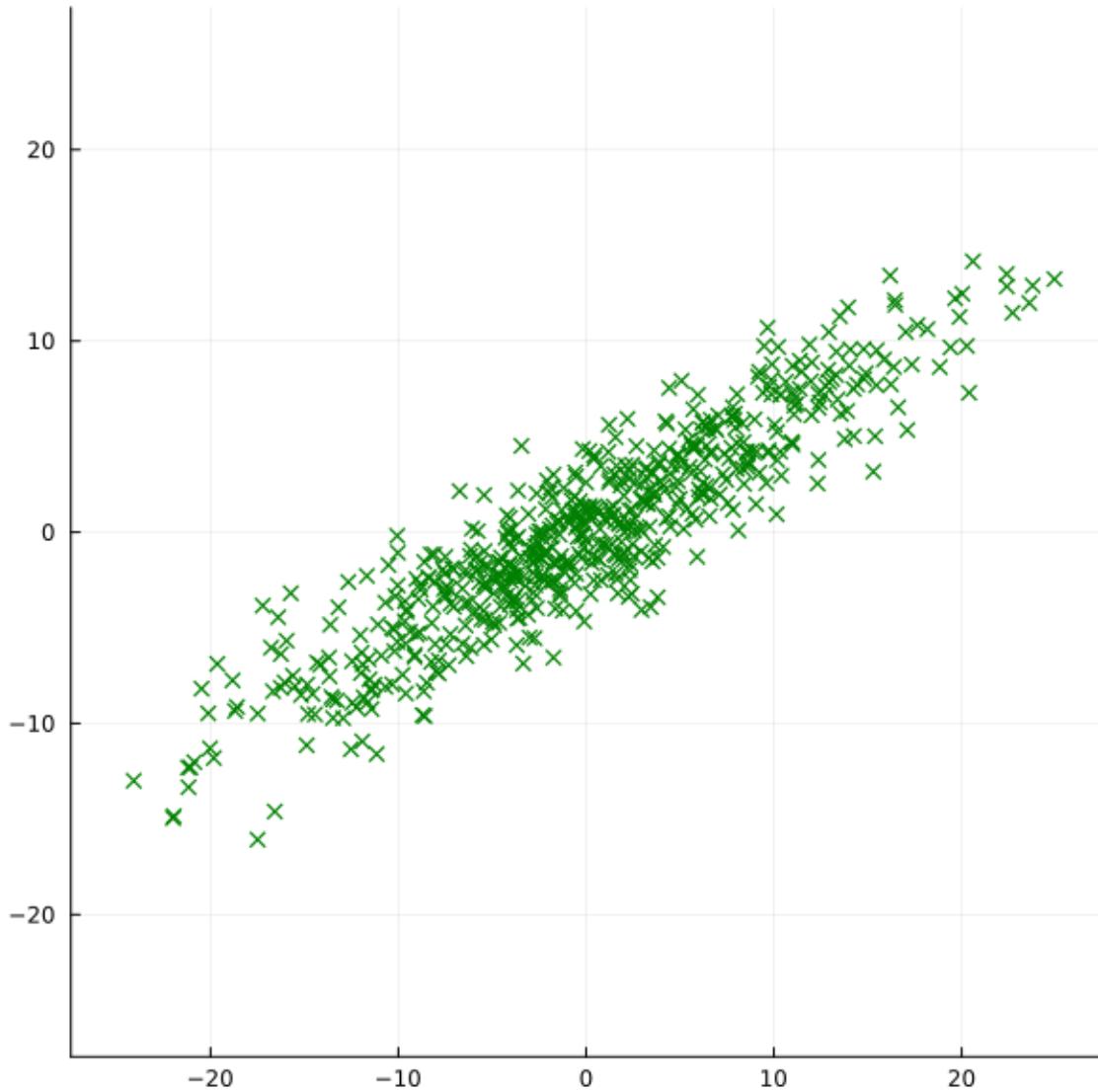
```
generate_point_cloud (generic function with 1 method)
```

For the sake of this example, let's take  $m = 600$ :

```
S = generate_point_cloud(600);
```

We will visualise the points (and ellipse) using the Plots package:

```
r = 1.1 * maximum(abs.(S))
plot = Plots.scatter(
    S[:, 1],
    S[:, 2];
    xlim = (-r, r),
    ylim = (-r, r),
    label = nothing,
    c = :green,
    shape = :x,
    size = (600, 600),
)
```



### JuMP formulation

Now let's build and the JuMP model. We'll compute  $D$  and  $c$  after the solve.

```
model = Model(SCS.Optimizer)
# We need to use a tighter tolerance for this example, otherwise the bounding
# ellipse won't actually be bounding...
set_attribute(model, "eps_rel", 1e-7)
set_silent(model)
m, n = size(S)
@variable(model, z[1:n])
@variable(model, Z[1:n, 1:n], PSD)
@variable(model, s)
@variable(model, t)
@constraint(model, [s z'; z Z] >= 0, PSDCone())
```

```

@constraint(
    model,
    [i in 1:m],
    S[i, :]' * Z * S[i, :] - 2 * S[i, :]' * z + s <= 1,
)
@constraint(model, [t; vec(Z)] in MOI.RootDetConeSquare(n))
@objective(model, Max, t)
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)

```

```

* Solver : SCS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "solved"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 5.12019e-03
  Dual objective value : 5.08382e-03

* Work counters
  Solve time (sec)   : 2.94236e-01

```

## Results

After solving the model to optimality we can recover the solution in terms of  $D$  and  $c$ :

```
D = value.(Z)
```

```

2x2 Matrix{Float64}:
 0.00755264  -0.0114233
 -0.0114233   0.0206963

```

```
c = D \ value.(z)
```

```

2-element Vector{Float64}:
 -3.3657411425923884
 -2.255547187078282

```

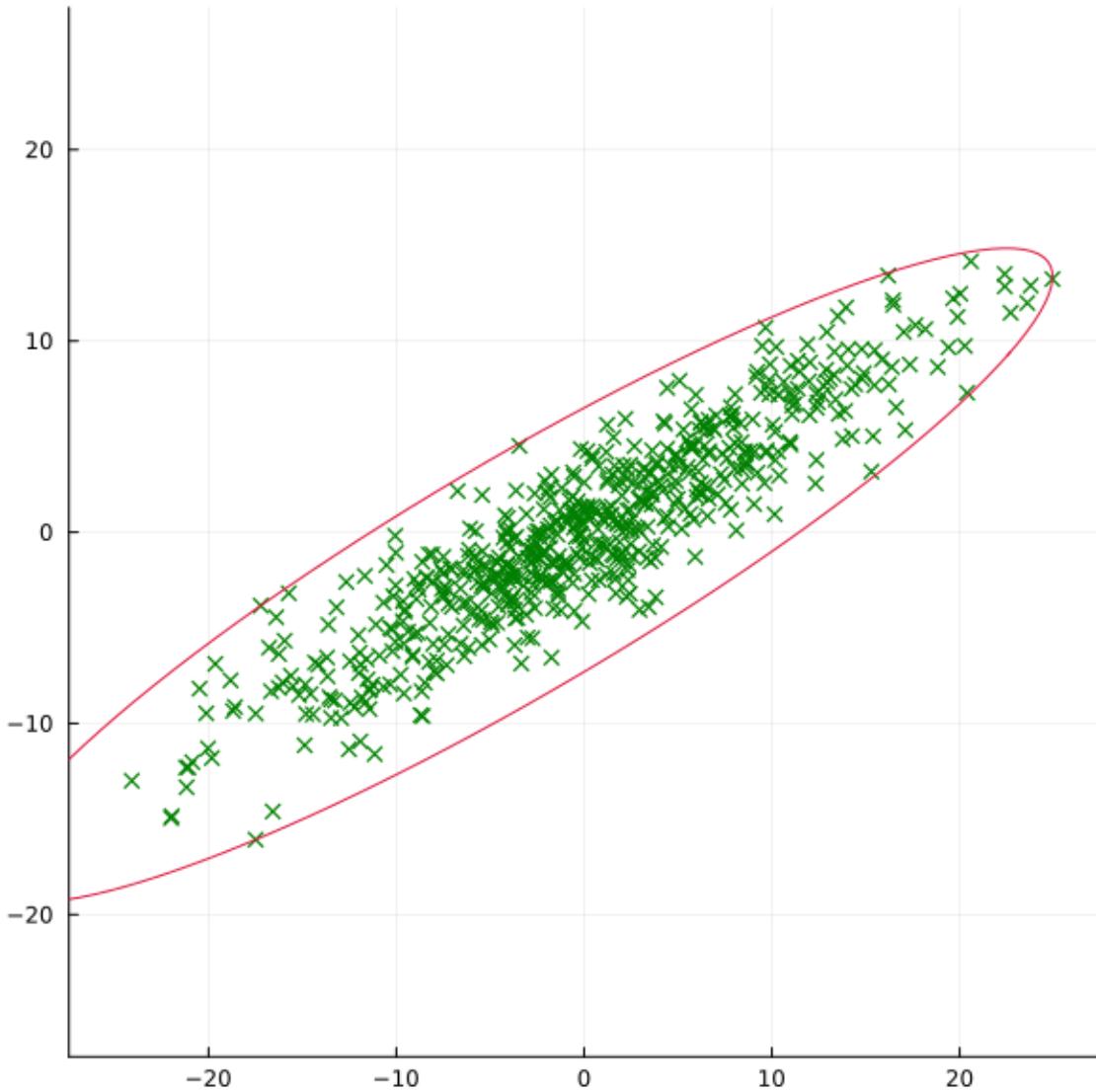
We can check that each point lies inside the ellipsoid, by checking if the largest normalized radius is less than 1:

```
largest_radius = maximum(map(x -> (x - c)' * D * (x - c), eachrow(S)))
```

```
0.999891803944291
```

Finally, overlaying the solution in the plot we see the minimal volume approximating ellipsoid:

```
P = sqrt(D)
q = -P * c
data = [tuple(P \ [cos(θ) - q[1], sin(θ) - q[2]]...) for θ in 0:0.05:(2pi+0.05)]
Plots.plot!(plot, data; c = :crimson, label = nothing)
```



### Alternative formulations

The formulation of model uses `MOI.RootDetConeSquare`. However, because SCS does not natively support this cone, JuMP automatically reformulates the problem into an equivalent problem that SCS does support. You can see the reformulation that JuMP chose using `print_active_bridges`:

```
print_active_bridges(model)
```

```
* Unsupported objective: MOI.VariableIndex
| bridged by:
| MOIB.Objective.FunctionConversionBridge{Float64, MOI.ScalarAffineFunction{Float64},
↪ MOI.VariableIndex}
| may introduce:
```

```

|   * Supported objective: MOI.ScalarAffineFunction{Float64}
* Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.LessThan{Float64}
|   bridged by:
|   MOIB.Constraint.LessToGreaterBridge{Float64, MOI.ScalarAffineFunction{Float64},
↪ MOI.ScalarAffineFunction{Float64}}
|   may introduce:
|   * Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.GreaterThan{Float64}
|   |   bridged by:
|   |   MOIB.Constraint.VectorizeBridge{Float64, MOI.VectorAffineFunction{Float64},
↪ MOI.Nonnegatives, MOI.ScalarAffineFunction{Float64}}
|   |   may introduce:
|   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
* Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeSquare
|   bridged by:
|   MOIB.Constraint.SquareBridge{Float64, MOI.VectorAffineFunction{Float64},
↪ MOI.ScalarAffineFunction{Float64}, MOI.PositiveSemidefiniteConeTriangle,
↪ MOI.PositiveSemidefiniteConeSquare}
|   may introduce:
|   * Unsupported constraint:
↪ MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeTriangle
|   |   bridged by:
|   |   MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
↪ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
|   |   may introduce:
|   |   * Unsupported constraint:
↪ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
|   |   |   bridged by:
|   |   |   SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
|   |   |   may introduce:
|   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
* Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.EqualTo{Float64}
|   bridged by:
|   MOIB.Constraint.VectorizeBridge{Float64, MOI.VectorAffineFunction{Float64}, MOI.Zeros,
↪ MOI.ScalarAffineFunction{Float64}}
|   may introduce:
|   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Zeros
* Unsupported constraint: MOI.VectorOfVariables-in-MOI.PositiveSemidefiniteConeTriangle
|   bridged by:
|   MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
↪ MOI.VectorAffineFunction{Float64}, MOI.VectorOfVariables}
|   may introduce:
|   * Unsupported constraint:
↪ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
|   |   bridged by:
|   |   SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
|   |   may introduce:
|   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
* Unsupported constraint: MOI.VectorOfVariables-in-MOI.RootDetConeSquare
|   bridged by:
|   MOIB.Constraint.FunctionConversionBridge{Float64, MOI.VectorAffineFunction{Float64},
↪ MOI.VectorOfVariables, MOI.RootDetConeSquare}
|   may introduce:
|   * Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.RootDetConeSquare
|   |   bridged by:
|   |   MOIB.Constraint.SquareBridge{Float64, MOI.VectorAffineFunction{Float64},
↪ MOI.ScalarAffineFunction{Float64}, MOI.RootDetConeTriangle, MOI.RootDetConeSquare}

```

```

|   |   may introduce:
|   |   * Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.RootDetConeTriangle
|   |   | bridged by:
|   |   |   MOIB.Constraint.RootDetBridge{Float64, MOI.VectorAffineFunction{Float64}},
→ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
|   |   |   may introduce:
|   |   |   * Unsupported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeTriangle
|   |   |   | bridged by:
|   |   |   |   MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle},
→ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
|   |   |   |   may introduce:
|   |   |   |   * Unsupported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
|   |   |   |   | bridged by:
|   |   |   |   |   SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
|   |   |   |   |   may introduce:
|   |   |   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
|   |   |   |   * Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.GeometricMeanCone
|   |   |   |   | bridged by:
|   |   |   |   |   MOIB.Constraint.GeoMeanToPowerBridge{Float64, MOI.VectorAffineFunction{Float64}}
|   |   |   |   |   may introduce:
|   |   |   |   |   * Supported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.PowerCone{Float64}
|   |   |   |   * Unsupported variable: MOI.Nonnegatives
|   |   |   |   | adding as constraint:
|   |   |   |   |   * Supported variable: MOI.Reals
|   |   |   |   |   * Unsupported constraint: MOI.VectorOfVariables-in-MOI.Nonnegatives
|   |   |   |   |   | bridged by:
|   |   |   |   |   |   MOIB.Constraint.FunctionConversionBridge{Float64,
→ MOI.VectorAffineFunction{Float64}, MOI.VectorOfVariables, MOI.Nonnegatives}
|   |   |   |   |   |   may introduce:
|   |   |   |   |   |   * Supported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
|   |   |   |   * Supported variable: MOI.Reals
|   |   |   * Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.EqualTo{Float64}
|   |   |   | bridged by:
|   |   |   |   MOIB.Constraint.VectorizeBridge{Float64, MOI.VectorAffineFunction{Float64}, MOI.Zeros,
→ MOI.ScalarAffineFunction{Float64}}
|   |   |   |   may introduce:
|   |   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Zeros

```

There's a lot going on here, but the first bullet is:

```

* Unsupported objective: MOI.VariableIndex
| bridged by:
|   MOIB.Objective.FunctionizeBridge{Float64}
| introduces:
|   * Supported objective: MOI.ScalarAffineFunction{Float64}

```

This says that SCS does not support a `MOI.VariableIndex` objective function, and that JuMP used a `MOI.Bridges.Objective.Fun` to convert it into a `MOI.ScalarAffineFunction{Float64}` objective function.

We can leave JuMP to do the reformulation, or we can rewrite our model to have an objective function that SCS natively supports:

```
@objective(model, Max, 1.0 * t + 0.0);
```

Re-printing the active bridges:

```
print_active_bridges(model)
```

```
* Supported objective: MOI.ScalarAffineFunction{Float64}
* Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.LessThan{Float64}
| bridged by:
| MOIB.Constraint.LessToGreaterBridge{Float64, MOI.ScalarAffineFunction{Float64},
↪ MOI.ScalarAffineFunction{Float64}}
| may introduce:
| * Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.GreaterThan{Float64}
| | bridged by:
| | MOIB.Constraint.VectorizeBridge{Float64, MOI.VectorAffineFunction{Float64},
↪ MOI.Nonnegatives, MOI.ScalarAffineFunction{Float64}}
| | may introduce:
| | * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
* Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeSquare
| bridged by:
| MOIB.Constraint.SquareBridge{Float64, MOI.VectorAffineFunction{Float64},
↪ MOI.ScalarAffineFunction{Float64}, MOI.PositiveSemidefiniteConeTriangle,
↪ MOI.PositiveSemidefiniteConeSquare}
| may introduce:
| * Unsupported constraint:
↪ MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeTriangle
| | bridged by:
| | MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
↪ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
| | may introduce:
| | * Unsupported constraint:
↪ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
| | | bridged by:
| | | SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
| | | may introduce:
| | | * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
* Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.EqualTo{Float64}
| bridged by:
| MOIB.Constraint.VectorizeBridge{Float64, MOI.VectorAffineFunction{Float64}, MOI.Zeros,
↪ MOI.ScalarAffineFunction{Float64}}
| may introduce:
| * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Zeros
* Unsupported constraint: MOI.VectorOfVariables-in-MOI.PositiveSemidefiniteConeTriangle
| bridged by:
| MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
↪ MOI.VectorAffineFunction{Float64}, MOI.VectorOfVariables}
| may introduce:
| * Unsupported constraint:
↪ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
| | bridged by:
```

```

|   |   SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
|   |   may introduce:
|   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
* Unsupported constraint: MOI.VectorOfVariables-in-MOI.RootDetConeSquare
|   bridged by:
|   MOIB.Constraint.FunctionConversionBridge{Float64, MOI.VectorAffineFunction{Float64},
→ MOI.VectorOfVariables, MOI.RootDetConeSquare}
|   may introduce:
|   * Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.RootDetConeSquare
|   |   bridged by:
|   |   MOIB.Constraint.SquareBridge{Float64, MOI.VectorAffineFunction{Float64},
→ MOI.ScalarAffineFunction{Float64}, MOI.RootDetConeTriangle, MOI.RootDetConeSquare}
|   |   may introduce:
|   |   * Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.RootDetConeTriangle
|   |   |   bridged by:
|   |   |   MOIB.Constraint.RootDetBridge{Float64, MOI.VectorAffineFunction{Float64},
→ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
|   |   |   may introduce:
|   |   |   * Unsupported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeTriangle
|   |   |   |   bridged by:
|   |   |   |   MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
→ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
|   |   |   |   may introduce:
|   |   |   |   * Unsupported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
|   |   |   |   |   bridged by:
|   |   |   |   |   SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
|   |   |   |   may introduce:
|   |   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
|   |   |   * Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.GeometricMeanCone
|   |   |   |   bridged by:
|   |   |   |   MOIB.Constraint.GeoMeanToPowerBridge{Float64, MOI.VectorAffineFunction{Float64}}
|   |   |   |   may introduce:
|   |   |   |   * Supported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.PowerCone{Float64}
|   |   |   |   * Unsupported variable: MOI.Nonnegatives
|   |   |   |   adding as constraint:
|   |   |   |   * Supported variable: MOI.Reals
|   |   |   |   * Unsupported constraint: MOI.VectorOfVariables-in-MOI.Nonnegatives
|   |   |   |   |   bridged by:
|   |   |   |   |   MOIB.Constraint.FunctionConversionBridge{Float64,
→ MOI.VectorAffineFunction{Float64}, MOI.VectorOfVariables, MOI.Nonnegatives}
|   |   |   |   |   may introduce:
|   |   |   |   |   |   * Supported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
|   |   |   |   * Supported variable: MOI.Reals
|   |   |   * Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.EqualTo{Float64}
|   |   |   bridged by:
|   |   |   MOIB.Constraint.VectorizeBridge{Float64, MOI.VectorAffineFunction{Float64}, MOI.Zeros,
→ MOI.ScalarAffineFunction{Float64}}
|   |   |   may introduce:
|   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Zeros

```

we get \* Supported objective: MOI.ScalarAffineFunction{Float64}.

We can manually implement some other reformulations to change our model to something that SCS more closely supports by:

- Replacing the `MOI.VectorOfVariables` in `MOI.PositiveSemidefiniteConeTriangle` constraint @variable(model,  $Z[1:n, 1:n]$ , PSD) with the `MOI.VectorAffineFunction` in `MOI.PositiveSemidefiniteConeTriangle` @constraint(model,  $Z \geq 0$ , PSDCone()).
- Replacing the `MOI.VectorOfVariables` in `MOI.PositiveSemidefiniteConeSquare` constraint  $[s z'; z Z] \geq 0$ , PSDCone() with the `MOI.VectorAffineFunction` in `MOI.PositiveSemidefiniteConeTriangle` @constraint(model,  $\text{LinearAlgebra.Symmetric}([s z'; z Z]) \geq 0$ , PSDCone()).
- Replacing the `MOI.ScalarAffineFunction` in `MOI.GreaterThan` constraints with the vectorized equivalent of `MOI.VectorAffineFunction` in `MOI.Nonnegatives`
- Replacing the `MOI.VectorOfVariables` in `MOI.RootDetConeSquare` constraint with `MOI.VectorAffineFunction` in `MOI.RootDetConeTriangle`.

Note that we still need to bridge `MOI.PositiveSemidefiniteConeTriangle` constraints because SCS uses an internal `SCS.ScaledPSDCone` set instead.

```
model = Model(SCS.Optimizer)
set_attribute(model, "eps_rel", 1e-6)
set_silent(model)
@variable(model, z[1:n])
@variable(model, s)
@variable(model, t)
# The former @variable(model, Z[1:n, 1:n], PSD)
@variable(model, Z[1:n, 1:n], Symmetric)
@constraint(model, Z >= 0, PSDCone())
# The former [s z'; z Z] >= 0, PSDCone()
@constraint(model, LinearAlgebra.Symmetric([s z'; z Z]) >= 0, PSDCone())
# The former constraint  $S[i, :]' * Z * S[i, :] - 2 * S[i, :]' * z + s \leq 1$ 
f = [1 - S[i, :]' * Z * S[i, :] + 2 * S[i, :]' * z - s for i in 1:m]
@constraint(model, f in MOI.Nonnegatives(m))
# The former constraint [t; vec(Z)] in MOI.RootDetConeSquare(n)
@constraint(model, 1 * [t; triangle_vec(Z)] .+ 0 in MOI.RootDetConeTriangle(n))
# The former @objective(model, Max, t)
@objective(model, Max, 1 * t + 0)
optimize!(model)
assert_is_solved_and_feasible(model)
solve_time_1 = solve_time(model)
```

0.358026862

This formulation gives the much smaller graph:

```
print_active_bridges(model)
```

```

* Supported objective: MOI.ScalarAffineFunction{Float64}
* Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
* Unsupported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeTriangle
| bridged by:
| MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
→ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
| may introduce:
| * Unsupported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
| | bridged by:
| | SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
| | may introduce:
| | * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
* Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.RootDetConeTriangle
| bridged by:
| MOIB.Constraint.RootDetBridge{Float64, MOI.VectorAffineFunction{Float64}},
→ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}
| may introduce:
| * Unsupported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeTriangle
| | bridged by:
| | MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
→ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
| | may introduce:
| | * Unsupported constraint:
→ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
| | | bridged by:
| | | SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
| | | may introduce:
| | | * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
* Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.GeometricMeanCone
| bridged by:
| MOIB.Constraint.GeoMeanToPowerBridge{Float64, MOI.VectorAffineFunction{Float64}}
| may introduce:
| * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.PowerCone{Float64}
| * Unsupported variable: MOI.Nonnegatives
| | adding as constraint:
| | * Supported variable: MOI.Reals
| | * Unsupported constraint: MOI.VectorOfVariables-in-MOI.Nonnegatives
| | | bridged by:
| | | MOIB.Constraint.FunctionConversionBridge{Float64,
→ MOI.VectorAffineFunction{Float64}, MOI.VectorOfVariables, MOI.Nonnegatives}
| | | | may introduce:
| | | | * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
| * Supported variable: MOI.Reals

```

The last bullet shows how JuMP reformulated the `MOI.RootDetConeTriangle` constraint by adding a mix of `MOI.PositiveSemidefiniteConeTriangle` and `MOI.GeometricMeanCone` constraints.

Because SCS doesn't natively support the `MOI.GeometricMeanCone`, these constraints were further bridged using a `MOI.Bridges.Constraint.GeoMeanToPowerBridge` to a series of `MOI.PowerCone` constraints.

However, there are many other ways that a `MOI.GeometricMeanCone` can be reformulated into something that SCS supports. Let's see what happens if we use `remove_bridge` to remove the `MOI.Bridges.Constraint.GeoMeanToPowerBridge`

```
remove_bridge(model, MOI.Bridges.Constraint.GeoMeanToPowerBridge)
optimize!(model)
assert_is_solved_and_feasible(model)
```

This time, the solve took:

```
solve_time_2 = solve_time(model)
```

```
0.288548466
```

where previously it took

```
solve_time_1
```

```
0.358026862
```

Why was the solve time different?

```
print_active_bridges(model)
```

```
* Supported objective: MOI.ScalarAffineFunction{Float64}
* Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
* Unsupported constraint:
  ↳ MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeTriangle
  | bridged by:
  | MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
  ↳ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
  | may introduce:
  | * Unsupported constraint:
  ↳ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
  | | bridged by:
  | | SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
  | | may introduce:
  | | * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
* Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.RootDetConeTriangle
| bridged by:
| MOIB.Constraint.RootDetBridge{Float64, MOI.VectorAffineFunction{Float64},
↪ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
| may introduce:
| * Unsupported constraint:
↪ MOI.VectorAffineFunction{Float64}-in-MOI.PositiveSemidefiniteConeTriangle
| | bridged by:
| | MOIB.Constraint.SetDotScalingBridge{Float64, MOI.PositiveSemidefiniteConeTriangle,
↪ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}}
| | may introduce:
```

```

|   |   * Unsupported constraint:
|→ MOI.VectorAffineFunction{Float64}-in-MOI.Scaled{MOI.PositiveSemidefiniteConeTriangle}
|   |   | bridged by:
|   |   |   SCS.ScaledPSDConeBridge{Float64, MOI.VectorAffineFunction{Float64}}
|   |   | may introduce:
|   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-SCS.ScaledPSDCone
|   * Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.GeometricMeanCone
|   | bridged by:
|   |   MOIB.Constraint.GeoMeanBridge{Float64, MOI.ScalarAffineFunction{Float64}},
|→ MOI.VectorAffineFunction{Float64}, MOI.VectorAffineFunction{Float64}
|   | may introduce:
|   |   * Unsupported constraint: MOI.ScalarAffineFunction{Float64}-in-MOI.LessThan{Float64}
|   |   | bridged by:
|   |   |   MOIB.Constraint.LessToGreaterBridge{Float64, MOI.ScalarAffineFunction{Float64}},
|→ MOI.ScalarAffineFunction{Float64}}
|   |   | may introduce:
|   |   |   * Unsupported constraint:
|→ MOI.ScalarAffineFunction{Float64}-in-MOI.GreaterThan{Float64}
|   |   |   | bridged by:
|   |   |   |   MOIB.Constraint.VectorizeBridge{Float64, MOI.VectorAffineFunction{Float64}},
|→ MOI.Nonnegatives, MOI.ScalarAffineFunction{Float64}}
|   |   |   | may introduce:
|   |   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
|   |   |   * Unsupported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.RotatedSecondOrderCone
|   |   |   | bridged by:
|   |   |   |   MOIB.Constraint.RSOCtoSOCBridge{Float64, MOI.VectorAffineFunction{Float64}},
|→ MOI.VectorAffineFunction{Float64}}
|   |   |   | may introduce:
|   |   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.SecondOrderCone
|   |   |   * Supported constraint: MOI.VectorAffineFunction{Float64}-in-MOI.Nonnegatives
|   |   |   * Supported variable: MOI.Reals
|   * Supported variable: MOI.Reals

```

This time, JuMP used a `MOI.Bridges.Constraint.GeoMeanBridge` to reformulate the constraint into a set of `MOI.RotatedSecondOrderCone` constraints, which were further reformulated into a set of supported `MOI.SecondOrderCone` constraints.

Since the two models are equivalent, we can conclude that for this particular model, the `MOI.SecondOrderCone` formulation is more efficient.

In general though, the performance of a particular reformulation is problem- and solver-specific. Therefore, JuMP chooses to minimize the number of bridges in the default reformulation, leaving you to explore alternative formulations using the tools and techniques shown in this tutorial.

## 8.11 Example: fitting of circles and ellipses

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

Ellipse fitting is a common task in data analysis and computer vision and is of key importance in many application areas. In this tutorial we show how to fit an ellipse to a set of points using a conic optimization approach.

### Required packages

This tutorial uses the following packages:

```

using JuMP
import Clarabel
import Clustering
import DSP
import Images
import LinearAlgebra
import LinearOperatorCollection as LOC
import Plots
import RegularizedLeastSquares as RLS
import Wavelets

```

### Parametrization of an ellipse

An ellipse is a set of the form:

$$\mathcal{E} = \{\xi : (\xi - c)^\top D(\xi - c) = r^2\}$$

where  $c \in \mathbb{R}^2$  is the center of the ellipse,  $D \in \mathbb{R}^{2 \times 2} \succ 0$  is a symmetric positive definite matrix and  $r > 0$ .

We can setup a coordinate system  $(x, y) \in \mathbb{X} \times \mathbb{Y}$  with  $x, y \geq 0$ . We use definition (1) to write an ellipse as the root of a quadratic form in homogeneous coordinates:

$$\begin{bmatrix} \xi \\ 1 \end{bmatrix}^T \begin{bmatrix} Q & d \\ d^T & e \end{bmatrix} \begin{bmatrix} \xi \\ 1 \end{bmatrix} = 0$$

where:

$$Q = D \tag{8.17}$$

$$d = -Dc \tag{8.18}$$

$$e = c^T D c - r^2 \tag{8.19}$$

The residual distance  $r_0$  of a random point  $\xi_0 = (x_0, y_0)$  to the ellipse is then given by:

$$r_0 \triangleq \begin{bmatrix} \xi_0 \\ 1 \end{bmatrix}^T \begin{bmatrix} Q & d \\ d^T & e \end{bmatrix} \begin{bmatrix} \xi_0 \\ 1 \end{bmatrix}$$

The value of  $r_0$  is positive if the point is outside the ellipse, zero if it is on the ellipse and negative if it is inside the ellipse. We also see we only need six parameters to uniquely define an ellipse.

### Helper functions

We define some helper functions to help us visualize the results.

```

function plot_dwt(x, sz = (500, 500))
    return Plots.heatmap(
        x;
        color = :grays,
        aspect_ratio = 1,
        cbar = false,
        xlims = (0, size(x, 2)),
        ylims = (0, size(x, 1)),
        size = sz,
        dpi = 300,
    )
end

function normalize(x::AbstractArray)
    l, u = extrema(x)
    return (x .- l) ./ (u - l)
end

```

normalize (generic function with 1 method)

### Reading the test image

To test our ellipse-fitting algorithm we need a test image with elliptical features. For our test image we will use an image of the cartwheel galaxy, [captured by the James Webb Space Telescope](#). Galaxies [come in many shapes and sizes](#), elliptical being one of them.

This is just a toy problem with little scientific value, but you can imagine how the rotation and position of elliptical galaxies can be useful information to astronomers.

```

filename = joinpath(@__DIR__, "..", "..", "assets", "cartwheel_galaxy.png")
img = Images.load(filename);

```

We convert the image to gray scale so that we can work with a single channel.

```

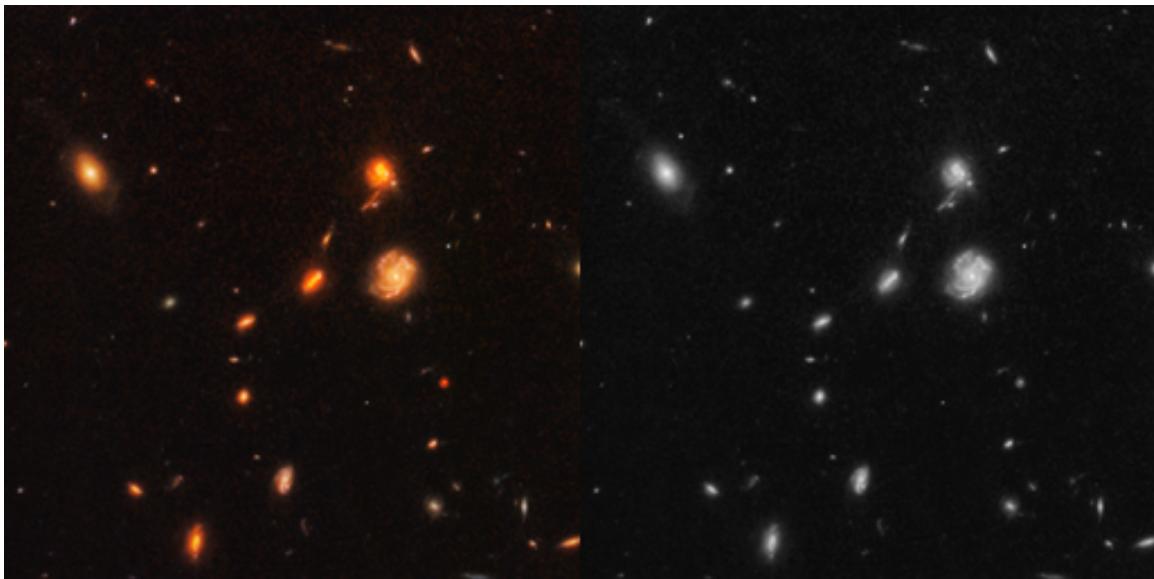
img_gray = Images.Gray.(img)
Images.mosaicview(img, img_gray; nrow = 1)

```



Instead of operating on the entire image, we select a region of interest (ROI) which is a subset of  $\mathbb{X} \times \mathbb{Y}$ .

```
sz = 256
X_c = 600
Y_c = 140
X = X_c:X_c+sz-1
Y = Y_c:Y_c+sz-1
roi = (X, Y)
img_roi = img[roi...]
img_gray_roi = img_gray[roi...]
Images.mosaicview(img_roi, img_gray_roi; nrow = 1)
```



### Extracting image features

We cannot directly fit ellipses to the image, so we need to extract features that enable us to find the elliptical galaxies.

The first step is to find a sparse representation of the image. We will use the discrete wavelet transform (DWT) in combination with the Iterative Shrinking and Thresholding (ISTA) algorithm to denoise the image and find a sparse representation. This will remove redundant information and make it much easier to detect the edges of galaxies.

Finding a sparse representation amounts to solving the following optimization problem:

$$\min_x \frac{1}{2} \|y - \Phi x\|_2^2 + \lambda \|x\|_1$$

where  $y$  is the noisy image,  $\Phi$  is the sparsifying basis,  $x$  is the sparse representation of our image, and  $\lambda$  is the regularization parameter which we set to 0.1.

To work with our image we must first convert it to Float64.

```
x = convert(Array{Float64}, img_gray_roi)
```

```
256×256 Matrix{Float64}:
 0.0823529  0.0588235  0.054902   ...  0.0431373  0.0666667  0.054902
 0.0784314  0.0588235  0.054902   ...  0.054902  0.0666667  0.0431373
 0.0705882  0.0666667  0.0627451   ...  0.0588235  0.0705882  0.0588235
 0.0627451  0.0666667  0.0705882   ...  0.054902  0.0627451  0.0627451
 0.0509804  0.0666667  0.0745098   ...  0.0509804  0.0509804  0.0588235
 0.0509804  0.0627451  0.054902   ...  0.054902  0.0588235  0.0588235
 0.0588235  0.0784314  0.054902   ...  0.0784314  0.0627451  0.0431373
 0.0627451  0.0509804  0.0509804   ...  0.0666667  0.0588235  0.0666667
 0.0627451  0.0470588  0.054902   ...  0.0470588  0.054902  0.0901961
 0.0588235  0.0509804  0.0470588   ...  0.0470588  0.0470588  0.054902
  ...
 0.054902  0.054902  0.0392157   ...  0.054902  0.0666667  0.0745098
 0.0470588  0.054902  0.0509804   ...  0.054902  0.054902  0.0666667
 0.0470588  0.0431373  0.0470588   ...  0.0823529  0.0588235  0.0588235
 0.0470588  0.0509804  0.0431373   ...  0.0784314  0.0588235  0.054902
 0.0509804  0.0509804  0.0431373   ...  0.054902  0.0627451  0.054902
 0.0431373  0.0470588  0.0431373   ...  0.054902  0.0705882  0.0666667
 0.0509804  0.0470588  0.0509804   ...  0.0666667  0.0705882  0.0588235
 0.0509804  0.0431373  0.0470588   ...  0.0627451  0.0627451  0.0509804
 0.054902  0.0470588  0.0470588   ...  0.0823529  0.0705882  0.0666667
```

We then use ISTA in combination with our wavelet sparsifying basis  $\Psi$  obtained from the [family of Daubechies wavelets](#). We use the db4 wavelet which has 4 vanishing moments. We set the number of iterations to 15.

```
reg = RLS.L1Regularization(0.1);
Φ = LOC.WaveletOp(
    Float64;
    shape = size(x),
    wt = Wavelets.wavelet(Wavelets.WT.db4),
```

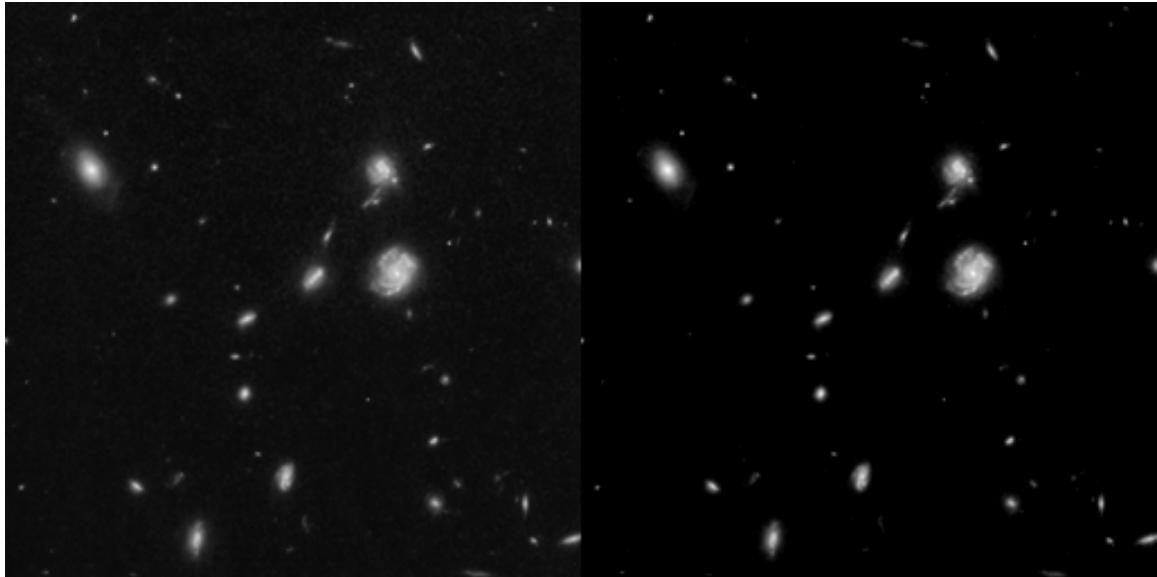
```
);
solver = RLS.createLinearSolver(RLS.OptISTA, Φ; reg = reg, iterations = 15);
```

The sampled image in wavelet domain is given by:

```
b = Φ * vec(x);
```

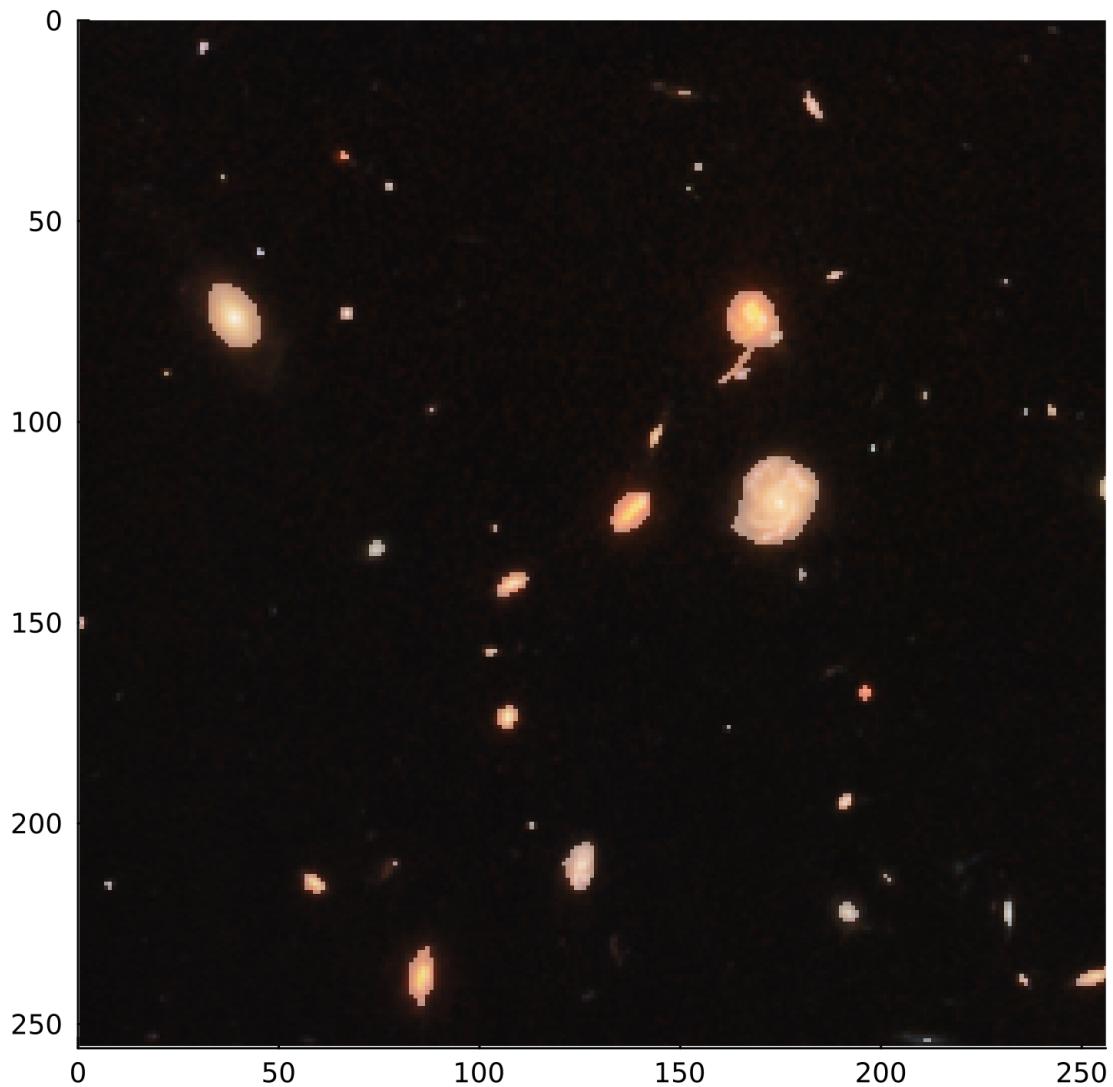
We can now solve the optimization problem to find the sparse representation of the image.

```
x_approx = RLS.solve!(solver, b)
x_approx = reshape(x_approx, size(x));
x_final = normalize(x_approx)
Images.mosaicview(x, Images.Gray.(x_final); nrow = 1)
```



We then use a binarization algorithm to map each grayscale pixel  $(x_i, y_i)$  to a binary value so  $x_i, y_i \rightarrow \{0, 1\}$ .

```
x_bin = Images.binarize(x_final, Images.Otsu(); nbins = 128)
x_bin = convert(Array{Bool}, x_bin)
plt = plot_dwt(img_roi)
Plots.heatmap!(x_bin; color = :grays, alpha = 0.45)
```



### Edge detection and clustering

Now that we have our binary image, we can use edge detection to find the edges of the galaxies. We will use the [Sobel operator](#) for this task.

```
function edge_detector(
    f_smooth::Matrix{Float64},
    d1::Float64 = 0.1,
    d2::Float64 = 0.1,
)
    rows, cols = size(f_smooth)
    gradient_magnitude = zeros(Float64, rows, cols)
    laplacian_magnitude = zeros(Float64, rows, cols)
    sobel_x = [-1 0 1; -2 0 2; -1 0 1]
    sobel_y = [-1 -2 -1; 0 0 0; 1 2 1]
```

```

sobel_xx = [-1 2 -1; 2 -4 2; -1 2 -1]
sobel_yy = [-1 2 -1; 2 -4 2; -1 2 -1]
gradient_x = DSP.conv(f_smooth, sobel_x)
gradient_y = DSP.conv(f_smooth, sobel_y)
gradient_magnitude = sqrt.(gradient_x .^ 2 + gradient_y .^ 2)
gradient_xx = DSP.conv(f_smooth, sobel_xx)
gradient_yy = DSP.conv(f_smooth, sobel_yy)
laplacian_magnitude = sqrt.(gradient_xx .^ 2 + gradient_yy .^ 2)
return (gradient_magnitude .> d1) .& (laplacian_magnitude .< d2)
end

```

`edge_detector` (generic function with 3 methods)

We apply the Sobel operator to the binary image:

```
edges = edge_detector(convert(Matrix{Float64}, x_bin), le-1, le2)
edges = Images.thinning(edges; algo = Images.GuoAlgo())
```

And finally we cluster the edges using `dbSCAN` so we can fit ellipses to individual galaxies. We can control the minimum size of galaxies by changing the minimum cluster size.

```
points = findall(edges)
points = getfield.(points, :I)
points = hcat([p[1] for p in points], [p[2] for p in points])'
result = Clustering.dbscan(
    convert(Matrix{Float64}, points),
```

```

    3.0;
    min_neighbors = 2,
    min_cluster_size = 15,
)

```

```

Clustering.DbscanResult(Clustering.DbscanCluster[Clustering.DbscanCluster(41, [12, 13, 14, 15, 16,
↳ 17, 18, 19, 20, 21 ... 47, 48, 49, 51, 52, 53, 54, 55, 56, 57], Int64[]),
↳ Clustering.DbscanCluster(28, [83, 84, 85, 86, 87, 88, 89, 90, 91, 92 ... 102, 105, 106, 107,
↳ 108, 109, 110, 111, 112, 113], Int64[]), Clustering.DbscanCluster(17, [121, 122, 125, 126, 127,
↳ 130, 131, 134, 135, 138, 139, 144, 145, 146, 147, 148, 149], Int64[]),
↳ Clustering.DbscanCluster(26, [152, 153, 154, 155, 156, 157, 158, 159, 160, 161 ... 168, 169,
↳ 170, 171, 172, 173, 174, 175, 176, 177], Int64[]), Clustering.DbscanCluster(27, [178, 179, 180,
↳ 181, 182, 183, 184, 185, 186, 187 ... 195, 196, 197, 198, 199, 200, 201, 202, 203, 204],
↳ Int64[]), Clustering.DbscanCluster(53, [220, 221, 222, 223, 224, 226, 227, 228, 229, 230 ...
↳ 297, 298, 301, 302, 303, 304, 305, 308, 309, 310], Int64[]), Clustering.DbscanCluster(62, [237,
↳ 238, 239, 245, 246, 247, 248, 249, 256, 257 ... 336, 337, 338, 341, 342, 343, 344, 345, 346,
↳ 347], Int64[])], [12, 83, 121, 152, 178, 220, 237], [41, 28, 17, 26, 27, 53, 62], [0, 0, 0, 0,
↳ 0, 0, 0, 0, 0 ... 0, 0, 0, 0, 0, 0, 0, 0, 0])

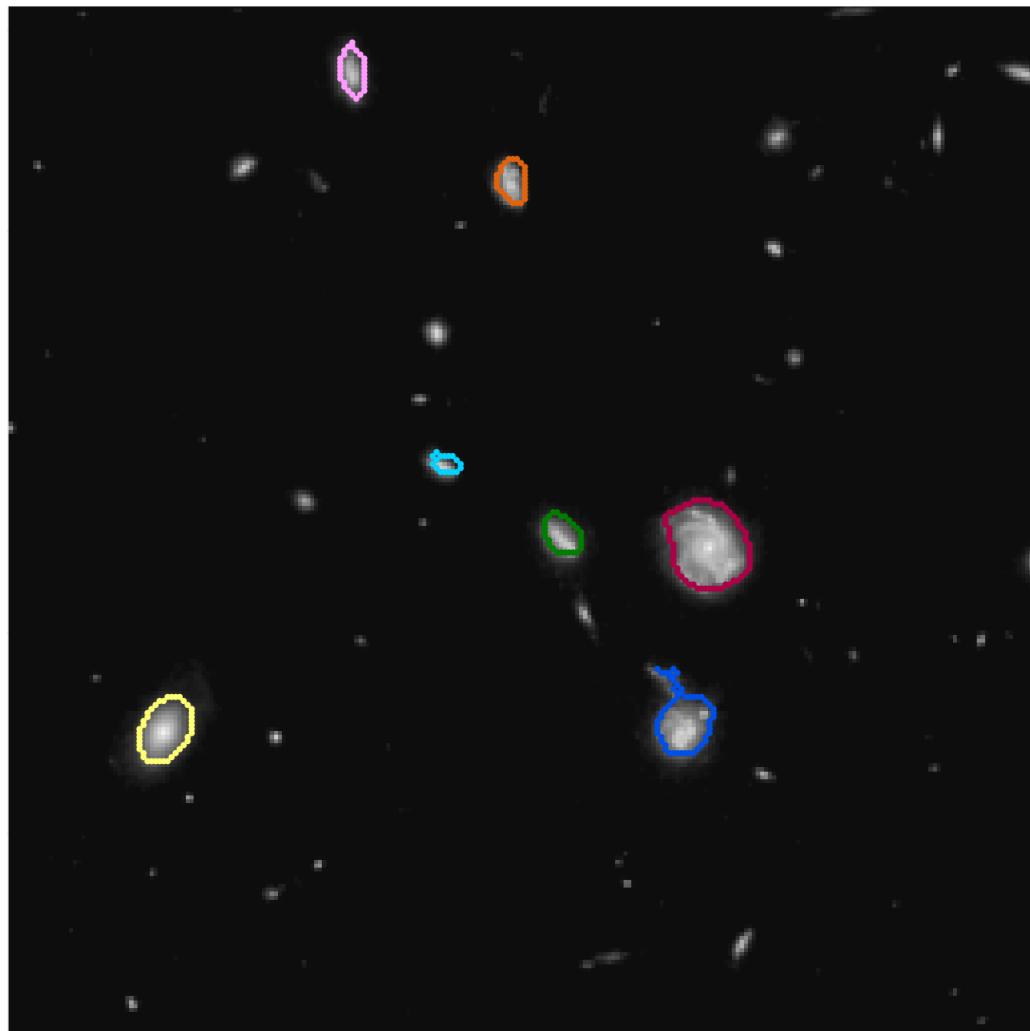
```

The result of the clustering is a list of clusters to which we will assign a unique color. Each cluster is a list of points that belong to the same galaxy.

```

clusters = result.clusters
N_clusters = length(clusters)
colors = Plots.distinguishable_colors(N_clusters + 1)[2:end]
plt = plot_dwt(x_final)
for (i, cluster) in enumerate(clusters)
    p_cluster = points[:, cluster.core_indices]
    Plots.scatter!(
        plt,
        p_cluster[2, :],
        p_cluster[1, :];
        color = colors[i],
        label = false,
        markerstrokewidth = 0,
        markersize = 1.5,
    )
end
Plots.plot!(
    plt;
    axis = false,
    legend = :topleft,
    legendcolumns = 1,
    legendfontsize = 12,
)

```



### Fitting ellipses

Now that we have all the ingredients we can finally start fitting ellipses. We will use a conic optimization approach to do so since it is a very natural way to represent ellipses.

First, we define the residual distance definition (6) of a point to an ellipse in JuMP:

```
function create_ellipse_model(Ξ::Array{Tuple{Int,Int},1}, ε = 1e-5)
    N = length(Ξ)
    model = Model(Clarabel.Optimizer)
    set_silent(model)
    @variable(model, Q[1:2, 1:2], PSD)
    @variable(model, d[1:2])
    @variable(model, e)
    @expression(
        model,
```

```

        r[i in 1:N],
        [Ξ[i][1], Ξ[i][2], 1]' * [Q d; d' e] * [Ξ[i][1], Ξ[i][2], 1]
    )
return model
end

```

create\_ellipse\_model (generic function with 2 methods)

### Objective 1: Minimize the total squared distance

For our first objective we will minimize the total squared distance of all points to the ellipse. Hence we will use the sum of the squared distances as our objective function, also known as the  $L^2$  norm:

$$\min_{Q,d,e} P_{\text{res}}(\mathcal{E}) = \min_{Q,d,e} \sum_{i \in N} d_{\text{res}}^2(\xi_i, \mathcal{E}) = \min_{Q,d,e} \|d_{\text{res}}\|_2^2$$

This problem is equivalent to:

$$\min_{Q,d,e} \quad \quad \quad (8.20)$$

$$\text{s.t. } \geq d_{\text{res}}^2(\xi_i, \mathcal{E}) \quad \forall i \in N \quad (8.21)$$

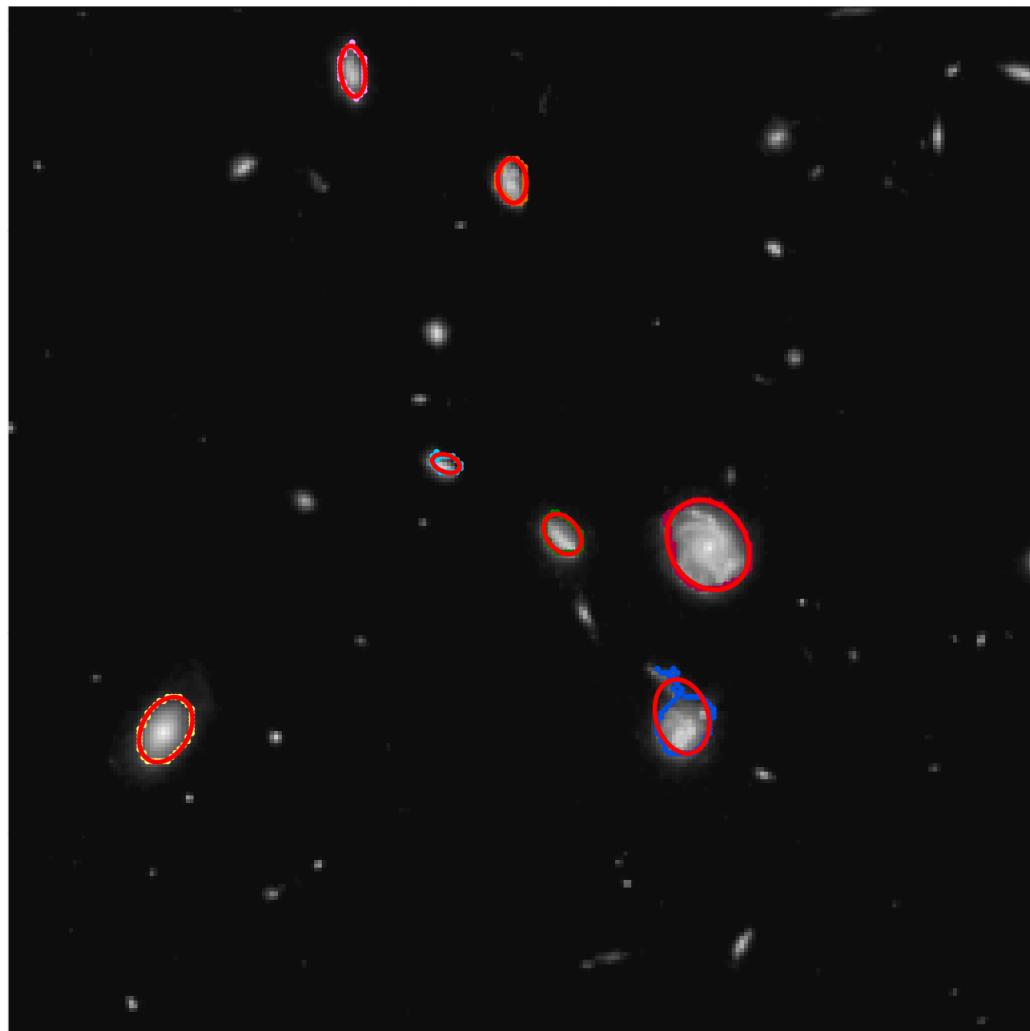
And hence can be modelled as a second-order cone program (SOCP) using `MOI.RotatedSecondOrderCone` as follows:

```

ellipses_C1 = Dict{Symbol,Any}[]
for (i, cluster) in enumerate(clusters)
    p_cluster = points[:, cluster.core_indices]
    Ξ = [(point[1], point[2]) for point in eachcol(p_cluster)]
    model = create_ellipse_model(Ξ)
    @variable(model, ζ >= 0)
    @constraint(
        model,
        [1 / 2; ζ; model[:r]] in
        MOI.RotatedSecondOrderCone(2 + length(model[:r]))
    )
    @objective(model, Min, ζ)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    Q, d, e = value.(model[:Q]), value.(model[:d]), value.(model[:e])
    push!(ellipses_C1, Dict(:Q => Q, :d => d, :e => e))
end
W, H = size(img_roi)
x_range = 0:1:W
y_range = 0:1:H
X, Y = [x for x in x_range], [y for y in y_range]
function ellipse_eq(x, y, Q, d, e)
    Z = zeros(length(x), length(y))

```

```
for i in eachindex(x), j in eachindex(y)
    ξ = [x[i], y[j]]
    Z[i, j] = [ξ; 1.0]' * [Q d; d' e] * [ξ; 1.0]
end
return Z
end
for ellipse in ellipses_C1
    Q, d, e = ellipse[:Q], ellipse[:d], ellipse[:e]
    Z_sq = ellipse_eq(X, Y, Q, d, e)
    Plots.contour!(
        plt,
        x_range,
        y_range,
        Z_sq;
        levels = [0.0],
        linewidth = 2,
        color = :red,
        cbar = false,
    )
end
plt
```



### Objective 2: Minimize the maximum residual distance

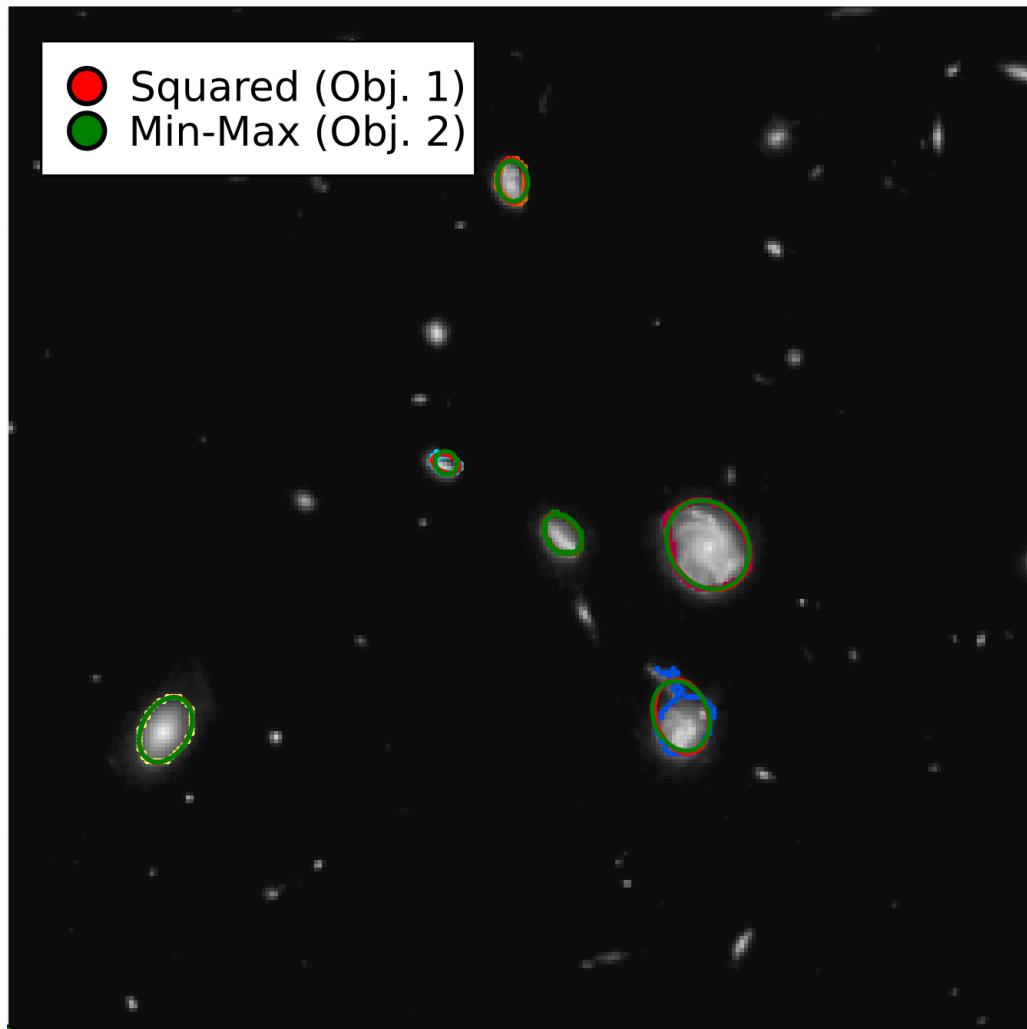
For our second objective we will minimize the maximum residual distance of all points to the ellipse:

$$\min_{Q,d,e} \max_{\xi_i \in \mathcal{F}} d_{\text{res}}(\xi_i, \mathcal{E}) = \min_{Q,d,e} \|d_{\text{res}}\|_{\infty}$$

This objective can be implemented in JuMP using [MOI.NormInfinityCone](#) as follows:

```
ellipses_C2 = Dict{Symbol,Any}[]
for (i, cluster) in enumerate(clusters)
    p_cluster = points[:, cluster.core_indices]
    Ξ = [(point[1], point[2]) for point in eachcol(p_cluster)]
    model = create_ellipse_model(Ξ)
```

```
N = length(Ξ)
@variable(model, ζ)
@constraint(
    model,
    [ζ; model[:r]] in MOI.NormInfinityCone(1 + length(model[:r]))
)
@objective(model, Min, ζ)
optimize!(model)
assert_is_solved_and_feasible(model; allow_almost = true)
Q, d, e = value.(model[:Q]), value.(model[:d]), value.(model[:e])
push!(ellipses_C2, Dict(:Q => Q, :d => d, :e => e))
end
for ellipse in ellipses_C2
    Q, d, e = ellipse[:Q], ellipse[:d], ellipse[:e]
    Z_sq = ellipse_eq(X, Y, Q, d, e)
    Plots.contour!(
        plt,
        x_range,
        y_range,
        Z_sq;
        levels = [0.0],
        linewidth = 2,
        color = :green,
        cbar = false,
    )
end
Plots.scatter!([0], [0]; color = :red, label = "Squared (Obj. 1)")
Plots.scatter!([0], [0]; color = :green, label = "Min-Max (Obj. 2)")
```



## 8.12 Example: quantum state discrimination

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

This tutorial solves the problem of [quantum state discrimination](#).

The purpose of this tutorial to demonstrate how to solve problems involving complex-valued decision variables and the `HermitianPSDConc`. See [Complex number support](#) for more details.

### Required packages

This tutorial uses the following packages:

```
using JuMP
import LinearAlgebra
import SCS
```

## Formulation

A d-dimensional quantum state,  $\rho$ , can be defined by a complex-valued Hermitian matrix with a trace of 1. Assume we have N d-dimensional quantum states,  $\{\rho_i\}_{i=1}^N$ , each of which is equally likely.

The goal of the quantum state discrimination problem is to choose a positive operator-valued measure (POVM),  $\{E_i\}_{i=1}^N$ , such that if we observe  $E_i$  then the most probable state that we are in is  $\rho_i$ .

Each POVM element,  $E_i$ , is a complex-valued Hermitian matrix, and there is a requirement that  $\sum_{i=1}^N E_i = \mathbf{I}$ .

To choose a POVM, we want to maximize the probability that we guess the quantum state correctly. This can be formulated as the following optimization problem:

$$\begin{aligned} \max_E \quad & \frac{1}{N} \sum_{i=1}^N \text{tr}(\rho_i E_i) \\ \text{s.t.} \quad & \sum_{i=1}^N E_i = \mathbf{I} \\ & E_i \succeq 0 \quad \forall i = 1, \dots, N. \end{aligned}$$

## Data

To setup our problem, we need N d-dimensional quantum states. To keep the problem simple, we use  $N = 2$  and  $d = 2$ .

```
N, d = 2, 2
```

```
(2, 2)
```

We then generated N random d-dimensional quantum states:

```
function random_state(d)
    x = randn(ComplexF64, (d, d))
    y = x * x'
    return LinearAlgebra.Hermitian(y / LinearAlgebra.tr(y))
end

ρ = [random_state(d) for i in 1:N]
```

```
2-element Vector{LinearAlgebra.Hermitian{ComplexF64, Matrix{ComplexF64}}}:
[0.9049983143615443 + 0.0im -0.11984167294191471 + 0.2224268161763913im; -0.11984167294191471 -
→ 0.2224268161763913im 0.09500168563845571 + 0.0im]
[0.2503060704439256 + 0.0im -0.16997258971668044 - 0.09226624832975384im; -0.16997258971668044 +
→ 0.09226624832975384im 0.7496939295560743 + 0.0im]
```

## JuMP formulation

To model the problem in JuMP, we need a solver that supports positive semidefinite matrices:

```
model = Model(SCS.Optimizer)
set_silent(model)
```

Then, we construct our set of E variables:

```
E = [@variable(model, [1:d, 1:d] in HermitianPSDCone()) for i in 1:N]
```

```
2-element Vector{LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef}},
↪ Matrix{GenericAffExpr{ComplexF64, VariableRef}}}:  
[_[1] _[2] + _[4] im; _[2] - _[4] im _[3]]  
[_[5] _[6] + _[8] im; _[6] - _[8] im _[7]]
```

Here we have created a vector of matrices. This is different to other modeling languages such as YALMIP, which allow you to create a multi-dimensional array in which 2-dimensional slices of the array are Hermitian matrices.

We also need to enforce the constraint that  $\sum_{i=1}^N E_i = \mathbf{I}$ :

```
@constraint(model, sum(E) == LinearAlgebra.I)
```

$$\begin{bmatrix} -_1 + -_5 - 1 & -_2 + -_6 + -_4im + -_8im \\ -_2 + -_6 - -_4im - -_8im & -_3 + -_7 - 1 \end{bmatrix} \in \text{Zeros}()$$

This constraint is a complex-valued equality constraint. In the solver, it will be decomposed onto two types of equality constraints: one to enforce equality of the real components, and one to enforce equality of the imaginary components.

Our objective is to maximize the expected probability of guessing correctly:

```
@objective(
    model,
    Max,
    sum(real(LinearAlgebra.tr(p[i] * E[i])) for i in 1:N) / N,
)
```

$0.45249915718077216_{-1} - 0.11984167294191471_{-2} + 0.2224268161763913_{-4} + 0.047500842819227854_{-3} + 0.1251530352219628_{-5} - 0.16997258971668044_{-6} - 0.09226624832975384_{-8} + 0.37484696477803714_{-7}$

Now we optimize:

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : SCS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "solved"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 8.64061e-01
  Dual objective value : 8.64062e-01

* Work counters
  Solve time (sec)   : 4.26904e-04
```

The probability of guessing correctly is:

```
objective_value(model)
```

```
0.8640614507314219
```

When  $N = 2$ , there is a known analytical solution of:

```
0.5 + 0.25 * sum(LinearAlgebra.svdvals(p[1] - p[2]))
```

```
0.8640627582954737
```

proving that we found the optimal solution.

Finally, the optimal POVM is:

```
solution = [value.(e) for e in E]
```

```
2-element Vector{Matrix{ComplexF64}}:
[0.9495721399750024 + 0.0im 0.03442451603977098 + 0.21609731371190505im; 0.03442451603977098 -
 ↵ 0.21609731371190505im 0.05042785512985496 + 0.0im]
[0.05042785517602001 + 0.0im -0.03442451605312517 - 0.21609731370614843im; -0.03442451605312517 +
 ↵ 0.21609731370614843im 0.9495721400119357 + 0.0im]
```

**Tip**

Duality plays a large role in solving conic optimization models. Depending on the solver, it can be more efficient to solve the dual of this problem instead of the primal. If performance is an issue, see the [Dualization tutorial](#) for more details.

**Alternative formulation**

The formulation above includes  $N$  Hermitian matrices and a set of linear equality constraints. We can simplify the problem by replacing  $E_N$  with  $E_N = I - \sum_{i=1}^{N-1} E_i$ . This results in:

```
model = Model(SCS.Optimizer)
set_silent(model)
E = [@variable(model, [1:d, 1:d] in HermitianPSDCone()) for i in 1:N-1]
E_N = LinearAlgebra.Hermitian(LinearAlgebra.I - sum(E))
@constraint(model, E_N in HermitianPSDCone())
push!(E, E_N)
```

```
2-element Vector{LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef}},
↪ Matrix{GenericAffExpr{ComplexF64, VariableRef}}}}:
[_[1] _[2] + _[4] im; _[2] - _[4] im _[3]]
[-_1 + 1 -_2 - _[4] im; -_2 + _[4] im -_3 + 1]
```

The objective can also be simplified, by observing that it is equivalent to:

```
@objective(model, Max, real(LinearAlgebra.dot(p, E)) / N)
```

$0.32734612195880936\text{e-}1 + 0.050130916774765735\text{e-}2 + 0.31469306450614515\text{e-}4 - 0.3273461219588093\text{e-}3 + 0.4999999999999994$

Then we can check that we get the same solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : SCS

* Status
Result count      : 1
Termination status : OPTIMAL
Message from the solver:
"solved"

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : FEASIBLE_POINT
```

```
Objective value      : 8.64060e-01
Dual objective value : 8.64062e-01

* Work counters
  Solve time (sec)    : 4.28417e-04
```

```
objective_value(model)
```

```
0.8640596603179975
```

# Chapter 9

## Algorithms

### 9.1 Benders decomposition

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

**This tutorial was originally contributed by Shuvomoy Das Gupta.**

This tutorial describes how to implement [Benders decomposition](#) in JuMP. It uses the following packages:

```
using JuMP
import Gurobi
import HiGHS
import Printf
```

### Theory

Benders decomposition is a useful algorithm for solving convex optimization problems with a large number of variables. It works best when a larger problem can be decomposed into two (or more) smaller problems that are individually much easier to solve.

This tutorial demonstrates Benders decomposition on the following mixed-integer linear program:

$$\begin{aligned} & \min c_1(x) + c_2(y) \\ \text{subject to } & f_1(x) \in S_1 \\ & f_2(y) \in S_2 \\ & f_3(x, y) \in S_3 \\ & x \in \mathbb{Z}^m \\ & y \in \mathbb{R}^n \end{aligned}$$

where the functions  $f$  and  $c$  are linear, and the sets  $S$  are inequality sets like  $\geq l$ ,  $\leq u$ , or  $= b$ .

Any mixed integer programming problem can be written in the form above.

If there are relatively few integer variables, and many more continuous variables, then it may be beneficial to decompose the problem into a small problem containing only integer variables and a linear program containing only continuous variables. Hopefully, the linear program will be much easier to solve in isolation than in the full mixed-integer linear program.

For example, if we knew a feasible solution for  $\bar{x}$ , we could obtain a solution for  $y$  by solving:

$$\begin{aligned} V_2(\bar{x}) = & \min c_2(y) \\ \text{subject to } & f_2(y) \in S_2 \\ & f_3(x, y) \in S_3 \\ & x = \bar{x} [\pi] \\ & y \in \mathbb{R}^n \end{aligned}$$

Note that we have included a "copy" of the  $x$  variable to simplify computing  $\pi$ , which is the dual of  $V_2$  with respect to  $\bar{x}$ .

Because this model is a linear program, it is easy to solve.

Replacing the  $c_2(y)$  component of the objective in our original problem with  $V_2$  yields:

$$\begin{aligned} V_1 = & \min c_1(x) + V_2(x) \\ \text{subject to } & f_1(x) \in S_1 \\ & x \in \mathbb{Z}^m. \end{aligned}$$

This problem looks a lot simpler to solve because it involves only  $x$  and a subset of the constraints, but we need to do something else with  $V_2$  first.

Because  $\bar{x}$  is a constant that appears on the right-hand side of the constraints,  $V_2$  is a convex function with respect to  $\bar{x}$ , and the dual variable  $\pi$  is a subgradient of  $V_2(x)$  with respect to  $x$ . Therefore, if we have a candidate solution  $x_k$ , then we can solve  $V_2(x_k)$  and obtain a feasible dual vector  $\pi_k$ . Using these values, we can construct a first-order Taylor-series approximation of  $V_2$  about the point  $x_k$ :

$$V_2(x) \geq V_2(x_k) + \pi_k^\top (x - x_k).$$

By convexity, we know that this inequality holds for all  $x$ , and we call these inequalities *cuts*.

Benders decomposition is an iterative technique that replaces  $V_2(x)$  with a new decision variable  $\theta$ , and approximates it from below using cuts:

$$\begin{aligned} V_1^K = & \min c_1(x) + \theta \\ \text{subject to } & f_1(x) \in S_1 \\ & x \in \mathbb{Z}^m \\ & \theta \geq M \\ & \theta \geq V_2(x_k) + \pi_k^\top (x - x_k) \quad \forall k = 1, \dots, K. \end{aligned}$$

This integer program is called the *first-stage* subproblem.

To generate cuts, we solve  $V_1^K$  to obtain a candidate first-stage solution  $x_k$ , then we use that solution to solve  $V_2(x_k)$ . Then, using the optimal objective value and dual solution from  $V_2$ , we add a new cut to form  $V_1^{K+1}$  and repeat.

## Bounds

Due to convexity, we know that  $V_2(x) \geq \theta$  for all  $x$ . Therefore, the optimal objective value of  $V_1^K$  provides a valid *lower* bound on the objective value of the full problem. In addition, if we take a feasible solution for  $x$  from the first-stage problem, then  $c_1(x) + V_2(x)$  is a valid *upper* bound on the objective value of the full problem.

Benders decomposition uses the lower and upper bounds to determine when it has found the global optimal solution.

## Monolithic problem

As an example problem, we consider the following variant of [The max-flow problem](#), in which there is a binary variable to decide whether to open each arc for a cost of 0.1 unit, and we can open at most 11 arcs:

```
G = [
    0 3 2 2 0 0 0 0
    0 0 0 0 5 1 0 0
    0 0 0 0 1 3 1 0
    0 0 0 0 0 1 0 0
    0 0 0 0 0 0 0 4
    0 0 0 0 0 0 0 2
    0 0 0 0 0 0 0 4
    0 0 0 0 0 0 0 0
]
n = size(G, 1)
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:n, 1:n], Bin)
@variable(model, y[1:n, 1:n] >= 0)
@constraint(model, sum(x) <= 11)
@constraint(model, [i = 1:n, j = 1:n], y[i, j] <= G[i, j] * x[i, j])
@constraint(model, [i = 2:n-1], sum(y[i, :]) == sum(y[:, i]))
@objective(model, Min, 0.1 * sum(x) - sum(y[1, :]))
optimize!(model)
solution_summary(model)
```

```
* Solver : HiGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status     : FEASIBLE_POINT
  Dual status       : NO_SOLUTION
  Objective value   : -5.10000e+00
  Objective bound   : -5.10000e+00
  Relative gap      : 0.00000e+00
  Dual objective value : NaN

* Work counters
```

```
Solve time (sec)    : 1.71781e-03
Simplex iterations : 15
Barrier iterations : -1
Node count         : 1
```

The optimal objective value is -5.1:

```
objective_value(model)
```

```
-5.1
```

and the optimal flows are:

```
function optimal_flows(x)
    return [(i, j) => x[i, j] for i in 1:n for j in 1:n if x[i, j] > 0]
end

monolithic_solution = optimal_flows(value.(y))
```

```
9-element Vector{Pair{Tuple{Int64, Int64}, Float64}}:
(1, 2) => 3.0
(1, 3) => 2.0
(1, 4) => 1.0
(2, 5) => 3.0
(3, 5) => 1.0
(3, 6) => 1.0
(4, 6) => 1.0
(5, 8) => 4.0
(6, 8) => 2.0
```

## Iterative method

### Warning

This is a basic implementation for pedagogical purposes. We haven't discussed any of the computational tricks that are required to build a performant implementation for large-scale problems. See [In-place iterative method](#) for one improvement that helps computation time.

We start by formulating the first-stage subproblem. It includes the  $x$  variables, and the constraints involving only  $x$ , and the terms in the objective containing only  $x$ . We also need an initial lower bound on the cost-to-go variable  $\theta$ . One valid lower bound is to assume that we do not pay for opening arcs, and there is flow all the arcs.

```
M = -sum(G)
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:n, 1:n], Bin)
@variable(model, θ >= M)
@constraint(model, sum(x) <= 11)
@objective(model, Min, 0.1 * sum(x) + θ)
model
```

```
A JuMP Model
├ solver: HiGHS
├ objective_sense: MIN_SENSE
|└ objective_function_type: AffExpr
├ num_variables: 65
├ num_constraints: 66
|└ AffExpr in MOI.LessThan{Float64}: 1
|└ VariableRef in MOI.GreaterThan{Float64}: 1
|└ VariableRef in MOI.ZeroOne: 64
└ Names registered in the model
  └ :x, :θ
```

For the next step, we need a function that takes a first-stage candidate solution  $x$  and returns the optimal solution from the second-stage subproblem:

```
function solve_subproblem(x_bar)
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, x[i in 1:n, j in 1:n] == x_bar[i, j])
    @variable(model, y[1:n, 1:n] >= 0)
    @constraint(model, [i = 1:n, j = 1:n], y[i, j] <= G[i, j] * x[i, j])
    @constraint(model, [i = 2:n-1], sum(y[i, :]) == sum(y[:, i]))
    @objective(model, Min, -sum(y[1, :]))
    optimize!(model)
    assert_is_solved_and_feasible(model; dual = true)
    return (obj = objective_value(model), y = value.(y), π = reduced_cost.(x))
end
```

```
solve_subproblem (generic function with 1 method)
```

Note that `solve_subproblem` returns a `NamedTuple` of the objective value, the optimal primal solution for  $y$ , and the optimal dual solution for  $\pi$ , which we obtained from the `reduced_cost` of the  $x$  variables.

We're almost ready for our optimization loop, but first, here's a helpful function for logging:

```
function print_iteration(k, args...)
    f(x) = Printf.@sprintf("%12.4e", x)
    println(lpad(k, 9), " ", join(f.(args), " "))
    return
end
```

```
print_iteration (generic function with 1 method)
```

We also need to put a limit on the number of iterations before termination:

```
MAXIMUM_ITERATIONS = 100
```

```
100
```

And a way to check if the lower and upper bounds are close-enough to terminate:

```
ABSOLUTE_OPTIMALITY_GAP = 1e-6
```

```
1.0e-6
```

Now we're ready to iterate Benders decomposition:

```
println("Iteration  Lower Bound  Upper Bound          Gap")
for k in 1:MAXIMUM_ITERATIONS
    optimize!(model)
    assert_is_solved_and_feasible(model)
    lower_bound = objective_value(model)
    x_k = value.(x)
    ret = solve_subproblem(x_k)
    upper_bound = (objective_value(model) - value(θ)) + ret.obj
    gap = abs(upper_bound - lower_bound) / abs(upper_bound)
    print_iteration(k, lower_bound, upper_bound, gap)
    if gap < ABSOLUTE_OPTIMALITY_GAP
        println("Terminating with the optimal solution")
        break
    end
    cut = @constraint(model, θ >= ret.obj + sum(ret.n .* (x .- x_k)))
    @info "Adding the cut $(cut)"
end
```

Iteration	Lower Bound	Upper Bound	Gap
1	-2.9000e+01	0.0000e+00	Inf
[ Info: Adding the cut	$3x[1,2] + 2x[1,3] + 2x[1,4] + \theta \geq 0$		
2	-6.7000e+00	3.0000e-01	2.3333e+01
[ Info: Adding the cut	$5x[2,5] + x[3,5] + x[2,6] + 3x[3,6] + x[4,6] + x[3,7] + \theta \geq 0$		
3	-6.5000e+00	5.0000e-01	1.4000e+01
[ Info: Adding the cut	$x[3,7] + 4x[5,8] + 2x[6,8] + \theta \geq 0$		
4	-6.2000e+00	-4.2000e+00	4.7619e-01
[ Info: Adding the cut	$3x[1,2] + x[3,5] + 2x[6,8] + 4x[7,8] + \theta \geq 0$		
5	-6.1000e+00	-4.1000e+00	4.8780e-01

```
[ Info: Adding the cut 3 x[1,2] + x[3,5] + 3 x[3,6] + x[4,6] + x[3,7] + θ ≥ 0
  6 -6.1000e+00 -4.1000e+00 4.8780e-01
[ Info: Adding the cut 3 x[1,2] + 2 x[1,3] + x[4,6] + θ ≥ 0
  7 -5.1000e+00 -5.1000e+00 0.0000e+00
Terminating with the optimal solution
```

Finally, we can obtain the optimal solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
x_optimal = value.(x)
optimal_ret = solve_subproblem(x_optimal)
iterative_solution = optimal_flows(optimal_ret.y)
```

```
9-element Vector{Pair{Tuple{Int64, Int64}, Float64}}:
(1, 2) => 3.0
(1, 3) => 2.0
(1, 4) => 1.0
(2, 5) => 3.0
(3, 5) => 1.0
(3, 6) => 1.0
(4, 6) => 1.0
(5, 8) => 4.0
(6, 8) => 2.0
```

which is the same as the monolithic solution:

```
iterative_solution == monolithic_solution
```

```
true
```

and it has the same objective value:

```
objective_value(model)
```

```
-5.1
```

### Callback method

The [Iterative method](#) section implemented Benders decomposition using a loop. In each iteration, we re-solved the first-stage subproblem to generate a candidate solution. However, modern MILP solvers such as CPLEX, Gurobi, and GLPK provide lazy constraint callbacks which allow us to add new cuts *while the solver is running*.

This can be more efficient than an iterative method because we can avoid repeating work such as solving the root node of the first-stage MILP at each iteration.

### Tip

We use Gurobi for this model because HiGHS does not support lazy constraints. For more information on callbacks, read the page [Solver-independent callbacks](#).

As before, we construct the same first-stage subproblem:

```
optimizer = Gurobi.Optimizer
lazy_model = Model(optimizer)
set_silent(lazy_model)
@variable(lazy_model, x[1:n, 1:n], Bin)
@variable(lazy_model, θ >= M)
@constraint(lazy_model, sum(x) <= 11)
@objective(lazy_model, Min, 0.1 * sum(x) + θ)
lazy_model
```

```
A JuMP Model
├ solver: Gurobi
├ objective_sense: MIN_SENSE
|└ objective_function_type: AffExpr
├ num_variables: 65
├ num_constraints: 66
|└ AffExpr in MOI.LessThan{Float64}: 1
|└ VariableRef in MOI.GreaterThan{Float64}: 1
|└ VariableRef in MOI.ZeroOne: 64
└ Names registered in the model
  └ :x, :θ
```

What differs is that we write a callback function instead of a loop:

```
number_of_subproblem_solves = 0
function my_callback(cb_data)
    status = callback_node_status(cb_data, lazy_model)
    if status != MOI.Callback_Node_Status_Integer
        # Only add the constraint if `x` is an integer feasible solution
        return
    end
    x_k = callback_value.(cb_data, x)
    θ_k = callback_value(cb_data, θ)
    global number_of_subproblem_solves += 1
    ret = solve_subproblem(x_k)
    if θ_k < (ret.obj - 1e-6)
        # Only add the constraint if θ_k violates the constraint
        cut = @build_constraint(θ >= ret.obj + sum(ret.π .* (x .- x_k)))
        MOI.submit(lazy_model, MOI.LazyConstraint(cb_data), cut)
    end
    return
end
```

```
set_attribute(lazy_model, MOI.LazyConstraintCallback(), my_callback)
```

Now when we optimize!, our callback is run:

```
optimize!(lazy_model)
assert_is_solved_and_feasible(lazy_model)
```

For this model, the callback algorithm required more solves of the subproblem:

```
number_of_subproblem_solves
```

```
17
```

But for larger problems, you can expect the callback algorithm to be more efficient than the iterative algorithm.

Finally, we can obtain the optimal solution:

```
x_optimal = value.(x)
optimal_ret = solve_subproblem(x_optimal)
callback_solution = optimal_flows(optimal_ret.y)
```

```
9-element Vector{Pair{Tuple{Int64, Int64}, Float64}}:
(1, 2) => 3.0
(1, 3) => 2.0
(1, 4) => 1.0
(2, 5) => 3.0
(3, 5) => 1.0
(3, 6) => 1.0
(4, 6) => 1.0
(5, 8) => 4.0
(6, 8) => 2.0
```

which is the same as the monolithic solution:

```
callback_solution == monolithic_solution
```

```
true
```

### In-place iterative method

Our implementation of the iterative method has a problem: every time we need to solve the subproblem, we must rebuild it from scratch. This is expensive, and it can be the bottleneck in the solution process. We can improve our implementation by using re-using the subproblem between solves.

First, we create our first-stage problem as usual:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:n, 1:n], Bin)
@variable(model, θ >= M)
@constraint(model, sum(x) <= 11)
@objective(model, Min, 0.1 * sum(x) + θ)
model
```

```
A JuMP Model
├ solver: HiGHS
├ objective_sense: MIN_SENSE
| └ objective_function_type: AffExpr
├ num_variables: 65
├ num_constraints: 66
| └ AffExpr in MOI.LessThan{Float64}: 1
| └ VariableRef in MOI.GreaterThan{Float64}: 1
| └ VariableRef in MOI.ZeroOne: 64
└ Names registered in the model
  └ :x, :θ
```

Then, instead of building the subproblem in a function, we build it once here:

```
subproblem = Model(HiGHS.Optimizer)
set_silent(subproblem)
@variable(subproblem, x_copy[i in 1:n, j in 1:n])
@variable(subproblem, y[1:n, 1:n] >= 0)
@constraint(subproblem, [i = 1:n, j = 1:n], y[i, j] <= G[i, j] * x_copy[i, j])
@constraint(subproblem, [i = 2:n-1], sum(y[i, :]) == sum(y[:, i]))
@objective(subproblem, Min, -sum(y[1, :]))
subproblem
```

```
A JuMP Model
├ solver: HiGHS
├ objective_sense: MIN_SENSE
| └ objective_function_type: AffExpr
├ num_variables: 128
├ num_constraints: 134
| └ AffExpr in MOI.EqualTo{Float64}: 6
| └ AffExpr in MOI.LessThan{Float64}: 64
| └ VariableRef in MOI.GreaterThan{Float64}: 64
└ Names registered in the model
  └ :x_copy, :y
```

Our function to solve the subproblem is also slightly different because we need to fix the value of the `x_copy` variables to the value of `x` from the first-stage problem:

```
function solve_subproblem(model, x)
    fix.(model[:x_copy], x)
    optimize!(model)
    assert_is_solved_and_feasible(model; dual = true)
    return (
        obj = objective_value(model),
        y = value.(model[:y]),
        π = reduced_cost.(model[:x_copy]),
    )
end
```

`solve_subproblem` (generic function with 2 methods)

Now we're ready to iterate our in-place Benders decomposition:

```
println("Iteration  Lower Bound  Upper Bound      Gap")
for k in 1:MAXIMUM_ITERATIONS
    optimize!(model)
    assert_is_solved_and_feasible(model)
    lower_bound = objective_value(model)
    x_k = value.(x)
    ret = solve_subproblem(subproblem, x_k)
    upper_bound = (objective_value(model) - value(θ)) + ret.obj
    gap = abs(upper_bound - lower_bound) / abs(upper_bound)
    print_iteration(k, lower_bound, upper_bound, gap)
    if gap < ABSOLUTE_OPTIMALITY_GAP
        println("Terminating with the optimal solution")
        break
    end
    cut = @constraint(model, θ >= ret.obj + sum(ret.π .* (x .- x_k)))
    @info "Adding the cut $(cut)"
end
```

Iteration	Lower Bound	Upper Bound	Gap
1	-2.9000e+01	0.0000e+00	Inf
[ Info: Adding the cut	3 x[1,2] + 2 x[1,3] + 2 x[1,4] + θ ≥ 0		
2	-6.7000e+00	3.0000e-01	2.3333e+01
[ Info: Adding the cut	5 x[2,5] + x[3,5] + x[2,6] + 3 x[3,6] + x[4,6] + x[3,7] + θ ≥ 0		
3	-6.5000e+00	5.0000e-01	1.4000e+01
[ Info: Adding the cut	x[3,7] + 4 x[5,8] + 2 x[6,8] + θ ≥ 0		
4	-6.2000e+00	-4.2000e+00	4.7619e-01
[ Info: Adding the cut	3 x[1,2] + x[3,5] + 2 x[6,8] + 4 x[7,8] + θ ≥ 0		
5	-6.1000e+00	-4.1000e+00	4.8780e-01
[ Info: Adding the cut	3 x[1,2] + x[3,5] + 3 x[3,6] + x[4,6] + x[3,7] + θ ≥ 0		
6	-6.1000e+00	-4.1000e+00	4.8780e-01
[ Info: Adding the cut	3 x[1,2] + 2 x[1,3] + x[4,6] + θ ≥ 0		
7	-5.1000e+00	-5.1000e+00	0.0000e+00
Terminating with the optimal solution			

Finally, we can obtain the optimal solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
x_optimal = value.(x)
optimal_ret = solve_subproblem(subproblem, x_optimal)
inplace_solution = optimal_flows(optimal_ret.y)
```

```
9-element Vector{Pair{Tuple{Int64, Int64}, Float64}}:
(1, 2) => 3.0
(1, 3) => 2.0
(1, 4) => 1.0
(2, 5) => 3.0
(3, 5) => 1.0
(3, 6) => 1.0
(4, 6) => 1.0
(5, 8) => 4.0
(6, 8) => 2.0
```

which is the same as the monolithic solution:

```
inplace_solution == monolithic_solution
```

```
true
```

## Feasibility cuts

So far, we have discussed only Benders optimality cuts. However, for some first-stage values of  $x$ , the subproblem might be infeasible. The solution is to add a Benders feasibility cut:

$$v_k + u_k^\top (x - x_k) \leq 0$$

where  $u_k$  is a dual unbounded ray of the subproblem and  $v_k$  is the intercept of the unbounded ray.

As a variation of our example which leads to infeasibilities, we add a constraint that  $\sum(y) \geq 1$ . This means we need a choice of first-stage  $x$  for which at least one unit can flow.

The first-stage problem remains the same:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:n, 1:n], Bin)
@variable(model, θ >= M)
@constraint(model, sum(x) <= 11)
@objective(model, Min, 0.1 * sum(x) + θ)
model
```

```
A JuMP Model
├ solver: HiGHS
├ objective_sense: MIN_SENSE
|└ objective_function_type: AffExpr
├ num_variables: 65
├ num_constraints: 66
|└ AffExpr in MOI.LessThan{Float64}: 1
|└ VariableRef in MOI.GreaterThan{Float64}: 1
|└ VariableRef in MOI.ZeroOne: 64
└ Names registered in the model
  └ :x, :θ
```

But the subproblem has a new constraint that  $\sum(y) \geq 1$ :

```
subproblem = Model(HiGHS.Optimizer)
set_silent(subproblem)
# We need to turn presolve off so that HiGHS will return an infeasibility
# certificate.
set_attribute(subproblem, "presolve", "off")
@variable(subproblem, x_copy[i in 1:n, j in 1:n])
@variable(subproblem, y[1:n, 1:n] >= 0)
@constraint(subproblem, sum(y) >= 1) # <--- THIS IS NEW
@constraint(subproblem, [i = 1:n, j = 1:n], y[i, j] <= G[i, j] * x_copy[i, j])
@constraint(subproblem, [i = 2:n-1], sum(y[i, :]) == sum(y[:, i]))
@objective(subproblem, Min, -sum(y[1, :]))
subproblem
```

```
A JuMP Model
├ solver: HiGHS
├ objective_sense: MIN_SENSE
|└ objective_function_type: AffExpr
├ num_variables: 128
├ num_constraints: 135
|└ AffExpr in MOI.EqualTo{Float64}: 6
|└ AffExpr in MOI.GreaterThan{Float64}: 1
|└ AffExpr in MOI.LessThan{Float64}: 64
|└ VariableRef in MOI.GreaterThan{Float64}: 64
└ Names registered in the model
  └ :x_copy, :y
```

The function to solve the subproblem now checks for feasibility, and returns the dual objective value and an dual unbounded ray if the subproblem is infeasible:

```
function solve_subproblem_with_feasibility(model, x)
    fix.(model[:x_copy], x)
    optimize!(model)
    if is_solved_and_feasible(model; dual = true)
        return (
            is_feasible = true,
            obj = objective_value(model),
```

```

        y = value.(model[:y]),
        π = reduced_cost.(model[:x_copy]),
    )
end
return (
    is_feasible = false,
    v = dual_objective_value(model),
    u = reduced_cost.(model[:x_copy]),
)
end

```

solve\_subproblem\_with\_feasibility (generic function with 1 method)

Now we're ready to iterate our in-place Benders decomposition:

```

println("Iteration  Lower Bound  Upper Bound      Gap")
for k in 1:MAXIMUM_ITERATIONS
    optimize!(model)
    assert_is_solved_and_feasible(model)
    lower_bound = objective_value(model)
    x_k = value.(x)
    ret = solve_subproblem_with_feasibility(subproblem, x_k)
    if ret.is_feasible
        # Benders Optimality Cuts
        upper_bound = (objective_value(model) - value(θ)) + ret.obj
        gap = abs(upper_bound - lower_bound) / abs(upper_bound)
        print_iteration(k, lower_bound, upper_bound, gap)
        if gap < ABSOLUTE_OPTIMALITY_GAP
            println("Terminating with the optimal solution")
            break
        end
        @constraint(model, θ >= ret.obj + sum(ret.π .* (x .- x_k)))
    else
        # Benders Feasibility Cuts
        cut = @constraint(model, ret.v + sum(ret.u .* (x .- x_k)) <= 0)
        @info "Adding the feasibility cut $(cut)"
    end
end

```

Iteration	Lower Bound	Upper Bound	Gap
[ Info: Adding the feasibility cut	$-3x[1,2] - 2x[1,3] - 2x[1,4] - 5.000000000000002x[2,5] -$		
$\hookrightarrow x[3,5] - 2x[2,6] - 6x[3,6] - 2x[4,6] - 2.000000000000004x[3,7] - 4x[5,8] \leq -1$			
[ Info: Adding the feasibility cut	$-2.999999999999999x[1,2] - 1.999999999999996x[1,3] -$		
$\hookrightarrow 1.999999999999996x[1,4] - 10x[2,5] - 2x[3,5] - 1.999999999999996x[2,6] -$			
$\hookrightarrow 5.99999999999998x[3,6] - 1.999999999999996x[4,6] - 1.999999999999998x[3,7] \leq$			
$\hookrightarrow -0.99999999999998$			
[ Info: Adding the feasibility cut	$-2.9999999999999987x[1,2] - 5.999999999999998x[1,3] -$		
$\hookrightarrow 1.999999999999991x[1,4] - 10x[2,5] - 1.999999999999991x[2,6] - 1.999999999999991x[4,6] \leq$			
$\hookrightarrow -0.99999999999996$			
[ Info: Adding the feasibility cut	$-4x[1,3] - 3.999999999999982x[1,4] - 9.99999999999998x[2,5]$		
$\hookrightarrow -2x[2,6] - 4x[5,8] - 1.99999999999996x[6,8] - 4x[7,8] \leq -1$			

```

[ Info: Adding the feasibility cut -3 x[1,2] - 4 x[1,3] - 2 x[1,4] - 10 x[2,5] - x[3,5] - 4 x[6,8]
↪ - 4 x[7,8] ≤ -1
[ Info: Adding the feasibility cut -6 x[1,2] - 6 x[1,3] - 4 x[1,4] - 4 x[5,8] - 2 x[6,8] ≤ -1
[ Info: Adding the feasibility cut -6 x[1,2] - 6 x[1,3] - 2 x[4,6] - 4 x[5,8] - 2 x[6,8] ≤ -1
[ Info: Adding the feasibility cut -6 x[1,2] - 2 x[1,4] - 2 x[3,5] - 6 x[3,6] - x[4,6] - 2 x[3,7] -
↪ 4 x[5,8] - 2 x[6,8] - 4 x[7,8] ≤ -1
[ Info: Adding the feasibility cut -6 x[1,2] - 2 x[3,5] - 6 x[3,6] - 2 x[4,6] - 2 x[3,7] - 4 x[5,8]
↪ - 2 x[6,8] - 4 x[7,8] ≤ -1
[ Info: Adding the feasibility cut -5 x[2,5] - x[3,5] - x[2,6] - 3 x[3,6] - x[4,6] - x[3,7] - 8
↪ x[5,8] - 4 x[6,8] - 8 x[7,8] ≤ -1
[ Info: Adding the feasibility cut -2 x[1,3] - 6 x[1,4] - 9.999999999999998 x[2,5] - x[3,5] - 3
↪ x[2,6] - 6.000000000000002 x[3,6] - x[3,7] - 3.999999999999999 x[5,8] - 3.999999999999999
↪ x[7,8] ≤ -0.999999999999998
[ Info: Adding the feasibility cut -1.999999999999997 x[1,3] - 5.999999999999997 x[1,4] -
↪ 14.999999999999996 x[2,5] - 1.999999999999991 x[3,5] - 2.999999999999997 x[2,6] -
↪ 5.999999999999996 x[3,6] - x[3,7] - 3.999999999999999 x[7,8] ≤ -0.999999999999998
[ Info: Adding the feasibility cut -3 x[1,2] - 5.999999999999997 x[1,4] - 9.999999999999996 x[2,5]
↪ - 2.999999999999999 x[3,5] - 1.999999999999999 x[2,6] - 8.999999999999996 x[3,6] -
↪ 1.999999999999996 x[3,7] - 3.999999999999999 x[7,8] ≤ -0.999999999999998
[ Info: Adding the feasibility cut -3 x[1,2] - 6 x[1,4] - 2 x[2,6] - 9 x[3,6] - 2 x[3,7] - 12
↪ x[5,8] - 4 x[7,8] ≤ -1
[ Info: Adding the feasibility cut -3 x[1,2] - 6 x[1,4] - 2 x[2,6] - 9 x[3,6] - 3 x[3,7] - 12
↪ x[5,8] ≤ -1
[ Info: Adding the feasibility cut -2 x[1,4] - 3 x[3,7] - 12 x[5,8] - 6 x[6,8] ≤ -1
[ Info: Adding the feasibility cut -3 x[3,7] - 12 x[5,8] - 6 x[6,8] ≤ -1
[ Info: Adding the feasibility cut -3 x[2,6] - 9 x[3,6] - 3.000000000000004 x[4,6] - x[3,7] - 12
↪ x[5,8] - 8 x[7,8] ≤ -1
[ Info: Adding the feasibility cut -15 x[2,5] - 3 x[3,5] - 3 x[2,6] - 9 x[3,6] - 3 x[4,6] - 2
↪ x[3,7] - 4 x[7,8] ≤ -1
[ Info: Adding the feasibility cut -9 x[1,2] - 3 x[3,5] - 9 x[3,6] - 3 x[4,6] - 2 x[3,7] - 4 x[7,8]
↪ ≤ -1
[ Info: Adding the feasibility cut -6 x[1,2] - 2 x[3,5] - 6 x[3,6] - 2 x[4,6] - 4 x[5,8] - 2 x[6,8]
↪ - 12 x[7,8] ≤ -1
[ Info: Adding the feasibility cut -3 x[1,2] - 5 x[2,5] - 2 x[3,5] - 2 x[2,6] - 9 x[3,6] - 3 x[4,6]
↪ - 4 x[5,8] - 12 x[7,8] ≤ -1
    23 -2.8700e+01 -7.0000e-01 4.0000e+01
[ Info: Adding the feasibility cut -4 x[1,3] - 4 x[1,4] - 15 x[2,5] - x[3,5] - 2 x[2,6] - x[3,7] -
↪ 2 x[6,8] ≤ -1
[ Info: Adding the feasibility cut -6 x[1,3] - 4 x[1,4] - 15 x[2,5] - 2 x[2,6] - 2 x[6,8] ≤ -1
[ Info: Adding the feasibility cut -x[1,4] - 7.5 x[2,5] - 1.5 x[3,5] - 1.5 x[3,7] - 3 x[6,8] ≤ -0.5
    27 -1.4400e+01 -2.4000e+00 5.0000e+00
[ Info: Adding the feasibility cut -6 x[1,3] - 15 x[2,5] - 3 x[2,6] - 3 x[4,6] ≤ -1
    29 -8.2000e+00 -2.0000e-01 4.0000e+01
    30 -7.9000e+00 -4.9000e+00 6.1224e-01
    31 -5.3000e+00 -3.3000e+00 6.0606e-01
    32 -5.3000e+00 -1.3000e+00 3.0769e+00
    33 -5.2000e+00 -4.2000e+00 2.3810e-01
    34 -5.2000e+00 -4.2000e+00 2.3810e-01
    35 -5.1000e+00 -4.1000e+00 2.4390e-01
    36 -5.1000e+00 -4.1000e+00 2.4390e-01
    37 -5.1000e+00 -5.1000e+00 0.0000e+00
Terminating with the optimal solution

```

Finally, we can obtain the optimal solution:

```
optimize!(model)
assert_is_solved_and_feasible(model)
x_optimal = value.(x)
optimal_ret = solve_subproblem(subproblem, x_optimal)
feasible_inplace_solution = optimal_flows(optimal_ret.y)
```

```
9-element Vector{Pair{Tuple{Int64, Int64}, Float64}}:
(1, 2) => 3.0
(1, 3) => 2.0
(1, 4) => 1.0
(2, 5) => 3.0
(3, 5) => 1.0
(3, 6) => 1.0
(4, 6) => 1.0
(5, 8) => 4.0
(6, 8) => 2.0
```

which is the same as the monolithic solution (because  $\text{sum}(y) \geq 1$  in the monolithic solution):

```
feasible_inplace_solution == monolithic_solution
```

```
true
```

## 9.2 Column generation

*This tutorial was generated using [Literate.jl](#). Download the source as a [.jl file](#).*

The purpose of this tutorial is to demonstrate the column generation algorithm. As an example, it solves the [Cutting stock problem](#).

This tutorial uses the following packages:

```
using JuMP
import DataFrames
import HiGHS
import Plots
import SparseArrays
```

### Background

The cutting stock problem is about cutting large rolls of paper into smaller pieces.

We denote the set of possible sized pieces that a roll can be cut into by  $i \in 1, \dots, I$ . Each piece  $i$  has a width,  $w_i$ , and a demand,  $d_i$ . The width of the large roll is  $W$ .

Our objective is to minimize the number of rolls needed to meet all demand.

Here's the data that we are going to use in this tutorial:

```

struct Piece
    w::Float64
    d::Int
end

struct Data
    pieces::Vector{Piece}
    W::Float64
end

function Base.show(io::IO, d::Data)
    println(io, "Data for the cutting stock problem:")
    println(io, " W = $(d.W)")
    println(io, "with pieces:")
    println(io, " i w_i d_i")
    println(io, " -----")
    for (i, p) in enumerate(d.pieces)
        println(io, lpad(i, 4), " ", lpad(p.w, 5), " ", lpad(p.d, 3))
    end
    return
end

function get_data()
    data = [
        75.0 38
        75.0 44
        75.0 30
        75.0 41
        75.0 36
        53.8 33
        53.0 36
        51.0 41
        50.2 35
        32.2 37
        30.8 44
        29.8 49
        20.1 37
        16.2 36
        14.5 42
        11.0 33
        8.6 47
        8.2 35
        6.6 49
        5.1 42
    ]
    return Data([Piece(data[i, 1], data[i, 2]) for i in axes(data, 1)], 100.0)
end

data = get_data()

```

```

Data for the cutting stock problem:
W = 100.0
with pieces:
i   w_i d_i

```

```

-----
1 75.0 38
2 75.0 44
3 75.0 30
4 75.0 41
5 75.0 36
6 53.8 33
7 53.0 36
8 51.0 41
9 50.2 35
10 32.2 37
11 30.8 44
12 29.8 49
13 20.1 37
14 16.2 36
15 14.5 42
16 11.0 33
17 8.6 47
18 8.2 35
19 6.6 49
20 5.1 42

```

### Mathematical formulation

To formulate the cutting stock problem as a mixed-integer linear program, we assume that there is a set of large rolls  $j = 1, \dots, J$  to use. Then, we introduce two classes of decision variables:

- $x_{ij} \geq 0$ , integer,  $\forall i = 1, \dots, I, j = 1, \dots, J$
- $y_j \in \{0, 1\}$ ,  $\forall j = 1, \dots, J$ .

$y_j$  is a binary variable that indicates if we use roll  $j$ , and  $x_{ij}$  counts how many pieces of size  $i$  that we cut from roll  $j$ .

Our mixed-integer linear program is therefore:

$$\min \sum_{j=1}^J y_j \quad (9.1)$$

$$\text{s.t. } \sum_{i=1}^N w_i x_{ij} \leq W y_j \quad \forall j = 1, \dots, J \quad (9.2)$$

$$\sum_{j=1}^J x_{ij} \geq d_i \quad \forall i = 1, \dots, I \quad (9.3)$$

$$x_{ij} \geq 0 \quad \forall i = 1, \dots, N, j = 1, \dots, J \quad (9.4)$$

$$x_{ij} \in \mathbb{Z} \quad \forall i = 1, \dots, I, j = 1, \dots, J \quad (9.5)$$

$$y_j \in \{0, 1\} \quad \forall j = 1, \dots, J \quad (9.6)$$

$$(9.7)$$

The objective is to minimize the number of rolls that we use, and the two constraints ensure that we respect the total width of each large roll and that we satisfy demand exactly.

The JuMP formulation of this model is:

```
I = length(data.pieces)
J = 1_000 # Some large number
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:I, 1:J] >= 0, Int)
@variable(model, y[1:J], Bin)
@objective(model, Min, sum(y))
@constraint(model, [i in 1:I], sum(x[i, :]) >= data.pieces[i].d)
@constraint(
    model,
    [j in 1:J],
    sum(data.pieces[i].w * x[i, j] for i in 1:I) <= data.W * y[j],
);
)
```

Unfortunately, we can't solve this formulation for realistic instances because it takes a very long time to solve. (Try removing the time limit.)

```
set_time_limit_sec(model, 5.0)
optimize!(model)
solution_summary(model)
```

```
* Solver : HiGHS

* Status
Result count      : 1
Termination status : TIME_LIMIT
Message from the solver:
"kHighsModelStatusTimeLimit"

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : NO_SOLUTION
Objective value   : 4.11000e+02
Objective bound    : 2.93000e+02
Relative gap       : 2.87105e-01
Dual objective value : NaN

* Work counters
Solve time (sec)   : 5.05623e+00
Simplex iterations : 20271
Barrier iterations : -1
Node count         : 0
```

However, there is a formulation that solves much faster, and that is to use a column generation scheme.

### Column generation theory

The key insight for column generation is to recognize that feasible columns in the  $x$  matrix of variables encode *cutting patterns*.

For example, if we look only at the roll  $j = 1$ , then a feasible solution is:

- $x_{1,1} = 1$  (1 unit of piece #1)
- $x_{13,1} = 1$  (1 unit of piece #13)
- All other  $x_{i,1} = 0$

Another solution is

- $x_{20,1} = 19$  (19 unit of piece #20)
- All other  $x_{i,1} = 0$

Cutting patterns like  $x_{1,1} = 1$  and  $x_{2,1} = 1$  are infeasible because the combined length is greater than  $W$ .

Since there are a finite number of ways that we could cut a roll into a valid cutting pattern, we could create a set of all possible cutting patterns  $p = 1, \dots, P$ , with data  $a_{i,p}$  indicating how many units of piece  $i$  we cut in pattern  $p$ . Then, we can formulate our mixed-integer linear program as:

$$\min \sum_{p=1}^P x_p \tag{9.8}$$

$$\text{s.t. } \sum_{p=1}^P a_{ip}x_p \geq d_i \quad \forall i = 1, \dots, I \tag{9.9}$$

$$x_p \geq 0 \quad \forall p = 1, \dots, P \tag{9.10}$$

$$x_p \in \mathbb{Z} \quad \forall p = 1, \dots, P \tag{9.11}$$

Unfortunately, there will be a very large number of these patterns, so it is often intractable to enumerate all columns  $p = 1, \dots, P$ .

Column generation is an iterative algorithm that starts with a small set of initial patterns, and then cleverly chooses new columns to add to the main MILP so that we find the optimal solution without having to enumerate every column.

### Choosing the initial set of patterns

For the initial set of patterns, we create a trivial cutting pattern which cuts as many units of piece  $i$  as will fit.

```
patterns = map(1:I) do i
    n_pieces = floor(Int, data.W / data.pieces[i].w)
    return SparseArrays.sparsevec([i], [n_pieces], I)
end
```

```
20-element Vector{SparseArrays.SparseVector{Int64, Int64}}:
sparsevec([1], [1], 20)
sparsevec([2], [1], 20)
sparsevec([3], [1], 20)
sparsevec([4], [1], 20)
sparsevec([5], [1], 20)
sparsevec([6], [1], 20)
sparsevec([7], [1], 20)
sparsevec([8], [1], 20)
sparsevec([9], [1], 20)
sparsevec([10], [3], 20)
sparsevec([11], [3], 20)
sparsevec([12], [3], 20)
sparsevec([13], [4], 20)
sparsevec([14], [6], 20)
sparsevec([15], [6], 20)
sparsevec([16], [9], 20)
sparsevec([17], [11], 20)
sparsevec([18], [12], 20)
sparsevec([19], [15], 20)
sparsevec([20], [19], 20)
```

We can visualize the patterns as follows:

```
"""
    cutting_locations(data::Data, pattern::SparseArrays.SparseVector)

A function which returns a vector of the locations along the roll at which to
cut in order to produce pattern `pattern`.
"""

function cutting_locations(data::Data, pattern::SparseArrays.SparseVector)
    locations = Float64[]
    offset = 0.0
    for (i, c) in zip(SparseArrays.findnz(pattern)...)

        for _ in 1:c
            offset += data.pieces[i].w
            push!(locations, offset)
        end
    end
    return locations
end

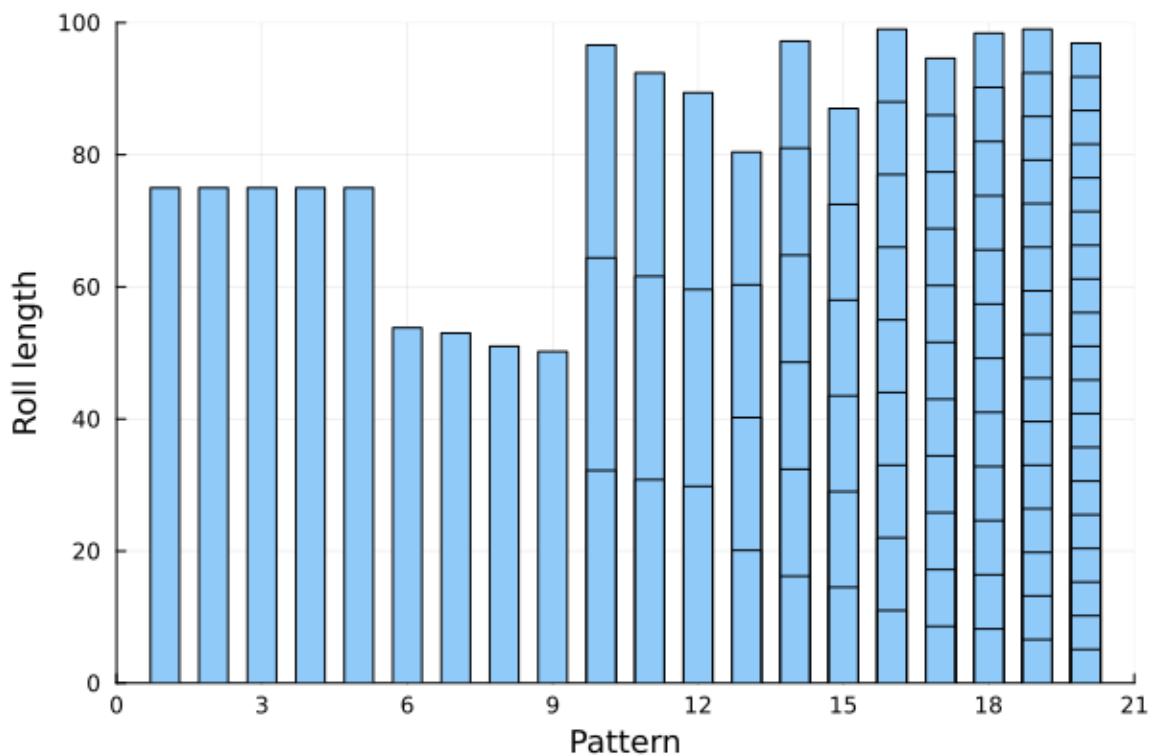
function plot_patterns(data::Data, patterns)
    plot = Plots.bar();
    xlims = (0, length(patterns) + 1),
    ylims = (0, data.W),
    xlabel = "Pattern",
    ylabel = "Roll length",
)
    for (i, p) in enumerate(patterns)
        locations = cutting_locations(data, p)
        Plots.bar!(
            plot,
            fill(i, length(locations)),
```

```

        reverse(locations);
        bar_width = 0.6,
        label = false,
        color = "#90caf9",
    )
end
return plot
end

plot_patterns(data, patterns)

```



### The base problem

Using the initial set of patterns, we can create and optimize our base model:

```

model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:length(patterns)] >= 0, Int)
@objective(model, Min, sum(x))
@constraint(model, demand[i in 1:I], patterns[i] * x >= data.pieces[i].d)
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)

```

```

* Solver : HIGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : NO_SOLUTION
  Objective value   : 4.21000e+02
  Objective bound    : 4.21000e+02
  Relative gap       : 0.00000e+00
  Dual objective value : NaN

* Work counters
  Solve time (sec)   : 1.91450e-04
  Simplex iterations : 0
  Barrier iterations : -1
  Node count         : 0

```

This solution requires 421 rolls. This solution is sub-optimal because the model does not contain the full set of possible patterns.

How do we find a new column that leads to an improved solution?

### Choosing new columns

Column generation chooses a new column by relaxing the integrality constraint on  $x$  and looking at the dual variable  $\pi_i$  associated with demand constraint  $i$ .

For example, the dual of demand[13] is:

```

unset_integer.(x)
optimize!(model)
assert_is_solved_and_feasible(model; dual = true)
π_13 = dual(demand[13])

```

0.25

Using the economic interpretation of the dual variable, we can say that a one unit increase in demand for piece  $i$  will cost an extra  $\pi_i$  rolls. Alternatively, we can say that a one unit increase in the left-hand side (for example, due to a new cutting pattern) will save us  $\pi_i$  rolls. Therefore, we want a new column that maximizes the savings associated with the dual variables, while respecting the total width of the roll:

$$\max \sum_{i=1}^I \pi_i y_i \quad (9.12)$$

$$\text{s.t. } \sum_{i=1}^I w_i y_i \leq W \quad (9.13)$$

$$y_i \geq 0 \quad \forall i = 1, \dots, I \quad (9.14)$$

$$y_i \in \mathbb{Z} \quad \forall i = 1, \dots, I \quad (9.15)$$

$$(9.16)$$

If this problem, called the *pricing problem*, has an objective value greater than 1, then we estimate that adding  $y$  as the coefficients of a new column will decrease the objective by more than the cost of an extra roll.

Here is code to solve the pricing problem:

```
function solve_pricing(data::Data, π::Vector{Float64})
    I = length(π)
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, y[1:I] >= 0, Int)
    @constraint(model, sum(data.pieces[i].w * y[i] for i in 1:I) <= data.W)
    @objective(model, Max, sum(π[i] * y[i] for i in 1:I))
    optimize!(model)
    assert_is_solved_and_feasible(model)
    number_of_rolls_saved = objective_value(model)
    if number_of_rolls_saved > 1 + 1e-8
        # Benefit of pattern is more than the cost of a new roll plus some
        # tolerance
        return SparseArrays.sparse(round.(Int, value.(y)))
    end
    return nothing
end
```

solve\_pricing (generic function with 1 method)

If we solve the pricing problem with an artificial dual vector:

```
solve_pricing(data, [1.0 / i for i in 1:I])
```

```
20-element SparseArrays.SparseVector{Int64, Int64} with 3 stored entries:
 [1]  =  1
 [17] =  1
 [20] =  3
```

the solution is a roll with 1 unit of piece #1, 1 unit of piece #17, and 3 units of piece #20.

If we solve the pricing problem with a dual vector of zeros, then the benefit of the new pattern is less than the cost of a roll, and so the function returns nothing:

```
solve_pricing(data, zeros(I))
```

### Iterative algorithm

Now we can combine our base model with the pricing subproblem in an iterative column generation scheme:

```
while true
    # Solve the linear relaxation
    optimize!(model)
    assert_is_solved_and_feasible(model; dual = true)
    # Obtain a new dual vector
    π = dual.(demand)
    # Solve the pricing problem
    new_pattern = solve_pricing(data, π)
    # Stop iterating if there is no new pattern
    if new_pattern === nothing
        @info "No new patterns, terminating the algorithm."
        break
    end
    push!(patterns, new_pattern)
    # Create a new column
    push!(x, @variable(model, lower_bound = 0))
    # Update the objective coefficient of the new column
    set_objective_coefficient(model, x[end], 1.0)
    # Update the non-zeros in the coefficient matrix
    for (i, count) in zip(SparseArrays.findnz(new_pattern)...),
        set_normalized_coefficient(demand[i], x[end], count)
    end
    println("Found new pattern. Total patterns = $(length(patterns))")
end
```

```
Found new pattern. Total patterns = 21
Found new pattern. Total patterns = 22
Found new pattern. Total patterns = 23
Found new pattern. Total patterns = 24
Found new pattern. Total patterns = 25
Found new pattern. Total patterns = 26
Found new pattern. Total patterns = 27
Found new pattern. Total patterns = 28
Found new pattern. Total patterns = 29
Found new pattern. Total patterns = 30
Found new pattern. Total patterns = 31
Found new pattern. Total patterns = 32
Found new pattern. Total patterns = 33
Found new pattern. Total patterns = 34
Found new pattern. Total patterns = 35
[ Info: No new patterns, terminating the algorithm.
```

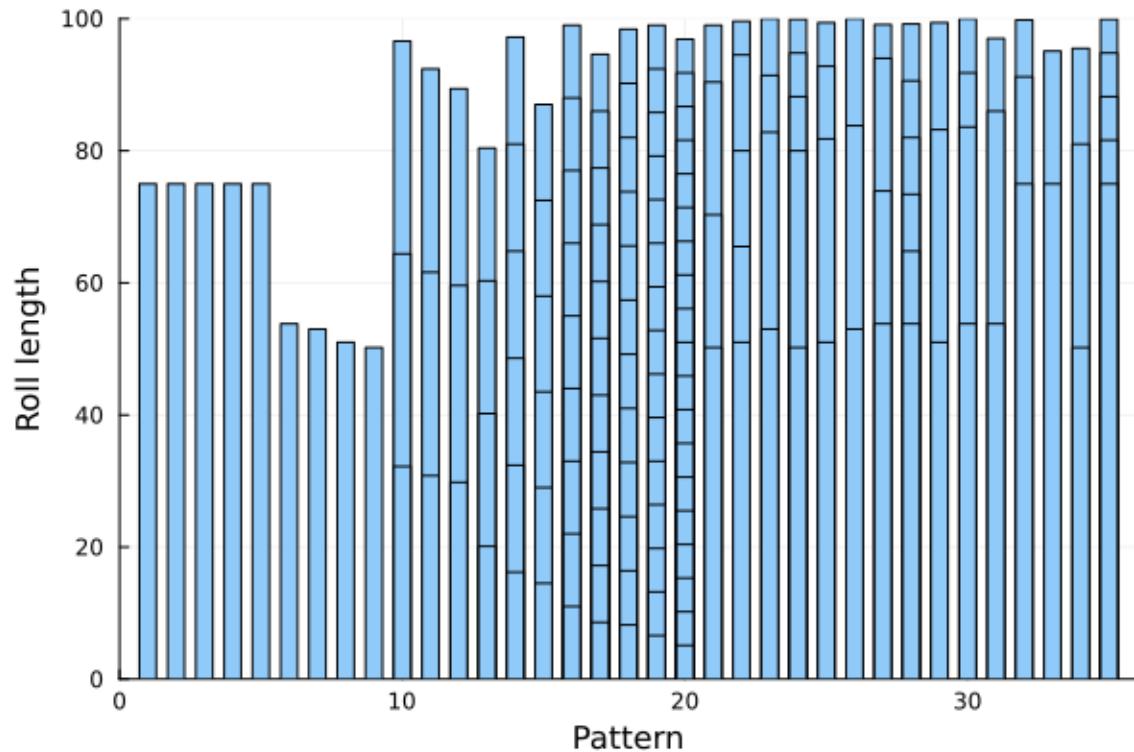
We found lots of new patterns. Here's pattern 21:

```
patterns[21]
```

```
20-element SparseArrays.SparseVector{Int64, Int64} with 3 stored entries:
 [9 ] = 1
 [13] = 2
 [17] = 1
```

Let's have a look at the patterns now:

```
plot_patterns(data, patterns)
```



### Looking at the solution

Let's see how many of each column we need:

```
solution = DataFrames.DataFrame([
    (pattern = p, rolls = value(x_p)) for (p, x_p) in enumerate(x)
])
filter!(row -> row.rolls > 0, solution)
```

Since we solved a linear program, some of our columns have fractional solutions. We can create a integer feasible solution by rounding up the orders. This requires 341 rolls:

	pattern	rolls
	Int64	Float64
1	1	38.0
2	2	44.0
3	3	30.0
4	21	0.5
5	22	10.2
6	23	14.65
7	24	23.1
8	25	11.25
9	26	21.35
10	28	4.3
11	29	19.55
12	30	11.25
13	31	17.45
14	33	36.0
15	34	11.4
16	35	41.0

```
sum(ceil.(Int, solution.rolls))
```

341

Alternatively, we can re-introduce the integrality constraints and resolve the problem:

```
set_integer.(x)
optimize!(model)
assert_is_solved_and_feasible(model)
solution = DataFrames.DataFrame([
    (pattern = p, rolls = value(x_p)) for (p, x_p) in enumerate(x)
])
filter!(row -> row.rolls > 0, solution)
```

This now requires 334 rolls:

```
sum(solution.rolls)
```

333.9999999999994

Note that this may not be the global minimum because we are not adding new columns during the solution of the mixed-integer problem model (an algorithm known as [branch and price](#)). Nevertheless, the column generation algorithm typically finds good integer feasible solutions to an otherwise intractable optimization problem.

	pattern	rolls
	Int64	Float64
1	1	38.0
2	2	44.0
3	3	30.0
4	21	1.0
5	22	9.0
6	23	19.0
7	24	19.0
8	25	13.0
9	26	17.0
10	28	2.0
11	29	19.0
12	30	13.0
13	31	18.0
14	33	36.0
15	34	15.0
16	35	41.0

## Next steps

- Our objective function is to minimize the total number of rolls. What is the total length of waste? How does that compare to the total demand?
- Writing the optimization algorithm is only part of the challenge. Can you develop a better way to communicate the solution to stakeholders?

## 9.3 Traveling Salesperson Problem

This tutorial was generated using [Literate.jl](#). Download the source as a [.jl file](#).

**This tutorial was originally contributed by Daniel Schermer.**

This tutorial describes how to implement the [Traveling Salesperson Problem](#) in JuMP using solver-independent lazy constraints that dynamically separate subtours. To be more precise, we use lazy constraints to cut off infeasible subtours only when necessary and not before needed.

It uses the following packages:

```
using JuMP
import Gurobi
import Plots
import Random
import Test
```

## Mathematical Formulation

Assume that we are given a complete graph  $\mathcal{G}(V, E)$  where  $V$  is the set of vertices (or cities) and  $E$  is the set of edges (or roads). For each pair of vertices  $i, j \in V, i \neq j$  the edge  $(i, j) \in E$  is associated with a weight (or distance)  $d_{ij} \in \mathbb{R}^+$ .

For this tutorial, we assume the problem to be symmetric, that is,  $d_{ij} = d_{ji} \forall i, j \in V$ .

In the Traveling Salesperson Problem, we are tasked with finding a tour with minimal length that visits every vertex exactly once and then returns to the point of origin, that is, a *Hamiltonian cycle* with minimal weight.

To model the problem, we introduce a binary variable,  $x_{ij} \in \{0, 1\} \forall i, j \in V$ , that indicates if edge  $(i, j)$  is part of the tour or not. Using these variables, the Traveling Salesperson Problem can be modeled as the following integer linear program.

### Objective Function

The objective is to minimize the length of the tour (due to the assumed symmetry, the second sum only contains  $i < j$ ):

$$\min \sum_{i \in V} \sum_{j \in V, i < j} d_{ij} x_{ij}.$$

Note that it is also possible to use the following objective function instead:

$$\min \sum_{i \in V} \sum_{j \in V} \frac{d_{ij} x_{ij}}{2}.$$

### Constraints

There are four classes of constraints in our formulation.

First, due to the presumed symmetry, the following constraints must hold:

$$x_{ij} = x_{ji} \quad \forall i, j \in V.$$

Second, for each vertex  $i$ , exactly two edges must be selected that connect it to other vertices  $j$  in the graph  $G$ :

$$\sum_{j \in V} x_{ij} = 2 \quad \forall i \in V.$$

Third, we do not permit loops to occur:

$$x_{ii} = 0 \quad \forall i \in V.$$

The fourth constraint is more complicated. A major difficulty of the Traveling Salesperson Problem arises from the fact that we need to prevent *subtours*, that is, several distinct Hamiltonian cycles existing on subgraphs of  $G$ .

Note that the previous constraints *do not* guarantee that the solution will be free of subtours. To this end, by  $S$  we label a subset of vertices. Then, for each proper subset  $S \subset V$ , the following constraints guarantee that no subtour may occur:

$$\sum_{i \in S} \sum_{j \in S, i < j} x_{ij} \leq |S| - 1 \quad \forall S \subset V.$$

Problematically, we require exponentially many of these constraints as  $|V|$  increases. Therefore, we will add these constraints only when necessary.

## Implementation

There are two ways we can eliminate subtours in JuMP, both of which will be shown in what follows:

- iteratively solving a new model that incorporates previously identified subtours,
- or adding violated subtours as *lazy constraints*.

## Data

The vertices are assumed to be randomly distributed in the Euclidean space; thus, the weight (distance) of each edge is defined as follows.

```
function generate_distance_matrix(n; random_seed = 1)
    rng = Random.MersenneTwister(random_seed)
    X = 100 * rand(rng, n)
    Y = 100 * rand(rng, n)
    d = [sqrt((X[i] - X[j])^2 + (Y[i] - Y[j])^2) for i in 1:n, j in 1:n]
    return X, Y, d
end

n = 100
X, Y, d = generate_distance_matrix(n)
```

```
([9.913970137863682, 70.19797138879542, 50.3261785841856, 87.58412053070398, 95.34654118744876,
  ↵ 50.7810571056071, 78.97511635624403, 7.125413261100788, 13.837807897217225, 39.31891799217675
  ↵ ... 84.87369607977678, 61.680928138712, 5.665730912653899, 15.622563304879634,
  ↵ 36.90767228785501, 70.07597765092129, 79.43901471209098, 46.482254570311675, 68.59072330642508,
  ↵ 86.69884288310024], [96.78179466896867, 56.23453714649542, 67.44638756669107,
  ↵ 7.1115103002265645, 92.78034391338332, 34.57366887562756, 76.53412034001651,
  ↵ 33.078576899782796, 62.27235533684083, 31.31072581673351 ... 1.4463814325218927,
  ↵ 42.253985947804495, 53.81635009641501, 76.50117040708963, 27.74238915740479, 60.20183753580153,
  ↵ 19.81346291572821, 90.60507365183767, 31.10234142135033, 21.085230265206945], [0.0
  ↵ 72.65150307747324 ... 88.07242440917794 107.82340444001487; 72.65150307747324 0.0 ...
  ↵ 25.183536454701592 38.829789264256306; ... ; 88.07242440917794 25.183536454701592 ... 0.0
  ↵ 20.69411777577625; 107.82340444001487 38.829789264256306 ... 20.69411777577625 0.0])
```

For the JuMP model, we first initialize the model object. Then, we create the binary decision variables and add the objective function and constraints. By defining the `x` matrix as `Symmetric`, we do not need to add explicit constraints that `x[i, j] == x[j, i]`.

```

function build_tsp_model(d, n, optimizer)
    model = Model(optimizer)
    set_silent(model)
    @variable(model, x[1:n, 1:n], Bin, Symmetric)
    @objective(model, Min, sum(d .* x) / 2)
    @constraint(model, [i in 1:n], sum(x[i, :]) == 2)
    @constraint(model, [i in 1:n], x[i, i] == 0)
    return model
end

```

build\_tsp\_model (generic function with 1 method)

To search for violated constraints, based on the edges that are currently in the solution (that is, those that have value  $x_{ij} = 1$ ), we identify the shortest cycle through the function `subtour()`. Whenever a subtour has been identified, a constraint corresponding to the form above can be added to the model.

```

function subtour(edges::Vector{Tuple{Int,Int}}, n)
    shortest_subtour, unvisited = collect(1:n), Set(collect(1:n))
    while !isempty(unvisited)
        this_cycle, neighbors = Int[], unvisited
        while !isempty(neighbors)
            current = pop!(neighbors)
            push!(this_cycle, current)
            if length(this_cycle) > 1
                pop!(unvisited, current)
            end
            neighbors =
                [j for (i, j) in edges if i == current && j in unvisited]
        end
        if length(this_cycle) < length(shortest_subtour)
            shortest_subtour = this_cycle
        end
    end
    return shortest_subtour
end

```

subtour (generic function with 1 method)

Let us declare a helper function `selected_edges()` that will be repeatedly used in what follows.

```

function selected_edges(x::Matrix{Float64}, n)
    return Tuple{Int,Int}[(i, j) for i in 1:n, j in 1:n if x[i, j] > 0.5]
end

```

selected\_edges (generic function with 1 method)

Other helper functions for computing subtours:

```
subtour(x::Matrix{Float64}) = subtour(selected_edges(x, size(x, 1)), size(x, 1))
subtour(x::AbstractMatrix{VariableRef}) = subtour(value.(x))
```

```
subtour (generic function with 3 methods)
```

### Iterative method

An iterative way of eliminating subtours is the following.

However, it is reasonable to assume that this is not the most efficient way: whenever a new subtour elimination constraint is added to the model, the optimization has to start from the very beginning.

That way, the solver will repeatedly discard useful information encountered during previous solves (for example, all cuts, the incumbent solution, or lower bounds).

#### Info

Note that, in principle, it would also be feasible to add all subtours (instead of just the shortest one) to the model. However, preventing just the shortest cycle is often sufficient for breaking other subtours and will keep the model size smaller.

```
optimizer = Gurobi.Optimizer
iterative_model = build_tsp_model(d, n, optimizer)
optimize!(iterative_model)
assert_is_solved_and_feasible(iterative_model)
time_iterated = solve_time(iterative_model)
cycle = subtour(iterative_model[:x])
while 1 < length(cycle) < n
    println("Found cycle of length $(length(cycle))")
    S = [(i, j) for (i, j) in Iterators.product(cycle, cycle) if i < j]
    @constraint(
        iterative_model,
        sum(iterative_model[:x][i, j] for (i, j) in S) <= length(cycle) - 1,
    )
    optimize!(iterative_model)
    assert_is_solved_and_feasible(iterative_model)
    global time_iterated += solve_time(iterative_model)
    global cycle = subtour(iterative_model[:x])
end
```

```
Set parameter WLSAccessID
Set parameter WLSSecret
Set parameter LicenseID to value 722777
Set parameter GURO_PAR_SPECIAL
WLS license 722777 - registered to JuMP Development
Found cycle of length 3
Found cycle of length 3
```

```

Found cycle of length 3
Found cycle of length 4
Found cycle of length 3
Found cycle of length 3
Found cycle of length 4
Found cycle of length 5
Found cycle of length 6
Found cycle of length 5
Found cycle of length 3
Found cycle of length 4
Found cycle of length 6
Found cycle of length 4
Found cycle of length 8
Found cycle of length 5
Found cycle of length 10
Found cycle of length 10
Found cycle of length 15
Found cycle of length 11
Found cycle of length 4
Found cycle of length 22
Found cycle of length 3
Found cycle of length 5
Found cycle of length 21

```

```
objective_value(iterative_model)
```

```
744.6016576596794
```

```
time_iterated
```

```
4.218470096588135
```

As a quick sanity check, we visualize the optimal tour to verify that no subtour is present:

```

function plot_tour(X, Y, x)
    plot = Plots.plot()
    for (i, j) in selected_edges(x, size(x, 1))
        Plots.plot!([X[i], X[j]], [Y[i], Y[j]]; legend = false)
    end
end

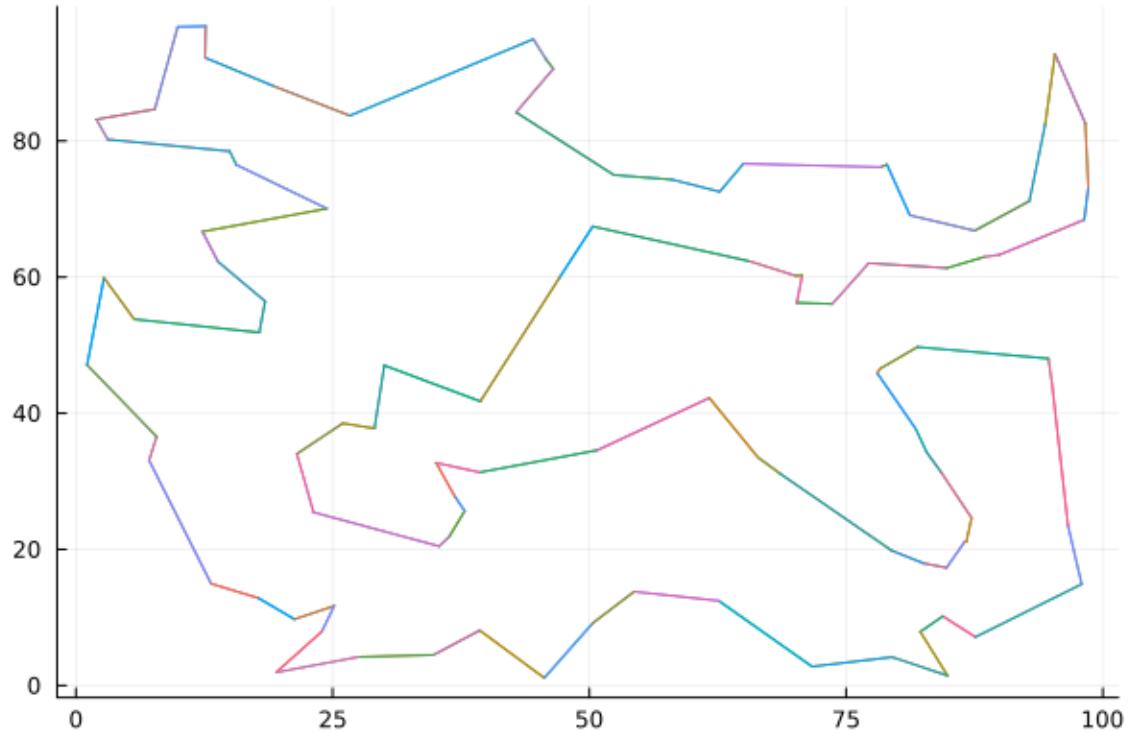
```

```

    return plot
end

plot_tour(X, Y, value.(iterative_model[:x]))

```



### Lazy constraint method

A more sophisticated approach makes use of *lazy constraints*. To be more precise, we do this through the `subtour_elimination_callback()` below, which is only run whenever we encounter a new integer-feasible solution.

#### Tip

We use Gurobi for this model because HiGHS does not support lazy constraints. For more information on callbacks, read the page [Solver-independent callbacks](#).

As before, we construct the same first-stage subproblem:

```

lazy_model = build_tsp_model(d, n, optimizer)
function subtour_elimination_callback(cb_data)
    status = callback_node_status(cb_data, lazy_model)
    if status != MOI.CALLBACK_NODE_STATUS_INTEGER
        return # Only run at integer solutions
    end
    cycle = subtour(callback_value.(cb_data, lazy_model[:x]))
    if !(1 < length(cycle) < n)

```

```
        return # Only add a constraint if there is a cycle
    end
    S = [(i, j) for (i, j) in Iterators.product(cycle, cycle) if i < j]
    con = @build_constraint(
        sum(lazy_model[:x][i, j] for (i, j) in S) <= length(cycle) - 1,
    )
    MOI.submit(lazy_model, MOI.LazyConstraint(cb_data), con)
    return
end
set_attribute(
    lazy_model,
    MOI.LazyConstraintCallback(),
    subtour_elimination_callback,
)
optimize!(lazy_model)
assert_is_solved_and_feasible(lazy_model)
objective_value(lazy_model)
```

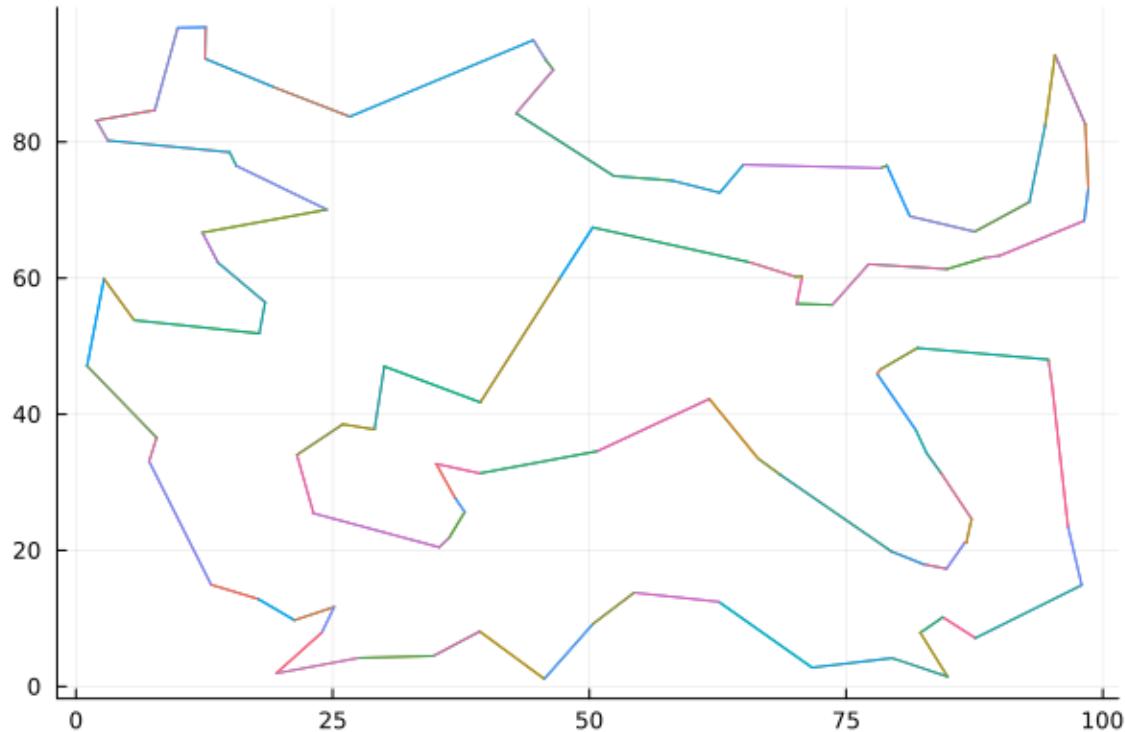
```
744.6016576596794
```

```
time_lazy = solve_time(lazy_model)
```

```
2.0749521255493164
```

This finds the same optimal tour:

```
plot_tour(X, Y, value.(lazy_model[:x]))
```



The solution time is faster than the iterative approach:

```
Test.@test time_lazy < time_iterated
```

Test Passed

## 9.4 Rolling horizon problems

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

**This tutorial was originally contributed by Diego Tejada.**

The purpose of this tutorial is to demonstrate how to use [ParametricOptInterface.jl](#) to solve a rolling horizon optimization problem.

The term "rolling horizon" refers to solving a time-dependent model repeatedly, where the planning interval is shifted forward in time during each solution step.

As a motivating example, this tutorial models the operations of a power system with solar generation and a battery.

### Required packages

This tutorial uses the following packages

```
using JuMP
import CSV
import DataFrames
import HiGHS
import ParametricOptInterface as POI
import Plots
```

### The optimization model

The model is a simplified model of a power system's operations with battery storage.

We model the system of a set of time-steps  $t \in 1, \dots, T$ , where each time step is a period of one hour.

There are five types of decision variables in the model:

- Renewable production:  $r_t \geq 0$
- Thermal production:  $0 \leq p_t \leq \bar{P}$
- Storage level:  $0 \leq s_t \leq \bar{S}$
- Storage charging:  $0 \leq c_t \leq \bar{C}$
- Storage discharging:  $0 \leq d_t \leq \bar{D}$

For the purpose of this tutorial, there are three parameters of interest:

- Demand at time  $t$ :  $D_t$
- Renewable availability at time  $t$ :  $A_t$
- Initial storage:  $S_0$

The objective function to minimize is the total cost of thermal generation:

$$\min \sum_t O \cdot p_t$$

For the constraints, we must balance power generation and consumption in all time periods:

$$p_t + r_t + d_t = D_t + c_t, \forall t$$

We need to account for the dynamics of the battery storage:

$$s_t = s_{t-1} + \eta^c \cdot c_t - \frac{d_t}{\eta^d}, \forall t$$

with the boundary condition that  $s_0 = S_0$ .

Finally, the level of renewable energy production is limited by the quantity of potential solar generation  $A$ :

$$r_t \leq A_t, \quad \forall t$$

Solving this problem with a large number of time steps is computationally challenging. A common practice is to use the rolling horizon idea to solve multiple identical problems of a smaller size. These problems differ only in parameters such as demand, renewable availability, and initial storage. By combining the solution of many smaller problems, we can recover a feasible solution to the full problem. However, because we don't optimize the full set of decisions in a single optimization problem, the recovered solution might be suboptimal.

### Parameter definition and input data

There are two main parameters for a rolling horizon implementation: the optimization window and the move forward.

**Optimization Window:** this value defines how many periods (for example, hours) we will optimize each time. For this example, we set the default value to 48 hours, meaning we will optimize two days each time.

```
optimization_window = 48;
```

**Move Forward:** this value defines how many periods (for example, hours) we will move forward to optimize the next optimization window. For this example, we set the default value in 24 hours, meaning we will move one day ahead each time.

```
move_forward = 24;
```

Note that the move forward parameter must be lower or equal to the optimization window parameter to work correctly.

```
@assert optimization_window >= move_forward
```

Let's explore the input data in file `rolling_horizon.csv`. We have a total time horizon of a week (that is, 168 hours), an electricity demand, and a solar production profile.

```
filename = joinpath(@__DIR__, "rolling_horizon.csv")
time_series = CSV.read(filename, DataFrames.DataFrame)
time_series[1:21:end, :]
```

We define the solar investment (for example, 150 MW) to determine the solar production during the operation optimization step.

```
solar_investment = 150;
```

We multiply the level of solar investment by the time series of availability to get actual MW generated.

	day	hour	demand_MW	solar_pu
	Int64	Int64	Float64	Float64
1	1	0	51.6	0.0
2	1	21	59.0	0.0
3	2	18	80.7	0.0
4	3	15	69.5	0.00966184
5	4	12	65.9	0.78744
6	5	9	83.8	0.628019
7	6	6	67.4	0.0
8	7	3	57.5	0.0

```
time_series.solar_MW = solar_investment * time_series.solar_pu;
```

In addition, we can determine some basic information about the rolling horizon, such as the number of data points we have:

```
total_time_length = size(time_series, 1)
```

168

and the number of windows that we are going to optimize given the problem's time horizon:

```
(total_time_length + move_forward - optimization_window) / move_forward
```

6.0

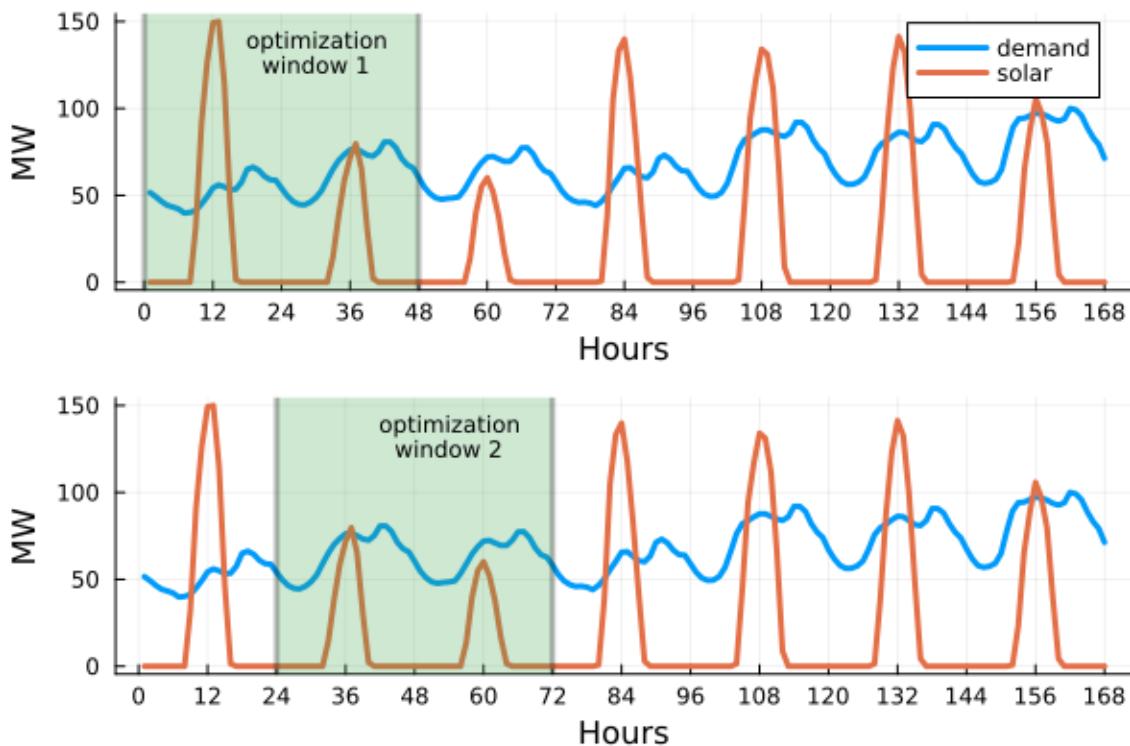
Finally, we can see a plot representing the first two optimization windows and the move forward parameter to have a better idea of how the rolling horizon works.

```
x_series = 1:total_time_length
y_series = [time_series.demand_MW, time_series.solar_MW]
plot_1 = Plots.plot(x_series, y_series; label = ["demand" "solar"])
plot_2 = Plots.plot(x_series, y_series; label = false)
window = [0, optimization_window]
Plots.vspan!(plot_1, window; alpha = 0.25, label = false)
Plots.vspan!(plot_2, move_forward .+ window; alpha = 0.25, label = false)
text_1 = Plots.text("optimization\n window 1", :top, :left, 8)
Plots.annotate!(plot_1, 18, time_series.solar_MW[12], text_1)
text_2 = Plots.text("optimization\n window 2", :top, :left, 8)
Plots.annotate!(plot_2, 42, time_series.solar_MW[12], text_2)
Plots.plot(
    plot_1,
    plot_2;
    layout = (2, 1),
    linewidth = 3,
```

```

    xticks = 0:12:total_time_length,
    xlabel = "Hours",
    ylabel = "MW",
)

```



### JuMP model

We have all the information we need to create a JuMP model to solve a single window of our rolling horizon problem.

As the optimizer, we use `POI.Optimizer`, which is part of `ParametricOptInterface.jl`. `POI.Optimizer` converts the `Parameter` decision variables into constants in the underlying optimization model, and it efficiently updates the solver in-place when we call `set_parameter_value` which avoids having to rebuild the problem each time we call `optimize!`.

```

model = Model(() -> POI.Optimizer(HiGHS.Optimizer()))
set_silent(model)
@variables(model, begin
    0 <= r[1:optimization_window]
    0 <= p[1:optimization_window] <= 150
    0 <= s[1:optimization_window] <= 40
    0 <= c[1:optimization_window] <= 10
    0 <= d[1:optimization_window] <= 10
    # Initialize empty parameters. These values will get updated later
    D[t in 1:optimization_window] in Parameter(0)
    A[t in 1:optimization_window] in Parameter(0)
)

```

```

S_0 in Parameter(0)
end)
@objective(model, Min, 50 * sum(p))
@constraints(
    model,
    begin
        p .+ r .+ d .== D .+ c
        s[1] == S_0 + 0.9 * c[1] - d[1] / 0.9
        [t in 2:optimization_window], s[t] == s[t-1] + 0.9 * c[t] - d[t] / 0.9
        r .<= A
    end
)
model

```

```

A JuMP Model
├ solver: Parametric Optimizer with HiGHS attached
├ objective_sense: MIN_SENSE
|└ objective_function_type: AffExpr
├ num_variables: 337
├ num_constraints: 673
|└ AffExpr in MOI.EqualTo{Float64}: 96
|└ AffExpr in MOI.LessThan{Float64}: 48
|└ VariableRef in MOI.GreaterThan{Float64}: 240
|└ VariableRef in MOI.LessThan{Float64}: 192
|└ VariableRef in MOI.Parameter{Float64}: 97
└ Names registered in the model
  └ :A, :D, :S_0, :c, :d, :p, :r, :s

```

After the optimization, we can store the results in vectors. It's important to note that despite optimizing for 48 hours (the default value), we only store the values for the "move forward" parameter (for example, 24 hours or one day using the default value). This approach ensures that there is a buffer of additional periods or hours beyond the "move forward" parameter to prevent the storage from depleting entirely at the end of the specified hours.

```

sol_complete = Dict(
    :r => zeros(total_time_length),
    :p => zeros(total_time_length),
    :c => zeros(total_time_length),
    :d => zeros(total_time_length),
    # The storage level is initialized with an initial value
    :s => zeros(total_time_length + 1),
)
sol_windows = Pair{Int,Dict{Symbol,Vector{Float64}}}[]

```

```
Pair{Int64, Dict{Symbol, Vector{Float64}}}[]
```

Now we can iterate across the windows of our rolling horizon problem, and at each window, we:

1. update the parameters in the models

2. solve the model for that window
3. store the results for later analysis

```

offsets = 0:move_forward:total_time_length-optimization_window
for offset in offsets
    # Step 1: update the parameter values over the optimization_window
    for t in 1:optimization_window
        set_parameter_value(model[:D][t], time_series[offset+t, :demand_MW])
        set_parameter_value(model[:A][t], time_series[offset+t, :solar_MW])
    end
    # Set the starting storage level as the value from the end of the previous
    # solve. The '+1' accounts for the initial storage value in time step "t=0"
    set_parameter_value(model[:S_0], sol_complete[:s][offset+1])
    # Step 2: solve the model
    optimize!(model)
    # Step 3: store the results of the move_forward values, except in the last
    #          horizon where we store the full `optimization_window`.
    for t in 1:(offset == last(offsets) ? optimization_window : move_forward)
        for key in (:r, :p, :c, :d)
            sol_complete[key][offset+t] = value(model[key][t])
        end
        sol_complete[:s][offset+t+1] = value(model[:s][t])
    end
    sol_window = Dict(key => value.(model[key])) for key in (:r, :p, :s, :c, :d)
    push!(sol_windows, offset => sol_window)
end

```

## Solution

Here is a function to plot the solution at each of the time-steps to help visualize the rolling horizon scheme:

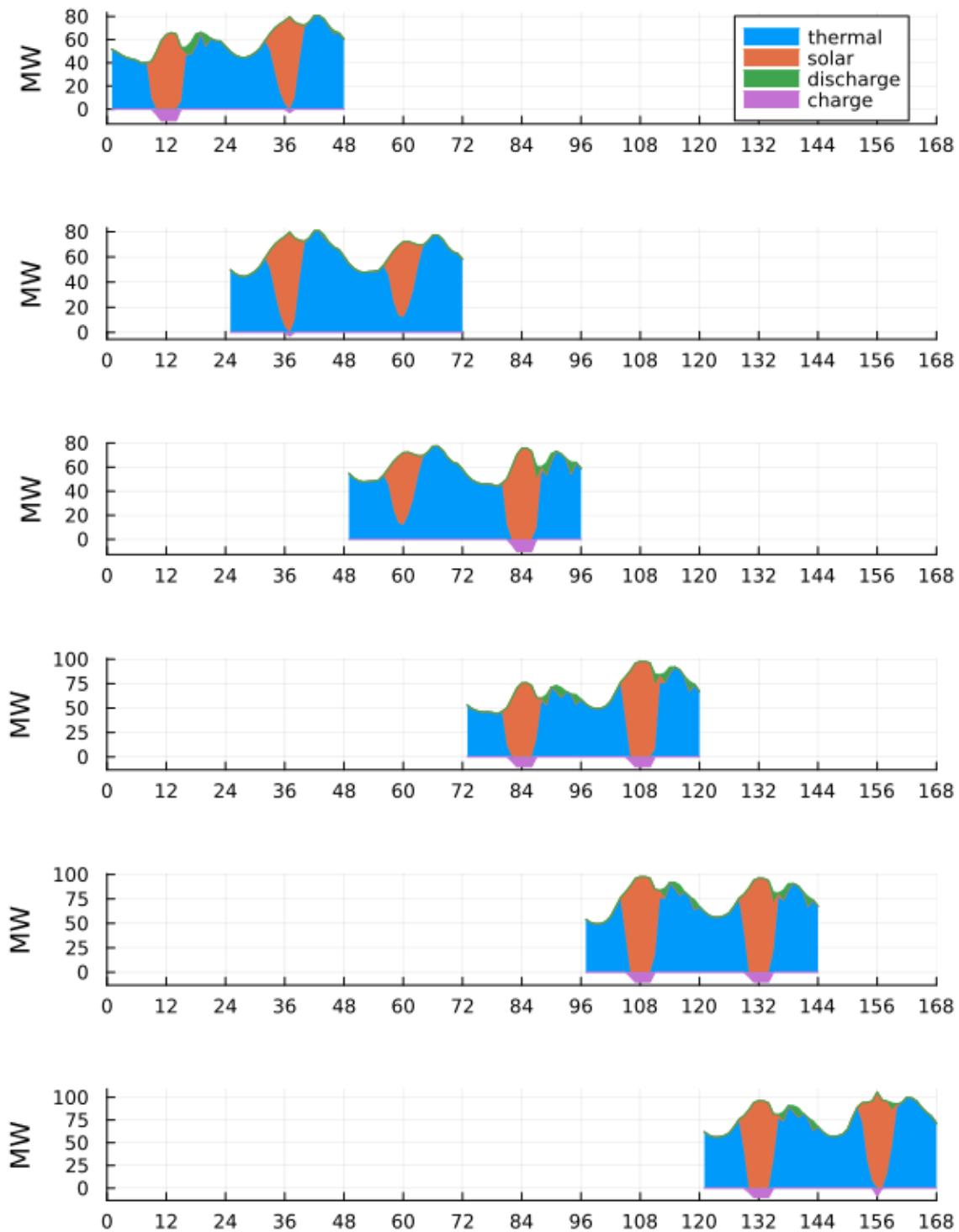
```

function plot_solution(sol; offset = 0, kwargs...)
    plot = Plots.plot();
    ylabel = "MW",
    xlims = (0, total_time_length),
    xticks = 0:12:total_time_length,
    kwargs...,
)
y = hcat(sol[:p], sol[:r], sol[:d])
x = offset .+ (1:size(y, 1))
if offset == 0
    Plots.areaplot!(x, y; label = ["thermal" "solar" "discharge"])
    Plots.areaplot!(x, -sol[:c]; label = "charge")
else
    Plots.areaplot!(x, y; label = false)
    Plots.areaplot!(x, -sol[:c]; label = false)
end
return plot
end

Plots.plot(
    [plot_solution(sol; offset) for (offset, sol) in sol_windows]...
)

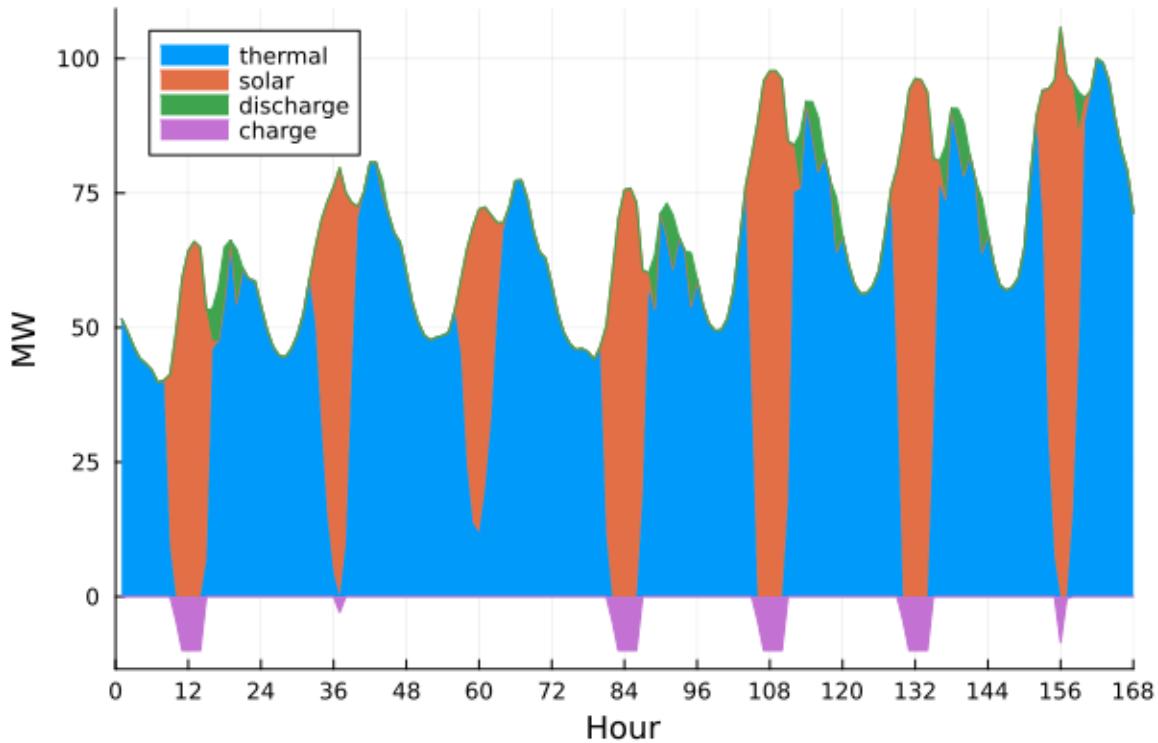
```

```
layout = (length(sol_windows), 1),
size = (600, 800),
margin = 3Plots.mm,
)
```



We can re-use the function to plot the recovered solution of the full problem:

```
plot_solution(sol_complete; offset = 0, xlabel = "Hour")
```



### Final remark

[ParametricOptInterface.jl](#) offers an easy way to update the parameters of an optimization problem that will be solved several times, as in the rolling horizon implementation. It has the benefit of avoiding rebuilding the model each time we want to solve it with new information in a new window.

## 9.5 Parallelism

The purpose of this tutorial is to give a brief overview of parallelism in Julia as it pertains to JuMP, and to explain some of the things to be aware of when writing parallel algorithms involving JuMP models.

### Overview

There are two main types of parallelism in Julia:

1. Multi-threading
2. Distributed computing

In multi-threading, multiple tasks are run in a single Julia process and share the same memory. In distributed computing, tasks are run in multiple Julia processes with independent memory spaces. This can include processes across multiple physical machines, such as in a high-performance computing cluster.

Choosing and understanding the type of parallelism you are using is important because the code you write for each type is different, and there are different limitations and benefits to each approach. However, the best choice is highly problem dependent, so you may want to experiment with both approaches to determine what works for your situation.

### Multi-threading

To use multi-threading with Julia, you must either start Julia with the command line flag `--threads=N`, or you must set the `JULIA_NUM_THREADS` environment variable before launching Julia. For this documentation, we set the environment variable to:

```
julia> ENV["JULIA_NUM_THREADS"]
"4"
```

You can check how many threads are available using:

```
julia> Threads.threads()
4
```

The easiest way to use multi-threading in Julia is by placing the `Threads.@threads` macro in front of a `for`-loop:

```
julia> @time begin
           ids = Int[]
           my_lock = Threads.ReentrantLock()
           Threads.@threads for i in 1:Threads.threads()
               global ids, my_lock
               Threads.lock(my_lock) do
                   push!(ids, Threads.threadid())
               end
               sleep(1.0)
           end
       end
1.037087 seconds (31.32 k allocations: 1.836 MiB, 2.02% compilation time)
```

This `for`-loop sleeps for 1 second on each iteration. Thus, if it had executed sequentially, it should have taken the same number of seconds as there are threads available. Instead, it took only 1 second, showing that the iterations were executed simultaneously. We can verify this by checking the `Threads.threadid()` of the thread that executed each iteration:

```
julia> ids
4-element Vector{Int64}:
 2
 4
 1
 3
```

**Danger**

The `Threads.threadid()` that a task runs on may change during execution. Therefore, it is not safe to use `Threads.threadid()` to index into, say, a vector of buffer or stateful objects. As an example, do not do:

```
x = rand(Threads.nthreads())
Threads.@threads for i in 1:Threads.nthreads()
    x[Threads.threadid()] *= 2 # Danger! This use of threadid is not safe
end
```

For more information, read [PSA: Thread-local state is no longer recommended](#).

**Thread safety**

When working with threads, you must avoid race conditions, in which two threads attempt to write to the same variable at the same time. In the above example we avoided a race condition by using `ReentrantLock`. See the [Multi-threading](#) section of the Julia documentation for more details.

JuMP models are not thread-safe. Code that uses multi-threading to simultaneously modify or optimize a single JuMP model across threads may error, crash Julia, or silently produce incorrect results.

For example, the following incorrect use of multi-threading crashes Julia:

```
julia> using JuMP, HiGHS

julia> function an_incorrect_way_to_use_threading()
           model = Model(HiGHS.Optimizer)
           set_silent(model)
           @variable(model, x)
           Threads.@threads for i in 1:10
               optimize!(model)
           end
           return
       end
an_incorrect_way_to_use_threading (generic function with 1 method)

julia> an_incorrect_way_to_use_threading()
julia(76918,0x16c92f000) malloc: *** error for object 0x600003e52220: pointer being freed was not
→ allocated
zsh: abort      julia -t 4
```

To avoid issues with thread safety, create a new instance of a JuMP model in each iteration of the for-loop. In addition, you must avoid race conditions in the rest of your Julia code, for example, by using a lock when pushing elements to a shared vector.

**Example: parameter search with multi-threading**

Here is an example of how to use multi-threading to solve a collection of JuMP models in parallel.

```
julia> using JuMP, HiGHS
```

```
julia> function a_good_way_to_use_threading()
           solutions = Pair{Int,Float64}[]
           my_lock = Threads.ReentrantLock();
           Threads.@threads for i in 1:10
               model = Model(HiGHS.Optimizer)
               set_silent(model)
               set_attribute(model, MOI.NumberOfThreads(), 1)
               @variable(model, x >= i)
               @objective(model, Min, x)
               optimize!(model)
               assert_is_solved_and_feasible(model)
               Threads.lock(my_lock) do
                   push!(solutions, i => objective_value(model))
               end
           end
           return solutions
       end
a_good_way_to_use_threading (generic function with 1 method)

julia> a_good_way_to_use_threading()
10-element Vector{Pair{Int64, Float64}}:
 7 => 7.0
 9 => 9.0
 4 => 4.0
 1 => 1.0
 5 => 5.0
 2 => 2.0
 8 => 8.0
 10 => 10.0
 3 => 3.0
 6 => 6.0
```

**Warning**

For some solvers, it may be necessary to limit the number of threads used internally by the solver to 1 by setting the `MOI.NumberOfThreads` attribute.

**Example: building data structures in parallel**

For large problems, building the model in JuMP can be a bottleneck, and you may consider trying to write code that builds the model in parallel, for example, by wrapping a `for`-loop that adds constraints with `Threads.@threads`. Here's an example:

```
julia> using JuMP

julia> function an_incorrect_way_to_build_with_multithreading()
           model = Model()
           @variable(model, x[1:10])
           Threads.@threads for i in 1:10
               @constraint(model, x[i] <= i)
           end
           return model
       end
```

```
julia> an_incorrect_way_to_build_with_multithreading()
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 10
├ num_constraints: 7
|└ AffExpr in MOI.LessThan{Float64}: 7
└ Names registered in the model
  └ :x
```

Unfortunately, this model is wrong. It has only seven constraints instead of the expected ten. This happens because JuMP models are not thread-safe. Code that uses multi-threading to simultaneously modify or optimize a single JuMP model across threads may error, crash Julia, or silently produce incorrect results.

The correct way to build a JuMP model with multi-threading is to build the data structures in parallel, but add them to the JuMP model in a thread-safe way:

```
julia> using JuMP

julia> function a_correct_way_to_build_with_multithreading()
    model = Model()
    @variable(model, x[1:10])
    my_lock = Threads.ReentrantLock()
    Threads.@threads for i in 1:10
        con = @build_constraint(x[i] <= i)
        Threads.lock(my_lock) do
            add_constraint(model, con)
        end
    end
    return model
end

julia> a_correct_way_to_build_with_multithreading()
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 10
├ num_constraints: 10
|└ AffExpr in MOI.LessThan{Float64}: 10
└ Names registered in the model
  └ :x
```

### Warning

**Do not use multi-threading to build a JuMP model just because your original code is slow.** In most cases, we find that the reason for the bottleneck is not JuMP, but in how you are constructing the problem data, and that with changes, it is possible to build a model in a way that is not the bottleneck in the solution process. If you need help to make your code run faster, ask for help on the [community forum](#). Make sure to include a reproducible example of your code.

## Distributed computing

To use distributed computing with Julia, use the `Distributed` package:

```
julia> import Distributed
```

Like multi-threading, we need to tell Julia how many processes to add. We can do this either by starting Julia with the `-p N` command line argument, or by using `Distributed.addprocs`:

```
julia> import Pkg

julia> project = Pkg.project();

julia> workers = Distributed.addprocs(4; exeflags = "--project=$(project.path)")
4-element Vector{Int64}:
 2
 3
 4
 5
```

### Warning

Not loading the parent environment with `--project` is a common mistake.

The added processes are "worker" processes that we can use to do computation with. They are orchestrated by the process with the id 1. You can check what process the code is currently running on using `Distributed.myid()`

```
julia> Distributed.myid()
1
```

As a general rule, to get maximum performance you should add as many processes as you have logical cores available.

Unlike the `for`-loop approach of multi-threading, distributed computing extends the Julia `map` function to a "parallel-map" function `Distributed.pmap`. For each element in the list of arguments to map over, Julia will copy the element to an idle worker process and evaluate the function, passing the element as an input argument.

```
julia> function hard_work(i::Int)
           sleep(1.0)
           return Distributed.myid()
       end
hard_work (generic function with 1 method)

julia> Distributed.pmap(hard_work, 1:4)
ERROR: On worker 2:
UndefVarError: #hard_work not defined
Stacktrace:
[...]
```

Unfortunately, if you try this code directly, you will get an error message that says `On worker 2: UndefVarError: hard_work not defined`. The error is thrown because, although process 1 knows what the `hard_work` function is, the worker processes do not.

To fix the error, we need to use `Distributed.@everywhere`, which evaluates the code on every process:

```
julia> Distributed.@everywhere begin
    function hard_work(i::Int)
        sleep(1.0)
        return Distributed.myid()
    end
end
```

Now if we run `pmap`, we see that it took only 1 second instead of 4, and that it executed on each of the worker processes:

```
julia> @time ids = Distributed.pmap(hard_work, 1:4)
  1.202006 seconds (216.39 k allocations: 13.301 MiB, 4.07% compilation time)
4-element Vector{Int64}:
 2
 3
 5
 4
```

### Tip

For more information, read the Julia documentation [Distributed Computing](#).

### Example: parameter search with distributed computing

With distributed computing, remember to evaluate all of the code on all of the processes using `Distributed.@everywhere`, and then write a function which creates a new instance of the model on every evaluation:

```
julia> Distributed.@everywhere begin
    using JuMP
    import HiGHS
end

julia> Distributed.@everywhere begin
    function solve_model_with_right_hand_side(i)
        model = Model(HiGHS.Optimizer)
        set_silent(model)
        @variable(model, x)
        @objective(model, Min, x)
        set_lower_bound(x, i)
        optimize!(model)
        assert_is_solved_and_feasible(sudoku)
        return objective_value(model)
    end
end

julia> solutions = Distributed.pmap(solve_model_with_right_hand_side, 1:10)
```

```
10-element Vector{Float64}:
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
```

### Parallelism within the solver

Many solvers use parallelism internally. For example, commercial solvers like [Gurobi.jl](#) and [CPLEX.jl](#) both parallelize the search in branch-and-bound.

Solvers supporting internal parallelism will typically support the `MOI.NumberOfThreads` attribute, which you can set using `set_attribute`:

```
using JuMP, Gurobi
model = Model(Gurobi.Optimizer)
set_attribute(model, MOI.NumberOfThreads(), 4)
```

### GPU parallelism

JuMP does not support GPU programming, but some solvers support execution on a GPU.

One example is [SCS.jl](#), which supports using a GPU to internally solve a system of linear equations. If you are on x86\_64 Linux machine, do:

```
using JuMP, SCS, SCS_GPU_jll
model = Model(SCS.Optimizer)
set_attribute(model, "linear_solver", SCS.GpuIndirectSolver)
```

## 9.6 Writing a solver interface

*This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.*

The purpose of this tutorial is to demonstrate how to implement a basic solver interface to MathOptInterface. As a motivating example, we implement the Primal Dual Hybrid Gradient (PDHG) method. PDHG is a first-order method that can solve convex optimization problems.

Google has a [good introduction to the math behind PDLP](#), which is a variant of PDHG specialized for linear programs.

### Required packages

This tutorial requires the following packages:

```
using JuMP
import LinearAlgebra
import MathOptInterface as MOI
import Printf
import SparseArrays
```

### Primal Dual Hybrid Gradient

The following function is a pedagogical implementation of PDHG that solves the linear program:

$$\begin{aligned} & \min c^\top x \\ & \text{subject to } Ax = b \\ & \quad x \geq 0. \end{aligned}$$

Note that this implementation is intentionally kept simple. It is not robust nor efficient, and it does not incorporate the theoretical improvements in the PDHG paper. It does use two workspace vectors so that the body of the iteration loop is non-allocating.

```
function solve_pdhg(
    A::SparseArrays.SparseMatrixCSC{Float64,Int},
    b::Vector{Float64},
    c::Vector{Float64};
    maximum_iterations::Int = 100_000,
    tol::Float64 = 1e-4,
    verbose::Bool = true,
    log_frequency::Int = 1_000,
)
    printf(x::Float64) = Printf.@sprintf("% 1.6e", x)
    printf(x::Int) = Printf.@sprintf("%6d", x)
    m, n = size(A)
    η = τ = 1 / LinearAlgebra.norm(A) - 1e-6
    x, x_next, y, k, status = zeros(n), zeros(n), zeros(m), 0, MOI.OTHER_ERROR
    m_workspace, n_workspace = zeros(m), zeros(n)
    if verbose
        println(
            " iter      pobj      dobj      pfeas      dfeas      objfeas",
        )
    end
    while status == MOI.OTHER_ERROR
        k += 1
        # =====#
        # This block computes x_next = max.(0.0, x - η * (A' * y + c))
        LinearAlgebra.mul!(x_next, A', y)
        LinearAlgebra.axpby!(-η, c, -η, x_next)
        x_next .+= x
        x_next .= max.(0.0, x_next)
        # =====#
        # This block computes y += τ * (A * (2 * x_next - x) - b)
        copy!(n_workspace, x_next)
        LinearAlgebra.axpby!(-1.0, x, 2.0, n_workspace)
        LinearAlgebra.mul!(y, A, n_workspace, τ, 1.0)
    end
end
```

```

LinearAlgebra.axpy!(-τ, b, y)
# =====
copy!(x, x_next)
# =====
# This block computes pfeas = LinearAlgebra.norm(A * x - b)
LinearAlgebra.mul!(m_workspace, A, x)
m_workspace .-= b
pfeas = LinearAlgebra.norm(m_workspace)
# =====
# This block computes dfeas = LinearAlgebra.norm(min.(0.0, A' * y + c))
LinearAlgebra.mul!(n_workspace, A', y)
n_workspace .+= c
n_workspace .= min.(0.0, n_workspace)
dfeas = LinearAlgebra.norm(n_workspace)
# =====
objfeas = abs(LinearAlgebra.dot(c, x) + LinearAlgebra.dot(b, y))
if pfeas <= tol && dfeas <= tol && objfeas <= tol
    status = MOI.OPTIMAL
elseif k == maximum_iterations
    status = MOI.ITERATION_LIMIT
end
if verbose && (mod(k, log_frequency) == 0 || status != MOI.OTHER_ERROR)
    logs = printf.((k, c' * x, -b' * y, pfeas, dfeas, objfeas))
    println(join(logs, " "))
end
end
return status, k, x, y
end

```

solve\_pdhg (generic function with 1 method)

Here's an example:

```

A = [0.0 -1.0 -1.0 0.0 0.0; 6.0 8.0 0.0 -1.0 0.0; 7.0 12.0 0.0 0.0 -1.0]
b = [-3.0, 100.0, 120.0]
c = [12.0, 20.0, 0.0, 0.0, 0.0]
status, k, x, y = solve_pdhg(SparseArrays.sparse(A), b, c);

```

iter	pobj	dobj	pfeas	dfeas	objfeas
1000	2.050187e+02	2.044002e+02	2.006420e-01	2.674295e-02	6.185366e-01
2000	2.049895e+02	2.051241e+02	1.705136e-02	2.746207e-02	1.346232e-01
3000	2.050050e+02	2.050805e+02	8.907061e-03	8.405470e-03	7.550812e-02
4000	2.050024e+02	2.049755e+02	4.046623e-03	9.374982e-04	2.689079e-02
5000	2.049995e+02	2.049831e+02	8.635908e-04	6.483234e-04	1.633722e-02
6000	2.049995e+02	2.050016e+02	7.833794e-04	1.676266e-04	2.095135e-03
7000	2.050000e+02	2.050030e+02	2.811341e-05	3.065459e-04	2.964863e-03
8000	2.050001e+02	2.050002e+02	1.316682e-04	1.674879e-05	8.453982e-05
8365	2.049999e+02	2.050000e+02	9.473351e-05	2.381905e-06	7.955573e-05

The termination status is:

```
status
```

```
OPTIMAL::TerminationStatusCode = 1
```

The solve took the following number of iterations:

```
k
```

```
8365
```

The primal solution is:

```
x
```

```
5-element Vector{Float64}:
15.000070735249105
1.2499547393201815
1.750098059200116
0.0
0.0
```

The dual multipliers are:

```
y
```

```
3-element Vector{Float64}:
1.931930909998547e-6
-0.2500022801722057
-1.4999982446009117
```

## The MOI interface

Converting a linear program from the modeler's form into the A, b, and c matrices of the standard form required by our implementation of PDHG is tedious and error-prone. This section walks through how to implement a basic interface to MathOptInterface, so that we can use our algorithm from JuMP.

For a more comprehensive guide, see [Implementing a solver interface](#).

### The Optimizer type

Create an optimizer by subtyping `MOI.AbstractOptimizer`. By convention, the name of this type is `Optimizer`, and most optimizers are available as `PackageName.Optimizer`.

The fields inside the optimizer are arbitrary. Store whatever is useful.

```
"""
Optimizer()

Create a new optimizer for PDHG.

mutable struct Optimizer <: MOI.AbstractOptimizer
    # A mapping from variable to column
    x_to_col::Dict{MOI.VariableIndex,Int}
    # A mapping from constraint to rows
    ci_to_rows::Dict{
        MOI.ConstraintIndex{MOI.VectorAffineFunction{Float64},MOI.Zeros},
        Vector{Int}},
    }
    # Information from solve_pdhg
    status::MOI.TerminationStatusCode
    iterations::Int
    x::Vector{Float64}
    y::Vector{Float64}
    # Other useful quantities
    solve_time::Float64
    obj_value::Float64

    function Optimizer()
        F = MOI.VectorAffineFunction{Float64}
        return new(
            Dict{MOI.VariableIndex,Int}(),
            Dict{MOI.ConstraintIndex{F,MOI.Zeros},Vector{Int}}(),
            MOI.OPTIMIZE_NOT_CALLED,
            0,
            Float64[],
            Float64[],
            0.0,
            0.0,
        )
    end
end
"""

Main.Optimizer
```

Now that we have an `Optimizer`, we need to implement two methods: `MOI.is_empty` and `MOI.empty!`. These are called whenever MOI needs to ensure that the optimizer is in a clean state.

```
function MOI.is_empty(model::Optimizer)
    # You might want to check every field, not just a few
    return isempty(model.x_to_col) && model.status == MOI.OPTIMIZE_NOT_CALLED
end
```

```

function MOI.empty!(model::Optimizer)
    empty!(model.x_to_col)
    empty!(model.ci_to_rows)
    model.status = MOI.OPTIMIZE_NOT_CALLED
    model.iterations = 0
    model.solve_time = 0.0
    model.obj_value = 0.0
    empty!(model.x)
    empty!(model.y)
    return
end

```

Next, we need to define what constraints the optimizer supports. Since our standard form was  $Ax = b$ , we support only  $Ax + b \in \{0\}$ , which is a `MOI.VectorAffineFunction` in `MOI.Zeros` constraint. Note that you might have expected  $Ax - b \in \{0\}$ . We'll address the difference in the sign of  $b$  in a few places later on.

```

function MOI.supports_constraint(
    ::Optimizer,
    ::Type{MOI.VectorAffineFunction{Float64}},
    ::Type{MOI.Zeros},
)
    return true
end

```

By default, MOI assumes that it can add free variables. This isn't true for our standard form, because we support only  $x \geq 0$ . Let's tell MOI that:

```

MOI.supports_add_constrained_variables(::Optimizer, ::Type{MOI.Reals}) = false

function MOI.supports_add_constrained_variables(
    ::Optimizer,
    ::Type{MOI.Nonnegatives},
)
    return true
end

```

The objective function that we support is `MOI.ScalarAffineFunction`:

```

function MOI.supports(
    ::Optimizer,
    ::MOI.ObjectiveFunction{MOI.ScalarAffineFunction{Float64}},
)
    return true
end

```

Finally, we'll implement `MOI.SolverName` so that MOI knows how to print the name of our optimizer:

```

MOI.get(::Optimizer, ::MOI.SolverName) = "PDHG"

```

### GenericModel

The simplest way to solve a problem with your optimizer is to implement the method `MOI.optimize!(dest::Optimizer, src::MOI.ModelLike)`, where `src` is an input model and `dest` is your empty optimizer.

To implement this method you would need to query the variables and constraints in `src` and then convert these into the matrix data expected by `solve_pdhg`. Since matrix input is a common requirement of solvers, MOI includes utilities to simplify the process.

The downside of the utilities is that they involve a highly parameterized type with a large number of possible configurations. The upside of the utilities is that, once setup, they require few lines of code to extract the problem matrices.

First, we need to define the set of sets that our standard form supports. For PDHG, we support only  $Ax + b$  in  $\{0\}$ :

```
MOI.Utilities.@product_of_sets(SetOfZeros, MOI.Zeros)
```

Then, we define a `MOI.Utilities.GenericModel`. This is the highly parameterized type that can be customized.

```
const CacheModel = MOI.Utilities.GenericModel{
    # The coefficient type is Float64
    Float64,
    # We use the default objective container
    MOI.Utilities.ObjectiveContainer{Float64},
    # We use the default variable container
    MOI.Utilities.VariablesContainer{Float64},
    # We use a Matrix of Constraints to represent `A * x + b` in K
    MOI.Utilities.MatrixOfConstraints{
        # The number type is Float64
        Float64,
        # The matrix type `A` is a sparse matrix
        MOI.Utilities.MutableSparseMatrixCSC{
            # ... with Float64 coefficients
            Float64,
            # ... Int64 row and column indices
            Int,
            # ... and it uses one-based indexing
            MOI.Utilities.OneBasedIndexing,
        },
        # The vector type `b` is a Julia `Vector`
        Vector{Float64},
        # The set type `K` is the SetOfZeros type we defined above
        SetOfZeros{Float64},
    },
}
```

```
MathOptInterface.Utilities.GenericModel{Float64,
    ↳ MathOptInterface.Utilities.ObjectiveContainer{Float64},
    ↳ MathOptInterface.Utilities.VariablesContainer{Float64},
    ↳ MathOptInterface.Utilities.MatrixOfConstraints{Float64},
    ↳ MathOptInterface.Utilities.MutableSparseMatrixCSC{Float64, Int64},
    ↳ MathOptInterface.Utilities.OneBasedIndexing}, Vector{Float64}, Main.SetOfZeros{Float64}}}
```

As one example of possible alternate configuration, if you were interfacing with a solver written in C that expected zero-based indices, you might use instead:

```
MOI.Utilities.MutableSparseMatrixCSC{
    Cdouble,
    Cint,
    MOI.Utilities.ZeroBasedIndexing,
}
```

```
MathOptInterface.Utilities.MutableSparseMatrixCSC{Float64, Int32,
↪ MathOptInterface.Utilities.ZeroBasedIndexing}
```

### Tip

The best place to look at how to configure GenericModel is to find an existing solver with the same input standard form that you require.

We need to make one modification to CacheModel to tell MOI that  $x \in \mathbb{R}_+$  is equivalent to adding variables in `MOI.GreaterThan`:

```
function MOI.add_constrained_variables(model::CacheModel, set::MOI.Nonnegatives)
    x = MOI.add_variables(model, MOI.dimension(set))
    MOI.add_constraint.(model, x, MOI.GreaterThan(0.0))
    ci = MOI.ConstraintIndex{MOI.VectorOfVariables, MOI.Nonnegatives}(x[1].value)
    return x, ci
end
```

### The optimize method

Now we define the most important method for our optimizer.

```
function MOI.optimize!(dest::Optimizer, src::MOI.ModelLike)
    # In addition to the values returned by `solve_pdhg`, it may be useful to
    # record other attributes, such as the solve time.
    start_time = time()
    # Construct a cache to store our problem data:
    cache = CacheModel()
    # MOI includes a utility to copy an arbitrary `src` model into `cache`. The
    # return, `index_map`, is a mapping from indices in `src` to indices in
    # `dest`.
    index_map = MOI.copy_to(cache, src)
    # Now we can access the `A` matrix:
    A = convert(
        SparseArrays.SparseMatrixCSC{Float64, Int},
        cache.constraints.coefficients,
    )
    # and the b vector (note that MOI models  $Ax = b$  as  $Ax + b$  in  $\{0\}$ , so b
    # differs by -):
    b = -cache.constraints.constants
```

```

# The `c` vector is more involved, because we need to account for the
# objective sense:
sense = ifelse(cache.objective.sense == MOI.MAX_SENSE, -1, 1)
F = MOI.ScalarAffineFunction{Float64}
obj = MOI.get(src, MOI.ObjectiveFunction{F}())
c = zeros(size(A, 2))
for term in obj.terms
    c[term.variable.value] += sense * term.coefficient
end
# Now we can solve the problem with PDHG and record the solution:
dest.status, dest.iterations, dest.x, dest.y = solve_pdhg(A, b, c)
# To help assign the values of the x and y vectors to the appropriate
# variables and constraints, we need a map of the constraint indices to their
# row in the `dest` matrix and a map of the variable indices to their
# column in the `dest` matrix:
F, S = MOI.VectorAffineFunction{Float64}, MOI.Zeros
for src_ci in MOI.get(src, MOI.ListOfConstraintIndices{F,S}())
    dest.ci_to_rows[index_map[src_ci]] =
        MOI.Utilities.rows(cache.constraints.sets, index_map[src_ci])
end
for (i, src_x) in enumerate(MOI.get(src, MOI.ListOfVariableIndices()))
    dest.x_to_col[index_map[src_x]] = i
end
# We can now record two derived quantities: the primal objective value and
# the solve time.
dest.obj_value = obj.constant + sense * c' * dest.x
dest.solve_time = time() - start_time
# We need to return the index map, and `false`, to indicate to MOI that we
# do not support incremental modification of the model.
return index_map, false
end

```

## Solutions

Now that we know how to solve a model, let's implement the required solution attributes.

First, we need to tell MOI how many solutions we found via `MOI.ResultCount`:

```

function MOI.get(model::Optimizer, ::MOI.ResultCount)
    return model.status == MOI.OPTIMAL ? 1 : 0
end

```

and implement `MOI.RawStatusString` to provide a user-readable string that describes what happened:

```

function MOI.get(model::Optimizer, ::MOI.RawStatusString)
    if model.status == MOI.OPTIMAL
        return "found a primal-dual optimal solution (subject to tolerances)"
    end
    return "failed to solve"
end

```

Then, we need to implement the three types of problem status: `MOI.TerminationStatus`, `MOI.PrimalStatus` and `MOI.DualStatus`:

```

MOI.get(model::Optimizer, ::MOI.TerminationStatus) = model.status

function MOI.get(model::Optimizer, attr::Union{MOI.PrimalStatus,MOI.DualStatus})
    if attr.result_index == 1 && model.status == MOI.OPTIMAL
        return MOI.FEASIBLE_POINT
    end
    return MOI.NO_SOLUTION
end

```

Now we can implement `MOI.ObjectiveValue`, `MOI.VariablePrimal`, and `MOI.ConstraintDual`:

```

function MOI.get(model::Optimizer, attr::MOI.ObjectiveValue)
    MOI.check_result_index_bounds(model, attr)
    return model.obj_value
end

function MOI.get(
    model::Optimizer,
    attr::MOI.VariablePrimal,
    x::MOI.VariableIndex,
)
    MOI.check_result_index_bounds(model, attr)
    return model.x[model.x_to_col[x]]
end

function MOI.get(
    model::Optimizer,
    attr::MOI.ConstraintDual,
    ci::MOI.ConstraintIndex{MOI.VectorAffineFunction{Float64},MOI.Zeros},
)
    MOI.check_result_index_bounds(model, attr)
    # MOI models Ax = b as Ax + b in {0}, so the dual differs by -
    return -model.y[model.ci_to_rows[ci]]
end

```

Some other useful result quantities are `MOI.SolveTimeSec` and `MOI.BarrierIterations`:

```

MOI.get(model::Optimizer, ::MOI.SolveTimeSec) = model.solve_time
MOI.get(model::Optimizer, ::MOI.BarrierIterations) = model.iterations

```

## A JuMP example

Now we can solve an arbitrary linear program with JuMP. Here's the same standard form as before:

```

model = Model(Optimizer)
@variable(model, x[1:5] >= 0)
@objective(model, Min, c' * x)
@constraint(model, c3, A * x == b)
optimize!(model)

```

iter	pobj	dobj	pfeas	dfeas	objfeas
1000	2.050187e+02	2.044002e+02	2.006420e-01	2.674295e-02	6.185366e-01
2000	2.049895e+02	2.051241e+02	1.705136e-02	2.746207e-02	1.346232e-01
3000	2.050050e+02	2.050805e+02	8.907061e-03	8.405470e-03	7.550812e-02
4000	2.050024e+02	2.049755e+02	4.046623e-03	9.374982e-04	2.689079e-02
5000	2.049995e+02	2.049831e+02	8.635908e-04	6.483234e-04	1.633722e-02
6000	2.049995e+02	2.050016e+02	7.833794e-04	1.676266e-04	2.095135e-03
7000	2.050000e+02	2.050030e+02	2.811341e-05	3.065459e-04	2.964863e-03
8000	2.050001e+02	2.050002e+02	1.316682e-04	1.674879e-05	8.453982e-05
8365	2.049999e+02	2.050000e+02	9.473351e-05	2.381905e-06	7.955573e-05

```
solution_summary(model; verbose = true)
```

```
* Solver : PDHG

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "found a primal-dual optimal solution (subject to tolerances)"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 2.05000e+02
  Dual objective value : 2.05000e+02
  Primal solution :
    x[1] : 1.50001e+01
    x[2] : 1.24995e+00
    x[3] : 1.75010e+00
    x[4] : 0.00000e+00
    x[5] : 0.00000e+00
  Dual solution :
    c3 : [-1.93193e-06, 2.50002e-01, 1.50000e+00]

* Work counters
  Solve time (sec)   : 2.41304e-01
  Barrier iterations : 8365
```

But we could also have written:

```
model = Model(Optimizer)
@variable(model, x >= 0)
@variable(model, 0 <= y <= 3)
@objective(model, Min, 12x + 20y)
@constraint(model, c1, 6x + 8y >= 100)
@constraint(model, c2, 7x + 12y >= 120)
optimize!(model)
```

iter	pobj	dobj	pfeas	dfeas	objfeas
1000	2.050187e+02	2.044002e+02	2.006420e-01	2.674295e-02	6.185366e-01
2000	2.049895e+02	2.051241e+02	1.705136e-02	2.746207e-02	1.346232e-01
3000	2.050050e+02	2.050805e+02	8.907061e-03	8.405470e-03	7.550812e-02
4000	2.050024e+02	2.049755e+02	4.046623e-03	9.374982e-04	2.689079e-02
5000	2.049995e+02	2.049831e+02	8.635908e-04	6.483234e-04	1.633722e-02
6000	2.049995e+02	2.050016e+02	7.833794e-04	1.676266e-04	2.095135e-03
7000	2.050000e+02	2.050030e+02	2.811341e-05	3.065459e-04	2.964863e-03
8000	2.050001e+02	2.050002e+02	1.316682e-04	1.674879e-05	8.453982e-05
8365	2.049999e+02	2.050000e+02	9.473351e-05	2.381905e-06	7.955573e-05

```
solution_summary(model; verbose = true)
```

```
* Solver : PDHG

* Status
Result count      : 1
Termination status : OPTIMAL
Message from the solver:
"found a primal-dual optimal solution (subject to tolerances)"

* Candidate solution (result #1)
Primal status      : FEASIBLE_POINT
Dual status        : FEASIBLE_POINT
Objective value    : 2.05000e+02
Dual objective value : 2.05000e+02
Primal solution :
  x : 1.50001e+01
  y : 1.24995e+00
Dual solution :
  c1 : 2.50002e-01
  c2 : 1.50000e+00

* Work counters
Solve time (sec)   : 1.80507e-03
Barrier iterations : 8365
```

Other variations are also possible:

```
model = Model(Optimizer)
@variable(model, x[1:5] >= 0)
@objective(model, Max, -c' * x)
@constraint(model, c4, A * x .== b)
optimize!(model)
```

iter	pobj	dobj	pfeas	dfeas	objfeas
1000	2.050187e+02	2.044002e+02	2.006420e-01	2.674295e-02	6.185366e-01

2000	2.049895e+02	2.051241e+02	1.705136e-02	2.746207e-02	1.346232e-01
3000	2.050050e+02	2.050805e+02	8.907061e-03	8.405470e-03	7.550812e-02
4000	2.050024e+02	2.049755e+02	4.046623e-03	9.374982e-04	2.689079e-02
5000	2.049995e+02	2.049831e+02	8.635908e-04	6.483234e-04	1.633722e-02
6000	2.049995e+02	2.050016e+02	7.833794e-04	1.676266e-04	2.095135e-03
7000	2.050000e+02	2.050030e+02	2.811341e-05	3.065459e-04	2.964863e-03
8000	2.050001e+02	2.050002e+02	1.316682e-04	1.674879e-05	8.453982e-05
8365	2.049999e+02	2.050000e+02	9.473351e-05	2.381905e-06	7.955573e-05

```
solution_summary(model; verbose = true)
```

```
* Solver : PDHG

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "found a primal-dual optimal solution (subject to tolerances)"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : -2.05000e+02
  Dual objective value : -2.05000e+02
  Primal solution :
    x[1] : 1.50001e+01
    x[2] : 1.24995e+00
    x[3] : 1.75010e+00
    x[4] : 0.00000e+00
    x[5] : 0.00000e+00
  Dual solution :
    c4 : multiple constraints with the same name

* Work counters
  Solve time (sec)   : 1.79601e-03
  Barrier iterations : 8365
```

Behind the scenes, JuMP and MathOptInterface reformulate the problem from the modeller's form into the standard form defined by our Optimizer.

# Chapter 10

## Applications

### 10.1 Power Systems

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

**This tutorial was originally contributed by Yury Dvorkin and Miles Lubin.**

This tutorial demonstrates how to formulate basic power systems engineering models in JuMP.

We will consider basic "economic dispatch" and "unit commitment" models without taking into account transmission constraints.

For this tutorial, we use the following packages:

```
using JuMP
import DataFrames
import HiGHS
import Plots
import StatsPlots
```

### Economic dispatch

Economic dispatch (ED) is an optimization problem that minimizes the cost of supplying energy demand subject to operational constraints on power system assets. In its simplest modification, ED is an LP problem solved for an aggregated load and wind forecast and for a single infinitesimal moment.

Mathematically, the ED problem can be written as follows:

$$\min \sum_{i \in I} c_i^g \cdot g_i + c^w \cdot w,$$

where  $c_i$  and  $g_i$  are the incremental cost (\$/MWh) and power output (MW) of the  $i^{th}$  generator, respectively, and  $c^w$  and  $w$  are the incremental cost (\$/MWh) and wind power injection (MW), respectively.

Subject to the constraints:

- Minimum ( $g_i^{\min}$ ) and maximum ( $g_i^{\max}$ ) limits on power outputs of generators:  $g_i^{\min} \leq g_i \leq g_i^{\max}$ .
- Constraint on the wind power injection:  $0 \leq w \leq w^f$ , where  $w$  and  $w^f$  are the wind power injection and wind power forecast, respectively.

- Power balance constraint:  $\sum_{i \in I} g_i + w = d^f$ , where  $d^f$  is the demand forecast.

Further reading on ED models can be found in A. J. Wood, B. F. Wollenberg, and G. B. Sheblé, "Power Generation, Operation and Control," Wiley, 2013.

Define some input data about the test system.

We define some thermal generators:

```
function ThermalGenerator(
    min::Float64,
    max::Float64,
    fixed_cost::Float64,
    variable_cost::Float64,
)
    return (
        min = min,
        max = max,
        fixed_cost = fixed_cost,
        variable_cost = variable_cost,
    )
end

generators = [
    ThermalGenerator(0.0, 1000.0, 1000.0, 50.0),
    ThermalGenerator(300.0, 1000.0, 0.0, 100.0),
]
```

```
2-element Vector{@NamedTuple{min::Float64, max::Float64, fixed_cost::Float64,
                           ↵ variable_cost::Float64}}:
  (min = 0.0, max = 1000.0, fixed_cost = 1000.0, variable_cost = 50.0)
  (min = 300.0, max = 1000.0, fixed_cost = 0.0, variable_cost = 100.0)
```

A wind generator

```
WindGenerator(variable_cost::Float64) = (variable_cost = variable_cost,)

wind_generator = WindGenerator(50.0)
```

```
(variable_cost = 50.0,)
```

And a scenario

```
function Scenario(demand::Float64, wind::Float64)
    return (demand = demand, wind = wind)
end

scenario = Scenario(1500.0, 200.0)
```

```
(demand = 1500.0, wind = 200.0)
```

Create a function `solve_economic_dispatch`, which solves the economic dispatch problem for a given set of input parameters.

```
function solve_economic_dispatch(generators::Vector, wind, scenario)
    # Define the economic dispatch (ED) model
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    # Define decision variables
    # power output of generators
    N = length(generators)
    @variable(model, generators[i].min <= g[i = 1:N] <= generators[i].max)
    # wind power injection
    @variable(model, 0 <= w <= scenario.wind)
    # Define the objective function
    @objective(
        model,
        Min,
        sum(generators[i].variable_cost * g[i] for i in 1:N) +
        wind.variable_cost * w,
    )
    # Define the power balance constraint
    @constraint(model, sum(g[i] for i in 1:N) + w == scenario.demand)
    # Solve statement
    optimize!(model)
    assert_is_solved_and_feasible(model)
    # return the optimal value of the objective function and its minimizers
    return (
        g = value.(g),
        w = value(w),
        wind_spill = scenario.wind - value(w),
        total_cost = objective_value(model),
    )
end
```

```
solve_economic_dispatch (generic function with 1 method)
```

Solve the economic dispatch problem

```
solution = solve_economic_dispatch(generators, wind_generator, scenario);

println("Dispatch of Generators: ", solution.g, " MW")
println("Dispatch of Wind: ", solution.w, " MW")
println("Wind spillage: ", solution.wind_spill, " MW")
println("Total cost: \$", solution.total_cost)
```

```
Dispatch of Generators: [1000.0, 300.0] MW
Dispatch of Wind: 200.0 MW
Wind spillage: 0.0 MW
Total cost: $90000.0
```

### Economic dispatch with adjustable incremental costs

In the following exercise we adjust the incremental cost of generator G1 and observe its impact on the total cost.

```
function scale_generator_cost(g, scale)
    return ThermalGenerator(g.min, g.max, g.fixed_cost, scale * g.variable_cost)
end

start = time()
c_g_scale_df = DataFrames.DataFrame();
# Scale factor
scale = Float64[],
# Dispatch of Generator 1 [MW]
dispatch_G1 = Float64[],
# Dispatch of Generator 2 [MW]
dispatch_G2 = Float64[],
# Dispatch of Wind [MW]
dispatch_wind = Float64[],
# Spillage of Wind [MW]
spillage_wind = Float64[],
# Total cost [$]
total_cost = Float64[],
)
for c_g1_scale in 0.5:0.1:3.0
    # Update the incremental cost of the first generator at every iteration.
    new_generators = scale_generator_cost.(generators, [c_g1_scale, 1.0])
    # Solve the economic-dispatch problem with the updated incremental cost
    sol = solve_economic_dispatch(new_generators, wind_generator, scenario)
    push!(
        c_g_scale_df,
        (c_g1_scale, sol.g[1], sol.g[2], sol.w, sol.wind_spill, sol.total_cost),
    )
end
print(string("elapsed time: ", time() - start, " seconds"))
```

```
elapsed time: 0.14296197891235352 seconds
```

```
c_g_scale_df
```

	scale	dispatch_G1	dispatch_G2	dispatch_wind	spillage_wind	total_cost
	Float64	Float64	Float64	Float64	Float64	Float64
1	0.5	1000.0	300.0	200.0	0.0	65000.0
2	0.6	1000.0	300.0	200.0	0.0	70000.0
3	0.7	1000.0	300.0	200.0	0.0	75000.0
4	0.8	1000.0	300.0	200.0	0.0	80000.0
5	0.9	1000.0	300.0	200.0	0.0	85000.0
6	1.0	1000.0	300.0	200.0	0.0	90000.0
7	1.1	1000.0	300.0	200.0	0.0	95000.0
8	1.2	1000.0	300.0	200.0	0.0	100000.0
9	1.3	1000.0	300.0	200.0	0.0	105000.0
10	1.4	1000.0	300.0	200.0	0.0	110000.0
11	1.5	1000.0	300.0	200.0	0.0	115000.0
12	1.6	1000.0	300.0	200.0	0.0	120000.0
13	1.7	1000.0	300.0	200.0	0.0	125000.0
14	1.8	1000.0	300.0	200.0	0.0	130000.0
15	1.9	1000.0	300.0	200.0	0.0	135000.0
16	2.0	300.0	1000.0	200.0	0.0	140000.0
17	2.1	300.0	1000.0	200.0	0.0	141500.0
18	2.2	300.0	1000.0	200.0	0.0	143000.0
19	2.3	300.0	1000.0	200.0	0.0	144500.0
20	2.4	300.0	1000.0	200.0	0.0	146000.0
21	2.5	300.0	1000.0	200.0	0.0	147500.0
22	2.6	300.0	1000.0	200.0	0.0	149000.0
23	2.7	300.0	1000.0	200.0	0.0	150500.0
24	2.8	300.0	1000.0	200.0	0.0	152000.0
25	2.9	300.0	1000.0	200.0	0.0	153500.0
26	3.0	300.0	1000.0	200.0	0.0	155000.0

### Modifying the JuMP model in-place

Note that in the previous exercise we entirely rebuilt the optimization model at every iteration of the internal loop, which incurs an additional computational burden. This burden can be alleviated if instead of re-building the entire model, we modify the constraints or objective function, as it shown in the example below.

Compare the computing time in case of the above and below models.

```
function solve_economic_dispatch_inplace(
    generators::Vector,
    wind,
    scenario,
    scale::AbstractVector{Float64},
)
    obj_out = Float64[]
    w_out = Float64[]
    g1_out = Float64[]
    g2_out = Float64[]
    # This function only works for two generators
    @assert length(generators) == 2
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    N = length(generators)
    @variable(model, generators[i].min <= g[i = 1:N] <= generators[i].max)
```

```

@variable(model, 0 <= w <= scenario.wind)
@objective(
    model,
    Min,
    sum(generators[i].variable_cost * g[i] for i in 1:N) +
    wind.variable_cost * w,
)
@constraint(model, sum(g[i] for i in 1:N) + w == scenario.demand)
for c_g1_scale in scale
    @objective(
        model,
        Min,
        c_g1_scale * generators[1].variable_cost * g[1] +
        generators[2].variable_cost * g[2] +
        wind.variable_cost * w,
    )
    optimize!(model)
    assert_is_solved_and_feasible(model)
    push!(obj_out, objective_value(model))
    push!(w_out, value(w))
    push!(g1_out, value(g[1]))
    push!(g2_out, value(g[2]))
end
df = DataFrame();
scale = scale,
dispatch_G1 = g1_out,
dispatch_G2 = g2_out,
dispatch_wind = w_out,
spillage_wind = scenario.wind .- w_out,
total_cost = obj_out,
)
return df
end

start = time()
inplace_df = solve_economic_dispatch_inplace(
    generators,
    wind_generator,
    scenario,
    0.5:0.1:3.0,
)
print(string("elapsed time: ", time() - start, " seconds"))

```

```
elapsed time: 0.1539909839630127 seconds
```

For small models, adjusting specific constraints or the objective function is sometimes faster and sometimes slower than re-building the entire model. However, as the problem size increases, updating the model in-place is usually faster.

```
inplace_df
```

	scale	dispatch_G1	dispatch_G2	dispatch_wind	spillage_wind	total_cost
	Float64	Float64	Float64	Float64	Float64	Float64
1	0.5	1000.0	300.0	200.0	0.0	65000.0
2	0.6	1000.0	300.0	200.0	0.0	70000.0
3	0.7	1000.0	300.0	200.0	0.0	75000.0
4	0.8	1000.0	300.0	200.0	0.0	80000.0
5	0.9	1000.0	300.0	200.0	0.0	85000.0
6	1.0	1000.0	300.0	200.0	0.0	90000.0
7	1.1	1000.0	300.0	200.0	0.0	95000.0
8	1.2	1000.0	300.0	200.0	0.0	100000.0
9	1.3	1000.0	300.0	200.0	0.0	105000.0
10	1.4	1000.0	300.0	200.0	0.0	110000.0
11	1.5	1000.0	300.0	200.0	0.0	115000.0
12	1.6	1000.0	300.0	200.0	0.0	120000.0
13	1.7	1000.0	300.0	200.0	0.0	125000.0
14	1.8	1000.0	300.0	200.0	0.0	130000.0
15	1.9	1000.0	300.0	200.0	0.0	135000.0
16	2.0	1000.0	300.0	200.0	0.0	140000.0
17	2.1	300.0	1000.0	200.0	0.0	141500.0
18	2.2	300.0	1000.0	200.0	0.0	143000.0
19	2.3	300.0	1000.0	200.0	0.0	144500.0
20	2.4	300.0	1000.0	200.0	0.0	146000.0
21	2.5	300.0	1000.0	200.0	0.0	147500.0
22	2.6	300.0	1000.0	200.0	0.0	149000.0
23	2.7	300.0	1000.0	200.0	0.0	150500.0
24	2.8	300.0	1000.0	200.0	0.0	152000.0
25	2.9	300.0	1000.0	200.0	0.0	153500.0
26	3.0	300.0	1000.0	200.0	0.0	155000.0

### Inefficient usage of wind generators

The economic dispatch problem does not perform commitment decisions and, thus, assumes that all generators must be dispatched at least at their minimum power output limit. This approach is not cost efficient and may lead to absurd decisions. For example, if  $d = \sum_{i \in I} g_i^{\min}$ , the wind power injection must be zero, that is, all available wind generation is spilled, to meet the minimum power output constraints on generators.

In the following example, we adjust the total demand and observed how it affects wind spillage.

```

demand_scale_df = DataFrames.DataFrame();
    demand = Float64[],
    dispatch_G1 = Float64[],
    dispatch_G2 = Float64[],
    dispatch_wind = Float64[],
    spillage_wind = Float64[],
    total_cost = Float64[],
)

function scale_demand(scenario, scale)
    return Scenario(scale * scenario.demand, scenario.wind)
end

for demand_scale in 0.2:0.1:1.4
    new_scenario = scale_demand(scenario, demand_scale)

```

```

sol = solve_economic_dispatch(generators, wind_generator, new_scenario)
push!(
    demand_scale_df,
    (
        new_scenario.demand,
        sol.g[1],
        sol.g[2],
        sol.w,
        sol.wind_spill,
        sol.total_cost,
    ),
)
end

demand_scale_df

```

	demand	dispatch_G1	dispatch_G2	dispatch_wind	spillage_wind	total_cost
	Float64	Float64	Float64	Float64	Float64	Float64
1	300.0	0.0	300.0	0.0	200.0	30000.0
2	450.0	150.0	300.0	0.0	200.0	37500.0
3	600.0	300.0	300.0	0.0	200.0	45000.0
4	750.0	450.0	300.0	0.0	200.0	52500.0
5	900.0	600.0	300.0	0.0	200.0	60000.0
6	1050.0	750.0	300.0	0.0	200.0	67500.0
7	1200.0	900.0	300.0	0.0	200.0	75000.0
8	1350.0	850.0	300.0	200.0	0.0	82500.0
9	1500.0	1000.0	300.0	200.0	0.0	90000.0
10	1650.0	1000.0	450.0	200.0	0.0	105000.0
11	1800.0	1000.0	600.0	200.0	0.0	120000.0
12	1950.0	1000.0	750.0	200.0	0.0	135000.0
13	2100.0	1000.0	900.0	200.0	0.0	150000.0

```

dispatch_plot = StatsPlots.@df(
    demand_scale_df,
    Plots.plot(
        :demand,
        [:dispatch_G1, :dispatch_G2],
        labels = ["G1" "G2"],
        title = "Thermal Dispatch",
        legend = :bottomright,
        linewidth = 3,
        xlabel = "Demand",
        ylabel = "Dispatch [MW]",
    ),
)

wind_plot = StatsPlots.@df(
    demand_scale_df,
    Plots.plot(
        :demand,
        [:dispatch_wind, :spillage_wind],
        labels = ["Dispatch" "Spillage"],
    )
)

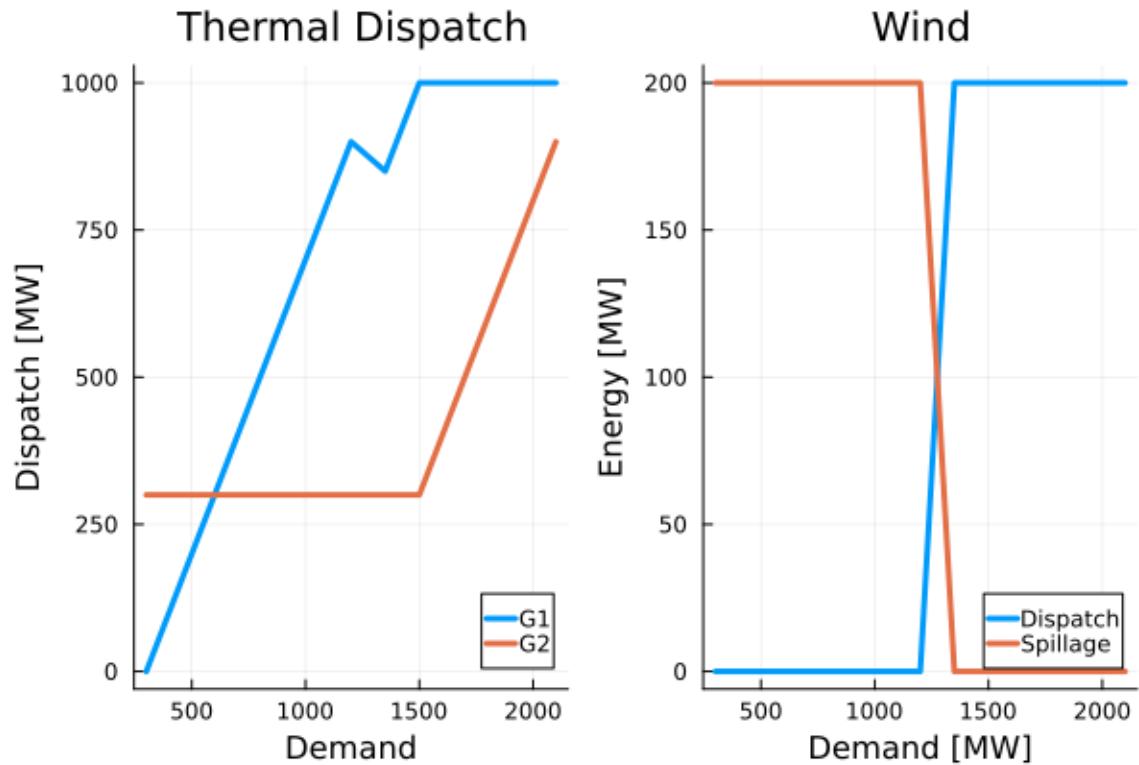
```

```

        title = "Wind",
        legend = :bottomright,
        linewidth = 3,
        xlabel = "Demand [MW]",
        ylabel = "Energy [MW]",
    ),
)

Plots.plot(dispatch_plot, wind_plot)

```



This particular drawback can be overcome by introducing binary decisions on the "on/off" status of generators. This model is called unit commitment and considered later in these notes.

For further reading on the interplay between wind generation and the minimum power output constraints of generators, we refer interested readers to R. Baldick, "Wind and energy markets: a case study of Texas," IEEE Systems Journal, vol. 6, pp. 27-34, 2012.

### **Unit commitment**

The Unit Commitment (UC) model can be obtained from ED model by introducing binary variable associated with each generator. This binary variable can attain two values: if it is "1," the generator is synchronized and, thus, can be dispatched, otherwise, that is, if the binary variable is "0," that generator is not synchronized and its power output is set to 0.

To obtain the mathematical formulation of the UC model, we will modify the constraints of the ED model as follows:

$$g_i^{\min} \cdot u_{t,i} \leq g_i \leq g_i^{\max} \cdot u_{t,i},$$

where  $u_i \in \{0, 1\}$ . In this constraint, if  $u_i = 0$ , then  $g_i = 0$ . On the other hand, if  $u_i = 1$ , then  $g_i^{\min} \leq g_i \leq g_i^{\max}$ .

For further reading on the UC problem we refer interested readers to G. Morales-Espana, J. M. Latorre, and A. Ramos, "Tight and Compact MILP Formulation for the Thermal Unit Commitment Problem," IEEE Transactions on Power Systems, vol. 28, pp. 4897-4908, 2013.

In the following example we convert the ED model explained above to the UC model.

```
function solve_unit_commitment(generators::Vector, wind, scenario)
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    N = length(generators)
    @variable(model, 0 <= g[i = 1:N] <= generators[i].max)
    @variable(model, 0 <= w <= scenario.wind)
    @constraint(model, sum(g[i] for i in 1:N) + w == scenario.demand)
    # !!! New: add binary on-off variables for each generator
    @variable(model, u[i = 1:N], Bin)
    @constraint(model, [i = 1:N], g[i] <= generators[i].max * u[i])
    @constraint(model, [i = 1:N], g[i] >= generators[i].min * u[i])
    @objective(
        model,
        Min,
        sum(generators[i].variable_cost * g[i] for i in 1:N) +
        wind.variable_cost * w +
        # !!! new
        sum(generators[i].fixed_cost * u[i] for i in 1:N)
    )
    optimize!(model)
    status = termination_status(model)
    if status != OPTIMAL
        return (status = status,)
    end
    @assert primal_status(model) == FEASIBLE_POINT
    return (
        status = status,
        g = value.(g),
        w = value(w),
        wind_spill = scenario.wind - value(w),
        u = value.(u),
        total_cost = objective_value(model),
    )
end
```

```
solve_unit_commitment (generic function with 1 method)
```

Solve the unit commitment problem

```
solution = solve_unit_commitment(generators, wind_generator, scenario)

println("Dispatch of Generators: ", solution.g, " MW")
println("Commitments of Generators: ", solution.u)
println("Dispatch of Wind: ", solution.w, " MW")
println("Wind spillage: ", solution.wind_spill, " MW")
println("Total cost: \$", solution.total_cost)
```

```
Dispatch of Generators: [1000.0, 300.0] MW
Commitments of Generators: [1.0, 1.0]
Dispatch of Wind: 200.0 MW
Wind spillage: 0.0 MW
Total cost: $91000.0
```

### Unit commitment as a function of demand

After implementing the unit commitment model, we can now assess the interplay between the minimum power output constraints on generators and wind generation.

```
uc_df = DataFrame();
demand = Float64[],
commitment_G1 = Float64[],
commitment_G2 = Float64[],
dispatch_G1 = Float64[],
dispatch_G2 = Float64[],
dispatch_wind = Float64[],
spillage_wind = Float64[],
total_cost = Float64[],
)

for demand_scale in 0.2:0.1:1.4
    new_scenario = scale_demand(scenario, demand_scale)
    sol = solve_unit_commitment(generators, wind_generator, new_scenario)
    if sol.status == OPTIMAL
        push!(
            uc_df,
            (
                new_scenario.demand,
                sol.u[1],
                sol.u[2],
                sol.g[1],
                sol.g[2],
                sol.w,
                sol.wind_spill,
                sol.total_cost,
            ),
        )
    end
    println("Status: $(sol.status) for demand_scale = $(demand_scale)")
end
```

```
Status: OPTIMAL for demand_scale = 0.2
Status: OPTIMAL for demand_scale = 0.3
Status: OPTIMAL for demand_scale = 0.4
Status: OPTIMAL for demand_scale = 0.5
Status: OPTIMAL for demand_scale = 0.6
Status: OPTIMAL for demand_scale = 0.7
Status: OPTIMAL for demand_scale = 0.8
Status: OPTIMAL for demand_scale = 0.9
Status: OPTIMAL for demand_scale = 1.0
Status: OPTIMAL for demand_scale = 1.1
Status: OPTIMAL for demand_scale = 1.2
Status: OPTIMAL for demand_scale = 1.3
Status: OPTIMAL for demand_scale = 1.4
```

uc\_df

	demand	commitment_G1	commitment_G2	dispatch_G1	dispatch_G2	dispatch_wind	spillage_wind	total_cost
	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64
1	300.0	1.0	0.0	100.0	0.0	200.0	0.0	16000.0
2	450.0	1.0	0.0	250.0	0.0	200.0	0.0	23500.0
3	600.0	1.0	0.0	400.0	0.0	200.0	0.0	31000.0
4	750.0	1.0	0.0	550.0	0.0	200.0	0.0	38500.0
5	900.0	1.0	0.0	700.0	0.0	200.0	0.0	46000.0
6	1050.0	1.0	0.0	850.0	0.0	200.0	0.0	53500.0
7	1200.0	1.0	0.0	1000.0	0.0	200.0	0.0	61000.0
8	1350.0	1.0	1.0	850.0	300.0	200.0	0.0	83500.0
9	1500.0	1.0	1.0	1000.0	300.0	200.0	0.0	91000.0
10	1650.0	1.0	1.0	1000.0	450.0	200.0	0.0	106000.0
11	1800.0	1.0	1.0	1000.0	600.0	200.0	0.0	121000.0
12	1950.0	1.0	1.0	1000.0	750.0	200.0	0.0	136000.0
13	2100.0	1.0	1.0	1000.0	900.0	200.0	0.0	151000.0

```
commitment_plot = StatsPlots.@df(
    uc_df,
    Plots.plot(
        :demand,
        [:commitment_G1, :commitment_G2],
        labels = ["G1" "G2"],
        title = "Commitment",
        legend = :bottomright,
        linewidth = 3,
        xlabel = "Demand [MW]",
        ylabel = "Commitment decision {0, 1}",
    ),
)

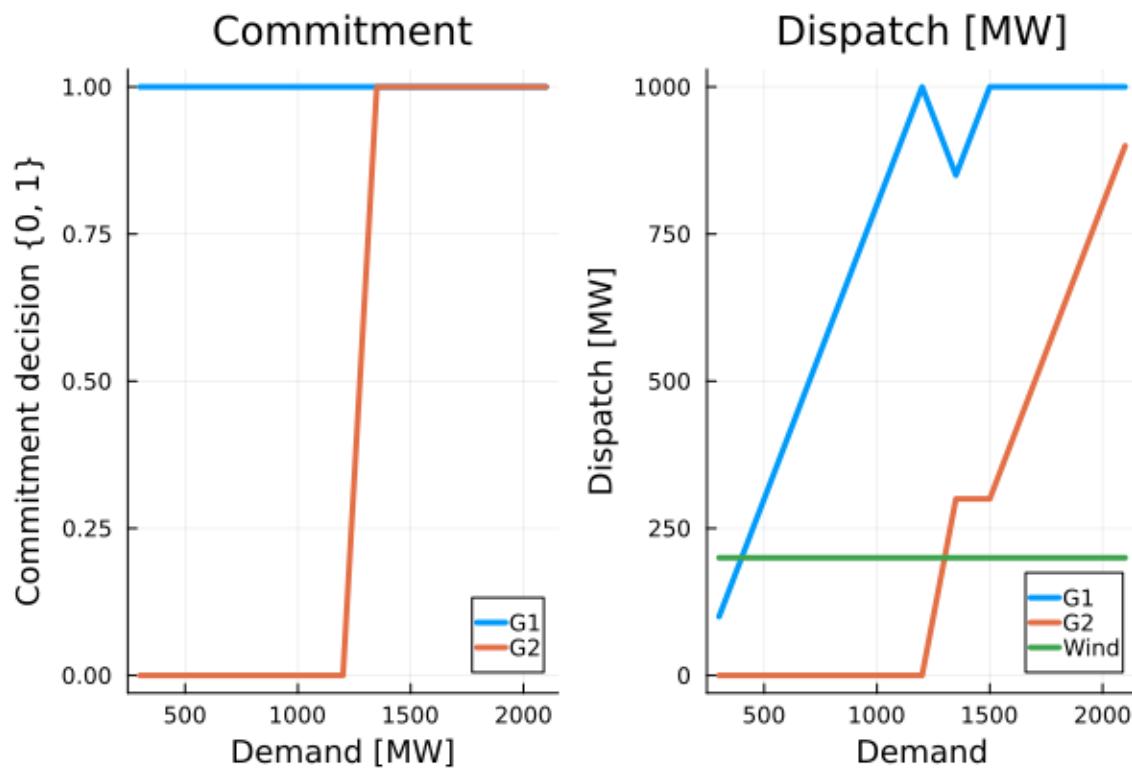
dispatch_plot = StatsPlots.@df(
    uc_df,
    Plots.plot(
        :demand,
        [:dispatch_G1, :dispatch_G2, :dispatch_wind],
        labels = ["G1" "G2" "Wind"],
        title = "Dispatch [MW]",
    ),
)
```

```

        legend = :bottomright,
        linewidth = 3,
        xlabel = "Demand",
        ylabel = "Dispatch [MW]",
    ),
)

Plots.plot(commitment_plot, dispatch_plot)

```



### Nonlinear economic dispatch

As a final example, we modify our economic dispatch problem in two ways:

- The thermal cost function is user-defined
- The output of the wind is only the square-root of the dispatch

```

import Ipopt

"""
    thermal_cost_function(g)

A user-defined thermal cost function in pure-Julia! You can include
nonlinearities, and even things like control flow.

```

```

!!! warning
    It's still up to you to make sure that the function has a meaningful
    derivative.

"""

function thermal_cost_function(g)
    if g <= 500
        return g
    else
        return g + 1e-2 * (g - 500)^2
    end
end

function solve_nonlinear_economic_dispatch(
    generators::Vector,
    wind,
    scenario;
    silent::Bool = false,
)
    model = Model(Ipopt.Optimizer)
    if silent
        set_silent(model)
    end
    @operator(model, op_tcf, 1, thermal_cost_function)
    N = length(generators)
    @variable(model, generators[i].min <= g[i = 1:N] <= generators[i].max)
    @variable(model, 0 <= w <= scenario.wind)
    @objective(
        model,
        Min,
        sum(generators[i].variable_cost * op_tcf(g[i]) for i in 1:N) +
        wind.variable_cost * w,
    )
    @constraint(model, sum(g[i] for i in 1:N) + sqrt(w) == scenario.demand)
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return (
        g = value.(g),
        w = value(w),
        wind_spill = scenario.wind - value(w),
        total_cost = objective_value(model),
    )
end

solution =
    solve_nonlinear_economic_dispatch(generators, wind_generator, scenario)

```

```
(g = [847.3509933774712, 648.6754966887423], w = 15.788781193899027, wind_spill = 184.211218806101,
↪ total_cost = 190455.298013245)
```

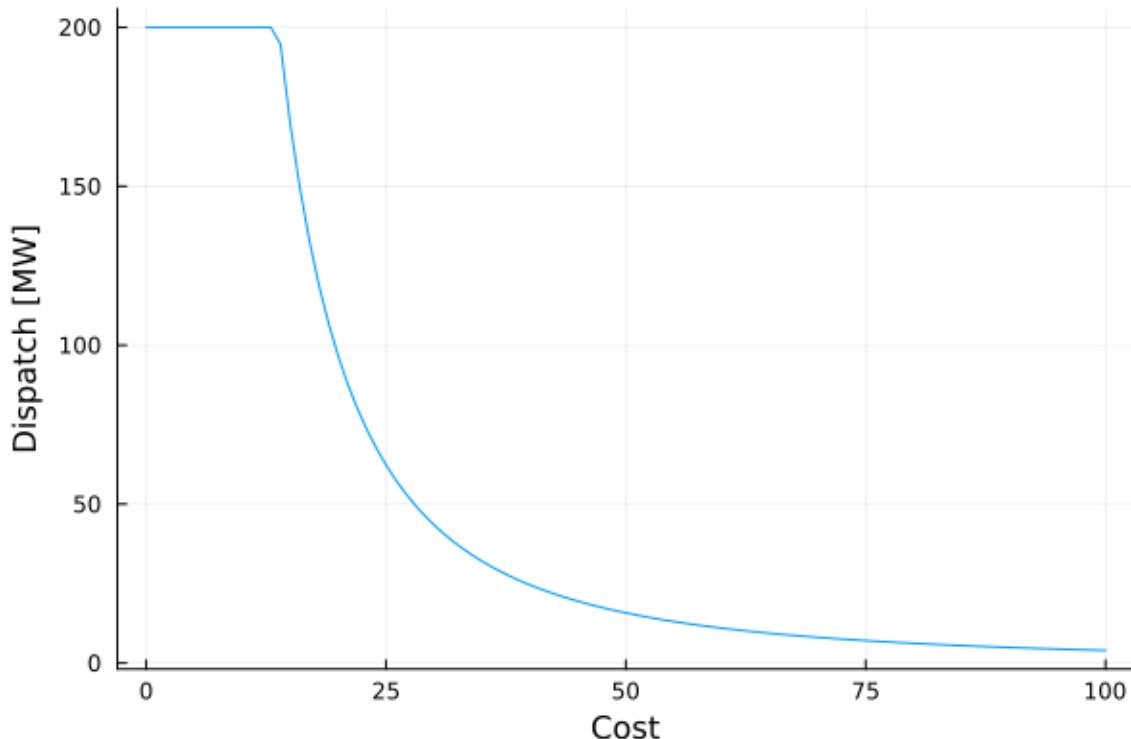
Now let's see how the wind is dispatched as a function of the cost:

```

wind_cost = 0.0:1:100
wind_dispatch = Float64[]
for c in wind_cost
    sol = solve_nonlinear_economic_dispatch(
        generators,
        WindGenerator(c),
        scenario;
        silent = true,
    )
    push!(wind_dispatch, sol.w)
end

Plots.plot(
    wind_cost,
    wind_dispatch;
    xlabel = "Cost",
    ylabel = "Dispatch [MW]",
    label = false,
)

```



## 10.2 Optimal power flow

*This tutorial was generated using [Literate.jl](#). Download the source as a [.jl file](#).*

This tutorial formulates and solves an alternating current optimal power flow (AC-OPF) problem, a much-studied nonlinear problem from the field of electrical engineering.

Once we've formulated and solved the nonlinear problem, we will turn our focus to obtaining a good estimate of the objective value at the global optimum through the use of semidefinite programming.

One main purpose of this tutorial is to highlight JuMP's ability to directly formulate problems involving complex-valued decision variables and complex matrix cones such as the `HermitianPSDCone` object.

For another example of modeling with complex decision variables, see the [Example: quantum state discrimination](#) tutorial, and see the [Complex number support](#) section of the manual for more details.

### Info

This tutorial takes a matrix-oriented approach focused on network nodes that simplifies the construction of semidefinite programs. Another approach is to formulate the problem focusing on network lines (known as a *branch model*) where it is easier to work with flow constraints. A general approach is provided by `PowerModels.jl`, an open-source framework to a broad range of power flow model formulations along with utilities for working with detailed network data.

## Required packages

This tutorial requires the following packages:

```
using JuMP
import Clarabel
import DataFrames
import Ipopt
import LinearAlgebra
import SparseArrays
import Test
```

## Initial formulation

Optimal power flow problems for electrical transmission typically pose the following question: what is the most cost-effective operation of electricity generators while meeting constraints on the safe limits of network components?

We'll use the 9-node network test case `case9mod` to explore this problem.

The graph of the network, shown here, has three nodes (or *buses*) each for the different purposes of generation  $G$  (nodes 1, 2, and 3), trans-shipment (nodes 4, 6, and 8), and demand  $D$  (nodes 5, 7, and 9).

This example is a modified version of the `MATPOWER` ((Zimmerman et al., 2011)) test case `case9` ([archive](#)) created by (Bukhsh et al., 2013) for their test case archive of optimal power flow problems with local optima. This test case is also extensively evaluated in (Krasko and Rebennack, 2017).

Here *bus* and *network node* are taken as analogous terms, as are *branch* and *transmission line*.

For future reference, let's name the number of nodes in the network:

```
N = 9;
```

The network data can be summarised using a small number of arrays. Using the `sparsevec` function from the `SparseArrays` standard library package, we can give the indices and values of the non-zero data points:

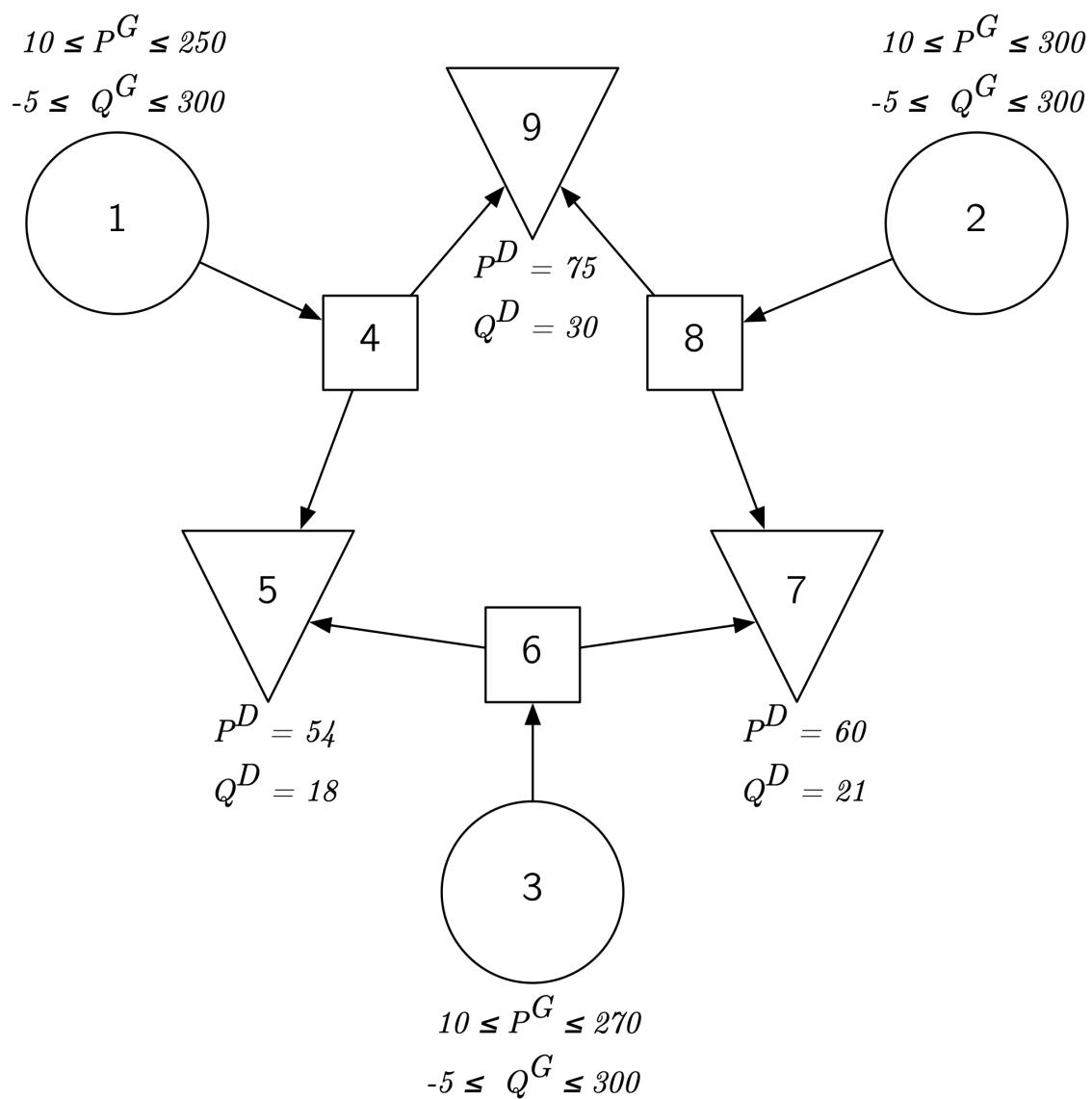


Figure 10.1: Nine Nodes

```
# Real generation: lower (`lb`) and upper (`ub`) bounds
P_Gen_lb = SparseArrays.sparsevec([1, 2, 3], [10, 10, 10], N)
P_Gen_ub = SparseArrays.sparsevec([1, 2, 3], [250, 300, 270], N)
# Reactive generation: lower (`lb`) and upper (`ub`) bounds
Q_Gen_lb = SparseArrays.sparsevec([1, 2, 3], [-5, -5, -5], N)
Q_Gen_ub = SparseArrays.sparsevec([1, 2, 3], [300, 300, 300], N)
# Power demand levels (real, reactive, and complex form)
P_Demand = SparseArrays.sparsevec([5, 7, 9], [54, 60, 75], N)
Q_Demand = SparseArrays.sparsevec([5, 7, 9], [18, 21, 30], N)
S_Demand = P_Demand + im * Q_Demand
```

```
9-element SparseArrays.SparseVector{Complex{Int64}, Int64} with 3 stored entries:
[5] = 54+18im
[7] = 60+21im
[9] = 75+30im
```

The key decision variables are the real power injections  $P^G$  and reactive power injections  $Q^G$  over the allowed range of the generators. All other buses must restrict their generation variables to 0. On the other hand, these non-generator nodes have a fixed real and reactive power demand, denoted  $P^D$  and  $Q^D$  respectively (these are fixed at 0 in the case of trans-shipment and generator nodes).

The cost of operating each generator is modeled as a quadratic function of its real power output; in our specific test case, the objective function to minimize is:

$$\min 0.11 (P_1^G)^2 + 5P_1^G + 150 \quad (10.1)$$

$$+ 0.085 (P_2^G)^2 + 1.2P_2^G + 600 \quad (10.2)$$

$$+ 0.1225 (P_3^G)^2 + P_3^G + 335 \quad (10.3)$$

$$(10.4)$$

Let's create an initial JuMP model with some of this data:

```
model = Model(Ipopt.Optimizer)
set_silent(model)
@variable(model, P_Gen_lb[i] <= P_G[i] in 1:N <= P_Gen_ub[i])
@objective(
    model,
    Min,
    (0.11 * P_G[1]^2 + 5 * P_G[1] + 150) +
    (0.085 * P_G[2]^2 + 1.2 * P_G[2] + 600) +
    (0.1225 * P_G[3]^2 + P_G[3] + 335),
);
```

Even before solving an optimization problem, we can estimate a lower bound on the best objective value by substituting the lower bound on each generator's real power range (all 10, as it turns out in this case):

```
basic_lower_bound = value(lower_bound, objective_function(model));
println("Objective value (basic lower bound) : $basic_lower_bound")
```

```
Objective value (basic lower bound) : 1188.75
```

to see that we can do no better than an objective cost of 1188.75.

(Direct substitution works because a quadratic function of a single variable  $x$  with positive coefficients is strictly increasing for all  $x \geq 0$ .)

In fact, we can get a quick but even better estimate from the direct observation that the real power generated must meet or exceed the real power demand:

```
@constraint(model, sum(P_G) >= sum(P_Demand))
optimize!(model)
assert_is_solved_and_feasible(model)
better_lower_bound = round(objective_value(model); digits = 2)
println("Objective value (better lower bound): $better_lower_bound")
```

```
Objective value (better lower bound): 2733.55
```

However, there are additional power flow constraints that must be satisfied.

Power must flow from one or more generation nodes through the transmission lines and end up at a demand node. The state variables of our steady-state alternating current (AC) electrical network are *complex-valued* voltage variables  $V_1, \dots, V_N$ . Voltages capture both a magnitude and phase of the node's electrical state in relation to the rest of the system. An AC power system also extends the notion of resistance in wires found in a direct current (DC) circuit to a complex quantity, known as the *impedance*, of each transmission line. The reciprocal of impedance is known as *admittance*. Together, these complex quantities are used to express a complex version of *Ohm's law*: current flow through a line is proportional to the difference in voltages on each end of the line, multiplied by the admittance.

## Network data

Let's assemble the data we need for writing the complex power flow constraints. The data for the problem consists of a list of the real and imaginary parts of the line impedance. We obtain the following data table from the branch data section of the case9mod MATPOWER format file:

```
branch_data = DataFrames.DataFrame([
    (1, 4, 0.0, 0.0576, 0.0),
    (4, 5, 0.017, 0.092, 0.158),
    (6, 5, 0.039, 0.17, 0.358),
    (3, 6, 0.0, 0.0586, 0.0),
    (6, 7, 0.0119, 0.1008, 0.209),
    (8, 7, 0.0085, 0.072, 0.149),
    (2, 8, 0.0, 0.0625, 0.0),
    (8, 9, 0.032, 0.161, 0.306),
    (4, 9, 0.01, 0.085, 0.176),
])
DataFrames.rename!(branch_data, [:F_BUS, :T_BUS, :BR_R, :BR_X, :BR_Bc])
```

The first two columns describe the network, supplying the *from* and *to* connection points of the lines. The last three columns give the branch resistance, branch reactance and *line-charging susceptance*.

	F_BUS	T_BUS	BR_R	BR_X	BR_Bc
	Int64	Int64	Float64	Float64	Float64
1	1	4	0.0	0.0576	0.0
2	4	5	0.017	0.092	0.158
3	6	5	0.039	0.17	0.358
4	3	6	0.0	0.0586	0.0
5	6	7	0.0119	0.1008	0.209
6	8	7	0.0085	0.072	0.149
7	2	8	0.0	0.0625	0.0
8	8	9	0.032	0.161	0.306
9	4	9	0.01	0.085	0.176

We will also need to reference the base\_MVA number (used for re-scaling):

```
base_MVA = 100;
```

and the number of lines:

```
M = size(branch_data, 1)
```

```
9
```

From the first two columns of the branch data table, we can create a sparse incidence matrix that simplifies handling of the network layout:

```
A =
SparseArrays.sparse(branch_data.F_BUS, 1:M, 1, N, M) +
SparseArrays.sparse(branch_data.T_BUS, 1:M, -1, N, M)
```

```
9x9 SparseArrays.SparseMatrixCSC{Int64, Int64} with 18 stored entries:
 1 . . . . . . . .
 . . . . . . 1 . .
 . . . 1 . . . . .
 -1 1 . . . . . . 1
 . -1 -1 . . . . .
 . . 1 -1 1 . . .
 . . . . -1 -1 . .
 . . . . . 1 -1 1 .
 . . . . . . -1 -1
```

We form the network impedance vector from the next two columns

```
z = (branch_data.BR_R .+ im * branch_data.BR_X) / base_MVA;
```

and calculate it's corresponding bus admittance matrix as

```
Y_0 = A * SparseArrays.spdiagm(1 ./ z) * A';
```

while the last column gives the branch line-charging susceptance

```
y_sh = 1 / 2 * (im * branch_data.BR_Bc) * base_MVA;
```

and leads to the shunt admittance matrix

```
Y_sh = SparseArrays.spdiagm(
    LinearAlgebra.diag(A * SparseArrays.spdiagm(y_sh) * A'),
);
```

(The construction of the shunt admittance matrix  $Y_{sh}$  looks somewhat more complicated than  $Y_0$  because we only want to add the diagonal elements in the calculation; the line-charging is used only in the nodal voltage terms and not the line voltage terms.)

The full bus admittance matrix  $Y$  is then defined as

```
Y = Y_0 + Y_sh;
```

## JuMP model

Now we're ready to write the complex power flow constraints we need to more accurately model the electricity system.

We'll introduce a number of constraints that model both the physics and operational requirements.

Let's start by initializing a new model:

```
model = Model(Ipopt.Optimizer)
set_silent(model)
```

Then we'll create the nodal power generation variables:

```
@variable(
    model,
    S_G[i in 1:N] in ComplexPlane(),
    lower_bound = P_Gen_lb[i] + Q_Gen_lb[i] * im,
    upper_bound = P_Gen_ub[i] + Q_Gen_ub[i] * im,
)
```

```
9-element Vector{GenericAffExpr{ComplexF64, VariableRef}}:
real(S_G[1]) + imag(S_G[1]) im
real(S_G[2]) + imag(S_G[2]) im
real(S_G[3]) + imag(S_G[3]) im
real(S_G[4]) + imag(S_G[4]) im
real(S_G[5]) + imag(S_G[5]) im
```

```
real(S_G[6]) + imag(S_G[6]) im
real(S_G[7]) + imag(S_G[7]) im
real(S_G[8]) + imag(S_G[8]) im
real(S_G[9]) + imag(S_G[9]) im
```

We need complex nodal voltages (the system state variables):

```
@variable(model, V[1:N] in ComplexPlane(), start = 1.0 + 0.0im)
```

```
9-element Vector{GenericAffExpr{ComplexF64, VariableRef}}:
real(V[1]) + imag(V[1]) im
real(V[2]) + imag(V[2]) im
real(V[3]) + imag(V[3]) im
real(V[4]) + imag(V[4]) im
real(V[5]) + imag(V[5]) im
real(V[6]) + imag(V[6]) im
real(V[7]) + imag(V[7]) im
real(V[8]) + imag(V[8]) im
real(V[9]) + imag(V[9]) im
```

and operational constraints for maintaining voltage magnitude levels:

```
@constraint(model, [i in 1:N], 0.9^2 <= real(V[i])^2 + imag(V[i])^2 <= 1.1^2)
```

```
9-element Vector{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarQuadraticFunction{Float64}},
    ↪ MathOptInterface.Interval{Float64}}, ScalarShape}:
real(V[1])^2 + imag(V[1])^2 ∈ [0.81, 1.2100000000000002]
real(V[2])^2 + imag(V[2])^2 ∈ [0.81, 1.2100000000000002]
real(V[3])^2 + imag(V[3])^2 ∈ [0.81, 1.2100000000000002]
real(V[4])^2 + imag(V[4])^2 ∈ [0.81, 1.2100000000000002]
real(V[5])^2 + imag(V[5])^2 ∈ [0.81, 1.2100000000000002]
real(V[6])^2 + imag(V[6])^2 ∈ [0.81, 1.2100000000000002]
real(V[7])^2 + imag(V[7])^2 ∈ [0.81, 1.2100000000000002]
real(V[8])^2 + imag(V[8])^2 ∈ [0.81, 1.2100000000000002]
real(V[9])^2 + imag(V[9])^2 ∈ [0.81, 1.2100000000000002]
```

We also need to fix an origin or *reference angle* from which all other complex voltage angles (arguments) are determined. Here we will use node 1 as the nominated *reference bus*. Fixing the imaginary component of a reference bus to zero sets its complex voltage angle to 0, while constraining the real part to be non-negative disallows equivalent solutions that are just a reflection by 180 degrees:

```
@constraint(model, imag(V[1]) == 0);
@constraint(model, real(V[1]) >= 0);
```

The power flow equations express a conservation of energy (power) principle, where power generated less the power consumed must balance the power exchanged with the network:

```
@constraint(model, S_G - S_Demand .== V .* conj(Y * V))
```

```
9-element Vector{ConstraintRef{Model,
    → MathOptInterface.ConstraintIndex{MathOptInterface.ScalarQuadraticFunction{ComplexF64},
    → MathOptInterface.EqualTo{ComplexF64}}, ScalarShape}}:
    → -1736.11111111111im real(V[1])2 + 1736.11111111111im real(V[1])*real(V[4]) + 1736.11111111111
    → real(V[1])*imag(V[4]) - 1736.11111111111im imag(V[1])2 - 1736.11111111111
    → imag(V[1])*real(V[4]) + 1736.11111111111im imag(V[1])*imag(V[4]) + real(S_G[1]) +
    → imag(S_G[1]) im = 0
    → -1600im real(V[2])2 + 1600im real(V[2])*real(V[8]) + 1600 real(V[2])*imag(V[8]) - 1600im
    → imag(V[2])2 - 1600 imag(V[2])*real(V[8]) + 1600im imag(V[2])*imag(V[8]) + real(S_G[2]) +
    → imag(S_G[2]) im = 0
    → -1706.484641638225im real(V[3])2 + 1706.484641638225im real(V[3])*real(V[6]) + 1706.484641638225
    → real(V[3])*imag(V[6]) - 1706.484641638225im imag(V[3])2 - 1706.484641638225
    → imag(V[3])*real(V[6]) + 1706.484641638225im imag(V[3])*imag(V[6]) + real(S_G[3]) +
    → imag(S_G[3]) im = 0
    → 1736.11111111111im real(V[4])*real(V[1]) - 1736.11111111111 imag(V[4])*real(V[1]) +
    → 1736.11111111111 real(V[4])*imag(V[1]) + 1736.11111111111im imag(V[4])*imag(V[1]) +
    → (-330.7378962025307 - 3930.8888726118976im) real(V[4])2 + (194.21912487147264 +
    → 1051.0682051867932im) real(V[4])*real(V[5]) + (1051.0682051867932 - 194.21912487147264im)
    → real(V[4])*imag(V[5]) + (136.51877133105802 + 1160.409556313993im) real(V[4])*real(V[9]) +
    → (1160.409556313993 - 136.51877133105802im) real(V[4])*imag(V[9]) + (-330.7378962025307 -
    → 3930.8888726118976im) imag(V[4])2 + (-1051.0682051867932 + 194.21912487147264im)
    → imag(V[4])*real(V[5]) + (194.21912487147264 + 1051.0682051867932im) imag(V[4])*imag(V[5]) +
    → (-1160.409556313993 + 136.51877133105802im) imag(V[4])*real(V[9]) + (136.51877133105802 +
    → 1160.409556313993im) imag(V[4])*imag(V[9]) + real(S_G[4]) + imag(S_G[4]) im = 0
    → (194.21912487147264 + 1051.0682051867932im) real(V[5])*real(V[4]) + (-1051.0682051867932 +
    → 194.21912487147264im) imag(V[5])*real(V[4]) + (1051.0682051867932 - 194.21912487147264im)
    → real(V[5])*imag(V[4]) + (194.21912487147264 + 1051.0682051867932im) imag(V[5])*imag(V[4]) +
    → (-322.4200387138841 - 1584.0927014229458im) real(V[5])2 + (128.20091384241147 +
    → 558.8244962361526im) real(V[5])*real(V[6]) + (558.8244962361526 - 128.20091384241147im)
    → real(V[5])*imag(V[6]) + (-322.4200387138841 - 1584.0927014229458im) imag(V[5])2 +
    → (-558.8244962361526 + 128.20091384241147im) imag(V[5])*real(V[6]) + (128.20091384241147 +
    → 558.8244962361526im) imag(V[5])*imag(V[6]) + real(S_G[5]) + imag(S_G[5]) im = (54 + 18im)
    → 1706.484641638225im real(V[6])*real(V[3]) - 1706.484641638225 imag(V[6])*real(V[3]) +
    → 1706.484641638225 real(V[6])*imag(V[3]) + 1706.484641638225im imag(V[6])*imag(V[3]) +
    → (128.20091384241147 + 558.8244962361526im) real(V[6])*real(V[5]) + (-558.8244962361526 +
    → 128.20091384241147im) imag(V[6])*real(V[5]) + (558.8244962361526 - 128.20091384241147im)
    → real(V[6])*imag(V[5]) + (128.20091384241147 + 558.8244962361526im) imag(V[6])*imag(V[5]) +
    → (-243.70966193142118 - 3215.386180510695im) real(V[6])2 + (115.5087480890097 +
    → 978.4270426363173im) real(V[6])*real(V[7]) + (978.4270426363173 - 115.5087480890097im)
    → real(V[6])*imag(V[7]) + (-243.70966193142118 - 3215.386180510695im) imag(V[6])2 +
    → (-978.4270426363173 + 115.5087480890097im) imag(V[6])*real(V[7]) + (115.5087480890097 +
    → 978.4270426363173im) imag(V[6])*imag(V[7]) + real(S_G[6]) + imag(S_G[6]) im = 0
    → (115.5087480890097 + 978.4270426363173im) real(V[7])*real(V[6]) + (-978.4270426363173 +
    → 115.5087480890097im) imag(V[7])*real(V[6]) + (978.4270426363173 - 115.5087480890097im)
    → real(V[7])*imag(V[6]) + (115.5087480890097 + 978.4270426363173im) imag(V[7])*imag(V[6]) +
    → (-277.22099541362326 - 2330.3249023271615im) real(V[7])2 + (161.71224732461357 +
    → 1369.7978596908442im) real(V[7])*real(V[8]) + (1369.7978596908442 - 161.71224732461357im)
    → real(V[7])*imag(V[8]) + (-277.22099541362326 - 2330.3249023271615im) imag(V[7])2 +
    → (-1369.7978596908442 + 161.71224732461357im) imag(V[7])*real(V[8]) + (161.71224732461357 +
    → 1369.7978596908442im) imag(V[7])*imag(V[8]) + real(S_G[7]) + imag(S_G[7]) im = (60 + 21im)
    → 1600im real(V[8])*real(V[2]) - 1600 imag(V[8])*real(V[2]) + 1600 real(V[8])*imag(V[2]) + 1600im
    → imag(V[8])*imag(V[2]) + (161.71224732461357 + 1369.7978596908442im) real(V[8])*real(V[7]) +
    → (-1369.7978596908442 + 161.71224732461357im) imag(V[8])*real(V[7]) + (1369.7978596908442 -
    → 161.71224732461357im) real(V[8])*imag(V[7]) + (161.71224732461357 + 1369.7978596908442im)
    → imag(V[8])*imag(V[7]) + (-280.4726852537284 - 3544.5613130217034im) real(V[8])2 +
    → (118.76043792911486 + 597.5134533308592im) real(V[8])*real(V[9]) + (597.5134533308592 -
    → 118.76043792911486im) real(V[8])*imag(V[9]) + (-280.4726852537284 - 3544.5613130217034im)
    → imag(V[8])2 + (-597.5134533308592 + 118.76043792911486im) imag(V[8])*real(V[9]) +
```

```
(136.51877133105802 + 1160.409556313993im) real(V[9])*real(V[4]) + (-1160.409556313993 +
 $\hookrightarrow$  136.51877133105802im) imag(V[9])*real(V[4]) + (1160.409556313993 - 136.51877133105802im)
 $\hookrightarrow$  real(V[9])*imag(V[4]) + (136.51877133105802 + 1160.409556313993im) imag(V[9])*imag(V[4]) +
 $\hookrightarrow$  (118.76043792911486 + 597.5134533308592im) real(V[9])*real(V[8]) + (-597.5134533308592 +
 $\hookrightarrow$  118.76043792911486im) imag(V[9])*real(V[8]) + (597.5134533308592 - 118.76043792911486im)
 $\hookrightarrow$  real(V[9])*imag(V[8]) + (118.76043792911486 + 597.5134533308592im) imag(V[9])*imag(V[8]) +
 $\hookrightarrow$  (-255.27920926017288 - 1733.8230096448524im) real(V[9])2 + (-255.27920926017288 -
 $\hookrightarrow$  1733.8230096448524im) imag(V[9])2 + real(S_G[9]) + imag(S_G[9]) im = (75 + 30im)
```

As above, the objective function is a quadratic cost of real power:

```
P_G = real(S_G)
@objective(
    model,
    Min,
    (0.11 * P_G[1]^2 + 5 * P_G[1] + 150) +
    (0.085 * P_G[2]^2 + 1.2 * P_G[2] + 600) +
    (0.1225 * P_G[3]^2 + P_G[3] + 335),
);
```

We're finally ready to solve our nonlinear AC-OPF problem:

```
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```
* Solver : Ipopt
* Status
  Result count      : 1
  Termination status : LOCALLY_SOLVED
  Message from the solver:
  "Solve_Succeeded"

* Candidate solution (result #1)
  Primal status       : FEASIBLE_POINT
  Dual status         : FEASIBLE_POINT
  Objective value    : 3.08784e+03

* Work counters
  Solve time (sec)   : 5.55110e-03
  Barrier iterations : 16
```

```
objval_solution = round(objective_value(model); digits = 2)
println("Objective value (feasible solution) : $(objval_solution)")
```

```
Objective value (feasible solution) : 3087.84
```

The solution's power generation (in rectangular form) and complex voltage values (in polar form using degrees) are:

```
DataFrames.DataFrame();
Bus = 1:N,
ComplexPowerGen = round.(value.(S_G); digits = 2),
VoltageMagnitude = round.(abs.(value.(V)); digits = 2),
VoltageAngle_Deg = round.(rad2deg.(angle.(value.(V)))); digits = 2),
)
```

	Bus	ComplexPowerGen	VoltageMagnitude	VoltageAngle_Deg
	Int64	Complex...	Float64	Float64
1	1	10.0-5.0im	0.91	-0.0
2	2	125.37-5.0im	0.92	12.37
3	3	57.03-5.0im	0.94	7.01
4	4	0.0+0.0im	0.91	-0.4
5	5	0.0+0.0im	0.92	-0.73
6	6	0.0+0.0im	0.94	4.84
7	7	0.0+0.0im	0.93	4.52
8	8	0.0+0.0im	0.93	7.12
9	9	0.0+0.0im	0.9	-0.63

### Relaxations and better objective bounds

The Ipopt solver uses an interior-point algorithm. It has local optimality guarantees, but is unable to certify whether the solution is globally optimal. The solution we found is indeed globally optimal. The work to verify this has been done in ([Bukhsh et al., 2013](#)) and ([Krasko and Rebennack, 2017](#)), and different solvers (such as Gurobi, SCIP and GLOMIQO) are also able to verify this.

The techniques of *convex relaxations* can also be used to improve on our current best lower bound:

```
better_lower_bound
```

```
2733.55
```

To this end, observe that the nonlinear constraints in the AC-OPF formulation are quadratic equalities for power flow along with quadratic voltage inequalities.

Let's linearize these constraints by first making the substitution  $W = VV^*$ , where:

$$W = VV^* \iff W_{ii} = |V_i|^2, \quad W_{ik} = V_i \overline{V_k}, \quad \forall i, k \in \{1, \dots, N\}$$

and where  $V^*$  is the [conjugate transpose](#) of  $V$ .

On the face of it, this turns a quadratic voltage bound constraint like:

$$v_L \leq |V_i|^2 \leq v_U, \quad i \in \{1, \dots, N\}$$

for some real  $v_L$  and  $v_U$  into a simple two-sided bound:

$$v_L \leq W_{ii} \leq v_U,$$

while each quadratic expression for the nodal power term:

$$S_i^{Node} = V_i \overline{(YV)_i}$$

becomes the linear combination:

$$S_i^{Node} = (E_{ii} Y^T) \bullet W.$$

Here  $A \bullet B = \text{tr}(A^*B)$  is the [Frobenius inner product](#) of two complex matrices, while  $E_{kn}$  denotes the [matrix unit](#) with a single nonzero entry of 1 in row  $k$  and column  $n$ .

```
E(k, n) = SparseArrays.sparse([k], [n], 1, N, N);
```

Of course, we've shifted the nonlinearity into the equality constraint  $W = VV^*$ : it is this constraint we will now relax using a semidefinite programming approach.

We will make use of complex voltages and relax  $W = VV^*$  to;

$$W \succeq VV^*,$$

where the relation  $\succeq$  is the ordering in the Hermitian positive semidefinite cone.

The above constraint is equivalent to:

$$\begin{bmatrix} 1 & V^* \\ V & W \end{bmatrix} \succeq 0$$

by the theory of the [Schur complement](#). This matrix inequality implies a number of second-order cone constraints by taking certain  $2 \times 2$  minors of the matrix for each  $i \in \{1, \dots, N\}$ :

$$\begin{bmatrix} 1 & V_i^* \\ V_i & W_{ii} \end{bmatrix} \succeq 0,$$

which is equivalent to the real second-order cone inequality:

$$\text{real}(W_{ii}) \geq \text{real}(V_i)^2 + \text{imag}(V_i)^2.$$

We include these implied constraints as well for demonstration purposes.

Putting it all together we get the following semidefinite relaxation of the AC-OPF problem:

```

model = Model(Clarabel.Optimizer)
set_attribute(model, "tol_gap_rel", 1e-3)
set_attribute(model, "tol feas", 1e-3)
set_attribute(model, "tol_ktratio", 1e-3)
@variable(
    model,
    S_G[i in 1:N] in ComplexPlane(),
    lower_bound = P_Gen_lb[i] + Q_Gen_lb[i] * im,
    upper_bound = P_Gen_ub[i] + Q_Gen_ub[i] * im,
)
@variable(model, W[1:N, 1:N] in HermitianPSDCone())
@variable(model, V[1:N] in ComplexPlane(), start = 1.0 + 0.0im)
@constraint(model, [i in 1:N], 0.9^2 <= real(W[i, i]) <= 1.1^2)
@constraint(model, real(V[1]) >= 0)
@constraint(model, imag(V[1]) == 0)
@constraint(model, 0.9 <= real(V[1]) <= 1.1)
@constraint(model, LinearAlgebra.Hermitian([1 V'; V W]) in HermitianPSDCone())
# 2 x 2 minor inequalities:
@constraint(
    model,
    [i in 1:N],
    [0.5, real(W[i, i]), real(V[i]), imag(V[i])] in RotatedSecondOrderCone()
)
@constraint(
    model,
    [i in 1:N],
    S_G[i] - S_Demand[i] == LinearAlgebra.tr((conj(Y) * E(i, i)) * W),
)
P_G = real(S_G)
@objective(
    model,
    Min,
    (0.11 * P_G[1]^2 + 5 * P_G[1] + 150) +
    (0.085 * P_G[2]^2 + 1.2 * P_G[2] + 600) +
    (0.1225 * P_G[3]^2 + P_G[3] + 335),
)
optimize!(model)

```

```

problem:
variables      = 117
constraints    = 493
nnz(P)        = 3
nnz(A)        = 547
cones (total) = 14
: Zero        = 1,  numel = 19
: Nonnegative = 2,  numel = (18,39)
: SecondOrder = 9,  numel = (4,4,4,4,...,4)
: PSDTriangle = 2,  numel = (171,210)

settings:
linear algebra: direct / qdldl, precision: Float64
max iter = 200, time limit = Inf, max step = 0.990
tol feas = 1.0e-03, tol gap abs = 1.0e-08, tol gap rel = 1.0e-03,
static reg : on, ε1 = 1.0e-08, ε2 = 4.9e-32
dynamic reg: on, ε = 1.0e-13, δ = 2.0e-07
iter refine: on, reltol = 1.0e-13, abstol = 1.0e-12,
             max iter = 10, stop ratio = 5.0
equilibrate: on, min scale = 1.0e-04, max scale = 1.0e+04
             max iter = 10

iter      pcost       dcost       gap       pres       dres       k/t       μ       step
-----
0   6.6673e+03 -3.0980e+05  4.75e+01  9.32e-02  8.43e-01  1.00e+00  3.34e+03  -----
1   3.3968e+03 -6.4534e+04  2.00e+01  1.95e-02  3.85e-01  2.41e+02  9.42e+02  8.13e-01
2   1.9798e+03 -1.7012e+04  9.59e+00  5.49e-03  2.64e-01  1.51e+02  3.06e+02  9.90e-01
3   2.1414e+03 -2.3620e+03  2.10e+00  1.22e-03  8.46e-02  3.29e+01  7.63e+01  8.60e-01
4   2.0597e+03  1.1123e+03  8.52e-01  2.41e-04  5.67e-02  5.52e+00  1.93e+01  8.55e-01
5   1.6312e+03  1.4437e+03  1.30e-01  3.59e-05  1.04e-02  9.18e-01  3.20e+00  9.12e-01
6   1.5768e+03  1.5579e+03  1.21e-02  3.46e-06  1.05e-03  9.28e-02  3.09e-01  9.19e-01
7   1.5691e+03  1.5654e+03  2.35e-03  6.96e-07  2.05e-04  1.96e-02  5.73e-02  8.55e-01
8   1.5657e+03  1.5640e+03  1.08e-03  4.01e-07  9.61e-05  8.54e-03  2.47e-02  7.64e-01
9   1.5653e+03  1.5641e+03  7.88e-04  2.96e-07  6.55e-05  6.14e-03  1.79e-02  4.07e-01
-----
Terminated with status = solved
solve time = 56.7ms

```

```

assert_is_solved_and_feasible(model; allow_almost = true)
sdp_relaxation_lower_bound = round(objective_value(model); digits = 2)
println(
    "Objective value (W & V relax. lower bound): $sdp_relaxation_lower_bound",
)

```

```
Objective value (W & V relax. lower bound): 2754.1
```

We can more easily see solution values by rounding out noisy data:

```
W_1 = SparseArrays.sparse(round.(value.(W); digits = 2))
```

```
9x9 SparseArrays.SparseMatrixCSC{ComplexF64, Int64} with 81 stored entries:
1.19+0.0im  1.14-0.07im  1.13-0.05im ... 1.15-0.02im  1.14+0.05im
1.14+0.07im  1.2+0.0im   1.15+0.02im   ... 1.17+0.05im  1.14+0.12im
1.13+0.05im  1.15-0.02im 1.19+0.0im    ... 1.16+0.03im  1.14+0.11im
1.14-0.03im  1.15-0.1im   1.15-0.08im   ... 1.17-0.05im  1.15+0.03im
1.15-0.05im  1.15-0.12im 1.15-0.1im    ... 1.17-0.07im  1.15+0.01im
1.15+0.01im  1.17-0.06im 1.16-0.03im   ... 1.18-0.0im   1.16+0.07im
1.15-0.01im  1.16-0.08im 1.16-0.06im   ... 1.18-0.03im  1.16+0.05im
1.15+0.02im  1.17-0.05im 1.16-0.03im   ... 1.18+0.0im   1.16+0.07im
1.14-0.05im  1.14-0.12im 1.14-0.1im    ... 1.16-0.07im  1.15+0.0im
```

and recover an approximation to the voltage variables as:

```
DataFrames.DataFrame();
Bus = 1:N,
Magnitude = round.(abs.(value.(V)); digits = 2),
AngleDeg = round.(rad2deg.(angle.(value.(V)))); digits = 2),
)
```

	Bus	Magnitude	AngleDeg
	Int64	Float64	Float64
1	1	0.95	-0.0
2	2	0.84	3.78
3	3	0.83	2.67
4	4	0.85	-1.21
5	5	0.85	-2.11
6	6	0.86	0.94
7	7	0.86	-0.17
8	8	0.86	1.15
9	9	0.85	-2.46

For further information on exploiting sparsity see ([Jabré, 2012](#)).

This relaxation has the advantage that we can work directly with complex voltages to extend the formulation, strengthen the relaxation and gain additional approximate information about the voltage variables.

### 10.3 Serving web apps

*This tutorial was generated using [Literate.jl](#). Download the source as a .jl file.*

This tutorial demonstrates how to setup and serve JuMP models via a REST API.

In the example app we are building, we solve a trivial mixed-integer program, which is parameterized by the lower bound of a variable. To call the service, users send an HTTP POST request with JSON contents indicating the lower bound. The returned value is the solution of the mixed-integer program as JSON.

First, we need JuMP and a solver:

```
using JuMP
import HiGHS
```

We also need `HTTP.jl` to act as our REST server, and `JSON.jl` to marshal data.

```
import HTTP
import JSON
```

### The server side

The core components of our REST server are *endpoints*. These are functions which accept a `Dict{String,Any}` of input parameters, and return a `Dict{String,Any}` as output. The types are `Dict{String,Any}` because we're going to read these to and from JSON.

Here's a very simple endpoint: it accepts params as input, formulates and solves a trivial mixed-integer program, and then returns a dictionary with the result.

```
function endpoint_solve(params::Dict{String,Any})
    if !haskey(params, "lower_bound")
        return Dict{String,Any}(
            "status" => "failure",
            "reason" => "missing lower_bound param",
        )
    elseif !(params["lower_bound"] isa Real)
        return Dict{String,Any}(
            "status" => "failure",
            "reason" => "lower_bound is not a number",
        )
    end
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, x >= params["lower_bound"], Int)
    optimize!(model)
    ret = Dict{String,Any}(
        "status" => "okay",
        "termination_status" => termination_status(model),
        "primal_status" => primal_status(model),
    )
    # Only include the `x` key if it has a value.
    if primal_status(model) == FEASIBLE_POINT
        ret["x"] = value(x)
    end
    return ret
end
```

```
endpoint_solve (generic function with 1 method)
```

When we call this, we get:

```
endpoint_solve(Dict{String,Any}("lower_bound" => 1.2))
```

```
Dict{String, Any} with 4 entries:
  "status"      => "okay"
  "x"           => 2.0
  "primal_status" => FEASIBLE_POINT
  "terminaton_status" => OPTIMAL
```

```
endpoint_solve(Dict{String,Any}())
```

```
Dict{String, Any} with 2 entries:
  "status" => "failure"
  "reason" => "missing lower_bound param"
```

For a second function, we need a function that accepts an `HTTP.Request` object and returns an `HTTP.Response` object.

```
function serve_solve(request::HTTP.Request)
    data = JSON.parse(String(request.body))
    solution = endpoint_solve(data)
    return HTTP.Response(200, JSON.json(solution))
end
```

```
serve_solve (generic function with 1 method)
```

Finally, we need an HTTP server. There are a variety of ways you can do this in `HTTP.jl`. We use an explicit `Sockets.listen` so we have manual control of when we shutdown the server.

```
function setup_server(host, port)
    server = HTTP.Sockets.listen(host, port)
    HTTP.serve!(host, port; server = server) do request
        try
            # Extend the server by adding other endpoints here.
            if request.target == "/api/solve"
                return serve_solve(request)
            else
                return HTTP.Response(404, "target $(request.target) not found")
            end
        catch err
            # Log details about the exception server-side
            @info "Unhandled exception: $err"
            # Return a response to the client
            return HTTP.Response(500, "internal error")
        end
    end
    return server
end
```

```
setup_server (generic function with 1 method)
```

### Warning

HTTP.jl does not serve requests on a separate thread. Therefore, a long-running job will block the main thread, preventing concurrent users from submitting requests. To work-around this, read [HTTP.jl issue 798](#) or watch [Building Microservices and Applications in Julia](#) from JuliaCon 2020.

```
server = setup_server(HTTP.ip"127.0.0.1", 8080)
```

```
Sockets.TCPServer(RawFD(40), active)
```

## The client side

Now that we have a server, we can send it requests via this function:

```
function send_request(data::Dict; endpoint::String = "solve")
    ret = HTTP.request(
        "POST",
        # This should match the URL and endpoint we defined for our server.
        "http://127.0.0.1:8080/api/$endpoint",
        ["Content-Type" => "application/json"],
        JSON.json(data),
    )
    if ret.status != 200
        # This could happen if there are time-outs, network errors, etc.
        return Dict(
            "status" => "failure",
            "code" => ret.status,
            "body" => String(ret.body),
        )
    end
    return JSON.parse(String(ret.body))
end
```

```
send_request (generic function with 1 method)
```

Let's see what happens:

```
send_request(Dict("lower_bound" => 0))
```

```
Dict{String, Any} with 4 entries:
"status"      => "okay"
"x"           => 0.0
"primal_status" => "FEASIBLE_POINT"
"terminaton_status" => "OPTIMAL"
```

```
send_request(Dict("lower_bound" => 1.2))
```

```
Dict{String, Any} with 4 entries:
"status"      => "okay"
"x"           => 2.0
"primal_status" => "FEASIBLE_POINT"
"terminaton_status" => "OPTIMAL"
```

If we don't send a `lower_bound`, we get:

```
send_request(Dict("invalid_param" => 1.2))
```

```
Dict{String, Any} with 2 entries:
"status" => "failure"
"reason" => "missing lower_bound param"
```

If we don't send a `lower_bound` that is a number, we get:

```
send_request(Dict("lower_bound" => "1.2"))
```

```
Dict{String, Any} with 2 entries:
"status" => "failure"
"reason" => "lower_bound is not a number"
```

Finally, we can shutdown our HTTP server:

```
close(server)
```

```
[ Info: Server on 127.0.0.1:8080 closing
```

## Next steps

For more complicated examples relating to HTTP servers, consult the [HTTP.jl documentation](#).

To see how you can integrate this with a larger JuMP model, read [Design patterns for larger models](#).

## 10.4 Two-stage stochastic programs

This tutorial was generated using [Literate.jl](#). Download the source as a `.jl` file.

The purpose of this tutorial is to demonstrate how to model and solve a two-stage stochastic program.

### Info

The JuMP extension [InfiniteOpt.jl](#) can also be used to model and solve two-stage stochastic programs.  
The JuMP extension [SDDP.jl](#) can be used to model and solve multi-stage stochastic programs.

This tutorial uses the following packages

```
using JuMP
import Distributions
import HiGHS
import Plots
import StatsPlots
import Statistics
```

### Background

During the week, you are a busy practitioner of Operations Research. To escape the drudgery of mathematics, you decide to open a side business selling creamy mushroom pies with puff pastry. After a few weeks, it quickly becomes apparent that operating a food business is not so easy.

The pies must be prepared in the morning, *before* you open for the day and can gauge the level of demand. If you bake too many, the unsold pies at the end of the day must be discarded and you have wasted time and money on their production. But if you bake too few, then there may be un-served customers and you could have made more money by baking more pies.

After a few weeks of poor decision making, you decide to put your knowledge of Operations Research to good use, starting with some data collection.

Each pie costs you \$2 to make, and you sell them at \$5 each. Disposal of an unsold pie costs \$0.10. Based on three weeks of data collected, in which you made 200 pies each week, you sold 150, 190, and 200 pies. Thus, as a guess, you assume a triangular distribution of demand with a minimum of 150, a median of 200, and a maximum of 250.

We can model this problem by a two-stage stochastic program. In the first stage, we decide a quantity of pies to make  $x$ . We make this decision before we observe the demand  $d_\omega$ . In the second stage, we sell  $y_\omega$  pies, and incur any costs for unsold pies.

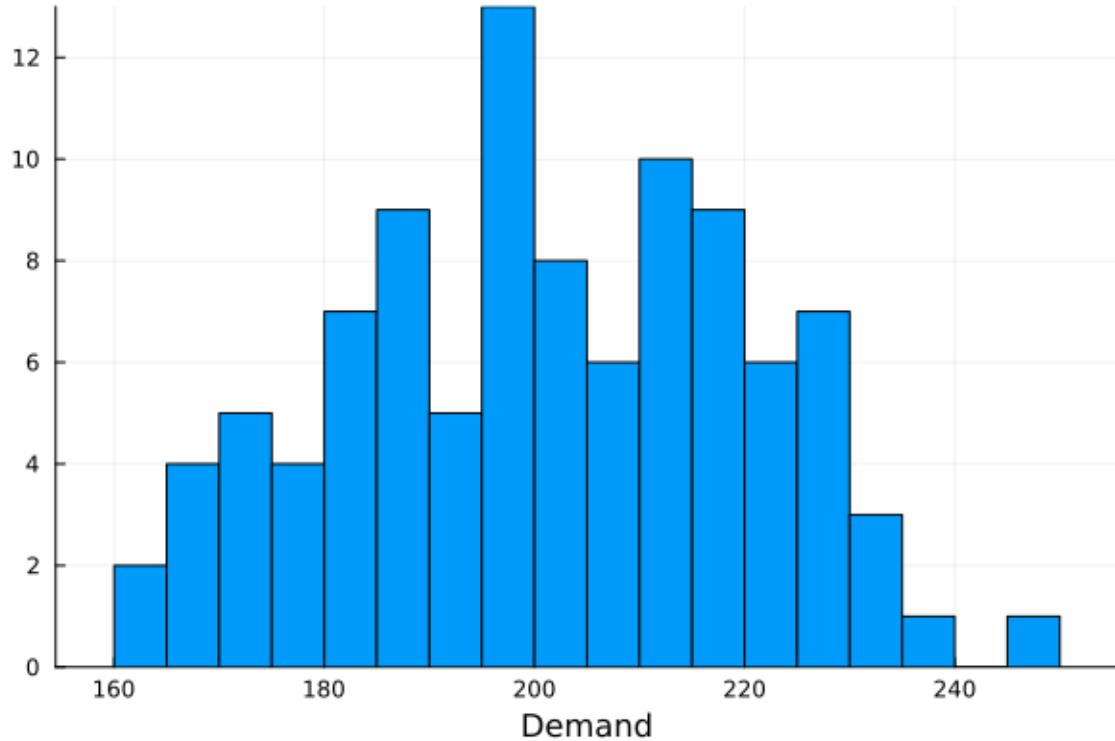
We can formulate this problem as follows:

$$\begin{aligned} \max_{x,y_\omega} \quad & -2x + \mathbb{E}_\omega[5y_\omega - 0.1(x - y_\omega)] \\ \text{s.t.} \quad & y_\omega \leq x \quad \forall \omega \in \Omega \\ & 0 \leq y_\omega \leq d_\omega \quad \forall \omega \in \Omega \\ & x \geq 0. \end{aligned}$$

### Sample Average approximation

If the distribution of demand is continuous, then our problem has an infinite number of variables and constraints. To form a computationally tractable problem, we instead use a finite set of samples drawn from the distribution. This is called sample average approximation (SAA).

```
D = Distributions.TriangularDist(150.0, 250.0, 200.0)
N = 100
d = sort!(rand(D, N));
Ω = 1:N
P = fill(1 / N, N);
StatsPlots.histogram(d; bins = 20, label = "", xlabel = "Demand")
```



### JuMP model

The implementation of our two-stage stochastic program in JuMP is:

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x >= 0)
@variable(model, 0 <= y[ω in Ω] <= d[ω])
@constraint(model, [ω in Ω], y[ω] <= x)
@expression(model, z[ω in Ω], 5y[ω] - 0.1 * (x - y[ω]))
@objective(model, Max, -2x + sum(P[ω] * z[ω] for ω in Ω))
optimize!(model)
assert_is_solved_and_feasible(model)
solution_summary(model)
```

```

* Solver : HIGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : 5.64271e+02
  Objective bound    : 5.64271e+02
  Relative gap       : 0.00000e+00
  Dual objective value : 5.64271e+02

* Work counters
  Solve time (sec)   : 3.86238e-04
  Simplex iterations : 42
  Barrier iterations : 0
  Node count         : -1

```

The optimal number of pies to make is:

```
value(x)
```

```
206.8364169803885
```

The distribution of total profit is:

```
total_profit = [-2 * value(x) + value(z[w]) for w in Q]
```

```

100-element Vector{Float64}:
399.9151768229468
405.7454219177082
417.61135488562354
420.5047206624374
424.1692725508499
426.7062730398078
434.2880791737741
434.96479364495735
444.5071682942105
449.5828663580197
⋮
620.5092509411653
620.5092509411653
620.5092509411653

```

```
620.5092509411653
620.5092509411653
620.5092509411653
620.5092509411653
620.5092509411653
620.5092509411653
```

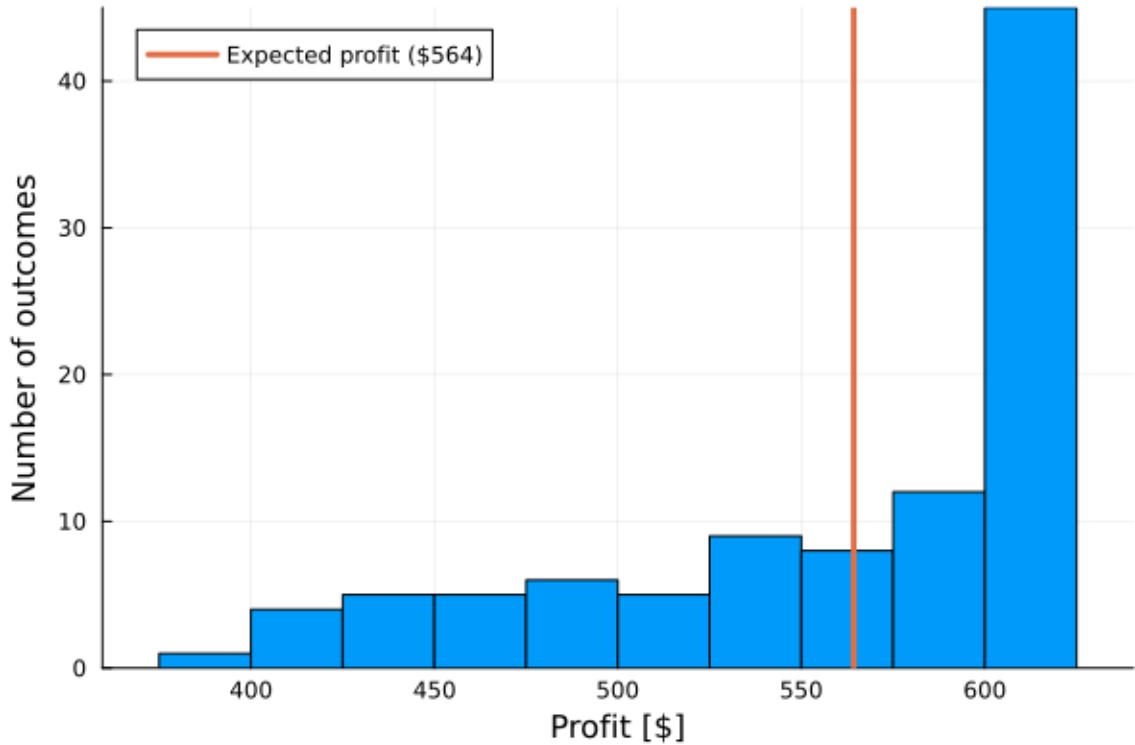
Let's plot it:

```
"""
bin_distribution(x::Vector{Float64}, N::Int)

A helper function that discretizes `x` into bins of width `N`.
"""

bin_distribution(x, N) = N * (floor(minimum(x) / N):ceil(maximum(x) / N))

plot = StatsPlots.histogram(
    total_profit;
    bins = bin_distribution(total_profit, 25),
    label = "",
    xlabel = "Profit [\$\$]",
    ylabel = "Number of outcomes",
)
μ = Statistics.mean(total_profit)
Plots.vline!(
    plot,
    [μ];
    label = "Expected profit (\$\$(round(Int, μ)))",
    linewidth = 3,
)
plot
```



### Risk measures

A risk measure is a function which maps a random variable to a real number. Common risk measures include the mean (expectation), median, mode, and maximum. We need a risk measure to convert the distribution of second stage costs into a single number that can be optimized.

Our model currently uses the expectation risk measure, but others are possible too. One popular risk measure is the conditional value at risk (CVaR).

CVaR has a parameter  $\gamma$ , and it computes the expectation of the worst  $\gamma$  fraction of outcomes.

If we are maximizing, so that small outcomes are bad, the definition of CVaR is:

$$CVaR_\gamma[Z] = \max_{\xi} \xi - \frac{1}{\gamma} \mathbb{E}_\omega [(\xi - Z)_+]$$

which can be formulated as the linear program:

$$\begin{aligned} CVaR_\gamma[Z] = \max_{\xi, z_\omega} & \quad \xi - \frac{1}{\gamma} \sum P_\omega z_\omega \\ \text{s.t. } & \quad z_\omega \geq \xi - Z_\omega \quad \forall \omega \\ & \quad z_\omega \geq 0 \quad \forall \omega. \end{aligned}$$

```

function CVaR(Z::Vector{Float64}, P::Vector{Float64}; γ::Float64)
    @assert 0 < γ <= 1
    N = length(Z)
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, ξ)
    @variable(model, z[1:N] >= 0)
    @constraint(model, [i in 1:N], z[i] >= ξ - Z[i])
    @objective(model, Max, ξ - 1 / γ * sum(P[i] * z[i] for i in 1:N))
    optimize!(model)
    assert_is_solved_and_feasible(model)
    return objective_value(model)
end

```

CVaR (generic function with 1 method)

When  $\gamma$  is 1.0, we compute the mean of the profit:

```
cvar_10 = CVaR(total_profit, P; γ = 1.0)
```

564.2707958834865

```
Statistics.mean(total_profit)
```

564.2707958834864

As  $\gamma$  approaches 0.0, we compute the worst-case (minimum) profit:

```
cvar_00 = CVaR(total_profit, P; γ = 0.0001)
```

399.9151768229468

```
minimum(total_profit)
```

399.9151768229468

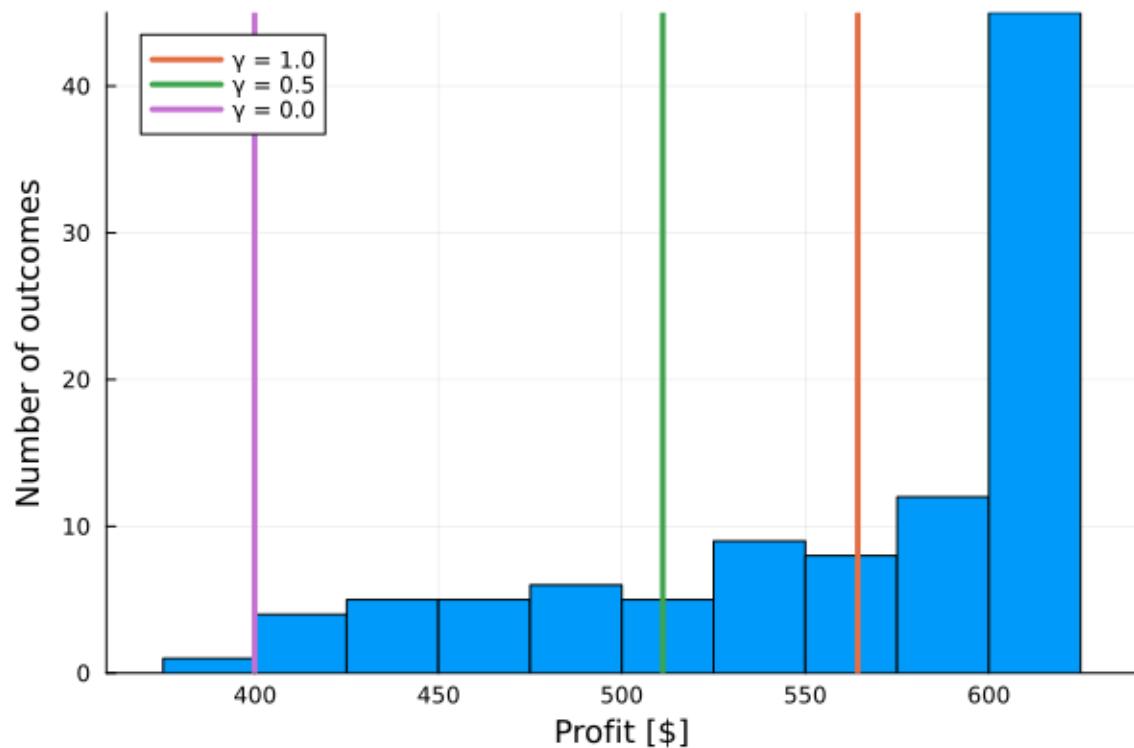
By varying  $\gamma$  between 0 and 1 we can compute some trade-off of these two extremes:

```
cvar_05 = CVaR(total_profit, P; γ = 0.5)
```

```
511.14442019068
```

Let's plot these outcomes on our distribution:

```
plot = StatsPlots.histogram(
    total_profit;
    bins = bin_distribution(total_profit, 25),
    label = "",
    xlabel = "Profit [\$\"]",
    ylabel = "Number of outcomes",
)
Plots.vline!(
    plot,
    [cvar_10 cvar_05 cvar_00];
    label = ["γ = 1.0" "γ = 0.5" "γ = 0.0"],
    linewidth = 3,
)
plot
```



### Risk averse sample average approximation

Because CVaR can be formulated as a linear program, we can form a risk averse sample average approximation model by combining the two formulations:

```

γ = 0.4
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x >= 0)
@variable(model, 0 <= y[ω in Ω] <= d[ω])
@constraint(model, [ω in Ω], y[ω] <= x)
@expression(model, Z[ω in Ω], 5 * y[ω] - 0.1(x - y[ω]))
@variable(model, ξ)
@variable(model, z[ω in Ω] >= 0)
@constraint(model, [ω in Ω], z[ω] >= ξ - Z[ω])
@objective(model, Max, -2x + ξ - 1 / γ * sum(P[ω] * z[ω] for ω in Ω))
optimize!(model)
assert_is_solved_and_feasible(model)

```

When  $\gamma = 0.4$ , the optimal number of pies to bake is:

```
value(x)
```

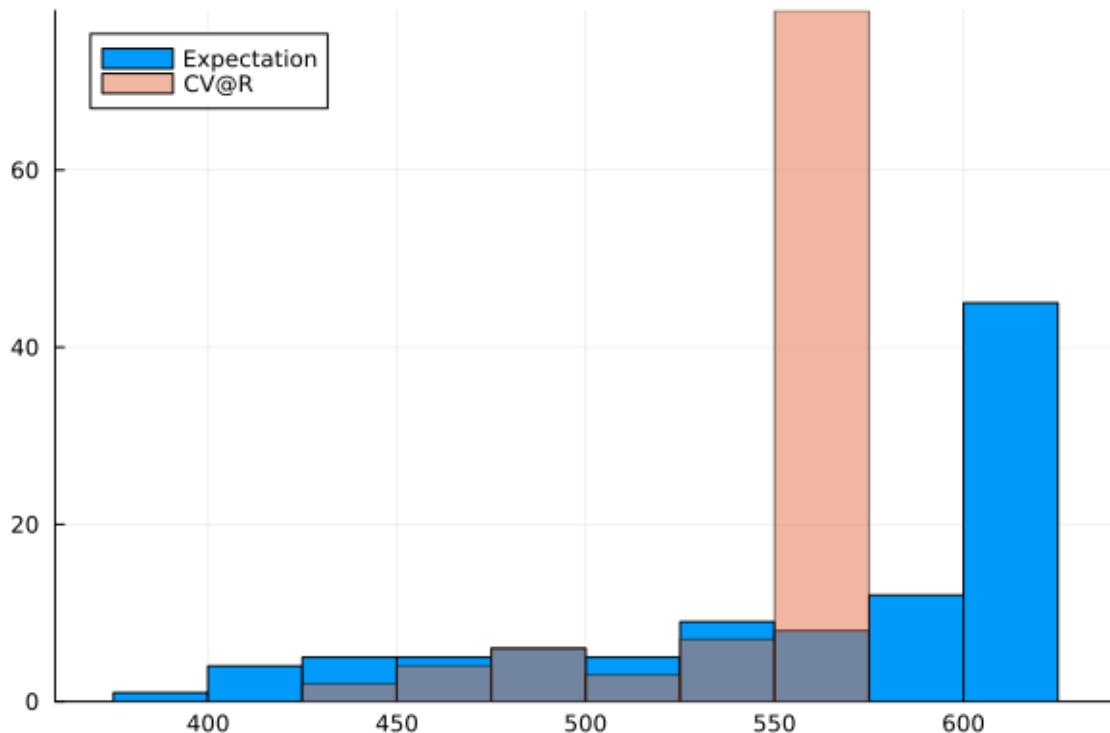
```
187.3712615331823
```

The distribution of total profit is:

```

risk_averse_total_profit = [value(-2x + Z[ω]) for ω in Ω]
bins = bin_distribution([total_profit; risk_averse_total_profit], 25)
plot = StatsPlots.histogram(total_profit; label = "Expectation", bins = bins)
StatsPlots.histogram!(
    plot,
    risk_averse_total_profit;
    label = "CV@R",
    bins = bins,
    alpha = 0.5,
)
plot

```



### Next steps

- Try solving this problem for different numbers of samples and different distributions.
- Refactor the example to avoid hard-coding the costs. What happens to the solution if the cost of disposing unsold pies increases?
- Plot the optimal number of pies to make for different values of the risk aversion parameter  $\gamma$ . What is the relationship?

## **Part III**

## **Manual**

# Chapter 11

## Models

JuMP models are the fundamental building block that we use to construct optimization problems. They hold things like the variables and constraints, as well as which solver to use and even solution information.

### Info

JuMP uses "optimizer" as a synonym for "solver." Our convention is to use "solver" to refer to the underlying software, and use "optimizer" to refer to the Julia object that wraps the solver. For example, HiGHS is a solver, and HiGHS.Optimizer is an optimizer.

### Tip

See [Supported solvers](#) for a list of available solvers.

### 11.1 Create a model

Create a model by passing an optimizer to `Model`:

```
julia> model = Model(HiGHS.Optimizer)
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

If you don't know which optimizer you will be using at creation time, create a model without an optimizer, and then call `set_optimizer` at any time prior to `optimize!`:

```
julia> model = Model()
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

```
julia> set_optimizer(model, HiGHS.Optimizer)
```

**Tip**

Don't know what the fields `Model` `mode` and `CachingOptimizer` state mean? Read the [Backends](#) section.

### What is the difference?

For most models, there is no difference between passing the optimizer to `Model`, and calling `set_optimizer`.

However, if an optimizer does not support a constraint in the model, the timing of when an error will be thrown can differ:

- If you pass an optimizer, an error will be thrown when you try to add the constraint.
- If you call `set_optimizer`, an error will be thrown when you try to solve the model via `optimize!`.

Therefore, most users should pass an optimizer to `Model` because it provides the earliest warning that your solver is not suitable for the model you are trying to build. However, if you are modifying a problem by adding and deleting different constraint types, you may need to use `set_optimizer`. See [Switching optimizer for the relaxed problem](#) for an example of when this is useful.

### Solvers which expect environments

Some solvers accept (or require) positional arguments such as a license environment or a path to a binary executable. For these solvers, you can pass a function to `Model` which takes zero arguments and returns an instance of the optimizer.

A common use-case for this is passing an environment or sub-solver to the optimizer:

```
julia> import HiGHS
julia> import MultiObjectiveAlgorithms as MOA
julia> model = Model(() -> MOA.Optimizer(HiGHS.Optimizer))
A JuMP Model
└ solver: MOA[algorithm=MultiObjectiveAlgorithms.Lexicographic, optimizer=HiGHS]
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none
```

## 11.2 Solver options

JuMP uses "attribute" as a synonym for "option." Use `optimizer_with_attributes` to create an optimizer with some attributes initialized:

```
julia> model = Model(
           optimizer_with_attributes(HiGHS.Optimizer, "output_flag" => false),
       )
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

Alternatively, use `set_attribute` to set an attribute after the model has been created:

```
julia> model = Model(HiGHS.Optimizer);

julia> set_attribute(model, "output_flag", false)

julia> get_attribute(model, "output_flag")
false
```

You can also modify attributes within an `optimizer_with_attributes` object:

```
julia> solver = optimizer_with_attributes(HiGHS.Optimizer, "output_flag" => true);

julia> get_attribute(solver, "output_flag")
true

julia> set_attribute(solver, "output_flag", false)

julia> get_attribute(solver, "output_flag")
false

julia> model = Model(solver);
```

### 11.3 Changing the number types

By default, the coefficients of affine and quadratic expressions are numbers of type either `Float64` or `Complex{Float64}` (see [Complex number support](#)).

The type `Float64` can be changed using the `GenericModel` constructor:

```
julia> model = GenericModel{Rational{BigInt}}();

julia> @variable(model, x)
x

julia> @expression(model, expr, 1 // 3 * x)
1//3 x

julia> typeof(expr)
GenericAffExpr{Rational{BigInt}, GenericVariableRef{Rational{BigInt}}}
```

Using a `value_type` other than `Float64` is an advanced operation and should be used only if the underlying solver actually solves the problem using the provided value type.

#### Warning

`Nonlinear Modeling` is currently restricted to the `Float64` number type.

## 11.4 Print the model

By default, `show(model)` will print a summary of the problem:

```
julia> model = Model(); @variable(model, x >= 0); @objective(model, Max, x);

julia> model
A JuMP Model
├ solver: none
├ objective_sense: MAX_SENSE
|└ objective_function_type: VariableRef
├ num_variables: 1
├ num_constraints: 1
|└ VariableRef in MOI.GreaterThan{Float64}: 1
└ Names registered in the model
  └ :x
```

Use `print` to print the formulation of the model (in IJulia, this will render as LaTeX).

```
julia> print(model)
Max x
Subject to
x ≥ 0
```

#### Warning

This format is specific to JuMP and may change in any future release. It is not intended to be an instance format. To write the model to a file, use `write_to_file` instead.

Use `latex_formulation` to display the model in LaTeX form.

```
julia> latex_formulation(model)
$$ \begin{aligned}
&\max\quad && x \\
&\text{Subject to} && x \geq 0 \\
&\end{aligned} $$
```

In IJulia (and Documenter), ending a cell in with `latex_formulation` will render the model in LaTeX:

```
latex_formulation(model)
```

$$\begin{aligned} & \max \quad x \\ \text{Subject to} \quad & x \geq 0 \end{aligned}$$

## 11.5 Turn off output

Use `set_silent` and `unset_silent` to disable or enable printing output from the solver.

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> unset_silent(model)
```

### Tip

Most solvers will also have a [solver-specific option](#) to provide finer-grained control over the output. Consult their README's for details.

## 11.6 Set a time limit

Use `set_time_limit_sec`, `unset_time_limit_sec`, and `time_limit_sec` to manage time limits.

```
julia> model = Model(HiGHS.Optimizer);

julia> set_time_limit_sec(model, 60.0)

julia> time_limit_sec(model)
60.0

julia> unset_time_limit_sec(model)

julia> limit = time_limit_sec(model)

julia> limit === nothing
true
```

If your time limit is encoded as a `Dates.Period` object, use the following code to convert it to `Float64` for `set_time_limit_sec`:

```
julia> import Dates

julia> seconds(x::Dates.Period) = 1e-3 * Dates.value(round(x, Dates.Millisecond))
seconds (generic function with 1 method)

julia> set_time_limit_sec(model, seconds(Dates.Hour(1)))

julia> time_limit_sec(model)
3600.0
```

**Info**

Some solvers do not support time limits. In these cases, an error will be thrown.

## 11.7 Write a model to file

JuMP can write models to a variety of file-formats using `write_to_file` and `Base.write`.

For most common file formats, the file type will be detected from the extension.

For example, here is how to write an [MPS file](#):

```
julia> model = Model();
julia> write_to_file(model, "model.mps")
```

Other supported file formats include:

- `.cbf` for the [Conic Benchmark Format](#)
- `.lp` for the [LP file format](#)
- `.mof.json` for the [MathOptFormat](#)
- `.nl` for [AMPL's NL file format](#)
- `.rew` for the [REW file format](#)
- `.sdpa` and `".dat-s"` for the [SDPA file format](#)

To write to a specific `io::IO`, use `Base.write`. Specify the file type by passing a `MOI.FileFormats.FileFormat` enum.

```
julia> model = Model();
julia> io = IOBuffer();
julia> write(io, model; format = MOI.FileFormats FORMAT_MPS)
```

## 11.8 Read a model from file

JuMP models can be created from file formats using `read_from_file` and `Base.read`.

```
julia> model = read_from_file("model.mps")
A JuMP Model
├ solver: none
├ objective_sense: MIN_SENSE
|└ objective_function_type: AffExpr
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

```
julia> seekstart(io);

julia> model2 = read(io, Model; format = MOI.FileFormats.FORMAT_MPS)
A JuMP Model
├ solver: none
├ objective_sense: MIN_SENSE
|└ objective_function_type: AffExpr
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none
```

**Note**

Because file formats do not serialize the containers of JuMP variables and constraints, the names in the model will *not* be registered. Therefore, you cannot access named variables and constraints via `model[:x]`. Instead, use `variable_by_name` or `constraint_by_name` to access specific variables or constraints.

## 11.9 Relax integrality

Use `relax_integrality` to remove any integrality constraints from the model, such as integer and binary restrictions on variables. `relax_integrality` returns a function that can be later called with zero arguments to re-add the removed constraints:

```
julia> model = Model();

julia> @variable(model, x, Int)
x

julia> num_constraints(model, VariableRef, MOI.Integer)
1

julia> undo = relax_integrality(model);

julia> num_constraints(model, VariableRef, MOI.Integer)
0

julia> undo()

julia> num_constraints(model, VariableRef, MOI.Integer)
1
```

### Switching optimizer for the relaxed problem

A common reason for relaxing integrality is to compute dual variables of the relaxed problem. However, some mixed-integer linear solvers (for example, Cbc) do not return dual solutions, even if the problem does not have integrality restrictions.

Therefore, after `relax_integrality` you should call `set_optimizer` with a solver that does support dual solutions, such as Clp.

For example, instead of:

```
using JuMP, Cbc
model = Model(Cbc.Optimizer)
@variable(model, x, Int)
undo = relax_integrality(model)
optimize!(model)
reduced_cost(x) # Errors
```

do:

```
using JuMP, Cbc, Clp
model = Model(Cbc.Optimizer)
@variable(model, x, Int)
undo = relax_integrality(model)
set_optimizer(model, Clp.Optimizer)
optimize!(model)
reduced_cost(x) # Works
```

## 11.10 Get the matrix representation

Use `lp_matrix_data` to return a data structure that represents the matrix form of a linear program.

```
julia> begin
           model = Model()
           @variable(model, x >= 1, Bin)
           @variable(model, 2 <= y)
           @variable(model, 3 <= z <= 4, Int)
           @constraint(model, x == 5)
           @constraint(model, 2x + 3y <= 6)
           @constraint(model, -4y >= 5z + 7)
           @constraint(model, -1 <= x + y <= 2)
           @objective(model, Max, 1 + 2x)
       end;

julia> data = lp_matrix_data(model);

julia> data.A
4x3 SparseArrays.SparseMatrixCSC{Float64, Int64} with 7 stored entries:
 1.0   .   .
   .  -4.0  -5.0
 2.0   3.0   .
 1.0   1.0   .

julia> data.b_lower
4-element Vector{Float64}:
 5.0
 7.0
 -Inf
 -1.0

julia> data.b_upper
```

```
4-element Vector{Float64}:
5.0
Inf
6.0
2.0

julia> data.x_lower
3-element Vector{Float64}:
1.0
2.0
3.0

julia> data.x_upper
3-element Vector{Float64}:
Inf
Inf
4.0

julia> data.c
3-element Vector{Float64}:
2.0
0.0
0.0

julia> data.c_offset
1.0

julia> data.sense
MAX_SENSE::OptimizationSense = 1

julia> data.integers
1-element Vector{Int64}:
3

julia> data.binaries
1-element Vector{Int64}:
1
```

**Warning**

`lp_matrix_data` is intentionally limited in the types of problems that it supports and the structure of the matrices it outputs. It is mainly intended as a pedagogical and debugging tool. It should not be used to interface solvers, see [Implementing a solver interface](#) instead.

## 11.11 Backends

**Info**

This section discusses advanced features of JuMP. For new users, you may want to skip this section. You don't need to know how JuMP manages problems behind the scenes to create and solve JuMP models.

A JuMP `Model` is a thin layer around a `backend` of type `MOI.ModelLike` that stores the optimization problem and acts as the optimization solver.

However, if you construct a model like `Model(HiGHS.Optimizer)`, the backend is not a `HiGHS.Optimizer`, but a more complicated object.

From JuMP, the MOI backend can be accessed using the `backend` function. Let's see what the `backend` of a JuMP `Model` is:

```
julia> model = Model(HiGHS.Optimizer);

julia> b = backend(model)
MOIU.CachingOptimizer
├ state: EMPTY_OPTIMIZER
├ mode: AUTOMATIC
├ model_cache: MOIU.UniversalFallback{MOIU.Model{Float64}}
│ ├ ObjectiveSense: FEASIBILITY_SENSE
│ ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
│ ├ NumberOfVariables: 0
│ └ NumberOfConstraints: 0
└ optimizer: MOIB.LazyBridgeOptimizer{HiGHS.Optimizer}
    ├ Variable bridges: none
    ├ Constraint bridges: none
    ├ Objective bridges: none
    └ model: A HiGHS model with 0 columns and 0 rows.
```

Uh oh. Even though we passed a `HiGHS.Optimizer`, the backend is a much more complicated object.

### CachingOptimizer

A `MOIU.CachingOptimizer` is a layer that abstracts the difference between solvers that support incremental modification (for example, they support adding variables one-by-one), and solvers that require the entire problem in a single API call (for example, they only accept the `A`, `b` and `c` matrices of a linear program).

It has two parts:

1. A cache, where the model can be built and modified incrementally

```
julia> b.model_cache
MOIU.UniversalFallback{MOIU.Model{Float64}}
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

2. An optimizer, which is used to solve the problem

```
julia> b.optimizer
MOIB.LazyBridgeOptimizer{HiGHS.Optimizer}
├ Variable bridges: none
├ Constraint bridges: none
├ Objective bridges: none
└ model: A HiGHS model with 0 columns and 0 rows.
```

**Info**

The [LazyBridgeOptimizer](#) section explains what a LazyBridgeOptimizer is.

The CachingOptimizer has logic to decide when to copy the problem from the cache to the optimizer, and when it can efficiently update the optimizer in-place.

A CachingOptimizer may be in one of three possible states:

- NO\_OPTIMIZER: The CachingOptimizer does not have any optimizer.
- EMPTY\_OPTIMIZER: The CachingOptimizer has an empty optimizer, and it is not synchronized with the cached model.
- ATTACHED\_OPTIMIZER: The CachingOptimizer has an optimizer, and it is synchronized with the cached model.

A CachingOptimizer has two modes of operation:

- AUTOMATIC: The CachingOptimizer changes its state when necessary. For example, `optimize!` will automatically call `attach_optimizer` (an optimizer must have been previously set). Attempting to add a constraint or perform a modification not supported by the optimizer results in a drop to EMPTY\_OPTIMIZER mode.
- MANUAL: The user must change the state of the CachingOptimizer using `MOIU.reset_optimizer(::JuMP.Model)`, `MOIU.drop_optimizer(::JuMP.Model)`, and `MOIU.attach_optimizer(::JuMP.Model)`. Attempting to perform an operation in the incorrect state results in an error.

By default `Model` will create a CachingOptimizer in AUTOMATIC mode.

## **LazyBridgeOptimizer**

The second layer that JuMP applies automatically is a `MOI.Bridges.LazyBridgeOptimizer`. A `MOI.Bridges.LazyBridgeOptimizer` is an MOI layer that attempts to transform the problem from the formulation provided by the user into an equivalent problem supported by the solver. This may involve adding new variables and constraints to the optimizer. The transformations are selected from a set of known recipes called *bridges*.

A common example of a bridge is one that splits an interval constraint like `@constraint(model, 1 <= x + y <= 2)` into two constraints, `@constraint(model, x + y >= 1)` and `@constraint(model, x + y <= 2)`.

Use the `add_bridges = false` keyword to remove the bridging layer:

```
julia> model = Model(HiGHS.Optimizer; add_bridges = false)
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> backend(model)
MOIU.CachingOptimizer
└ state: EMPTY_OPTIMIZER
```

```

├ mode: AUTOMATIC
├ model_cache: MOIU.UniversalFallback{MOIU.Model{Float64}}
| ├ ObjectiveSense: FEASIBILITY_SENSE
| ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
| ├ NumberOfVariables: 0
| └ NumberOfConstraints: 0
└ optimizer: A HiGHS model with 0 columns and 0 rows.

```

Bridges can be added and removed from a `MOI.Bridges.LazyBridgeOptimizer` using `add_bridge` and `remove_bridge`. Use `print_active_bridges` to see which bridges are used to reformulate the model. Read the [Example: ellipsoid approximation](#) tutorial for more details.

### Unsafe backend

In some advanced use-cases, it is necessary to work with the inner optimization model directly. To access this model, use `unsafe_backend`:

```

julia> backend(model)
MOIU.CachingOptimizer
├ state: EMPTY_OPTIMIZER
├ mode: AUTOMATIC
├ model_cache: MOIU.UniversalFallback{MOIU.Model{Float64}}
| ├ ObjectiveSense: FEASIBILITY_SENSE
| ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
| ├ NumberOfVariables: 0
| └ NumberOfConstraints: 0
└ optimizer: MOIB.LazyBridgeOptimizer{HiGHS.Optimizer}
    ├ Variable bridges: none
    ├ Constraint bridges: none
    ├ Objective bridges: none
    └ model: A HiGHS model with 0 columns and 0 rows.

julia> unsafe_backend(model)
A HiGHS model with 0 columns and 0 rows.

```

#### Warning

`backend` and `unsafe_backend` are advanced routines. Read their docstrings to understand the caveats of their usage, and only call them if you wish to access low-level solver-specific functions.

### 11.12 Direct mode

Using a `CachingOptimizer` results in an additional copy of the model being stored by JuMP in the `.model_cache` field. To avoid this overhead, create a JuMP model using `direct_model`:

```

julia> model = direct_model(HiGHS.Optimizer())
A JuMP Model
├ mode: DIRECT
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE

```

```
| num_variables: 0
| num_constraints: 0
└ Names registered in the model: none
```

**Warning**

Solvers that do not support incremental modification do not support `direct_model`. An error will be thrown, telling you to use a `CachingOptimizer` instead.

The benefit of using `direct_model` is that there are no extra layers (for example, `Cachingoptimizer` or `LazyBridgeOptimizer`) between model and the provided optimizer:

```
julia> backend(model)
A HiGHS model with 0 columns and 0 rows.
```

A downside of direct mode is that there is no bridging layer. Therefore, only constraints which are natively supported by the solver are supported. For example, `HiGHS.jl` does not implement quadratic constraints:

```
julia> model = direct_model(HiGHS.Optimizer());
julia> set_silent(model)
julia> @variable(model, x[1:2]);
julia> @constraint(model, x[1]^2 + x[2]^2 <= 2)
ERROR: Constraints of type
→ MathOptInterface.ScalarQuadraticFunction{Float64}-in-MathOptInterface.LessThan{Float64} are not
→ supported by the solver.

If you expected the solver to support your problem, you may have an error in your formulation.
→ Otherwise, consider using a different solver.

The list of available solvers, along with the problem types they support, is available at
→ https://jump.dev/JuMP.jl/stable/installation/#Supported-solvers.
Stacktrace:
```

**Warning**

Another downside of direct mode is that the behavior of querying solution information after modifying the problem is solver-specific. This can lead to errors, or the solver silently returning an incorrect value. See `OptimizeNotCalled` errors for more information.

## Chapter 12

# Variables

The term *variable* in mathematical optimization has many meanings. For example, *optimization variables* (also called decision variables) are the unknowns  $x$  that we are solving for in the problem:

$$\min_{x \in \mathbb{R}^n} f_0(x) \quad (12.1)$$

$$\text{s.t.} \quad f_i(x) \in \mathcal{S}_i \quad i = 1 \dots m \quad (12.2)$$

To complicate things, Julia uses *variable* to mean a binding between a name and a value. For example, in the statement:

```
julia> x = 1  
1
```

`x` is a variable that stores the value 1.

JuMP uses *variable* in a third way, to mean an instance of the `VariableRef` struct. JuMP variables are the link between Julia and the optimization variables inside a JuMP model.

This page explains how to create and manage JuMP variables in a variety of contexts.

### 12.1 Create a variable

Create variables using the `@variable` macro:

```
julia> model = Model();  
  
julia> @variable(model, x)  
x  
  
julia> typeof(x)  
VariableRef (alias for GenericVariableRef{Float64})  
  
julia> num_variables(model)  
1
```

Here `x` is a Julia variable that is bound to a `VariableRef` object, and we have added 1 decision variable to our model.

To make the binding more explicit, we could have written:

```
julia> model = Model();
julia> x = @variable(model, x)
x
```

but there is no need to in general; the macro does it for us.

When creating a variable, you can also specify variable bounds:

```
julia> model = Model();
julia> @variable(model, x_free)
x_free

julia> @variable(model, x_lower >= 0)
x_lower

julia> @variable(model, x_upper <= 1)
x_upper

julia> @variable(model, 2 <= x_interval <= 3)
x_interval

julia> @variable(model, x_fixed == 4)
x_fixed

julia> print(model)
Feasibility
Subject to
x_fixed = 4
x_lower ≥ 0
x_interval ≥ 2
x_upper ≤ 1
x_interval ≤ 3
```

### Warning

When creating a variable with a single lower- or upper-bound, and the value of the bound is not a numeric literal (for example, 1 or 1.0), the name of the variable *must* appear on the left-hand side. Putting the name on the right-hand side is an error. For example, to create a variable x:

```
a = 1
@variable(model, x >= 1)      # ✅ Okay
@variable(model, 1.0 <= x)    # ✅ Okay
@variable(model, x >= a)      # ✅ Okay
@variable(model, a <= x)      # ✗ Not okay
@variable(model, x >= 1 / 2)  # ✅ Okay
@variable(model, 1 / 2 <= x)  # ✗ Not okay
```

## Containers of variables

The `@variable` macro also supports creating collections of JuMP variables. We'll cover some brief syntax here; read the [Variable containers](#) section for more details.

You can create arrays of JuMP variables:

```
julia> model = Model();
julia> @variable(model, x[1:2, 1:2])
2×2 Matrix{VariableRef}:
 x[1,1]  x[1,2]
 x[2,1]  x[2,2]

julia> x[1, 2]
x[1,2]
```

Index sets can be named, and bounds can depend on those names:

```
julia> model = Model();
julia> @variable(model, sqrt(i) <= x[i = 1:3] <= i^2)
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]

julia> x[2]
x[2]
```

Sets can be any Julia type that supports iteration:

```
julia> model = Model();
julia> @variable(model, x[i = 2:3, j = 1:2:3, ["red", "blue"]] >= 0)
3-dimensional DenseAxisArray{VariableRef,3,...} with index sets:
    Dimension 1, 2:3
    Dimension 2, 1:2:3
    Dimension 3, ["red", "blue"]
And data, a 2×2×2 Array{VariableRef, 3}:
[:, :, "red"] =
 x[2,1,red]  x[2,3,red]
 x[3,1,red]  x[3,3,red]

[:, :, "blue"] =
 x[2,1,blue]  x[2,3,blue]
 x[3,1,blue]  x[3,3,blue]

julia> x[2, 1, "red"]
x[2,1,red]
```

Sets can depend upon previous indices:

```
julia> model = Model();

julia> @variable(model, u[i = 1:2, j = i:3])
JuMP.Containers.SparseAxisArray{VariableRef, 2, Tuple{Int64, Int64}} with 5 entries:
 [1, 1]  =  u[1,1]
 [1, 2]  =  u[1,2]
 [1, 3]  =  u[1,3]
 [2, 2]  =  u[2,2]
 [2, 3]  =  u[2,3]
```

and we can filter elements in the sets using the ; syntax:

```
julia> model = Model();

julia> @variable(model, v[i = 1:9; mod(i, 3) == 0])
JuMP.Containers.SparseAxisArray{VariableRef, 1, Tuple{Int64}} with 3 entries:
 [3]  =  v[3]
 [6]  =  v[6]
 [9]  =  v[9]
```

## 12.2 Registered variables

When you create variables, JuMP registers them inside the model using their corresponding symbol. Get a registered name using `model[:key]`:

```
julia> model = Model()
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none

julia> @variable(model, x)
x

julia> model
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 1
├ num_constraints: 0
└ Names registered in the model
    └ :x

julia> model[:x] === x
true
```

Registered names are most useful when you start to write larger models and want to break up the model construction into functions:

```
julia> function set_objective(model::Model)
           @objective(model, Min, 2 * model[:my_x] + 1)
           return
       end
set_objective (generic function with 1 method)

julia> model = Model();

julia> @variable(model, my_x);

julia> set_objective(model)

julia> print(model)
Min 2 my_x + 1
Subject to
```

### 12.3 Anonymous variables

To reduce the likelihood of accidental bugs, and because JuMP registers variables inside a model, creating two variables with the same name is an error:

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, x)
ERROR: An object of name x is already attached to this model. If this
      is intended, consider using the anonymous construction syntax, for example,
      `x = @variable(model, [1:N], ...)` where the name of the object does
      not appear inside the macro.

      Alternatively, use `unregister(model, :x)` to first unregister
      the existing name from the model. Note that this will not delete the
      object; it will just remove the reference at `model[:x]`.

[...]
```

A common reason for encountering this error is adding variables in a loop.

As a work-around, JuMP provides *anonymous* variables. Create a scalar valued anonymous variable by omitting the name argument:

```
julia> model = Model();

julia> x = @variable(model)
_ [1]
```

Anonymous variables get printed as an underscore followed by a unique index of the variable.

**Warning**

The index of the variable may not correspond to the column of the variable in the solver.

Create a container of anonymous JuMP variables by dropping the name in front of the [:]

```
julia> model = Model();

julia> y = @variable(model, [1:2])
2-element Vector{VariableRef}:
 _[1]
 _[2]
```

The <= and >= short-hand cannot be used to set bounds on scalar-valued anonymous JuMP variables. Instead, use the `lower_bound` and `upper_bound` keywords:

```
julia> model = Model();

julia> x_lower = @variable(model, lower_bound = 1.0)
_[1]

julia> x_upper = @variable(model, upper_bound = 2.0)
_[2]

julia> x_interval = @variable(model, lower_bound = 3.0, upper_bound = 4.0)
_[3]
```

## 12.4 Variable names

In addition to the symbol that variables are registered with, JuMP variables have a String name that is used for printing and writing to file formats.

Get and set the name of a variable using `name` and `set_name`:

```
julia> model = Model();

julia> @variable(model, x)
x

julia> name(x)
"x"

julia> set_name(x, "my_x_name")

julia> x
my_x_name
```

Override the default choice of name using the `base_name` keyword:

```
julia> model = Model();

julia> @variable(model, x[i=1:2], base_name = "my_var")
2-element Vector{VariableRef}:
 my_var[1]
 my_var[2]
```

Note that names apply to each element of the container, not to the container of variables:

```
julia> name(x[1])
"my_var[1]"

julia> set_name(x[1], "my_x")

julia> x
2-element Vector{VariableRef}:
 my_x
 my_var[2]
```

### Tip

For some models, setting the string name of each variable can take a non-trivial portion of the total time required to build the model. Turn off String names by passing `set_string_name = false` to `@variable`:

```
julia> model = Model();

julia> @variable(model, x, set_string_name = false)
_[1]
```

See [Disable string names](#) for more information.

## Retrieve a variable by name

Retrieve a variable from a model using `variable_by_name`:

```
julia> variable_by_name(model, "my_x")
my_x
```

If the name is not present, nothing will be returned:

```
julia> variable_by_name(model, "bad_name")
```

You can only look up individual variables using `variable_by_name`. Something like this will not work:

```
julia> model = Model();
```

```
julia> @variable(model, [i = 1:2], base_name = "my_var")
2-element Vector{VariableRef}:
my_var[1]
my_var[2]

julia> variable_by_name(model, "my_var")
```

To look up a collection of variables, do not use `variable_by_name`. Instead, register them using the `model[:key] = value` syntax:

```
julia> model = Model();

julia> model[:x] = @variable(model, [i = 1:2], base_name = "my_var")
2-element Vector{VariableRef}:
my_var[1]
my_var[2]

julia> model[:x]
2-element Vector{VariableRef}:
my_var[1]
my_var[2]
```

## 12.5 String names, symbolic names, and bindings

It's common for new users to experience confusion relating to JuMP variables. Part of the problem is the overloaded use of "variable" in mathematical optimization, along with the difference between the name that a variable is registered under and the String name used for printing.

Here's a summary of the differences:

- JuMP variables are created using `@variable`.
- JuMP variables can be named or anonymous.
- Named JuMP variables have the form `@variable(model, x)`. For named variables:
  - The String name of the variable is set to "x".
  - A Julia variable `x` is created that binds `x` to the JuMP variable.
  - The name `:x` is registered as a key in the model with the value `x`.
- Anonymous JuMP variables have the form `x = @variable(model)`. For anonymous variables:
  - The String name of the variable is set to "". When printed, this is replaced with "`_i`" where `i` is the index of the variable.
  - You control the name of the Julia variable used as the binding.
  - No name is registered as a key in the model.
- The `base_name` keyword can override the String name of the variable.
- You can manually register names in the model via `model[:key] = value`

Here's an example that should make things clearer:

```
julia> model = Model();

julia> x_binding = @variable(model, base_name = "x")
x

julia> model
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 1
└ num_constraints: 0
└ Names registered in the model: none

julia> x
ERROR: UndefVarError: `x` not defined

julia> x_binding
x

julia> name(x_binding)
"x"

julia> model[:x_register] = x_binding
x

julia> model
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 1
└ num_constraints: 0
└ Names registered in the model
    └ :x_register

julia> model[:x_register]
x

julia> model[:x_register] === x_binding
true

julia> x
ERROR: UndefVarError: `x` not defined
```

## 12.6 Create, delete, and modify variable bounds

Query whether a variable has a bound using `has_lower_bound`, `has_upper_bound`, and `is_fixed`:

```
julia> has_lower_bound(x_free)
false

julia> has_upper_bound(x_upper)
true
```

```
julia> is_fixed(x_fixed)
true
```

If a variable has a particular bound, query the value of it using [lower\\_bound](#), [upper\\_bound](#), and [fix\\_value](#):

```
julia> lower_bound(x_interval)
2.0

julia> upper_bound(x_interval)
3.0

julia> fix_value(x_fixed)
4.0
```

Querying the value of a bound that does not exist will result in an error.

Delete variable bounds using [delete\\_lower\\_bound](#), [delete\\_upper\\_bound](#), and [unfix](#):

```
julia> delete_lower_bound(x_lower)

julia> has_lower_bound(x_lower)
false

julia> delete_upper_bound(x_upper)

julia> has_upper_bound(x_upper)
false

julia> unfix(x_fixed)

julia> is_fixed(x_fixed)
false
```

Set or update variable bounds using [set\\_lower\\_bound](#), [set\\_upper\\_bound](#), and [fix](#):

```
julia> set_lower_bound(x_lower, 1.1)

julia> set_upper_bound(x_upper, 2.1)

julia> fix(x_fixed, 4.1)
```

Fixing a variable with existing bounds will throw an error. To delete the bounds prior to fixing, use `fix(variable, value; force = true)`.

```
julia> model = Model();

julia> @variable(model, x >= 1)
x

julia> fix(x, 2)
```

```

ERROR: Unable to fix x to 2 because it has existing variable bounds. Consider calling
→ `JuMP.fix(variable, value; force=true)` which will delete existing bounds before fixing the
→ variable.

julia> fix(x, 2; force = true)

julia> fix_value(x)
2.0

```

**Tip**

Use `fix` instead of `@constraint(model, x == 2)`. The former modifies variable bounds, while the latter adds a new linear constraint to the problem.

**12.7 Binary variables**

Binary variables are constrained to the set  $x \in \{0, 1\}$ .

Create a binary variable by passing `Bin` as an optional positional argument:

```

julia> model = Model();
julia> @variable(model, x, Bin)
x

```

**Warning**

Solvers use tolerances to decide whether a variable satisfies the binary constraint. Thus, the true feasible region is  $[-\varepsilon, \varepsilon] \cup [1 - \varepsilon, 1 + \varepsilon]$ , where  $\varepsilon$  is solver-specific, but typically  $1e-6$ . As a result, you should expect the `value(x)` of a `Bin` variable to sometimes take a value like  $-0.0$ ,  $1e-8$ , or  $0.999999$ .

Check if a variable is binary using `is_binary`:

```

julia> is_binary(x)
true

```

Delete a binary constraint using `unset_binary`:

```

julia> unset_binary(x)

julia> is_binary(x)
false

```

Binary variables can also be created by setting the `binary` keyword to `true`:

```
julia> model = Model();
julia> @variable(model, x, binary=true)
x
```

or by using `set_binary`:

```
julia> model = Model();
julia> @variable(model, x)
x

julia> set_binary(x)
```

## 12.8 Integer variables

Integer variables are constrained to the set  $x \in \mathbb{Z}$ .

Create an integer variable by passing `Int` as an optional positional argument:

```
julia> model = Model();
julia> @variable(model, x, Int)
x
```

### Warning

Solvers use tolerances to decide whether a variable satisfies the integer constraint. Thus, the true feasible region is  $\cup_{z \in \mathbb{Z}} [z - \varepsilon, z + \varepsilon]$ , where  $\varepsilon$  is solver-specific, but typically  $1e-6$ . As a result, you should expect the `value(x)` of an `Int` variable to sometimes take a value like  $1e-8$ , or  $2.999999$ .

Check if a variable is integer using `is_integer`:

```
julia> is_integer(x)
true
```

Delete an integer constraint using `unset_integer`.

```
julia> unset_integer(x)

julia> is_integer(x)
false
```

Integer variables can also be created by setting the `integer` keyword to `true`:

```
julia> model = Model();
julia> @variable(model, x, integer=true)
x
```

or by using `set_integer`:

```
julia> model = Model();
julia> @variable(model, x)
x
julia> set_integer(x)
```

### Tip

The `relax_integrality` function relaxes all integrality constraints in the model, returning a function that can be called to undo the operation later on.

## 12.9 Semi-integer and semi-continuous variables

Semi-continuous variables are constrained to the set  $x \in \{0\} \cup [l, u]$ .

Create a semi-continuous variable using the `Semicontinuous` set:

```
julia> model = Model();
julia> @variable(model, x in Semicontinuous(1.5, 3.5))
x
```

Semi-integer variables are constrained to the set  $x \in \{0\} \cup \{l, l+1, \dots, u\}$ .

Create a semi-integer variable using the `Semiinteger` set:

```
julia> model = Model();
julia> @variable(model, x in Semiinteger(1.0, 3.0))
x
```

## 12.10 Start values

There are two ways to provide a primal starting solution (also called MIP-start or a warmstart) for each variable:

- using the `start` keyword in the `@variable` macro
- using `set_start_value`

The starting value of a variable can be queried using `start_value`. If no start value has been set, `start_value` will return `nothing`.

```
julia> model = Model();
julia> @variable(model, x)
x
```

```
julia> start_value(x)

julia> @variable(model, y, start = 1)
y

julia> start_value(y)
1.0

julia> set_start_value(y, 2)

julia> start_value(y)
2.0
```

The `start` keyword argument can depend on the indices of a variable container:

```
julia> model = Model();

julia> @variable(model, z[i = 1:2], start = i^2)
2-element Vector{VariableRef}:
z[1]
z[2]

julia> start_value.(z)
2-element Vector{Float64}:
1.0
4.0
```

### Warning

Some solvers do not support start values. If a solver does not support start values, an `MathOptInterface.UnsupportedAttribute{MathOptInterface.VariablePrimalStart}` error will be thrown.

### Tip

To set the optimal solution from a previous solve as a new starting value, use `all_variables` to get a vector of all the variables in the model, then run:

```
x = all_variables(model)
x_solution = value.(x)
set_start_value.(x, x_solution)
```

Alternatively, use `set_start_values`.

## 12.11 Delete a variable

Use `delete` to delete a variable from a model. Use `is_valid` to check if a variable belongs to a model and has not been deleted.

```
julia> model = Model();
julia> @variable(model, x)
x

julia> is_valid(model, x)
true

julia> delete(model, x)

julia> is_valid(model, x)
false
```

Deleting a variable does not unregister the corresponding name from the model. Therefore, creating a new variable of the same name will throw an error:

```
julia> @variable(model, x)
ERROR: An object of name x is already attached to this model. If this
is intended, consider using the anonymous construction syntax, for example,
`x = @variable(model, [1:N], ...)` where the name of the object does
not appear inside the macro.

Alternatively, use `unregister(model, :x)` to first unregister
the existing name from the model. Note that this will not delete the
object; it will just remove the reference at `model[:x]`.
[...]
```

After calling `delete`, call `unregister` to remove the symbolic reference:

```
julia> unregister(model, :x)
julia> @variable(model, x)
x
```

### Info

`delete` does not automatically `unregister` because we do not distinguish between names that are automatically registered by JuMP macros and names that are manually registered by the user by setting values in `object_dictionary`. In addition, deleting a variable and then adding a new variable of the same name is an easy way to introduce bugs into your code.

## 12.12 Variable containers

JuMP provides a mechanism for creating collections of variables in three types of data structures, which we refer to as *containers*.

The three types are `Arrays`, `DenseAxisArrays`, and `SparseAxisArrays`. We explain each of these in the following.

**Tip**

You can read more about containers in the [Containers](#) section.

**Arrays**

We have already seen the creation of an array of JuMP variables with the `x[1:2]` syntax. This can be extended to create multi-dimensional arrays of JuMP variables. For example:

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2])
2x2 Matrix{VariableRef}:
 x[1,1]  x[1,2]
 x[2,1]  x[2,2]
```

Arrays of JuMP variables can be indexed and sliced as follows:

```
julia> x[1, 2]
x[1,2]

julia> x[2, :]
2-element Vector{VariableRef}:
 x[2,1]
 x[2,2]
```

Variable bounds can depend upon the indices:

```
julia> model = Model();

julia> @variable(model, x[i=1:2, j=1:2] >= 2i + j)
2x2 Matrix{VariableRef}:
 x[1,1]  x[1,2]
 x[2,1]  x[2,2]

julia> lower_bound.(x)
2x2 Matrix{Float64}:
 3.0  4.0
 5.0  6.0
```

JuMP will form an Array of JuMP variables when it can determine at compile time that the indices are one-based integer ranges. Therefore `x[1:b]` will create an Array of JuMP variables, but `x[a:b]` will not. If JuMP cannot determine that the indices are one-based integer ranges (for example, in the case of `x[a:b]`), JuMP will create a DenseAxisArray instead.

**DenseAxisArrays**

We often want to create arrays where the indices are not one-based integer ranges. For example, we may want to create a variable indexed by the name of a product or a location. The syntax is the same as that above, except with an arbitrary vector as an index as opposed to a one-based range. The biggest difference is that instead of returning an Array of JuMP variables, JuMP will return a DenseAxisArray. For example:

```
julia> model = Model();

julia> @variable(model, x[1:2, [:A,:B]])
2-dimensional DenseAxisArray{VariableRef,2,...} with index sets:
  Dimension 1, Base.OneTo(2)
  Dimension 2, [:A, :B]
And data, a 2x2 Matrix{VariableRef}:
  x[1,A]  x[1,B]
  x[2,A]  x[2,B]
```

DenseAxisArrays can be indexed and sliced as follows:

```
julia> x[1, :A]
x[1,A]

julia> x[2, :]
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
  Dimension 1, [:A, :B]
And data, a 2-element Vector{VariableRef}:
  x[2,A]
  x[2,B]
```

Bounds can depend upon indices:

```
julia> model = Model();

julia> @variable(model, x[i=2:3, j=1:2:3] >= 0.5i + j)
2-dimensional DenseAxisArray{VariableRef,2,...} with index sets:
  Dimension 1, 2:3
  Dimension 2, 1:2:3
And data, a 2x2 Matrix{VariableRef}:
  x[2,1]  x[2,3]
  x[3,1]  x[3,3]

julia> lower_bound.(x)
2-dimensional DenseAxisArray{Float64,2,...} with index sets:
  Dimension 1, 2:3
  Dimension 2, 1:2:3
And data, a 2x2 Matrix{Float64}:
  2.0  4.0
  2.5  4.5
```

## SparseAxisArrays

The third container type that JuMP natively supports is SparseAxisArray. These arrays are created when the indices do not form a rectangular set. For example, this applies when indices have a dependence upon previous indices (called *triangular indexing*). JuMP supports this as follows:

```
julia> model = Model();

julia> @variable(model, x[i=1:2, j=i:2])
```

```
JuMP.Containers.SparseAxisArray{VariableRef, 2, Tuple{Int64, Int64}} with 3 entries:
[1, 1] = x[1,1]
[1, 2] = x[1,2]
[2, 2] = x[2,2]
```

We can also conditionally create variables via a JuMP-specific syntax. This syntax appends a comparison check that depends upon the named indices and is separated from the indices by a semi-colon (;). For example:

```
julia> model = Model();

julia> @variable(model, x[i=1:4; mod(i, 2)==0])
JuMP.Containers.SparseAxisArray{VariableRef, 1, Tuple{Int64}} with 2 entries:
[2] = x[2]
[4] = x[4]
```

### Performance considerations

When using the semi-colon as a filter, JuMP iterates over *all* indices and evaluates the conditional for each combination. If there are many index dimensions and a large amount of sparsity, this can be inefficient.

For example:

```
julia> model = Model();

julia> N = 10
10

julia> S = [(1, 1, 1), (N, N, N)]
2-element Vector{Tuple{Int64, Int64, Int64}}:
 (1, 1, 1)
 (10, 10, 10)

julia> @time @variable(model, x1[i=1:N, j=1:N, k=1:N; (i, j, k) in S])
 0.203861 seconds (392.22 k allocations: 23.977 MiB, 99.10% compilation time)
JuMP.Containers.SparseAxisArray{VariableRef, 3, Tuple{Int64, Int64, Int64}} with 2 entries:
[1, 1, 1] = x1[1,1,1]
[10, 10, 10] = x1[10,10,10]

julia> @time @variable(model, x2[S])
 0.045407 seconds (65.24 k allocations: 3.771 MiB, 99.15% compilation time)
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
 Dimension 1, [(1, 1, 1), (10, 10, 10)]
And data, a 2-element Vector{VariableRef}:
x2[(1, 1, 1)]
x2[(10, 10, 10)]
```

The first option is slower because it is equivalent to:

```
julia> model = Model();

julia> x1 = Dict{NTuple{3,Int},VariableRef}()
Dict{Tuple{Int64, Int64, Int64}, VariableRef}()
```

```
julia> for i in 1:N
    for j in 1:N
        for k in 1:N
            if (i, j, k) in S
                x1[i, j, k] = @variable(model, base_name = "x1[$i,$j,$k]")
            end
        end
    end
end

julia> x1
Dict{Tuple{Int64, Int64, Int64}, VariableRef} with 2 entries:
(1, 1, 1)  => x1[1,1,1]
(10, 10, 10)  => x1[10,10,10]
```

If performance is a concern, explicitly construct the set of indices instead of using the filtering syntax.

### Forcing the container type

When creating a container of JuMP variables, JuMP will attempt to choose the tightest container type that can store the JuMP variables. Thus, it will prefer to create an Array before a DenseAxisArray and a DenseAxisArray before a SparseAxisArray. However, because this happens at compile time, JuMP does not always make the best choice. To illustrate this, consider the following example:

```
julia> model = Model();

julia> A = 1:2
1:2

julia> @variable(model, x[A])
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
Dimension 1, 1:2
And data, a 2-element Vector{VariableRef}:
x[1]
x[2]
```

Since the value (and type) of A is unknown at parsing time, JuMP is unable to infer that A is a one-based integer range. Therefore, JuMP creates a DenseAxisArray, even though it could store these two variables in a standard one-dimensional Array.

We can share our knowledge that it is possible to store these JuMP variables as an array by setting the `container` keyword:

```
julia> @variable(model, y[A], container=Array)
2-element Vector{VariableRef}:
y[1]
y[2]
```

JuMP now creates a vector of JuMP variables instead of a DenseAxisArray. Choosing an invalid container type will throw an error.

### User-defined containers

In addition to the built-in container types, you can create your own collections of JuMP variables.

#### Tip

This is a point that users often overlook: you are not restricted to the built-in container types in JuMP.

For example, the following code creates a dictionary with symmetric matrices as the values:

```
julia> model = Model();

julia> variables = Dict{Symbol, Array{VariableRef,2}}(
    key => @variable(model, [1:2, 1:2], Symmetric, base_name = "$(key)"')
    for key in [:A, :B]
)
Dict{Symbol, Matrix{VariableRef}} with 2 entries:
:A => [A[1,1] A[1,2]; A[1,2] A[2,2]]
:B => [B[1,1] B[1,2]; B[1,2] B[2,2]]
```

Another common scenario is a request to add variables to existing containers, for example:

```
using JuMP
model = Model()
@variable(model, x[1:2] >= 0)
# Later I want to add
@variable(model, x[3:4] >= 0)
```

This is not possible with the built-in JuMP container types. However, you can use regular Julia types instead:

```
julia> model = Model();

julia> x = model[:x] = @variable(model, [1:2], lower_bound = 0, base_name = "x")
2-element Vector{VariableRef}:
x[1]
x[2]

julia> append!(x, @variable(model, [1:2], lower_bound = 0, base_name = "y"));

julia> model[:x]
4-element Vector{VariableRef}:
x[1]
x[2]
y[1]
y[2]
```

### 12.13 Semidefinite variables

Declare a square matrix of JuMP variables to be positive semidefinite by passing PSD as an optional positional argument:

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2], PSD)
2×2 LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}:
 x[1,1]  x[1,2]
 x[1,2]  x[2,2]
```

This will ensure that  $x$  is symmetric, and that all of its eigenvalues are nonnegative.

#### Note

$x$  must be a square 2-dimensional Array of JuMP variables; it cannot be a DenseAxisArray or a SparseAxisArray.

## 12.14 Symmetric variables

Declare a square matrix of JuMP variables to be symmetric (but not necessarily positive semidefinite) by passing `Symmetric` as an optional positional argument:

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2], Symmetric)
2×2 LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}:
 x[1,1]  x[1,2]
 x[1,2]  x[2,2]
```

## 12.15 The `@variables` macro

If you have many `@variable` calls, JuMP provides the macro `@variables` that can improve readability:

```
julia> model = Model();

julia> @variables(model, begin
           x
           y[i=1:2] >= i, (start = i, base_name = "Y_{$i}")
           z, Bin
       end)
(x, VariableRef[Y_1[1], Y_2[2]], z)

julia> print(model)
Feasibility
Subject to
Y_1[1] ≥ 1
Y_2[2] ≥ 2
z binary
```

The `@variables` macro returns a tuple of the variables that were defined.

**Note**

Keyword arguments must be contained within parentheses.

## 12.16 Variables constrained on creation

All uses of the `@variable` macro documented so far translate into separate calls for variable creation and the adding of any bound or integrality constraints.

For example, `@variable(model, x >= 0, Int)`, is equivalent to:

```
julia> model = Model();
julia> @variable(model, x)
x
julia> set_lower_bound(x, 0.0)
julia> set_integer(x)
```

Importantly, the bound and integrality constraints are added *after* the variable has been created.

However, some solvers require a set specifying the variable domain to be given when the variable is first created. We say that these variables are *constrained on creation*.

Use `in` within `@variable` to access the special syntax for constraining variables on creation.

For example, the following creates a vector of variables that belong to the `SecondOrderCone`:

```
julia> model = Model();
julia> @variable(model, y[1:3] in SecondOrderCone())
3-element Vector{VariableRef}:
y[1]
y[2]
y[3]
```

For contrast, the standard syntax is as follows:

```
julia> @variable(model, x[1:3])
3-element Vector{VariableRef}:
x[1]
x[2]
x[3]

julia> @constraint(model, x in SecondOrderCone())
[x[1], x[2], x[3]] ∈ MathOptInterface.SecondOrderCone(3)
```

An alternate syntax to `x in Set` is to use the `set` keyword of `@variable`. This is most useful when creating anonymous variables:

```
julia> model = Model();

julia> x = @variable(model, [1:3], set = SecondOrderCone())
3-element Vector{VariableRef}:
 _[1]
 _[2]
 _[3]
```

**Note**

You cannot delete the constraint associated with a variable constrained on creation.

**Example: positive semidefinite variables**

An alternative to the syntax in [Semidefinite variables](#), declare a matrix of JuMP variables to be positive semidefinite using [PSDCone](#):

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2] in PSDCone())
2x2 LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}:
 x[1,1]  x[1,2]
 x[1,2]  x[2,2]
```

**Example: symmetric variables**

As an alternative to the syntax in [Symmetric variables](#), declare a matrix of JuMP variables to be symmetric using [SymmetricMatrixSpace](#):

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2] in SymmetricMatrixSpace())
2x2 LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}:
 x[1,1]  x[1,2]
 x[1,2]  x[2,2]
```

**Example: skew-symmetric variables**

Declare a matrix of JuMP variables to be skew-symmetric using [SkewSymmetricMatrixSpace](#):

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2] in SkewSymmetricMatrixSpace())
2x2 Matrix{AffExpr}:
 0      x[1,2]
 -x[1,2]  0
```

**Note**

Even though  $x$  is a 2 by 2 matrix, only one decision variable is added to `model`; the remaining elements in  $x$  are linear transformations of the single variable.

**Example: Hermitian positive semidefinite variables**

Declare a matrix of JuMP variables to be Hermitian positive semidefinite using `HermitianPSDConc`:

```
julia> model = Model();

julia> @variable(model, H[1:2, 1:2] in HermitianPSDConc())
2x2 LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef},
                           Matrix{GenericAffExpr{ComplexF64, VariableRef}}}
real(H[1,1])           real(H[1,2]) + imag(H[1,2]) im
real(H[1,2]) - imag(H[1,2]) im  real(H[2,2])
```

This adds 4 real variables in the `MOI.HermitianPositiveSemidefiniteConeTriangle`:

```
julia> first(all_constraints(model, Vector{VariableRef}),
              MOI.HermitianPositiveSemidefiniteConeTriangle)
[real(H[1,1]), real(H[1,2]), real(H[2,2]), imag(H[1,2])] ∈
MathOptInterface.HermitianPositiveSemidefiniteConeTriangle(2)
```

**Example: Hermitian variables**

Declare a matrix of JuMP variables to be Hermitian using the `Hermitian` tag:

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2], Hermitian)
2x2 LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef},
                           Matrix{GenericAffExpr{ComplexF64, VariableRef}}}
real(x[1,1])           real(x[1,2]) + imag(x[1,2]) im
real(x[1,2]) - imag(x[1,2]) im  real(x[2,2])
```

This is equivalent to declaring the variable in `HermitianMatrixSpace`:

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2] in HermitianMatrixSpace())
2x2 LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef},
                           Matrix{GenericAffExpr{ComplexF64, VariableRef}}}
real(x[1,1])           real(x[1,2]) + imag(x[1,2]) im
real(x[1,2]) - imag(x[1,2]) im  real(x[2,2])
```

### Why use variables constrained on creation?

For most users, it does not matter if you use the constrained on creation syntax. Therefore, use whatever syntax you find most convenient.

However, if you use `direct_model`, you may be forced to use the constrained on creation syntax.

The technical difference between variables constrained on creation and the standard JuMP syntax is that variables constrained on creation calls `MOI.add_constrained_variables`, while the standard JuMP syntax calls `MOI.add_variables` and then `MOI.add_constraint`.

Consult the implementation of solver package you are using to see if your solver requires `MOI.add_constrained_variables`.

## 12.17 Parameters

Some solvers have explicit support for parameters, which are constants in the model that can be efficiently updated between solves.

JuMP implements parameters by a decision variable constrained on creation to a value of the `Parameter` set. For example, the following creates two parameters, `p[1]` and `p[2]`, with parameter values 2.0 and 4.0:

```
julia> model = Model();
julia> @variable(model, x);
julia> @variable(model, p[i in 1:2] in Parameter(2.0 * i))
2-element Vector{VariableRef}:
p[1]
p[2]
```

Use `parameter_value` and `set_parameter_value` to query or update the value of a parameter.

```
julia> parameter_value.(p)
2-element Vector{Float64}:
2.0
4.0

julia> set_parameter_value(p[2], 3.0)

julia> parameter_value.(p)
2-element Vector{Float64}:
2.0
3.0
```

Use `is_parameter` and `ParameterRef` to check if the variable is a parameter and to get the constraint that makes the variable a parameter.

```
julia> is_parameter(p[1])
true

julia> is_parameter(x)
false

julia> ParameterRef(p[2])
p[2] ∈ MathOptInterface.Parameter{Float64}(3.0)
```

Create anonymous parameters using the `set` keyword:

```
julia> anon_parameter = @variable(model, set = Parameter(1.0))
_ [4]
```

## Limitations

Parameters are implemented as decision variables belonging to the `Parameter` set. If the solver supports the `MOI.Parameter` set, it may decide to replace all instances of the parameter variable by the associated constant. If the solver does not support parameters, it will add the parameter as a decision variable with fixed bounds.

The most important implication of this design is that JuMP treats a parameter multiplied by a decision variable as a quadratic expression, even though it is equivalent to a linear expression.

```
julia> model = Model();
julia> @variable(model, x);
julia> @variable(model, p in Parameter(2));
julia> px = @expression(model, p * x)
p*x
julia> typeof(px)
QuadExpr (alias for GenericQuadExpr{Float64, GenericVariableRef{Float64}})
```

## When to use a parameter

Parameters are most useful when solving nonlinear models in a sequence:

```
julia> using JuMP, Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> set_silent(model)

julia> @variable(model, x)
x

julia> @variable(model, p in Parameter(1.0))
p

julia> @objective(model, Min, (x - p)^2)
x^2 - 2 p*x + p^2

julia> optimize!(model)

julia> value(x)
```

```
1.0  
julia> set_parameter_value(p, 5.0)  
  
julia> optimize!(model)  
  
julia> value(x)  
5.0
```

Using parameters can be faster than creating a new model from scratch with updated data because JuMP is able to avoid repeating a number of steps in processing the model before handing it off to the solver.

# Chapter 13

## Constraints

JuMP is based on the [MathOptInterface \(MOI\) API](#). Because of this, JuMP uses the following standard form to represent problems:

$$\min_{x \in \mathbb{R}^n} f_0(x) \quad (13.1)$$

$$\text{s.t.} \quad f_i(x) \in \mathcal{S}_i \quad i = 1 \dots m \quad (13.2)$$

Each constraint,  $f_i(x) \in \mathcal{S}_i$ , is composed of a function and a set. For example, instead of calling  $a^\top x \leq b$  a *less-than-or-equal-to* constraint, we say that it is a *scalar-affine-in-less-than* constraint, where the function  $a^\top x$  belongs to the *less-than* set  $(-\infty, b]$ . We use the shorthand *function-in-set* to refer to constraints composed of different types of functions and sets.

This page explains how to write various types of constraints in JuMP. For nonlinear constraints, see [Nonlinear Modeling](#) instead.

### 13.1 Add a constraint

Add a constraint to a JuMP model using the `@constraint` macro. The syntax to use depends on the type of constraint you wish to add.

#### Add a linear constraint

Create linear constraints using the `@constraint` macro:

```
julia> model = Model();
julia> @variable(model, x[1:3]);
julia> @constraint(model, c1, sum(x) <= 1)
c1 : x[1] + x[2] + x[3] ≤ 1

julia> @constraint(model, c2, x[1] + 2 * x[3] >= 2)
c2 : x[1] + 2 x[3] ≥ 2

julia> @constraint(model, c3, sum(i * x[i] for i in 1:3) == 3)
c3 : x[1] + 2 x[2] + 3 x[3] = 3
```

```
julia> @constraint(model, c4, 4 <= 2 * x[2] <= 5)
c4 : 2 x[2] ∈ [4, 5]
```

## Normalization

JuMP normalizes constraints by moving all of the terms containing variables to the left-hand side and all of the constant terms to the right-hand side. Thus, we get:

```
julia> model = Model();
julia> @variable(model, x);
julia> @constraint(model, c, 2x + 1 <= 4x + 4)
c : -2 x ≤ 3
```

## Add a quadratic constraint

In addition to affine functions, JuMP also supports constraints with quadratic terms. For example:

```
julia> model = Model();
julia> @variable(model, x[i=1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]
julia> @variable(model, t ≥ 0)
t
julia> @constraint(model, my_q, x[1]^2 + x[2]^2 ≤ t^2)
my_q : x[1]^2 + x[2]^2 - t^2 ≤ 0
```

### Tip

Because solvers can take advantage of the knowledge that a constraint is quadratic, prefer adding quadratic constraints using `@constraint`, rather than `@NLconstraint`.

## 13.2 Vectorized constraints

You can also add constraints to JuMP using vectorized linear algebra. For example:

```
julia> model = Model();
julia> @variable(model, x[i=1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]
```

```

julia> A = [1 2; 3 4]
2×2 Matrix{Int64}:
 1  2
 3  4

julia> b = [5, 6]
2-element Vector{Int64}:
 5
 6

julia> @constraint(model, con_vector, A * x == b)
con_vector : [x[1] + 2 x[2] - 5, 3 x[1] + 4 x[2] - 6] ∈ Zeros()

julia> @constraint(model, con_scalar, A * x .== b)
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.EqualTo{Float64}}, ScalarShape}}:
con_scalar : x[1] + 2 x[2] = 5
con_scalar : 3 x[1] + 4 x[2] = 6

```

The two constraints, `==` and `.==` are similar, but subtly different. The first creates a single constraint that is a `MOI.VectorAffineFunction` in `MOI.Zeros` constraint. The second creates a vector of `MOI.ScalarAffineFunction` in `MOI.EqualTo` constraints.

Which formulation to choose depends on the solver, and what you want to do with the constraint object `con_vector` or `con_scalar`.

- If you are using a conic solver, expect the dual of `con_vector` to be a `Vector{Float64}`, and do not intend to delete a row in the constraint, choose the `==` formulation.
- If you are using a solver that expects a list of scalar constraints, for example HiGHS, or you wish to delete part of the constraint or access a single row of the constraint, for example, `dual(con_scalar[2])`, then use the broadcast `.==`.

JuMP reformulates both constraints into the other form if needed by the solver, but choosing the right format for a particular solver is more efficient.

You can also use `<=`, `.<=`, `>=`, and `.>=` as comparison operators in the constraint.

```

julia> @constraint(model, A * x <= b)
[x[1] + 2 x[2] - 5, 3 x[1] + 4 x[2] - 6] ∈ Nonpositives()

julia> @constraint(model, A * x .<= b)
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
x[1] + 2 x[2] ≤ 5
3 x[1] + 4 x[2] ≤ 6

julia> @constraint(model, A * x >= b)
[x[1] + 2 x[2] - 5, 3 x[1] + 4 x[2] - 6] ∈ Nonnegatives()

julia> @constraint(model, A * x .>= b)
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.GreaterThan{Float64}}, ScalarShape}}:

```

```
x[1] + 2 x[2] ≥ 5
3 x[1] + 4 x[2] ≥ 6
```

### 13.3 Matrix inequalities

Inequalities between matrices are not supported, due to the common ambiguity between elementwise inequalities and a `PSDCone` constraint.

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:2], Symmetric);

julia> @variable(model, y[1:2, 1:2], Symmetric);

julia> @constraint(model, x >= y)
ERROR: At none:1: `@constraint(model, x >= y)`:
The syntax `x >= y` is ambiguous for matrices because we cannot tell if
you intend a positive semidefinite constraint or an elementwise
inequality.

To create a positive semidefinite constraint, pass `PSDCone()` or
`HermitianPSDCone()`:

```julia
@constraint(model, x >= y, PSDCone())
```

To create an element-wise inequality, pass `Nonnegatives()`, or use
broadcasting:

```julia
@constraint(model, x >= y, Nonnegatives())
# or
@constraint(model, x .>= y)
```

Stacktrace:
[...]
```

Instead, use the [Set inequality syntax](#) to specify a set like `PSDCone` or `Nonnegatives`:

```
julia> @constraint(model, x >= y, PSDCone())
[x[1,1] - y[1,1] x[1,2] - y[1,2]
 ...
 x[2,2] - y[2,2]] ∈ PSDCone()

julia> @constraint(model, x >= y, Nonnegatives())
[x[1,1] - y[1,1] x[1,2] - y[1,2]
 ...
 x[2,2] - y[2,2]] ∈ Nonnegatives()

julia> @constraint(model, x >= y, Nonpositives())
[x[1,1] - y[1,1] x[1,2] - y[1,2]
 ...
 x[2,2] - y[2,2]] ∈ Nonpositives()
```

```
julia> @constraint(model, x >= y, Zeros())
[x[1,1] - y[1,1]  x[1,2] - y[1,2]
 ...
           x[2,2] - y[2,2]] ∈ Zeros()
```

### Special cases

There are two exceptions: if the result of the left-hand side minus the right-hand side is a `LinearAlgebra.Symmetric` matrix or a `LinearAlgebra.Hermitian` matrix, you may use the non-broadcasting equality syntax:

```
julia> using LinearAlgebra

julia> model = Model();

julia> @variable(model, X[1:2, 1:2], Symmetric)
2×2 Symmetric{VariableRef, Matrix{VariableRef}}:
 X[1,1]  X[1,2]
 X[1,2]  X[2,2]

julia> @constraint(model, X == LinearAlgebra.I)
[X[1,1] - 1  X[1,2]
 ...
           X[2,2] - 1] ∈ Zeros()
```

This will add only three rows to the constraint matrix because the symmetric constraints are redundant. In contrast, the broadcasting syntax adds four linear constraints:

```
julia> @constraint(model, X .== LinearAlgebra.I)
2×2 Matrix{ConstraintRef{Model},
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↪ MathOptInterface.EqualTo{Float64}}, ScalarShape}:
 X[1,1] = 1  X[1,2] = 0
 X[1,2] = 0  X[2,2] = 1
```

The same holds for `LinearAlgebra.Hermitian` matrices:

```
julia> using LinearAlgebra

julia> model = Model();

julia> @variable(model, X[1:2, 1:2] in HermitianPSDCones())
2×2 Hermitian{GenericAffExpr{ComplexF64, VariableRef}, Matrix{GenericAffExpr{ComplexF64,
    ↪ VariableRef}}}:
 real(X[1,1])           real(X[1,2]) + imag(X[1,2]) im
 real(X[1,2]) - imag(X[1,2]) im  real(X[2,2])

julia> @constraint(model, X == LinearAlgebra.I)
[real(X[1,1]) - 1           real(X[1,2]) + imag(X[1,2]) im
 real(X[1,2]) - imag(X[1,2]) im  real(X[2,2]) - 1] ∈ Zeros()

julia> @constraint(model, X .== LinearAlgebra.I)
2×2 Matrix{ConstraintRef{Model},
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{ComplexF64},
    ↪ MathOptInterface.EqualTo{ComplexF64}}, ScalarShape}:
```

```
real(X[1,1]) = 1           real(X[1,2]) + imag(X[1,2]) im = 0
real(X[1,2]) - imag(X[1,2]) im = 0  real(X[2,2]) = 1
```

### 13.4 Containers of constraints

The `@constraint` macro supports creating collections of constraints. We'll cover some brief syntax here; read the [Constraint containers](#) section for more details:

Create arrays of constraints:

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> @constraint(model, c[i=1:3], x[i] <= i^2)
3-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
c[1] : x[1] ≤ 1
c[2] : x[2] ≤ 4
c[3] : x[3] ≤ 9

julia> c[2]
c[2] : x[2] ≤ 4
```

Sets can be any Julia type that supports iteration:

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> @constraint(model, c[i=2:3, ["red", "blue"]], x[i] <= i^2)
2-dimensional DenseAxisArray{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape},2,...} with index sets:
    Dimension 1, 2:3
    Dimension 2, ["red", "blue"]
And data, a 2×2 Matrix{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
c[2,red] : x[2] ≤ 4  c[2,blue] : x[2] ≤ 4
c[3,red] : x[3] ≤ 9  c[3,blue] : x[3] ≤ 9

julia> c[2, "red"]
c[2,red] : x[2] ≤ 4
```

Sets can depend upon previous indices:

```
julia> model = Model();

julia> @variable(model, x[1:3]);
```

```
julia> @constraint(model, c[i=1:3, j=i:3], x[i] <= j)
JuMP.Containers.SparseAxisArray{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↪ MathOptInterface.LessThan{Float64}}, ScalarShape}, 2, Tuple{Int64, Int64}} with 6 entries:
[1, 1] = c[1,1] : x[1] ≤ 1
[1, 2] = c[1,2] : x[1] ≤ 2
[1, 3] = c[1,3] : x[1] ≤ 3
[2, 2] = c[2,2] : x[2] ≤ 2
[2, 3] = c[2,3] : x[2] ≤ 3
[3, 3] = c[3,3] : x[3] ≤ 3
```

and you can filter elements in the sets using the ; syntax:

```
julia> model = Model();

julia> @variable(model, x[1:9]);

julia> @constraint(model, c[i=1:9; mod(i, 3) == 0], x[i] <= i)
JuMP.Containers.SparseAxisArray{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↪ MathOptInterface.LessThan{Float64}}, ScalarShape}, 1, Tuple{Int64}} with 3 entries:
[3] = c[3] : x[3] ≤ 3
[6] = c[6] : x[6] ≤ 6
[9] = c[9] : x[9] ≤ 9
```

## 13.5 Registered constraints

When you create constraints, JuMP registers them inside the model using their corresponding symbol. Get a registered name using `model[:key]`:

```
julia> model = Model()
A JuMP Model
└ solver: none
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> @variable(model, x)
x

julia> @constraint(model, my_c, 2x <= 1)
my_c : 2 x ≤ 1

julia> model
A JuMP Model
└ solver: none
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 1
└ num_constraints: 1
└ AffExpr in MOI.LessThan{Float64}: 1
```

```

└ Names registered in the model
  └ :my_c, :x

julia> model[:my_c] === my_c
true

```

## 13.6 Anonymous constraints

To reduce the likelihood of accidental bugs, and because JuMP registers constraints inside a model, creating two constraints with the same name is an error:

```

julia> model = Model();

julia> @variable(model, x)
x

julia> @constraint(model, c, 2x <= 1)
c : 2 x ≤ 1

julia> @constraint(model, c, 2x <= 1)
ERROR: An object of name c is already attached to this model. If this
      is intended, consider using the anonymous construction syntax, for example,
      `x = @variable(model, [1:N], ...)` where the name of the object does
      not appear inside the macro.

      Alternatively, use `unregister(model, :c)` to first unregister
      the existing name from the model. Note that this will not delete the
      object; it will just remove the reference at `model[:c]`.

[...]

```

A common reason for encountering this error is adding constraints in a loop.

As a work-around, JuMP provides *anonymous* constraints. Create an anonymous constraint by omitting the name argument:

```

julia> model = Model();

julia> @variable(model, x);

julia> c = @constraint(model, 2x <= 1)
2 x ≤ 1

```

Create a container of anonymous constraints by dropping the name in front of the [:

```

julia> model = Model();

julia> @variable(model, x[1:3]);

julia> c = @constraint(model, [i = 1:3], x[i] <= i)
3-element Vector{ConstraintRef{Model,
  ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
  ↪ MathOptInterface.LessThan{Float64}}, ScalarShape}}:

```

```
x[1] ≤ 1
x[2] ≤ 2
x[3] ≤ 3
```

### 13.7 Constraint names

In addition to the symbol that constraints are registered with, constraints have a `String` name that is used for printing and writing to file formats.

Get and set the name of a constraint using `name(::JuMP.ConstraintRef)` and `set_name(::JuMP.ConstraintRef, ::String)`:

```
julia> model = Model(); @variable(model, x);

julia> @constraint(model, con, x <= 1)
con : x ≤ 1

julia> name(con)
"con"

julia> set_name(con, "my_con_name")

julia> con
my_con_name : x ≤ 1
```

Override the default choice of name using the `base_name` keyword:

```
julia> model = Model(); @variable(model, x);

julia> con = @constraint(model, [i=1:2], x <= i, base_name = "my_con")
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
my_con[1] : x ≤ 1
my_con[2] : x ≤ 2
```

Note that names apply to each element of the container, not to the container of constraints:

```
julia> name(con[1])
"my_con[1]"

julia> set_name(con[1], "c")

julia> con
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
c : x ≤ 1
my_con[2] : x ≤ 2
```

**Tip**

For some models, setting the string name of each constraint can take a non-trivial portion of the total time required to build the model. Turn off String names by passing `set_string_name = false` to `@constraint`:

```
julia> model = Model();
julia> @variable(model, x);
julia> @constraint(model, con, x <= 2, set_string_name = false)
x ≤ 2
```

See [Disable string names](#) for more information.

**Retrieve a constraint by name**

Retrieve a constraint from a model using `constraint_by_name`:

```
julia> constraint_by_name(model, "c")
c : x ≤ 1
```

If the name is not present, nothing will be returned:

```
julia> constraint_by_name(model, "bad_name")
```

You can only look up individual constraints using `constraint_by_name`. Something like this will not work:

```
julia> model = Model(); @variable(model, x);

julia> con = @constraint(model, [i=1:2], x <= i, base_name = "my_con")
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
    my_con[1] : x ≤ 1
    my_con[2] : x ≤ 2

julia> constraint_by_name(model, "my_con")
```

To look up a collection of constraints, do not use `constraint_by_name`. Instead, register them using the `model[:key] = value` syntax:

```
julia> model = Model(); @variable(model, x);

julia> model[:con] = @constraint(model, [i=1:2], x <= i, base_name = "my_con")
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
    my_con[1] : x ≤ 1
```

```

my_con[2] : x ≤ 2

julia> model[:con]
2-element Vector{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↪ MathOptInterface.LessThan{Float64}}, ScalarShape}}:
my_con[1] : x ≤ 1
my_con[2] : x ≤ 2

```

## 13.8 String names, symbolic names, and bindings

It's common for new users to experience confusion relating to constraints. Part of the problem is the difference between the name that a constraint is registered under and the String name used for printing.

Here's a summary of the differences:

- Constraints are created using `@constraint`.
- Constraints can be named or anonymous.
- Named constraints have the form `@constraint(model, c, expr)`. For named constraints:
  - The String name of the constraint is set to "c".
  - A Julia variable `c` is created that binds `c` to the JuMP constraint.
  - The name `:c` is registered as a key in the model with the value `c`.
- Anonymous constraints have the form `c = @constraint(model, expr)`. For anonymous constraints:
  - The String name of the constraint is set to "".
  - You control the name of the Julia variable used as the binding.
  - No name is registered as a key in the model.
- The `base_name` keyword can override the String name of the constraint.
- You can manually register names in the model via `model[:key] = value`.

Here's an example of the differences:

```

julia> model = Model();

julia> @variable(model, x)
x

julia> c_binding = @constraint(model, 2x <= 1, base_name = "c")
c : 2 x ≤ 1

julia> model
A JuMP Model
└ solver: none
└ objective_sense: FEASIBILITY_SENSE
└ num_variables: 1

```

```

├ num_constraints: 1
| └ AffExpr in MOI.LessThan{Float64}: 1
└ Names registered in the model
  └ :x

julia> c
ERROR: UndefVarError: `c` not defined

julia> c_binding
c : 2 x ≤ 1

julia> name(c_binding)
"c"

julia> model[:c_register] = c_binding
c : 2 x ≤ 1

julia> model
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 1
├ num_constraints: 1
| └ AffExpr in MOI.LessThan{Float64}: 1
└ Names registered in the model
  └ :c_register, :x

julia> model[:c_register]
c : 2 x ≤ 1

julia> model[:c_register] === c_binding
true

julia> c
ERROR: UndefVarError: `c` not defined

```

### 13.9 The @constraints macro

If you have many `@constraint` calls, use the `@constraints` macro to improve readability:

```

julia> model = Model();

julia> @variable(model, x);

julia> @constraints(model, begin
           2x <= 1
           c, x >= -1
         end)
(2 x ≤ 1, c : x ≥ -1)

julia> print(model)
Feasibility
Subject to

```

```
c : x ≥ -1
2 x ≤ 1
```

The `@constraints` macro returns a tuple of the constraints that were defined.

### 13.10 Duality

JuMP adopts the notion of [conic duality from MathOptInterface](#). For linear programs, a feasible dual on a  $\geq$  constraint is nonnegative and a feasible dual on a  $\leq$  constraint is nonpositive. If the constraint is an equality constraint, it depends on which direction is binding.

#### Warning

JuMP's definition of duality is independent of the objective sense. That is, the sign of feasible duals associated with a constraint depends on the direction of the constraint and not whether the problem is maximization or minimization. **This is a different convention from linear programming duality in some common textbooks.** If you have a linear program, and you want the textbook definition, you probably want to use `shadow_price` and `reduced_cost` instead.

The dual value associated with a constraint in the most recent solution can be accessed using the `dual` function. Use `has_duals` to check if the model has a dual solution available to query. For example:

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x)
x

julia> @constraint(model, con, x <= 1)
con : x ≤ 1

julia> @objective(model, Min, -2x)
-2 x

julia> has_duals(model)
false

julia> optimize!(model)

julia> has_duals(model)
true

julia> dual(con)
-2.0

julia> @objective(model, Max, 2x)
2 x

julia> optimize!(model)

julia> dual(con)
-2.0
```

To help users who may be less familiar with conic duality, JuMP provides `shadow_price`, which returns a value that can be interpreted as the improvement in the objective in response to an infinitesimal relaxation (on the scale of one unit) in the right-hand side of the constraint. `shadow_price` can be used only on linear constraints with a `<=`, `>=`, or `==` comparison operator.

In the example above, `dual(con)` returned `-2.0` regardless of the optimization sense. However, in the second case when the optimization sense is Max, `shadow_price` returns:

```
julia> shadow_price(con)
2.0
```

### Duals of variable bounds

To query the dual variables associated with a variable bound, first obtain a constraint reference using one of `UpperBoundRef`, `LowerBoundRef`, or `FixRef`, and then call `dual` on the returned constraint reference. The `reduced_cost` function may simplify this process as it returns the shadow price of an active bound of a variable (or zero, if no active bound exists).

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x <= 1)
x

julia> @objective(model, Min, -2x)
-2 x

julia> optimize!(model)

julia> dual(UpperBoundRef(x))
-2.0

julia> reduced_cost(x)
-2.0
```

### 13.11 Modify a constant term

This section explains how to modify the constant term in a constraint. There are multiple ways to achieve this goal; we explain three options.

#### Option 1: change the right-hand side

Use `set_normalized_rhs` to modify the right-hand side (constant) term of a linear or quadratic constraint. Use `normalized_rhs` to query the right-hand side term.

```
julia> model = Model();
```

```
julia> @variable(model, x);

julia> @constraint(model, con, 2x <= 1)
con : 2 x ≤ 1

julia> set_normalized_rhs(con, 3)

julia> con
con : 2 x ≤ 3

julia> normalized_rhs(con)
3.0
```

**Warning**

`set_normalized_rhs` sets the right-hand side term of the normalized constraint. See [Normalization](#) for more details.

**Option 2: use fixed variables**

If constraints are complicated, for example, they are composed of a number of components, each of which has a constant term, then it may be difficult to calculate what the right-hand side term is in the standard form.

For this situation, JuMP includes the ability to *fix* variables to a value using the `fix` function. Fixing a variable sets its lower and upper bound to the same value. Thus, changes in a constant term can be simulated by adding a new variable and fixing it to different values. Here is an example:

```
julia> model = Model();

julia> @variable(model, x);

julia> @variable(model, const_term)
const_term

julia> @constraint(model, con, 2x <= const_term + 1)
con : 2 x - const_term ≤ 1

julia> fix(const_term, 1.0)
```

The constraint `con` is now equivalent to  $2x \leq 2$ .

**Warning**

Fixed variables are not replaced with constants when communicating the problem to a solver. Therefore, even though `const_term` is fixed, it is still a decision variable, and so `const_term * x` is bilinear.

**Option 3: modify the function's constant term**

The third option is to use `add_to_function_constant`. The constant given is added to the function of a func-in-set constraint. In the following example, adding 2 to the function has the effect of removing 2 to the right-hand side:

```
julia> model = Model();
julia> @variable(model, x);
julia> @constraint(model, con, 2x <= 1)
con : 2 x ≤ 1
julia> add_to_function_constant(con, 2)
julia> con
con : 2 x ≤ -1
julia> normalized_rhs(con)
-1.0
```

In the case of interval constraints, the constant is removed from each bound:

```
julia> model = Model();
julia> @variable(model, x);
julia> @constraint(model, con, 0 <= 2x + 1 <= 2)
con : 2 x ∈ [-1, 1]
julia> add_to_function_constant(con, 3)
julia> con
con : 2 x ∈ [-4, -2]
```

## 13.12 Modify a variable coefficient

### Scalar constraints

To modify the coefficients for a linear term in a constraint, use `set_normalized_coefficient`. To query the current coefficient, use `normalized_coefficient`.

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @constraint(model, con, 2x[1] + x[2] <= 1)
con : 2 x[1] + x[2] ≤ 1
julia> set_normalized_coefficient(con, x[2], 0)
julia> con
con : 2 x[1] ≤ 1
julia> normalized_coefficient(con, x[2])
0.0
```

To modify quadratic terms, pass two variables:

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @constraint(model, con, x[1]^2 + x[1] * x[2] <= 1)
con : x[1]^2 + x[1]*x[2] ≤ 1
julia> set_normalized_coefficient(con, x[1], x[1], 2)
julia> set_normalized_coefficient(con, x[1], x[2], 3)
julia> con
con : 2 x[1]^2 + 3 x[1]*x[2] ≤ 1
julia> normalized_coefficient(con, x[1], x[1])
2.0
julia> normalized_coefficient(con, x[1], x[2])
3.0
```

**Warning**

`set_normalized_coefficient` sets the coefficient of the normalized constraint. See [Normalization](#) for more details.

**Vector constraints**

To modify the coefficients of a vector-valued constraint, use `set_normalized_coefficient`.

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @constraint(model, con, [2x + 3x, 4x] in MOI.Nonnegatives(2))
con : [5 x, 4 x] ∈ MathOptInterface.Nonnegatives(2)

julia> set_normalized_coefficient(con, x, [(1, 3.0)])
julia> con
con : [3 x, 4 x] ∈ MathOptInterface.Nonnegatives(2)

julia> set_normalized_coefficient(con, x, [(1, 2.0), (2, 5.0)])
julia> con
con : [2 x, 5 x] ∈ MathOptInterface.Nonnegatives(2)
```

**13.13 Delete a constraint**

Use `delete` to delete a constraint from a model. Use `is_valid` to check if a constraint belongs to a model and has not been deleted.

```
julia> model = Model();
julia> @variable(model, x);
julia> @constraint(model, con, 2x <= 1)
con : 2 x ≤ 1

julia> is_valid(model, con)
true

julia> delete(model, con)

julia> is_valid(model, con)
false
```

Deleting a constraint does not unregister the symbolic reference from the model. Therefore, creating a new constraint of the same name will throw an error:

```
julia> @constraint(model, con, 2x <= 1)
ERROR: An object of name con is already attached to this model. If this
is intended, consider using the anonymous construction syntax, for example,
`x = @variable(model, [1:N], ...)` where the name of the object does
not appear inside the macro.

Alternatively, use `unregister(model, :con)` to first unregister
the existing name from the model. Note that this will not delete the
object; it will just remove the reference at `model[:con]`.
[...]
```

After calling `delete`, call `unregister` to remove the symbolic reference:

```
julia> unregister(model, :con)

julia> @constraint(model, con, 2x <= 1)
con : 2 x ≤ 1
```

### Info

`delete` does not automatically `unregister` because we do not distinguish between names that are automatically registered by JuMP macros, and names that are manually registered by the user by setting values in `object_dictionary`. In addition, deleting a constraint and then adding a new constraint of the same name is an easy way to introduce bugs into your code.

## 13.14 Start values

Provide a starting value (also called warmstart) for a constraint's primal and dual solutions using `set_start_value` and `set_dual_start_value`.

Query the starting value for a constraint's primal and dual solution using `start_value` and `dual_start_value`. If no start value has been set, the methods will return nothing.

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @constraint(model, con, x >= 10)
con : x ≥ 10

julia> start_value(con)

julia> set_start_value(con, 10.0)

julia> start_value(con)
10.0

julia> dual_start_value(con)

julia> set_dual_start_value(con, 2)

julia> dual_start_value(con)
2.0
```

Vector-valued constraints require a vector:

```
julia> model = Model();

julia> @variable(model, x[1:3])
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]

julia> @constraint(model, con, x in SecondOrderCone())
con : [x[1], x[2], x[3]] in MathOptInterface.SecondOrderCone(3)

julia> dual_start_value(con)

julia> set_dual_start_value(con, [1.0, 2.0, 3.0])

julia> dual_start_value(con)
3-element Vector{Float64}:
 1.0
 2.0
 3.0
```

### Tip

To simplify setting start values for all variables and constraints in a model, see `set_start_values`. The [Primal and dual warm-starts](#) tutorial also gives a detailed description of how to iterate over constraints in the model to set custom start values.

### 13.15 Constraint containers

Like [Variable containers](#), JuMP provides a mechanism for building groups of constraints compactly. References to these groups of constraints are returned in *containers*. Three types of constraint containers are supported: Arrays, DenseAxisArrays, and SparseAxisArrays. We explain each of these in the following.

#### Tip

You can read more about containers in the [Containers](#) section.

#### Arrays

One way of adding a group of constraints compactly is the following:

```
julia> model = Model();
julia> @variable(model, x);
julia> @constraint(model, con[i = 1:3], i * x <= i + 1)
3-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
con[1] : x ≤ 2
con[2] : 2 x ≤ 3
con[3] : 3 x ≤ 4
```

JuMP returns references to the three constraints in an Array that is bound to the Julia variable `con`. This array can be accessed and sliced as you would with any Julia array:

```
julia> con[1]
con[1] : x ≤ 2
julia> con[2:3]
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
con[2] : 2 x ≤ 3
con[3] : 3 x ≤ 4
```

Anonymous containers can also be constructed by dropping the name (for example, `con`) before the square brackets:

```
julia> con = @constraint(model, [i = 1:2], i * x <= i + 1)
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
x ≤ 2
2 x ≤ 3
```

Just like [@variable](#), JuMP will form an Array of constraints when it can determine at parse time that the indices are one-based integer ranges. Therefore `con[1:b]` will create an Array, but `con[a:b]` will not. A special case

is `con[Base.OneTo(n)]` which will produce an Array. If JuMP cannot determine that the indices are one-based integer ranges (for example, in the case of `con[a:b]`), JuMP will create a `DenseAxisArray` instead.

### DenseAxisArrays

The syntax for constructing a `DenseAxisArray` of constraints is very similar to the [syntax for constructing a DenseAxisArray of variables](#).

```
julia> model = Model();
julia> @variable(model, x);

julia> @constraint(model, con[i = 1:2, j = 2:3], i * x <= j + 1)
2-dimensional DenseAxisArray{ConstraintRef{Model},
                           MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64}},
                           MathOptInterface.LessThan{Float64}}, ScalarShape}, 2,...} with index sets:
Dimension 1, Base.OneTo(2)
Dimension 2, 2:3
And data, a 2×2 Matrix{ConstraintRef{Model},
                           MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64}},
                           MathOptInterface.LessThan{Float64}}, ScalarShape}:
con[1,2] : x ≤ 3    con[1,3] : x ≤ 4
con[2,2] : 2 x ≤ 3  con[2,3] : 2 x ≤ 4
```

### SparseAxisArrays

The syntax for constructing a `SparseAxisArray` of constraints is very similar to the [syntax for constructing a SparseAxisArray of variables](#).

```
julia> model = Model();
julia> @variable(model, x);

julia> @constraint(model, con[i = 1:2, j = 1:2; i != j], i * x <= j + 1)
JuMP.Containers.SparseAxisArray{ConstraintRef{Model},
                               MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64}},
                               MathOptInterface.LessThan{Float64}}, ScalarShape}, 2, Tuple{Int64, Int64}} with 2 entries:
[1, 2]  =  con[1,2] : x ≤ 3
[2, 1]  =  con[2,1] : 2 x ≤ 2
```

#### Warning

If you have many index dimensions and a large amount of sparsity, read [Performance considerations](#).

### Forcing the container type

When creating a container of constraints, JuMP will attempt to choose the tightest container type that can store the constraints. However, because this happens at parse time, it does not always make the best choice. Just like in `@variable`, you can force the type of container using the `container` keyword. For syntax and the reason behind this, take a look at the [variable docs](#).

### Constraints with similar indices

Containers are often used to create constraints over a set of indices. However, you'll often have cases in which you are repeating the indices:

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @variable(model, y[1:2]);
julia> @constraints(model, begin
           [i=1:2, j=1:2, k=1:2], i * x[j] <= k
           [i=1:2, j=1:2, k=1:2], i * y[j] <= k
         end);
```

This is hard to read and leads to a lot of copy-paste. A more readable way is to use a for-loop:

```
julia> for i=1:2, j=1:2, k=1:2
           @constraints(model, begin
             i * x[j] <= k
             i * y[j] <= k
           end)
       end
```

### 13.16 Accessing constraints from a model

Query the types of function-in-set constraints in a model using `list_of_constraint_types`:

```
julia> model = Model();
julia> @variable(model, x[i=1:2] >= i, Int);
julia> @constraint(model, x[1] + x[2] <= 1);
julia> list_of_constraint_types(model)
3-element Vector{Tuple{Type, Type}}:
 (AffExpr, MathOptInterface.LessThan{Float64})
 (VariableRef, MathOptInterface.GreaterThan{Float64})
 (VariableRef, MathOptInterface.Integer)
```

For a given combination of function and set type, use `num_constraints` to access the number of constraints and `all_constraints` to access a list of their references:

```
julia> num_constraints(model, VariableRef, MOI.Integer)
2
julia> cons = all_constraints(model, VariableRef, MOI.Integer)
2-element Vector{ConstraintRef{Model,
                           MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.Integer},
                           ScalarShape}}:
```

```
x[1] integer
x[2] integer
```

You can also count the total number of constraints in the model, but you must explicitly choose whether to count VariableRef constraints such as bound and integrality constraints:

```
julia> num_constraints(model; count_variable_in_set_constraints = true)
5

julia> num_constraints(model; count_variable_in_set_constraints = false)
1
```

The same also applies for `all_constraints`:

```
julia> all_constraints(model; include_variable_in_set_constraints = true)
5-element Vector{ConstraintRef}:
 x[1] + x[2] ≤ 1
 x[1] ≥ 1
 x[2] ≥ 2
 x[1] integer
 x[2] integer

julia> all_constraints(model; include_variable_in_set_constraints = false)
1-element Vector{ConstraintRef}:
 x[1] + x[2] ≤ 1
```

If you need finer-grained control on which constraints to include, use a variant of:

```
julia> sum(
    num_constraints(model, F, S) for
    (F, S) in list_of_constraint_types(model) if F != VariableRef
)
1
```

Use `constraint_object` to get an instance of an `AbstractConstraint` object that stores the constraint data:

```
julia> con = constraint_object(cons[1])
ScalarConstraint{VariableRef, MathOptInterface.Integer}(x[1], MathOptInterface.Integer())

julia> con.func
x[1]

julia> con.set
MathOptInterface.Integer()
```

## 13.17 MathOptInterface constraints

Because JuMP is based on MathOptInterface, you can add any constraints supported by MathOptInterface using the function-in-set syntax. For a list of supported functions and sets, read [Standard form problem](#).

**Note**

We use MOI as an alias for the MathOptInterface module. This alias is defined by using JuMP. You may also define it in your code as follows:

```
import MathOptInterface as MOI
```

For example, the following two constraints are equivalent:

```
julia> model = Model();
julia> @variable(model, x[1:3]);
julia> @constraint(model, 2 * x[1] <= 1)
2 x[1] ≤ 1
julia> @constraint(model, 2 * x[1] in MOI.LessThan(1.0))
2 x[1] ≤ 1
```

You can also use any set defined by MathOptInterface:

```
julia> @constraint(model, x - [1; 2; 3] in MOI.Nonnegatives(3))
[x[1] - 1, x[2] - 2, x[3] - 3] ∈ MathOptInterface.Nonnegatives(3)
julia> @constraint(model, x in MOI.ExponentialCone())
[x[1], x[2], x[3]] ∈ MathOptInterface.ExponentialCone()
```

**Info**

Similar to how JuMP defines the `<=` and `>=` syntax as a convenience way to specify `MOI.LessThan` and `MOI.GreaterThan` constraints, the remaining sections in this page describe functions and syntax that have been added for the convenience of common modeling situations.

### 13.18 Set inequality syntax

For modeling convenience, the syntax `@constraint(model, x >= y, Set())` is short-hand for `@constraint(model, x - y in Set())`.

Therefore, the following calls are equivalent:

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> y = [0.5, 0.75];
julia> @constraint(model, x >= y, MOI.Nonnegatives(2))
[x[1] - 0.5, x[2] - 0.75] ∈ MathOptInterface.Nonnegatives(2)
```

```
julia> @constraint(model, x - y in MOI.Nonnegatives(2))
[x[1] - 0.5, x[2] - 0.75] ∈ MathOptInterface.Nonnegatives(2)
```

Non-zero constants are not supported in this syntax:

```
julia> @constraint(model, x >= 1, MOI.Nonnegatives(2))
ERROR: Operation `sub_mul` between `Vector{VariableRef}` and `Int64` is not allowed. This most
→ often happens when you write a constraint like `x >= y` where `x` is an array and `y` is a
→ constant. Use the broadcast syntax `x .- y >= 0` instead.
Stacktrace:
[...]
```

Use instead:

```
julia> @constraint(model, x .- 1 >= 0, MOI.Nonnegatives(2))
[x[1] - 1, x[2] - 1] ∈ MathOptInterface.Nonnegatives(2)
```

### Warning

The syntax `@constraint(model, y <= x, Set())` is supported, but it is not recommended because the value of the primal and dual solutions associated with the constraint may be the negative of what you expect.

## 13.19 Second-order cone constraints

A `SecondOrderCone` constrains the variables `t` and `x` to the set:

$$\|x\|_2 \leq t,$$

and  $t \geq 0$ . It can be added as follows:

```
julia> model = Model();
julia> @variable(model, t)
t

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> @constraint(model, [t; x] in SecondOrderCone())
[t, x[1], x[2]] ∈ MathOptInterface.SecondOrderCone(3)
```

## 13.20 Rotated second-order cone constraints

A `RotatedSecondOrderCone` constrains the variables  $t$ ,  $u$ , and  $x$  to the set:

$$\|x\|_2^2 \leq 2t \cdot u$$

and  $t, u \geq 0$ . It can be added as follows:

```
julia> model = Model();

julia> @variable(model, t)
t

julia> @variable(model, u)
u

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> @constraint(model, [t; u; x] in RotatedSecondOrderCone())
[t, u, x[1], x[2]] ∈ MathOptInterface.RotatedSecondOrderCone(4)
```

## 13.21 Special Ordered Sets of Type 1

In a Special Ordered Set of Type 1 (often denoted SOS-I or SOS1), at most one element can take a non-zero value.

Construct SOS-I constraints using the `SOS1` set:

```
julia> model = Model();

julia> @variable(model, x[1:3])
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]

julia> @constraint(model, x in SOS1())
[x[1], x[2], x[3]] in MathOptInterface.SOS1{Float64}([1.0, 2.0, 3.0])
```

Although not required for feasibility, solvers can benefit from an ordering of the variables (for example, the variables represent different factories to build, at most one factory can be built, and the factories can be ordered according to cost). To induce an ordering, a vector of weights can be provided, and the variables are ordered according to their corresponding weight.

For example, in the constraint:

```
julia> @constraint(model, x in SOS1([3.1, 1.2, 2.3]))
[x[1], x[2], x[3]] in MathOptInterface.SOS1{Float64}([3.1, 1.2, 2.3])
```

the variables x have precedence x[2], x[3], x[1].

## 13.22 Special Ordered Sets of Type 2

In a Special Ordered Set of Type 2 (SOS-II), at most two elements can be non-zero, and if there are two non-zeros, they must be consecutive according to the ordering induced by a weight vector.

Construct SOS-II constraints using the `SOS2` set:

```
julia> @constraint(model, x in SOS2([3.0, 1.0, 2.0]))
[x[1], x[2], x[3]] in MathOptInterface.SOS2{Float64}([3.0, 1.0, 2.0])
```

The possible non-zero pairs are (x[1], x[3]) and (x[2], x[3]):

If the weight vector is omitted, JuMP induces an ordering from 1:length(x):

```
julia> @constraint(model, x in SOS2())
[x[1], x[2], x[3]] in MathOptInterface.SOS2{Float64}([1.0, 2.0, 3.0])
```

## 13.23 Indicator constraints

Indicator constraints consist of a binary variable and a linear constraint. The constraint holds when the binary variable takes the value 1. The constraint may or may not hold when the binary variable takes the value 0.

To enforce the constraint  $x + y \leq 1$  when the binary variable a is 1, use:

```
julia> model = Model();
julia> @variable(model, x)
x
julia> @variable(model, y)
y
julia> @variable(model, a, Bin)
a
julia> @constraint(model, a --> {x + y <= 1})
a --> {x + y ≤ 1}
```

If the constraint must hold when a is zero, add ! or  $\neg$  before the binary variable;

```
julia> @constraint(model, !a --> {x + y <= 1})
!a --> {x + y ≤ 1}
```

**Warning**

You cannot use an expression for the left-hand side of an indicator constraint.

**13.24 Semidefinite constraints**

To constrain a matrix to be positive semidefinite (PSD), use `PSDCone`:

```
julia> model = Model();

julia> @variable(model, X[1:2, 1:2])
2×2 Matrix{VariableRef}:
 X[1,1]  X[1,2]
 X[2,1]  X[2,2]

julia> @constraint(model, X >= 0, PSDCone())
[X[1,1]  X[1,2]
 X[2,1]  X[2,2]] ∈ PSDCone()
```

**Tip**

Where possible, prefer constructing a matrix of [Semidefinite variables](#) using the `@variable` macro, rather than adding a constraint like `@constraint(model, X >= 0, PSDCone())`. In some solvers, adding the constraint via `@constraint` is less efficient, and can result in additional intermediate variables and constraints being added to the model.

The inequality  $X \geq Y$  between two square matrices  $X$  and  $Y$  is understood as constraining  $X - Y$  to be positive semidefinite.

```
julia> Y = [1 2; 2 1]
2×2 Matrix{Int64}:
 1  2
 2  1

julia> @constraint(model, X >= Y, PSDCone())
[X[1,1] - 1  X[1,2] - 2
 X[2,1] - 2  X[2,2] - 1] ∈ PSDCone()
```

**Warning**

The syntax `@constraint(model, Y <= X, PSDCone())` is supported, but it is not recommended because the value of the primal and dual solutions associated with the constraint may be the negative of what you expect.

**Symmetry**

Solvers supporting PSD constraints usually expect to be given a matrix that is *symbolically* symmetric, that is, for which the expression in corresponding off-diagonal entries are the same. In our example, the expressions of entries (1, 2) and (2, 1) are respectively  $X[1,2] - 2$  and  $X[2,1] - 2$  which are different.

To bridge the gap between the constraint modeled and what the solver expects, solvers may add an equality constraint  $X[1,2] - 2 == X[2,1] - 2$  to force symmetry. Use `LinearAlgebra.Symmetric` to explicitly tell the solver that the matrix is symmetric:

```
julia> import LinearAlgebra

julia> Z = [X[1, 1] X[1, 2]; X[1, 2] X[2, 2]]
2×2 Matrix{VariableRef}:
 X[1,1]  X[1,2]
 X[1,2]  X[2,2]

julia> @constraint(model, LinearAlgebra.Symmetric(Z) >= 0, PSDCone())
[X[1,1]  X[1,2]
 ...      X[2,2]] ∈ PSDCone()
```

Note that the lower triangular entries are ignored even if they are different so use it with caution:

```
julia> @constraint(model, LinearAlgebra.Symmetric(X) >= 0, PSDCone())
[X[1,1]  X[1,2]
 ...      X[2,2]] ∈ PSDCone()
```

(Note that no error is thrown, even though  $X$  is not symmetric.)

### 13.25 Complementarity constraints

A mixed complementarity constraint  $F(x) \perp x$  consists of finding  $x$  in the interval  $[lb, ub]$ , such that the following holds:

- $F(x) == 0$  if  $lb < x < ub$
- $F(x) >= 0$  if  $lb == x$
- $F(x) <= 0$  if  $x == ub$

JuMP supports mixed complementarity constraints via `complements(F(x), x)` or  $F(x) \perp x$  in the `@constraint` macro. The interval set  $[lb, ub]$  is obtained from the variable bounds on  $x$ .

For example, to define the problem  $2x - 1 \perp x$  with  $x \in [0, \infty)$ , do:

```
julia> model = Model();

julia> @variable(model, x >= 0)
x

julia> @constraint(model, 2x - 1 ⊥ x)
[2 x - 1, x] ∈ MathOptInterface.Complements(2)
```

This problem has a unique solution at  $x = 0.5$ .

The perp operator  $\perp$  can be entered in most editors (and the Julia REPL) by typing `\perp<tab>`.

An alternative approach that does not require the  $\perp$  symbol uses the `complements` function as follows:

```
julia> @constraint(model, complements(2x - 1, x))
[2 x - 1, x] ∈ MathOptInterface.Complements(2)
```

In both cases, the mapping  $F(x)$  is supplied as the first argument, and the matching variable  $x$  is supplied as the second.

Vector-valued complementarity constraints are also supported:

```
julia> @variable(model, -2 <= y[1:2] <= 2)
2-element Vector{VariableRef}:
y[1]
y[2]

julia> M = [1 2; 3 4]
2×2 Matrix{Int64}:
 1  2
 3  4

julia> q = [5, 6]
2-element Vector{Int64}:
 5
 6

julia> @constraint(model, M * y + q ⊥ y)
[y[1] + 2 y[2] + 5, 3 y[1] + 4 y[2] + 6, y[1], y[2]] ∈ MathOptInterface.Complements(4)
```

## 13.26 Boolean constraints

Add a Boolean constraint (a `MOI.EqualTo{Bool}` set) using the `:=` operator with a `Bool` right-hand side term:

```
julia> model = GenericModel{Bool}();
julia> @variable(model, x[1:2]);
julia> @constraint(model, x[1] || x[2] := true)
x[1] || x[2] = true

julia> @constraint(model, x[1] && x[2] := false)
x[1] && x[2] = false

julia> model
A JuMP Model
├ value_type: Bool
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 2
├ num_constraints: 2
└ GenericNonlinearExpr{GenericVariableRef{Bool}} in MOI.EqualTo{Bool}: 2
└ Names registered in the model
  └ :x
```

Boolean constraints should not be added using the `==` operator because JuMP will rewrite the constraint as `lhs - rhs = 0`, and because constraints like `a == b == c` require parentheses to disambiguate between `(a == b) == c` and `a == (b == c)`. In contrast, `a == b := c` is equivalent to `(a == b) := c`:

```
julia> model = Model();  
julia> @variable(model, x[1:2]);  
  
julia> rhs = false  
false  
  
julia> @constraint(model, (x[1] == x[2]) == rhs)  
(x[1] == x[2]) - 0.0 = 0  
  
julia> @constraint(model, x[1] == x[2] := rhs)  
x[1] == x[2] = false
```

## Chapter 14

# Expressions

JuMP has three types of expressions: affine, quadratic, and nonlinear. These expressions can be inserted into constraints or into the objective. This is particularly useful if an expression is used in multiple places in the model.

### 14.1 Affine expressions

There are four ways of constructing an affine expression in JuMP: with the `@expression` macro, with operator overloading, with the `AffExpr` constructor, and with `add_to_expression!`.

#### Macros

The recommended way to create an affine expression is via the `@expression` macro.

```
julia> model = Model();  
  
julia> @variable(model, x)  
x  
  
julia> @variable(model, y)  
y  
  
julia> ex = @expression(model, 2x + y - 1)  
2 x + y - 1
```

This expression can be used in the objective or added to a constraint. For example:

```
julia> @objective(model, Min, 2 * ex - 1)  
4 x + 2 y - 3  
  
julia> objective_function(model)  
4 x + 2 y - 3
```

Just like variables and constraints, named expressions can also be created. For example

```
julia> model = Model();
```

```
julia> @variable(model, x[i = 1:3]);  
  
julia> @expression(model, expr[i = 1:3], i * sum(x[j] for j in i:3));  
  
julia> expr  
3-element Vector{AffExpr}:  
x[1] + x[2] + x[3]  
2 x[2] + 2 x[3]  
3 x[3]
```

**Tip**

You can read more about containers in the [Containers](#) section.

## Operator overloading

Expressions can also be created without macros. However, note that in some cases, this can be much slower than constructing an expression using macros.

```
julia> model = Model();  
  
julia> @variable(model, x)  
x  
  
julia> @variable(model, y)  
y  
  
julia> ex = 2x + y - 1  
2 x + y - 1
```

## Constructors

A third way to create an affine expression is by the `AffExpr` constructor. The first argument is the constant term, and the remaining arguments are variable-coefficient pairs.

```
julia> model = Model();  
  
julia> @variable(model, x)  
x  
  
julia> @variable(model, y)  
y  
  
julia> ex = AffExpr(-1.0, x => 2.0, y => 1.0)  
2 x + y - 1
```

**`add_to_expression!`**

The fourth way to create an affine expression is by using `add_to_expression!`. Compared to the operator overloading method, this approach is faster because it avoids constructing temporary objects. The `@expression` macro uses `add_to_expression!` behind-the-scenes.

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> ex = AffExpr(-1.0)
-1

julia> add_to_expression!(ex, 2.0, x)
2 x - 1

julia> add_to_expression!(ex, 1.0, y)
2 x + y - 1
```

`add_to_expression!` can also be used to sum expressions in-place:

```
julia> model = Model();
julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> @expression(model, ex1, sum(x))
x[1] + x[2]

julia> @expression(model, ex2, 2 * sum(x))
2 x[1] + 2 x[2]

julia> add_to_expression!(ex1, ex2)
3 x[1] + 3 x[2]

julia> ex1
3 x[1] + 3 x[2]

julia> ex2
2 x[1] + 2 x[2]
```

**Warning**

Read the section [Initializing arrays](#) for some cases to be careful about when using `add_to_expression!`.

### Removing zero terms

Use `drop_zeros!` to remove terms from an affine expression with a 0 coefficient.

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @expression(model, ex, x + 1 - x)
0 x + 1

julia> drop_zeros!(ex)

julia> ex
1
```

### Coefficients

Use `coefficient` to return the coefficient associated with a variable in an affine expression.

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> @expression(model, ex, 2x + 1)
2 x + 1

julia> coefficient(ex, x)
2.0

julia> coefficient(ex, y)
0.0
```

## 14.2 Quadratic expressions

Like affine expressions, there are four ways of constructing a quadratic expression in JuMP: macros, operator overloading, constructors, and `add_to_expression!`.

### Macros

The `@expression` macro can be used to create quadratic expressions by including quadratic terms.

```
julia> model = Model();
julia> @variable(model, x)
x
```

```
julia> @variable(model, y)
y

julia> ex = @expression(model, x^2 + 2 * x * y + y^2 + x + y - 1)
x^2 + 2 x*y + y^2 + x + y - 1
```

## Operator overloading

Operator overloading can also be used to create quadratic expressions. The same performance warning (discussed in the affine expression section) applies.

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> ex = x^2 + 2 * x * y + y^2 + x + y - 1
x^2 + 2 x*y + y^2 + x + y - 1
```

## Constructors

Quadratic expressions can also be created using the QuadExpr constructor. The first argument is an affine expression, and the remaining arguments are pairs, where the first term is a JuMP.UnorderedPair and the second term is the coefficient.

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> aff_expr = AffExpr(-1.0, x => 1.0, y => 1.0)
x + y - 1

julia> quad_expr = QuadExpr(
    aff_expr,
    UnorderedPair(x, x) => 1.0,
    UnorderedPair(x, y) => 2.0,
    UnorderedPair(y, y) => 1.0,
)
x^2 + 2 x*y + y^2 + x + y - 1
```

## `add_to_expression!`

Finally, `add_to_expression!` can also be used to add quadratic terms.

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> ex = QuadExpr(x + y - 1.0)
x + y - 1

julia> add_to_expression!(ex, 1.0, x, x)
x^2 + x + y - 1

julia> add_to_expression!(ex, 2.0, x, y)
x^2 + 2 x*y + x + y - 1

julia> add_to_expression!(ex, 1.0, y, y)
x^2 + 2 x*y + y^2 + x + y - 1
```

**Warning**

Read the section [Initializing arrays](#) for some cases to be careful about when using `add_to_expression!`.

**Removing zero terms**

Use `drop_zeros!` to remove terms from a quadratic expression with a 0 coefficient.

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @expression(model, ex, x^2 + x + 1 - x^2)
0 x^2 + x + 1

julia> drop_zeros!(ex)

julia> ex
x + 1
```

**Coefficients**

Use `coefficient` to return the coefficient associated with a pair of variables in a quadratic expression.

```
julia> model = Model();

julia> @variable(model, x)
x
```

```
julia> @variable(model, y)
y

julia> @expression(model, ex, 2*x*y + 3*x)
2 x*y + 3 x

julia> coefficient(ex, x, y)
2.0

julia> coefficient(ex, x, x)
0.0

julia> coefficient(ex, y, x)
2.0

julia> coefficient(ex, x)
3.0
```

### 14.3 Nonlinear expressions

Nonlinear expressions in JuMP are represented by a `NonlinearExpr` object. See [Nonlinear expressions in detail](#) for more details.

### 14.4 Initializing arrays

JuMP implements `zero(AffExpr)` and `one(AffExpr)` to support various functions in `LinearAlgebra` (for example, accessing the off-diagonal of a `Diagonal` matrix).

```
julia> zero(AffExpr)
0

julia> one(AffExpr)
1
```

However, this can result in a subtle bug if you call `add_to_expression!` or the `MutableArithmetics API` on an element created by `zeros` or `ones`:

```
julia> x = zeros(AffExpr, 2)
2-element Vector{AffExpr}:
 0
 0

julia> add_to_expression!(x[1], 1.1)
1.1

julia> x
2-element Vector{AffExpr}:
 1.1
 1.1
```

Notice how we modified `x[1]`, but we also changed `x[2]!`

This happened because `zeros(AffExpr, 2)` calls `zero(AffExpr)` once to obtain a zero element, and then creates an appropriately sized array filled with the same element.

This also happens with broadcasting calls containing a conversion of 0 or 1:

```
julia> x = Vector{AffExpr}(undef, 2)
2-element Vector{AffExpr}:
#undef
#undef

julia> x .= 0
2-element Vector{AffExpr}:
0
0

julia> add_to_expression!(x[1], 1.1)
1.1

julia> x
2-element Vector{AffExpr}:
1.1
1.1
```

The recommended way to create an array of empty expressions is as follows:

```
julia> x = Vector{AffExpr}(undef, 2)
2-element Vector{AffExpr}:
#undef
#undef

julia> for i in eachindex(x)
           x[i] = AffExpr(0.0)
       end

julia> add_to_expression!(x[1], 1.1)
1.1

julia> x
2-element Vector{AffExpr}:
1.1
0
```

Alternatively, use non-mutating operation to avoid updating `x[1]` in-place:

```
julia> x = zeros(AffExpr, 2)
2-element Vector{AffExpr}:
0
0

julia> x[1] += 1.1
1.1

julia> x
2-element Vector{AffExpr}:
```

```
1.1  
0
```

Note that for large expressions this will be slower due to the allocation of additional temporary objects.

# Chapter 15

## Objectives

This page describes macros and functions related to linear and quadratic objective functions only, unless otherwise indicated. For nonlinear objective functions, see [Nonlinear Modeling](#).

### 15.1 Set a linear objective

Use the `@objective` macro to set a linear objective function.

Use `Min` to create a minimization objective:

```
julia> model = Model();  
  
julia> @variable(model, x);  
  
julia> @objective(model, Min, 2x + 1)  
2 x + 1
```

Use `Max` to create a maximization objective:

```
julia> model = Model();  
  
julia> @variable(model, x);  
  
julia> @objective(model, Max, 2x + 1)  
2 x + 1
```

### 15.2 Set a quadratic objective

Use the `@objective` macro to set a quadratic objective function.

Use `^2` to have a variable squared:

```
julia> model = Model();  
  
julia> @variable(model, x);  
  
julia> @objective(model, Min, x^2 + 2x + 1)  
x^2 + 2 x + 1
```

You can also have bilinear terms between variables:

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> @objective(model, Max, x * y + x + y)
x*y + x + y
```

### 15.3 Set a nonlinear objective

Use the `@objective` macro to set a nonlinear objective function:

```
julia> model = Model();
julia> @variable(model, x <= 1);
julia> @objective(model, Max, log(x))
log(x)
```

### 15.4 Query the objective function

Use `objective_function` to return the current objective function.

```
julia> model = Model();
julia> @variable(model, x);
julia> @objective(model, Min, 2x + 1)
2 x + 1

julia> objective_function(model)
2 x + 1
```

### 15.5 Evaluate the objective function at a point

Use `value` to evaluate an objective function at a point specifying values for variables.

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @objective(model, Min, 2x[1]^2 + x[1] + 0.5*x[2])
2 x[1]^2 + x[1] + 0.5 x[2]
```

```
julia> f = objective_function(model)
2 x[1]^2 + x[1] + 0.5 x[2]

julia> point = Dict(x[1] => 2.0, x[2] => 1.0);

julia> value(z -> point[z], f)
10.5
```

## 15.6 Query the objective sense

Use `objective_sense` to return the current objective sense.

```
julia> model = Model();

julia> @variable(model, x);

julia> @objective(model, Min, 2x + 1)
2 x + 1

julia> objective_sense(model)
MIN_SENSE::OptimizationSense = 0
```

## 15.7 Modify an objective

To modify an objective, call `@objective` with the new objective function.

```
julia> model = Model();

julia> @variable(model, x);

julia> @objective(model, Min, 2x)
2 x

julia> @objective(model, Max, -2x)
-2 x
```

Alternatively, use `set_objective_function`.

```
julia> model = Model();

julia> @variable(model, x);

julia> @objective(model, Min, 2x)
2 x

julia> new_objective = @expression(model, -2 * x)
-2 x

julia> set_objective_function(model, new_objective)
```

## 15.8 Modify an objective coefficient

Use `set_objective_coefficient` to modify an objective coefficient.

```
julia> model = Model();
julia> @variable(model, x);
julia> @objective(model, Min, 2x)
2 x
julia> set_objective_coefficient(model, x, 3)
julia> objective_function(model)
3 x
```

Use `set_objective_coefficient` with two variables to modify a quadratic objective coefficient:

```
julia> model = Model();
julia> @variable(model, x);
julia> @variable(model, y);
julia> @objective(model, Min, x^2 + x * y)
x^2 + x*y
julia> set_objective_coefficient(model, x, x, 2)
julia> set_objective_coefficient(model, x, y, 3)
julia> objective_function(model)
2 x^2 + 3 x*y
```

## 15.9 Modify the objective sense

Use `set_objective_sense` to modify the objective sense.

```
julia> model = Model();
julia> @variable(model, x);
julia> @objective(model, Min, 2x)
2 x
julia> objective_sense(model)
MIN_SENSE::OptimizationSense = 0
julia> set_objective_sense(model, MAX_SENSE);
julia> objective_sense(model)
MAX_SENSE::OptimizationSense = 1
```

Alternatively, call `@objective` and pass the existing objective function.

```
julia> model = Model();
julia> @variable(model, x);
julia> @objective(model, Min, 2x)
2 x
julia> @objective(model, Max, objective_function(model))
2 x
```

## 15.10 Set a vector-valued objective

Define a multi-objective optimization problem by passing a vector of objectives:

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @objective(model, Min, [1 + x[1], 2 * x[2]])
2-element Vector{AffExpr}:
 x[1] + 1
 2 x[2]
julia> f = objective_function(model)
2-element Vector{AffExpr}:
 x[1] + 1
 2 x[2]
```

### Tip

The [Multi-objective knapsack](#) tutorial provides an example of solving a multi-objective integer program.

In most cases, multi-objective optimization solvers will return multiple solutions, corresponding to points on the Pareto frontier. See [Multiple solutions](#) for information on how to query and work with multiple solutions.

Note that you must set a single objective sense, that is, you cannot have both minimization and maximization objectives. Work around this limitation by choosing `Min` and negating any objectives you want to maximize:

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @expression(model, obj1, 1 + x[1])
x[1] + 1
julia> @expression(model, obj2, 2 * x[1])
2 x[1]
julia> @objective(model, Min, [obj1, -obj2])
2-element Vector{AffExpr}:
```

```
x[1] + 1  
-2 x[1]
```

Defining your objectives as expressions allows flexibility in how you can solve variations of the same problem, with some objectives removed and constrained to be no worse than a fixed value.

```
julia> model = Model();  
  
julia> @variable(model, x[1:2]);  
  
julia> @expression(model, obj1, 1 + x[1])  
x[1] + 1  
  
julia> @expression(model, obj2, 2 * x[1])  
2 x[1]  
  
julia> @expression(model, obj3, x[1] + x[2])  
x[1] + x[2]  
  
julia> @objective(model, Min, [obj1, obj2, obj3]) # Three-objective problem  
3-element Vector{AffExpr}:  
x[1] + 1  
2 x[1]  
x[1] + x[2]  
  
julia> # optimize!(model), look at the solution, talk to stakeholders, then  
# decide you want to solve a new problem where the third objective is  
# removed and constrained to be better than 2.0.  
nothing  
  
julia> @objective(model, Min, [obj1, obj2]) # Two-objective problem  
2-element Vector{AffExpr}:  
x[1] + 1  
2 x[1]  
  
julia> @constraint(model, obj3 <= 2.0)  
x[1] + x[2] ≤ 2
```

# Chapter 16

## Containers

JuMP provides specialized containers similar to `AxisArrays` that enable multi-dimensional arrays with non-integer indices.

These containers are created automatically by JuMP's macros. Each macro has the same basic syntax:

```
@macro_name(model, name[key1=index1, index2; optional_condition], other stuff)
```

The containers are generated by the `name[key1=index1, index2; optional_condition]` syntax. Everything else is specific to the particular macro.

Containers can be named, for example, `name[key=index]`, or unnamed, for example, `[key=index]`. We call unnamed containers *anonymous*.

We call the bits inside the square brackets and before the ; the *index sets*. The index sets can be named, for example, `[i = 1:4]`, or they can be unnamed, for example, `[1:4]`.

We call the bit inside the square brackets and after the ; the *condition*. Conditions are optional.

In addition to the standard JuMP macros like `@variable` and `@constraint`, which construct containers of variables and constraints respectively, you can use `Containers.@container` to construct containers with arbitrary elements.

We will use this macro to explain the three types of containers that are natively supported by JuMP: `Array`, `Containers.DenseAxisArray`, and `Containers.SparseAxisArray`.

### 16.1 Array

An `Array` is created when the index sets are rectangular and the index sets are of the form `1:n`.

```
julia> Containers.@container(x[i = 1:2, j = 1:3], (i, j))
2x3 Matrix{Tuple{Int64, Int64}}:
 (1, 1)  (1, 2)  (1, 3)
 (2, 1)  (2, 2)  (2, 3)
```

The result is a normal Julia `Array`, so you can do all the usual things.

#### Slicing

Arrays can be sliced

```
julia> x[:, 1]
2-element Vector{Tuple{Int64, Int64}}:
 (1, 1)
 (2, 1)

julia> x[2, :]
3-element Vector{Tuple{Int64, Int64}}:
 (2, 1)
 (2, 2)
 (2, 3)
```

## Looping

Use `eachindex` to loop over the elements:

```
julia> for key in eachindex(x)
           println(x[key])
       end
(1, 1)
(2, 1)
(1, 2)
(2, 2)
(1, 3)
(2, 3)
```

## Get the index sets

Use `axes` to obtain the index sets:

```
julia> axes(x)
(Base.OneTo(2), Base.OneTo(3))
```

## Broadcasting

Broadcasting over an Array returns an Array

```
julia> swap(x::Tuple) = (last(x), first(x))
swap (generic function with 1 method)

julia> swap.(x)
2×3 Matrix{Tuple{Int64, Int64}}:
 (1, 1)  (2, 1)  (3, 1)
 (1, 2)  (2, 2)  (3, 2)
```

## Tables

Use `Containers.rowtable` to convert the Array into a `Tables.jl` compatible `Vector{<:NamedTuple}>`:

```
julia> table = Containers.rowtable(x; header = [:I, :J, :value])
6-element Vector{@NamedTuple{I::Int64, J::Int64, value::Tuple{Int64, Int64}}}:  

(I = 1, J = 1, value = (1, 1))  

(I = 2, J = 1, value = (2, 1))  

(I = 1, J = 2, value = (1, 2))  

(I = 2, J = 2, value = (2, 2))  

(I = 1, J = 3, value = (1, 3))  

(I = 2, J = 3, value = (2, 3))
```

Because it supports the [Tables.jl](#) interface, you can pass it to any function which accepts a table as input:

```
julia> import DataFrames;  
  
julia> DataFrames.DataFrame(table)  
6×3 DataFrame  
Row | I      J      value  
     | Int64  Int64  Tuple...  
---  
1   | 1      1      (1, 1)  
2   | 2      1      (2, 1)  
3   | 1      2      (1, 2)  
4   | 2      2      (2, 2)  
5   | 1      3      (1, 3)  
6   | 2      3      (2, 3)
```

## 16.2 DenseAxisArray

A [Containers.DenseAxisArray](#) is created when the index sets are rectangular, but not of the form 1:n. The index sets can be of any type.

```
julia> x = Containers.@container([i = 1:2, j = [:A, :B]], (i, j))
2-dimensional DenseAxisArray{Tuple{Int64, Symbol},2,...} with index sets:  

    Dimension 1, Base.OneTo(2)  

    Dimension 2, [:A, :B]  

And data, a 2×2 Matrix{Tuple{Int64, Symbol}}:  

(1, :A)  (1, :B)  

(2, :A)  (2, :B)
```

### Slicing

DenseAxisArrays can be sliced

```
julia> x[:, :A]
1-dimensional DenseAxisArray{Tuple{Int64, Symbol},1,...} with index sets:  

    Dimension 1, Base.OneTo(2)  

And data, a 2-element Vector{Tuple{Int64, Symbol}}:  

(1, :A)  

(2, :A)  
  
julia> x[1, :]
```

```
1-dimensional DenseAxisArray{Tuple{Int64, Symbol},1,...} with index sets:
  Dimension 1, [:A, :B]
And data, a 2-element Vector{Tuple{Int64, Symbol}}:
(1, :A)
(1, :B)
```

## Looping

Use `eachindex` to loop over the elements:

```
julia> for key in eachindex(x)
           println(x[key])
       end
(1, :A)
(2, :A)
(1, :B)
(2, :B)
```

## Get the index sets

Use `axes` to obtain the index sets:

```
julia> axes(x)
(Base.OneTo(2), [:A, :B])
```

## Broadcasting

Broadcasting over a `DenseAxisArray` returns a `DenseAxisArray`

```
julia> swap(x::Tuple) = (last(x), first(x))
swap (generic function with 1 method)

julia> swap.(x)
2-dimensional DenseAxisArray{Tuple{Symbol, Int64},2,...} with index sets:
  Dimension 1, Base.OneTo(2)
  Dimension 2, [:A, :B]
And data, a 2×2 Matrix{Tuple{Symbol, Int64}}:
 (:A, 1)  (:B, 1)
 (:A, 2)  (:B, 2)
```

## Access internal data

Use `Array(x)` to copy the internal data array into a new Array:

```
julia> Array(x)
2×2 Matrix{Tuple{Int64, Symbol}}:
 (1, :A)  (1, :B)
 (2, :A)  (2, :B)
```

To access the internal data without a copy, use `x.data`.

```
julia> x.data
2x2 Matrix{Tuple{Int64, Symbol}}:
 (1, :A)  (1, :B)
 (2, :A)  (2, :B)
```

## Tables

Use `Containers.rowtable` to convert the `DenseAxisArray` into a `Tables.jl` compatible `Vector{<:NamedTuple>}`:

```
julia> table = Containers.rowtable(x; header = [:I, :J, :value])
4-element Vector{NamedTuple{(:I, :J, :value), Tuple{Int64, Symbol, Tuple{Int64, Symbol}}}}:
 (I = 1, J = :A, value = (1, :A))
 (I = 2, J = :A, value = (2, :A))
 (I = 1, J = :B, value = (1, :B))
 (I = 2, J = :B, value = (2, :B))
```

Because it supports the [Tables.jl](#) interface, you can pass it to any function which accepts a table as input:

```
julia> import DataFrames;  
  
julia> DataFrames.DataFrame(table)  
4x3 DataFrame  
Row | I           J           value  
     | Int64       Symbol      Tuple...  
--- | ---  
 1 | 1           A           (1, :A)  
 2 | 2           A           (2, :A)  
 3 | 1           B           (1, :B)  
 4 | 2           B           (2, :B)
```

## Keyword indexing

If all axes are named, you can use keyword indexing:

```
julia> x[i = 2, j = :A]
(2, :A)

julia> x[i = :, j = :B]
1-dimensional DenseAxisArray{Tuple{Int64, Symbol},1,...} with index sets:
    Dimension 1, Base.OneTo(2)
And data, a 2-element Vector{Tuple{Int64, Symbol}}:
 (1, :B)
 (2, :B)
```

## 16.3 SparseAxisArray

A `Containers.SparseAxisArray` is created when the index sets are non-rectangular. This occurs in two circumstances:

An index depends on a prior index:

```
julia> Containers.@container([i = 1:2, j = i:2], (i, j))
JuMP.Containers.SparseAxisArray{Tuple{Int64, Int64}, 2, Tuple{Int64, Int64}} with 3 entries:
[1, 1]  =  (1, 1)
[1, 2]  =  (1, 2)
[2, 2]  =  (2, 2)
```

The [indices; condition] syntax is used:

```
julia> x = Containers.@container([i = 1:3, j = [:A, :B]; i > 1], (i, j))
JuMP.Containers.SparseAxisArray{Tuple{Int64, Symbol}, 2, Tuple{Int64, Symbol}} with 4 entries:
[2, A]  =  (2, :A)
[2, B]  =  (2, :B)
[3, A]  =  (3, :A)
[3, B]  =  (3, :B)
```

Here we have the index sets  $i = 1:3$ ,  $j = [:A, :B]$ , followed by ;, and then a condition, which evaluates to true or false:  $i > 1$ .

## Slicing

Slicing is supported:

```
julia> y = x[:, :B]
JuMP.Containers.SparseAxisArray{Tuple{Int64, Symbol}, 1, Tuple{Int64}} with 2 entries:
[2]  =  (2, :B)
[3]  =  (3, :B)
```

## Looping

Use `eachindex` to loop over the elements:

```
julia> for key in eachindex(x)
           println(x[key])
       end
(2, :A)
(2, :B)
(3, :A)
(3, :B)

julia> for key in eachindex(y)
           println(y[key])
       end
(2, :B)
(3, :B)
```

**Warning**

If you use a macro to construct a `SparseAxisArray`, then the iteration order is row-major, that is, indices are varied from right to left. As an example, when iterating over `x` above, the `j` index is iterated, keeping `i` constant. This order is in contrast to `Base.Arrays`, which iterate in column-major order, that is, by varying indices from left to right.

**Broadcasting**

Broadcasting over a `SparseAxisArray` returns a `SparseAxisArray`

```
julia> swap(x::Tuple) = (last(x), first(x))
swap (generic function with 1 method)

julia> swap.(y)
JuMP.Containers.SparseAxisArray{Tuple{Symbol, Int64}, 1, Tuple{Int64}} with 2 entries:
 [2]  =  (:B, 2)
 [3]  =  (:B, 3)
```

**Tables**

Use `Containers.rowtable` to convert the `SparseAxisArray` into a `Tables.jl` compatible `Vector{<:NamedTuple}>`:

```
julia> table = Containers.rowtable(x; header = [:I, :J, :value])
4-element Vector{@NamedTuple{I::Int64, J::Symbol, value::Tuple{Int64, Symbol}}}:
 (I = 2, J = :A, value = (2, :A))
 (I = 2, J = :B, value = (2, :B))
 (I = 3, J = :A, value = (3, :A))
 (I = 3, J = :B, value = (3, :B))
```

Because it supports the `Tables.jl` interface, you can pass it to any function which accepts a table as input:

```
julia> import DataFrames;

julia> DataFrames.DataFrame(table)
4x3 DataFrame
Row | I      J      value
    | Int64  Symbol Tuple...
  --|--
  1 | 2      A      (2, :A)
  2 | 2      B      (2, :B)
  3 | 3      A      (3, :A)
  4 | 3      B      (3, :B)
```

**Keyword indexing**

If all axes are named, you can use keyword indexing:

```
julia> x[i = 2, j = :A]
(2, :A)

julia> x[i = :, j = :B]
JuMP.Containers.SparseAxisArray{Tuple{Int64, Symbol}, 1, Tuple{Int64}} with 2 entries:
 [2] = (2, :B)
 [3] = (3, :B)
```

## 16.4 Forcing the container type

Pass `container = T` to use `T` as the container. For example:

```
julia> Containers.@container([i = 1:2, j = 1:2], i + j, container = Array)
2×2 Matrix{Int64}:
 2  3
 3  4

julia> Containers.@container([i = 1:2, j = 1:2], i + j, container = Dict)
Dict{Tuple{Int64, Int64}, Int64} with 4 entries:
 (1, 2) => 3
 (1, 1) => 2
 (2, 2) => 4
 (2, 1) => 3
```

You can also pass `DenseAxisArray` or `SparseAxisArray`.

## 16.5 How different container types are chosen

If the compiler can prove at *compile time* that the index sets are rectangular, and indexed by a compact set of integers that start at 1, `Containers.@container` will return an array. This is the case if your index sets are visible to the macro as `1:n`:

```
julia> Containers.@container([i=1:3, j=1:5], i + j)
3×5 Matrix{Int64}:
 2  3  4  5  6
 3  4  5  6  7
 4  5  6  7  8
```

or an instance of `Base.OneTo`:

```
julia> set = Base.OneTo(3)
Base.OneTo(3)

julia> Containers.@container([i=set, j=1:5], i + j)
3×5 Matrix{Int64}:
 2  3  4  5  6
 3  4  5  6  7
 4  5  6  7  8
```

If the compiler can prove that the index set is rectangular, but not necessarily of the form `1:n` at compile time, then a `Containers.DenseAxisArray` will be constructed instead:

```
julia> set = 1:3
1:3

julia> Containers.@container([i=set, j=1:5], i + j)
2-dimensional DenseAxisArray{Int64,2,...} with index sets:
  Dimension 1, 1:3
  Dimension 2, Base.OneTo(5)
And data, a 3x5 Matrix{Int64}:
 2  3  4  5  6
 3  4  5  6  7
 4  5  6  7  8
```

### Info

What happened here? Although we know that `set` contains `1:3`, at compile time the `typeof(set)` is a `UnitRange{Int}`. Therefore, Julia can't prove that the range starts at 1 (it only finds this out at runtime), and it defaults to a `DenseAxisArray`. The case where we explicitly wrote `i = 1:3` worked because the macro can "see" the `1` at compile time.

However, if you know that the indices do form an Array, you can force the container type with `container = Array`:

```
julia> set = 1:3
1:3

julia> Containers.@container([i=set, j=1:5], i + j, container = Array)
3x5 Matrix{Int64}:
 2  3  4  5  6
 3  4  5  6  7
 4  5  6  7  8
```

Here's another example with something similar:

```
julia> a = 1
1

julia> Containers.@container([i=a:3, j=1:5], i + j)
2-dimensional DenseAxisArray{Int64,2,...} with index sets:
  Dimension 1, 1:3
  Dimension 2, Base.OneTo(5)
And data, a 3x5 Matrix{Int64}:
 2  3  4  5  6
 3  4  5  6  7
 4  5  6  7  8

julia> Containers.@container([i=1:a, j=1:5], i + j)
1x5 Matrix{Int64}:
 2  3  4  5  6
```

Finally, if the compiler cannot prove that the index set is rectangular, a `Containers.SparseAxisArray` will be created.

This occurs when some indices depend on a previous one:

```
julia> Containers.@container([i=1:3, j=1:i], i + j)
JuMP.Containers.SparseAxisArray{Int64, 2, Tuple{Int64, Int64}} with 6 entries:
[1, 1] = 2
[2, 1] = 3
[2, 2] = 4
[3, 1] = 4
[3, 2] = 5
[3, 3] = 6
```

or if there is a condition on the index sets:

```
julia> Containers.@container([i = 1:5; isodd(i)], i^2)
JuMP.Containers.SparseAxisArray{Int64, 1, Tuple{Int64}} with 3 entries:
[1] = 1
[3] = 9
[5] = 25
```

The condition can depend on multiple indices, the only requirement is that it is an expression that returns `true` or `false`:

```
julia> condition(i, j) = isodd(i) && iseven(j)
condition (generic function with 1 method)

julia> Containers.@container([i = 1:2, j = 1:4; condition(i, j)], i + j)
JuMP.Containers.SparseAxisArray{Int64, 2, Tuple{Int64, Int64}} with 2 entries:
[1, 2] = 3
[1, 4] = 5
```

# Chapter 17

## Solutions

This section of the manual describes how to access a solved solution to a problem. It uses the following model as an example:

```
julia> begin
           model = Model(HiGHS.Optimizer)
           set_silent(model)
           @variable(model, x >= 0)
           @variable(model, y[[:a, :b]] <= 1)
           @objective(model, Max, -12x - 20y[:a])
           @expression(model, my_expr, 6x + 8y[:a])
           @constraint(model, my_expr >= 100)
           @constraint(model, c1, 7x + 12y[:a] >= 120)
           optimize!(model)
           print(model)
       end
Max -12 x - 20 y[a]
Subject to
 6 x + 8 y[a] ≥ 100
 c1 : 7 x + 12 y[a] ≥ 120
 x ≥ 0
 y[a] ≤ 1
 y[b] ≤ 1
```

### 17.1 Check if an optimal solution exists

Use `is_solved_and_feasible` to check if the solver found an optimal solution:

```
julia> is_solved_and_feasible(model)
true
```

By default, `is_solved_and_feasible` returns `true` for both global and local optima. Pass `allow_local = false` to check if the solver found a globally optimal solution:

```
julia> is_solved_and_feasible(model; allow_local = false)
true
```

Pass `dual = true` to check if the solver found an optimal dual solution in addition to an optimal primal solution:

```
julia> is_solved_and_feasible(model; dual = true)
true
```

If this function returns `false`, use the functions mentioned below like `solution_summary`, `termination_status`, `primal_status`, and `dual_status` to understand what solution (if any) the solver found.

## 17.2 Solutions summary

`solution_summary` can be used for checking the summary of the optimization solutions.

```
julia> solution_summary(model)
* Solver : HiGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : -2.05143e+02
  Objective bound    : -2.05143e+02
  Relative gap       : 1.38546e-16
  Dual objective value : -2.05143e+02

* Work counters
  Solve time (sec)   : 6.01048e-04
  Simplex iterations : 2
  Barrier iterations : 0
  Node count         : -1

julia> solution_summary(model; verbose = true)
* Solver : HiGHS

* Status
  Result count      : 1
  Termination status : OPTIMAL
  Message from the solver:
  "kHighsModelStatusOptimal"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : FEASIBLE_POINT
  Objective value    : -2.05143e+02
  Objective bound    : -2.05143e+02
  Relative gap       : 1.38546e-16
  Dual objective value : -2.05143e+02
  Primal solution :
    x : 1.54286e+01
    y[a] : 1.00000e+00
```

```

y[b] : 1.00000e+00
Dual solution :
c1 : 1.71429e+00

* Work counters
Solve time (sec) : 6.01048e-04
Simplex iterations : 2
Barrier iterations : 0
Node count : -1

```

### 17.3 Why did the solver stop?

Use `termination_status` to understand why the solver stopped.

```
julia> termination_status(model)
OPTIMAL::TerminationStatusCode = 1
```

The `MOI.TerminationStatusCode` enum describes the full list of statuses that could be returned.

Common return values include `OPTIMAL`, `LOCALLY_SOLVED`, `INFEASIBLE`, `DUAL_INFEASIBLE`, and `TIME_LIMIT`.

#### Info

A return status of `OPTIMAL` means the solver found (and proved) a globally optimal solution. A return status of `LOCALLY_SOLVED` means the solver found a locally optimal solution (which may also be globally optimal, but it could not prove so).

#### Warning

A return status of `DUAL_INFEASIBLE` does not guarantee that the primal is unbounded. When the dual is infeasible, the primal is unbounded if there exists a feasible primal solution.

Use `raw_status` to get a solver-specific string explaining why the optimization stopped:

```
julia> raw_status(model)
"kHighsModelStatusOptimal"
```

### 17.4 Primal solutions

#### Primal solution status

Use `primal_status` to return an `MOI.ResultStatusCode` enum describing the status of the primal solution.

```
julia> primal_status(model)
FEASIBLE_POINT::ResultStatusCode = 1
```

Other common returns are `NO_SOLUTION`, and `INFEASIBILITY_CERTIFICATE`. The first means that the solver doesn't have a solution to return, and the second means that the primal solution is a certificate of dual infeasibility (a primal unbounded ray).

You can also use `has_values`, which returns `true` if there is a solution that can be queried, and `false` otherwise.

```
julia> has_values(model)
true
```

## Objective values

The objective value of a solved problem can be obtained via `objective_value`. The best known bound on the optimal objective value can be obtained via `objective_bound`. If the solver supports it, the value of the dual objective can be obtained via `dual_objective_value`.

```
julia> objective_value(model)
-205.14285714285714

julia> objective_bound(model)
-205.1428571428571

julia> dual_objective_value(model)
-205.1428571428571
```

## Primal solution values

If the solver has a primal solution to return, use `value` to access it:

```
julia> value(x)
15.428571428571429
```

Broadcast `value` over containers:

```
julia> value.(y)
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, [:a, :b]
And data, a 2-element Vector{Float64}:
 1.0
 1.0
```

`value` also works on expressions:

```
julia> value(my_expr)
100.57142857142857
```

and constraints:

```
julia> value(c1)
120.0
```

### Info

Calling `value` on a constraint returns the constraint function evaluated at the solution.

## 17.5 Dual solutions

### Dual solution status

Use `dual_status` to return an `MOI.ResultStatusCode` enum describing the status of the dual solution.

```
julia> dual_status(model)
FEASIBLE_POINT::ResultStatusCode = 1
```

Other common returns are `NO_SOLUTION`, and `INFEASIBILITY_CERTIFICATE`. The first means that the solver doesn't have a solution to return, and the second means that the dual solution is a certificate of primal infeasibility (a dual unbounded ray).

You can also use `has_duals`, which returns `true` if there is a solution that can be queried, and `false` otherwise.

```
julia> has_duals(model)
true
```

### Dual solution values

If the solver has a dual solution to return, use `dual` to access it:

```
julia> dual(c1)
1.7142857142857142
```

Query the duals of variable bounds using `LowerBoundRef`, `UpperBoundRef`, and `FixRef`:

```
julia> dual(LowerBoundRef(x))
0.0

julia> dual.(UpperBoundRef.(y))
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
  Dimension 1, [:a, :b]
And data, a 2-element Vector{Float64}:
 -0.5714285714285694
 0.0
```

#### Warning

JuMP's definition of duality is independent of the objective sense. That is, the sign of feasible duals associated with a constraint depends on the direction of the constraint and not whether the problem is maximization or minimization. **This is a different convention from linear programming duality in some common textbooks.** If you have a linear program, and you want the textbook definition, you probably want to use `shadow_price` and `reduced_cost` instead.

```
julia> shadow_price(c1)
1.7142857142857142

julia> reduced_cost(x)
```

```
-0.0

julia> reduced_cost.(y)
1-dimensional DenseAxisArray{Float64,1,...} with index sets:
Dimension 1, [:a, :b]
And data, a 2-element Vector{Float64}:
 0.5714285714285694
-0.0
```

## 17.6 Recommended workflow

You should always check whether the solver found a solution before calling solution functions like `value` or `objective_value`.

A simple approach for small scripts and notebooks is to use `is_solved_and_feasible`:

```
julia> function solve_and_print_solution(model)
    optimize!(model)
    if !is_solved_and_feasible(model; dual = true)
        error(
            """
            The model was not solved correctly:
            termination_status : $(termination_status(model))
            primal_status      : $(primal_status(model))
            dual_status         : $(dual_status(model))
            raw_status          : $(raw_status(model))
            """,
        )
    end
    println("Solution is optimal")
    println(" objective value = ", objective_value(model))
    println(" primal solution: x = ", value(x))
    println(" dual solution: c1 = ", dual(c1))
    return
end
solve_and_print_solution (generic function with 1 method)

julia> solve_and_print_solution(model)
Solution is optimal
objective value = -205.14285714285714
primal solution: x = 15.428571428571429
dual solution: c1 = 1.7142857142857142
```

For code like libraries that should be more robust to the range of possible termination and result statuses, do some variation of the following:

```
julia> function solve_and_print_solution(model)
    optimize!(model)
    status = termination_status(model)
    if status in (OPTIMAL, LOCALLY_SOLVED)
        println("Solution is optimal")
    elseif status in (ALMOST_OPTIMAL, ALMOST_LOCALLY_SOLVED)
```

```

        println("Solution is optimal to a relaxed tolerance")
    elseif status == TIME_LIMIT
        println(
            "Solver stopped due to a time limit. If a solution is available, * "
            "it may be suboptimal."
        )
    elseif status in (
        ITERATION_LIMIT, NODE_LIMIT, SOLUTION_LIMIT, MEMORY_LIMIT,
        OBJECTIVE_LIMIT, NORM_LIMIT, OTHER_LIMIT,
    )
        println(
            "Solver stopped due to a limit. If a solution is available, it " *
            "may be suboptimal."
        )
    elseif status in (INFEASIBLE, LOCALLY_INFEASIBLE)
        println("The problem is primal infeasible")
    elseif status == DUAL_INFEASIBLE
        println(
            "The problem is dual infeasible. If a primal feasible solution " *
            "exists, the problem is unbounded. To check, set the objective " *
            "to `@objective(model, Min, 0)` and re-solve. If the problem is " *
            "feasible, the primal is unbounded. If the problem is " *
            "infeasible, both the primal and dual are infeasible.",
        )
    elseif status == INFEASIBLE_OR_UNBOUNDED
        println(
            "The model is either infeasible or unbounded. Set the objective " *
            "to `@objective(model, Min, 0)` and re-solve to disambiguate. If " *
            "the problem was infeasible, it will still be infeasible. If the " *
            "problem was unbounded, it will now have a finite optimal solution.",
        )
    else
        println(
            "The model was not solved correctly. The termination status is $status",
        )
    end
    if primal_status(model) in (FEASIBLE_POINT, NEARLY_FEASIBLE_POINT)
        println("  objective value = ", objective_value(model))
        println("  primal solution: x = ", value(x))
    elseif primal_status(model) == INFEASIBILITY_CERTIFICATE
        println("  primal certificate: x = ", value(x))
    end
    if dual_status(model) in (FEASIBLE_POINT, NEARLY_FEASIBLE_POINT)
        println("  dual solution: cl = ", dual(c1))
    elseif dual_status(model) == INFEASIBILITY_CERTIFICATE
        println("  dual certificate: cl = ", dual(c1))
    end
    return
end
solve_and_print_solution (generic function with 1 method)

julia> solve_and_print_solution(model)
Solution is optimal
objective value = -205.14285714285714
primal solution: x = 15.428571428571429

```

```
dual solution: c1 = 1.7142857142857142
```

## 17.7 OptimizeNotCalled errors

Due to differences in how solvers cache solutions internally, modifying a model after calling `optimize!` will reset the model into the `OPTIMIZE_NOT_CALLED` state. If you then attempt to query solution information, an `OptimizeNotCalled` error will be thrown.

If you are iteratively querying solution information and modifying a model, query all the results first, then modify the problem.

For example, instead of:

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0);

julia> optimize!(model)

julia> termination_status(model)
OPTIMAL::TerminationStatusCode = 1

julia> set_upper_bound(x, 1)

julia> x_val = value(x)
Warning: The model has been modified since the last call to `optimize!` (or `optimize!` has not
→ been called yet). If you are iteratively querying solution information and modifying a model,
→ query all the results first, then modify the model.
└ @ JuMP ~/julia/dev/JuMP/src/optimizer_interface.jl:1085
ERROR: OptimizeNotCalled()
Stacktrace:
[...]

julia> termination_status(model)
OPTIMIZE_NOT_CALLED::TerminationStatusCode = 0
```

do

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0);

julia> optimize!(model);

julia> x_val = value(x)
0.0

julia> termination_status(model)
OPTIMAL::TerminationStatusCode = 1
```

```
julia> set_upper_bound(x, 1)
julia> set_lower_bound(x, x_val)
julia> termination_status(model)
OPTIMIZE_NOT_CALLED::TerminationStatusCode = 0
```

If you know that your particular solver supports querying solution information after modifications, you can use `direct_model` to bypass the `OPTIMIZE_NOT_CALLED` state:

```
julia> model = direct_model(HiGHS.Optimizer());
julia> set_silent(model)
julia> @variable(model, x >= 0);
julia> optimize!(model)
julia> termination_status(model)
OPTIMAL::TerminationStatusCode = 1
julia> set_upper_bound(x, 1)
julia> x_val = value(x)
0.0
julia> set_lower_bound(x, x_val)
julia> termination_status(model)
OPTIMAL::TerminationStatusCode = 1
```

### Warning

Be careful doing this. If your particular solver does not support querying solution information after modification, it may silently return incorrect solutions or throw an error.

## 17.8 Accessing attributes

`MathOptInterface` defines many model attributes that can be queried. Some attributes can be directly accessed by getter functions. These include:

- `solve_time`
- `relative_gap`
- `simplex_iterations`
- `barrier_iterations`
- `node_count`

## 17.9 Sensitivity analysis for LP

Given an LP problem and an optimal solution corresponding to a basis, we can question how much an objective coefficient or standard form right-hand side coefficient (c.f., `normalized_rhs`) can change without violating primal or dual feasibility of the basic solution.

Note that not all solvers compute the basis, and for sensitivity analysis, the solver interface must implement `MOI.ConstraintBasisStatus`.

### Tip

Read the [Sensitivity analysis of a linear program](#) for more information on sensitivity analysis.

To give a simple example, we could analyze the sensitivity of the optimal solution to the following (non-degenerate) LP problem:

```
julia> begin
        model = Model(HiGHS.Optimizer)
        set_silent(model)
        @variable(model, x[1:2])
        set_lower_bound(x[2], -0.5)
        set_upper_bound(x[2], 0.5)
        @constraint(model, c1, x[1] + x[2] <= 1)
        @constraint(model, c2, x[1] - x[2] <= 1)
        @objective(model, Max, x[1])
        print(model)
    end
Max x[1]
Subject to
c1 : x[1] + x[2] ≤ 1
c2 : x[1] - x[2] ≤ 1
x[2] ≥ -0.5
x[2] ≤ 0.5
```

To analyze the sensitivity of the problem we could check the allowed perturbation ranges of, for example, the cost coefficients and the right-hand side coefficient of the constraint `c1` as follows:

```
julia> optimize!(model)

julia> value.(x)
2-element Vector{Float64}:
 1.0
 -0.0

julia> report = lp_sensitivity_report(model);

julia> x1_lo, x1_hi = report[x[1]]
(-1.0, Inf)

julia> println("The objective coefficient of x[1] could decrease by $(x1_lo) or increase by
           ↪ $(x1_hi).")
The objective coefficient of x[1] could decrease by -1.0 or increase by Inf.

julia> x2_lo, x2_hi = report[x[2]]
```

```
(-1.0, 1.0)

julia> println("The objective coefficient of x[2] could decrease by $(x2_lo) or increase by
           ↑ $(x2_hi).")
The objective coefficient of x[2] could decrease by -1.0 or increase by 1.0.

julia> c_lo, c_hi = report[c1]
(-1.0, 1.0)

julia> println("The RHS of c1 could decrease by $(c_lo) or increase by $(c_hi).")
The RHS of c1 could decrease by -1.0 or increase by 1.0.
```

The range associated with a variable is the range of the allowed perturbation of the corresponding objective coefficient. Note that the current primal solution remains optimal within this range; however the corresponding dual solution might change since a cost coefficient is perturbed. Similarly, the range associated with a constraint is the range of the allowed perturbation of the corresponding right-hand side coefficient. In this range the current dual solution remains optimal, but the optimal primal solution might change.

If the problem is degenerate, there are multiple optimal bases and hence these ranges might not be as intuitive and seem too narrow, for example, a larger cost coefficient perturbation might not invalidate the optimality of the current primal solution. Moreover, if a problem is degenerate, due to finite precision, it can happen that, for example, a perturbation seems to invalidate a basis even though it doesn't (again providing too narrow ranges). To prevent this, increase the `atol` keyword argument to `lp_sensitivity_report`. Note that this might make the ranges too wide for numerically challenging instances. Thus, do not blindly trust these ranges, especially not for highly degenerate or numerically unstable instances.

## 17.10 Conflicts

When the model you input is infeasible, some solvers can help you find the cause of this infeasibility by offering a conflict, that is, a subset of the constraints that create this infeasibility. Depending on the solver, this can also be called an IIS (irreducible inconsistent subsystem).

If supported by the solver, use `compute_conflict!` to trigger the computation of a conflict. Once this process is finished, query the `MOI.ConflictStatus` attribute to check if a conflict was found.

If found, copy the IIS to a new model using `copy_conflict`, which you can then print or write to a file for easier debugging:

```
julia> using JuMP

julia> import Gurobi

julia> model = Model(Gurobi.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0)
x

julia> @constraint(model, c1, x >= 2)
c1 : x ≥ 2.0

julia> @constraint(model, c2, x <= 1)
c2 : x ≤ 1.0
```

```
julia> optimize!(model)

julia> compute_conflict!(model)

julia> if get_attribute(model, MOI.ConflictStatus()) == MOI.CONFLICT_FOUND
    iis_model, _ = copy_conflict(model)
    print(iis_model)
end
Feasibility
Subject to
c1 : x ≥ 2.0
c2 : x ≤ 1.0
```

If you need more control over the list of constraints that appear in the conflict, iterate over the list of constraints and query the `MOI.ConstraintConflictStatus` attribute:

```
julia> list_of_conflicting_constraints = ConstraintRef[]
ConstraintRef[]

julia> for (F, S) in list_of_constraint_types(model)
    for con in all_constraints(model, F, S)
        if get_attribute(con, MOI.ConstraintConflictStatus()) == MOI.IN_CONFLICT
            push!(list_of_conflicting_constraints, con)
        end
    end
end

julia> list_of_conflicting_constraints
2-element Vector{ConstraintRef}:
c1 : x ≥ 2.0
c2 : x ≤ 1.0
```

## 17.11 Multiple solutions

Some solvers support returning multiple solutions. You can check how many solutions are available to query using `result_count`.

Functions for querying the solutions, for example, `primal_status`, `dual_status`, `value`, `dual`, and `solution_summary` all take an additional keyword argument `result` which can be used to specify which result to return.

### Warning

Even if `termination_status` is `OPTIMAL`, some of the returned solutions may be suboptimal. However, if the solver found at least one optimal solution, then `result = 1` will always return an optimal solution. Use `objective_value` to assess the quality of the remaining solutions.

```
julia> using JuMP

julia> import MultiObjectiveAlgorithms as MOA
```

```
julia> import HiGHS

julia> model = Model(() -> MOA.Optimizer(HiGHS.Optimizer));

julia> set_attribute(model, MOA.Algorithm(), MOA.Dichotomy())

julia> set_silent(model)

julia> @variable(model, x1 >= 0)
x1

julia> @variable(model, 0 <= x2 <= 3)
x2

julia> @objective(model, Min, [3x1 + x2, -x1 - 2x2])
2-element Vector{AffExpr}:
 3 x1 + x2
 -x1 - 2 x2

julia> @constraint(model, 3x1 - x2 <= 6)
3 x1 - x2 ≤ 6

julia> optimize!(model)

julia> solution_summary(model; result = 1)
* Solver : MOA[algorithm=MultiObjectiveAlgorithms.Dichotomy, optimizer=HiGHS]

* Status
  Result count      : 3
  Termination status : OPTIMAL
  Message from the solver:
  "Solve complete. Found 3 solution(s)"

* Candidate solution (result #1)
  Primal status      : FEASIBLE_POINT
  Dual status        : NO_SOLUTION
  Objective value    : [0.00000e+00, 0.00000e+00]
  Objective bound    : [0.00000e+00, -9.00000e+00]

* Work counters
  Solve time (sec)   : 5.34880e-01

julia> for i in 1:result_count(model)
         println("Solution $i")
         println("  x = ", value.([x1, x2]; result = i))
         println("  obj = ", objective_value(model; result = i))
     end
Solution 1
  x = [0.0, 0.0]
  obj = [0.0, 0.0]
Solution 2
  x = [0.0, 3.0]
  obj = [3.0, -6.0]
Solution 3
  x = [3.0, 3.0]
```

```
obj = [12.0, -9.0]
```

**Tip**

The [Multi-objective knapsack](#) tutorial provides more examples of querying multiple solutions.

## 17.12 Checking feasibility of solutions

To check the feasibility of a primal solution, use `primal_feasibility_report`, which takes a model, a dictionary mapping each variable to a primal solution value (defaults to the last solved solution), and a tolerance `atol` (defaults to 0.0).

The function returns a dictionary which maps the infeasible constraint references to the distance between the primal value of the constraint and the nearest point in the corresponding set. A point is classed as infeasible if the distance is greater than the supplied tolerance `atol`.

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 1, Int);

julia> @variable(model, y);

julia> @constraint(model, c1, x + y <= 1.95);

julia> point = Dict(x => 1.9, y => 0.06);

julia> primal_feasibility_report(model, point)
Dict{Any, Float64} with 2 entries:
  x integer      => 0.1
  c1 : x + y ≤ 1.95 => 0.01

julia> primal_feasibility_report(model, point; atol = 0.02)
Dict{Any, Float64} with 1 entry:
  x integer => 0.1
```

If the point is feasible, an empty dictionary is returned:

```
julia> primal_feasibility_report(model, Dict(x => 1.0, y => 0.0))
Dict{Any, Float64}()
```

To use the primal solution from a solve, omit the `point` argument:

```
julia> optimize!(model)

julia> primal_feasibility_report(model; atol = 0.0)
Dict{Any, Float64}()
```

Calling `primal_feasibility_report` without the `point` argument is useful when `primal_status` is `FEASIBLE_POINT` or `NEARLY_FEASIBLE_POINT`, and you want to assess the solution quality.

**Warning**

To apply `primal_feasibility_report` to infeasible models, you must also provide a candidate point (solvers generally do not provide one). To diagnose the source of infeasibility, see [Conflicts](#).

Pass `skip_missing = true` to skip constraints which contain variables that are not in `point`:

```
julia> primal_feasibility_report(model, Dict(x => 2.1); skip_missing = true)
Dict{Any, Float64} with 1 entry:
  x integer => 0.1
```

You can also use the functional form, where the first argument is a function that maps variables to their primal values:

```
julia> optimize!(model)

julia> primal_feasibility_report(v -> value(v), model)
Dict{Any, Float64}()
```

## Chapter 18

# Solver-independent Callbacks

Many mixed-integer (linear, conic, and nonlinear) programming solvers offer the ability to modify the solve process. Examples include changing branching decisions in branch-and-bound, adding custom cutting planes, providing custom heuristics to find feasible solutions, or implementing on-demand separators to add new constraints only when they are violated by the current solution (also known as lazy constraints).

While historically this functionality has been limited to solver-specific interfaces, JuMP provides solver-independent support for three types of callbacks:

1. lazy constraints
2. user-cuts
3. heuristic solutions

### 18.1 Available solvers

Solver-independent callback support is limited to a few solvers. This includes [CPLEX](#), [GLPK](#), [Gurobi](#), [Xpress](#), and [SCIP](#) (SCIP does not support lazy constraints).

#### Warning

While JuMP provides a solver-independent way of accessing callbacks, you should not assume that you will see identical behavior when running the same code on different solvers. For example, some solvers may ignore user-cuts for various reasons, while other solvers may add every user-cut. Read the underlying solver's callback documentation to understand details specific to each solver.

#### Tip

This page discusses solver-*independent* callbacks. However, each solver listed above also provides a solver-*dependent* callback to provide access to the full range of solver-specific features. Consult the solver's README for an example of how to use the solver-dependent callback. This will require you to understand the C interface of the solver.

### 18.2 Things you can and cannot do during solver-independent callbacks

There is a limited range of things you can do during a callback. Only use the functions and macros explicitly stated in this page of the documentation, or in the [Callbacks tutorial](#).

Using any other part of the JuMP API (for example, adding a constraint with `@constraint` or modifying a variable bound with `set_lower_bound`) is undefined behavior, and your solver may throw an error, return an incorrect solution, or result in a segfault that aborts Julia.

In each of the three solver-independent callbacks, there are two things you may query:

- `callback_node_status` returns an `MOI.CallbackNodeStatusCode` enum indicating if the current primal solution is integer feasible.
- `callback_value` returns the current primal solution of a variable.

If you need to query any other information, use a solver-dependent callback instead. Each solver supporting a solver-dependent callback has information on how to use it in the README of their GitHub repository.

If you want to modify the problem in a callback, you *must* use a lazy constraint.

#### Warning

You can only set each callback once. Calling `set` twice will over-write the earlier callback. In addition, if you use a solver-independent callback, you cannot set a solver-dependent callback.

### 18.3 Lazy constraints

Lazy constraints are useful when the full set of constraints is too large to explicitly include in the initial formulation. When a MIP solver reaches a new solution, for example with a heuristic or by solving a problem at a node in the branch-and-bound tree, it will give the user the chance to provide constraints that would make the current solution infeasible. For some more information about lazy constraints, see this [blog post by Paul Rubin](#).

A lazy constraint callback can be set using the following syntax:

```
julia> model = Model();

julia> @variable(model, x <= 10, Int)
x

julia> @objective(model, Max, x)
x

julia> function my_callback_function(cb_data)
    status = callback_node_status(cb_data, model)
    if status == MOI.CALLBACK_NODE_STATUS_FRACTIONAL
        # `callback_value(cb_data, x)` is not integer (to some tolerance).
        # If, for example, your lazy constraint generator requires an
        # integer-feasible primal solution, you can add a `return` here.
        return
    elseif status == MOI.CALLBACK_NODE_STATUS_INTEGER
        # `callback_value(cb_data, x)` is integer (to some tolerance).
    else
        @assert status == MOI.CALLBACK_NODE_STATUS_UNKNOWN
        # `callback_value(cb_data, x)` might be fractional or integer.
    end
    x_val = callback_value(cb_data, x)
    if x_val > 2 + 1e-6
```

```

        con = @build_constraint(x <= 2)
        MOI.submit(model, MOI.LazyConstraint(cb_data), con)
    end
    return
end
my_callback_function (generic function with 1 method)

julia> set_attribute(model, MOI.LazyConstraintCallback(), my_callback_function)

```

**Info**

The lazy constraint callback *may* be called at fractional or integer nodes in the branch-and-bound tree. There is no guarantee that the callback is called at every primal solution.

**Warning**

Only add a lazy constraint if your primal solution violates the constraint. Adding the lazy constraint irrespective of feasibility may result in the solver returning an incorrect solution, or lead to many constraints being added, slowing down the solution process.

```

model = Model()
@variable(model, x <= 10, Int)
@objective(model, Max, x)
function bad_callback_function(cb_data)
    # Don't do this!
    con = @build_constraint(x <= 2)
    MOI.submit(model, MOI.LazyConstraint(cb_data), con)
    return
end
function good_callback_function(cb_data)
    if callback_value(x) > 2
        con = @build_constraint(x <= 2)
        MOI.submit(model, MOI.LazyConstraint(cb_data), con)
    end
    return
end
set_attribute(model, MOI.LazyConstraintCallback(), good_callback_function)

```

**Warning**

During the solve, a solver may visit a point that was cut off by a previous lazy constraint, for example, because the earlier lazy constraint was removed during presolve. If this happens, you must re-add the lazy constraint.

## 18.4 User cuts

User cuts, or simply cuts, provide a way for the user to tighten the LP relaxation using problem-specific knowledge that the solver cannot or is unable to infer from the model. Just like with lazy constraints, when a MIP solver reaches a new node in the branch-and-bound tree, it will give the user the chance to provide cuts to

make the current relaxed (fractional) solution infeasible in the hopes of obtaining an integer solution. For more details about the difference between user cuts and lazy constraints see the aforementioned [blog post](#).

A user-cut callback can be set using the following syntax:

```
julia> model = Model();

julia> @variable(model, x <= 10.5, Int)
x

julia> @objective(model, Max, x)
x

julia> function my_callback_function(cb_data)
    x_val = callback_value(cb_data, x)
    con = @build_constraint(x <= floor(x_val))
    MOI.submit(model, MOI.UserCut(cb_data), con)
    return
end
my_callback_function (generic function with 1 method)

julia> set_attribute(model, MOI.UserCutCallback(), my_callback_function)
```

#### Warning

User cuts must not change the set of integer feasible solutions. Equivalently, user cuts can only remove fractional solutions. If you add a cut that removes an integer solution (even one that is not optimal), the solver may return an incorrect solution.

#### Info

The user-cut callback *may* be called at fractional nodes in the branch-and-bound tree. There is no guarantee that the callback is called at every fractional primal solution.

## 18.5 Heuristic solutions

Integer programming solvers frequently include heuristics that run at the nodes of the branch-and-bound tree. They aim to find integer solutions quicker than plain branch-and-bound would to tighten the bound, allowing us to fathom nodes quicker and to tighten the integrality gap.

Some heuristics take integer solutions and explore their "local neighborhood" (for example, flipping binary variables, fix some variables and solve a smaller MILP) and others take fractional solutions and attempt to round them in an intelligent way.

You may want to add a heuristic of your own if you have some special insight into the problem structure that the solver is not aware of, for example, you can consistently take fractional solutions and intelligently guess integer solutions from them.

A heuristic solution callback can be set using the following syntax:

```
julia> model = Model();
```

```
julia> @variable(model, x <= 10.5, Int);
julia> @objective(model, Max, x);

julia> function my_callback_function(cb_data)
    x_val = callback_value(cb_data, x)
    status = MOI.submit(
        model, MOI.HeuristicSolution(cb_data), [x], [floor(Int, x_val)])
    )
    println("I submitted a heuristic solution, and the status was: ", status)
    return
end
my_callback_function (generic function with 1 method)

julia> set_attribute(model, MOI.HeuristicCallback(), my_callback_function)
```

The third argument to `submit` is a vector of JuMP variables, and the fourth argument is a vector of values corresponding to each variable.

`MOI.submit` returns an enum that depends on whether the solver accepted the solution. The possible return codes are:

- `MOI.HEURISTIC_SOLUTION_ACCEPTED`
- `MOI.HEURISTIC_SOLUTION_REJECTED`
- `MOI.HEURISTIC_SOLUTION_UNKNOWN`

#### Warning

Some solvers may accept partial solutions. Others require a feasible integer solution for every variable. If in doubt, provide a complete solution.

#### Info

The heuristic solution callback *may* be called at fractional nodes in the branch-and-bound tree. There is no guarantee that the callback is called at *every* fractional primal solution.

## Chapter 19

# Complex number support

This page explains the complex-valued variables and constraints that JuMP supports. For a worked-example using these features, read the [Example: quantum state discrimination](#) tutorial.

### 19.1 Complex-valued variables

Create a complex-valued variable using `ComplexPlane`:

```
julia> model = Model();
julia> @variable(model, x in ComplexPlane())
real(x) + imag(x) im
```

Note that `x` is not a `VariableRef`; instead, it is an affine expression with `Complex{Float64}`-valued coefficients:

```
julia> typeof(x)
GenericAffExpr{ComplexF64, VariableRef}
```

Behind the scenes, JuMP has created two real-valued variables, with names "`real(x)`" and "`imag(x)`":

```
julia> all_variables(model)
2-element Vector{VariableRef}:
 real(x)
 imag(x)

julia> name.(all_variables(model))
2-element Vector{String}:
 "real(x)"
 "imag(x)"
```

Use the `real` and `imag` functions on `x` to return a real-valued affine expression representing each variable:

```
julia> typeof(real(x))
AffExpr (alias for GenericAffExpr{Float64, GenericVariableRef{Float64}})

julia> typeof(imag(x))
AffExpr (alias for GenericAffExpr{Float64, GenericVariableRef{Float64}})
```

To create an anonymous variable, use the `set` keyword argument:

```
julia> model = Model();

julia> x = @variable(model, set = ComplexPlane())
_[1] + _[2] im
```

## 19.2 Complex-valued variable and start values bounds

Because complex-valued variables lack a total ordering, the definition of a variable bound for a complex-valued variable is ambiguous. If you pass a real- or complex-valued argument to keywords such as `lower_bound`, `upper_bound`, and `start_value`, JuMP will apply the real and imaginary parts to the associated real-valued variables.

```
julia> model = Model();

julia> @variable(
    model,
    x in ComplexPlane(),
    lower_bound = 1.0,
    upper_bound = 2.0 + 3.0im,
    start = 4im,
)
real(x) + imag(x) im

julia> vars = all_variables(model)
2-element Vector{VariableRef}:
 real(x)
 imag(x)

julia> lower_bound.(vars)
2-element Vector{Float64}:
 1.0
 0.0

julia> upper_bound.(vars)
2-element Vector{Float64}:
 2.0
 3.0

julia> start_value.(vars)
2-element Vector{Float64}:
 0.0
 4.0
```

You can modify the bounds and start values by passing `imag(x)` or `real(x)` to the appropriate function:

```
julia> set_lower_bound(imag(x), 2)

julia> lower_bound(imag(x))
2.0
```

```
julia> delete_upper_bound(real(x))

julia> has_upper_bound(real(x))
false

julia> set_start_value(imag(x), 3)

julia> start_value(imag(x))
3.0
```

### 19.3 Complex-valued equality constraints

JuMP reformulates complex-valued equality constraints into two real-valued constraints: one representing the real part, and one representing the imaginary part. Thus, complex-valued equality constraints can be solved any solver that supports the real-valued constraint type.

For example:

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x[1:2]);

julia> @constraint(model, (1 + 2im) * x[1] + 3 * x[2] == 4 + 5im)
(1 + 2im) x[1] + 3 x[2] = (4 + 5im)

julia> optimize!(model)

julia> value.(x)
2-element Vector{Float64}:
 2.5
 0.5
```

is equivalent to

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x[1:2]);

julia> @constraint(model, 1 * x[1] + 3 * x[2] == 4) # real component
x[1] + 3 x[2] = 4

julia> @constraint(model, 2 * x[1] == 5) # imag component
2 x[1] = 5

julia> optimize!(model)

julia> value.(x)
2-element Vector{Float64}:
```

```
2.5
0.5
```

This also applies if the variables are complex-valued:

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x in ComplexPlane());

julia> @constraint(model, (1 + 2im) * x + 3 * x == 4 + 5im)
(4 + 2im) real(x) + (-2 + 4im) imag(x) = (4 + 5im)

julia> optimize!(model)

julia> value(x)
1.3 + 0.6000000000000001im
```

which is equivalent to

```
julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x_real);

julia> @variable(model, x_imag);

julia> @constraint(model, x_real - 2 * x_imag + 3 * x_real == 4)
4 x_real - 2 x_imag = 4

julia> @constraint(model, x_imag + 2 * x_real + 3 * x_imag == 5)
2 x_real + 4 x_imag = 5

julia> optimize!(model)

julia> value(x_real) + value(x_imag) * im
1.3 + 0.6000000000000001im
```

## 19.4 Hermitian PSD Cones

JuMP supports creating matrices where are Hermitian.

```
julia> model = Model();

julia> @variable(model, H[1:3, 1:3] in HermitianPSDCone())
3x3 LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef},
                           Matrix{GenericAffExpr{ComplexF64, VariableRef}}}
    ↳ real(H[1,1])           .. real(H[1,3]) + imag(H[1,3]) im
```

```
real(H[1,2]) - imag(H[1,2]) im      real(H[2,3]) + imag(H[2,3]) im
real(H[1,3]) - imag(H[1,3]) im      real(H[3,3])
```

Behind the scenes, JuMP has created nine real-valued decision variables:

```
julia> all_variables(model)
9-element Vector{VariableRef}:
real(H[1,1])
real(H[1,2])
real(H[2,2])
real(H[1,3])
real(H[2,3])
real(H[3,3])
imag(H[1,2])
imag(H[1,3])
imag(H[2,3])
```

and a `Vector{VariableRef}`-in-`MOI.HermitianPositiveSemidefiniteConeTriangle` constraint:

```
julia> num_constraints(model, Vector{VariableRef}, MOI.HermitianPositiveSemidefiniteConeTriangle)
1
```

The `MOI.HermitianPositiveSemidefiniteConeTriangle` set can be efficiently bridged to `MOI.PositiveSemidefiniteConeTriangle` so it can be solved by any solver that supports PSD constraints.

Each element of `H` is an affine expression with `Complex{Float64}`-valued coefficients:

```
julia> typeof(H[1, 1])
GenericAffExpr{ComplexF64, VariableRef}

julia> typeof(H[2, 1])
GenericAffExpr{ComplexF64, VariableRef}
```

## Start values

When setting the start value, you must be careful to set only the upper triangle of real variables, and the upper triangle excluding the diagonal of imaginary variables:

```
julia> import LinearAlgebra

julia> function set_hermitian_start(
    H::LinearAlgebra.Hermitian,
    start::LinearAlgebra.Hermitian,
)
    for j in 1:size(H, 2), i in 1:j
        set_start_value(real(H[i, j]), real(start[i, j]))
        if i < j
            set_start_value(imag(H[i, j]), imag(start[i, j]))
        end
    end
end
```

```

        return
    end
set_hermitian_start (generic function with 1 method)

julia> H0 = LinearAlgebra.Hermitian(
           [1 (2+3im) (5+6im); (2-3im) 4 (7+8im); (5-6im) (7-8im) 9],
           )
3x3 LinearAlgebra.Hermitian{Complex{Int64}, Matrix{Complex{Int64}}}:
 1+0im  2+3im  5+6im
 2-3im  4+0im  7+8im
 5-6im  7-8im  9+0im

julia> set_hermitian_start(H, H0)

julia> start_value.(all_variables(model))
9-element Vector{Float64}:
 1.0
 2.0
 4.0
 5.0
 7.0
 9.0
 3.0
 6.0
 8.0

```

## 19.5 Hermitian PSD constraints

The `HermitianPSDCone` can also be used in the `@constraint` macro:

```

julia> model = Model();

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> import LinearAlgebra

julia> H = LinearAlgebra.Hermitian([x[1] im; -im -x[2]])
2x2 LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef}},
 ↳ Matrix{GenericAffExpr{ComplexF64, VariableRef}}:
 x[1]  im
 -im  -x[2]

julia> @constraint(model, H in HermitianPSDCone())
[x[1]  im
 -im  -x[2]] ∈ HermitianPSDCone()

```

**Note**

The matrix `H` in `H` in `HermitianPSDCone()` must be a `LinearAlgebra.Hermitian` matrix type. A `build_constraint` error will be thrown if the matrix is a different matrix type.

## Chapter 20

# Nonlinear Modeling

JuMP has support for nonlinear (convex and nonconvex) optimization problems. JuMP is able to automatically provide exact, sparse second-order derivatives to solvers. This information can improve solver accuracy and performance.

### 20.1 Set a nonlinear objective

Use `@objective` to set a nonlinear objective.

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @objective(model, Min, exp(x[1]) - sqrt(x[2]))
exp(x[1]) - sqrt(x[2])
```

To modify a nonlinear objective, call `@objective` again.

### 20.2 Add a nonlinear constraint

Use `@constraint` to add a nonlinear constraint.

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @constraint(model, exp(x[1]) <= 1)
exp(x[1]) - 1.0 ≤ 0

julia> @constraint(model, con[i = 1:2], 2^x[i] ≥ i)
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarNonlinearFunction,
    MathOptInterface.GreaterThan{Float64}}, ScalarShape}}:
con[1] : (2.0 ^ x[1]) - 1.0 ≥ 0
con[2] : (2.0 ^ x[2]) - 2.0 ≥ 0
```

Delete a nonlinear constraint using `delete`:

```
julia> delete(model, con[1])
```

### 20.3 Add a parameter

Some solvers have explicit support for parameters, which are constants in the model that can be efficiently updated between solves.

JuMP implements parameters by a decision variable constrained on creation to the [Parameter](#) set.

```
julia> model = Model();

julia> @variable(model, x);

julia> @variable(model, p[i = 1:2] in Parameter(i))
2-element Vector{VariableRef}:
 p[1]
 p[2]

julia> parameter_value(p[1])
1.0

julia> set_parameter_value(p[1], 3.5)

julia> @objective(model, Max, log(p[1] * x + p[2]))
log(p[1]*x + p[2])
```

See [Parameters](#) for more information on how to create and manage parameters.

Parameters are most useful when solving nonlinear models in a sequence:

```
julia> using JuMP, Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> set_silent(model)

julia> @variable(model, x)
x

julia> @variable(model, p in Parameter(1.0))
p

julia> @objective(model, Min, (x - p)^2)
x^2 - 2 p*x + p^2

julia> optimize!(model)

julia> value(x)
1.0
```

```
julia> set_parameter_value(p, 5.0)

julia> optimize!(model)

julia> value(x)
5.0
```

Using parameters can be faster than creating a new model from scratch with updated data because JuMP is able to avoid repeating a number of steps in processing the model before handing it off to the solver.

## 20.4 Create a nonlinear expression

Use `@expression` to create nonlinear expression objects:

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> expr = @expression(model, exp(x[1]) + sqrt(x[2]))
exp(x[1]) + sqrt(x[2])

julia> my_anon_expr = @expression(model, [i = 1:2], sin(x[i]))
2-element Vector{NonlinearExpr}:
sin(x[1])
sin(x[2])

julia> @expression(model, my_expr[i = 1:2], sin(x[i]))
2-element Vector{NonlinearExpr}:
sin(x[1])
sin(x[2])
```

A `NonlinearExpr` can be used in `@objective`, `@constraint`, and even nested in other `@expression`s.

```
julia> @objective(model, Min, expr^2 + 1)
((exp(x[1]) + sqrt(x[2])) ^ 2.0) + 1.0

julia> @constraint(model, [i = 1:2], my_expr[i] <= i)
2-element Vector{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarNonlinearFunction,
    MathOptInterface.LessThan{Float64}}, ScalarShape}}:
sin(x[1]) - 1.0 ≤ 0
sin(x[2]) - 2.0 ≤ 0

julia> @expression(model, nested[i = 1:2], sin(my_expr[i]))
2-element Vector{NonlinearExpr}:
sin(sin(x[1]))
sin(sin(x[2]))
```

Use `value` to query the value of a nonlinear expression:

```
julia> set_start_value(x[1], 1.0)

julia> value(start_value, nested[1])
0.7456241416655579

julia> sin(sin(1.0))
0.7456241416655579
```

## 20.5 Common subexpressions

JuMP does not perform common subexpression elimination. Instead, if you re-use an expression in multiple places, JuMP will insert a copy of the expression.

JuMP's lack of common subexpression elimination is a common cause of performance problems, particularly in nonlinear models with a pattern like `sum(t / common_term for t in terms)`. One example is the logistic loss:

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @expression(model, expr, sum(exp.(x)))
0.0 + exp(x[2]) + exp(x[1])

julia> @objective(model, Min, sum(exp(x[i]) / expr for i in 1:2))
(exp(x[1]) / (0.0 + exp(x[2]) + exp(x[1]))) + (exp(x[2]) / (0.0 + exp(x[2]) + exp(x[1])))
```

In this model, JuMP will compute the value (and derivatives) of the denominator twice, without realizing that it is the same expression.

As a work-around, create a new `@variable` and use an `== @constraint` to constrain the value of the variable to the subexpression.

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @variable(model, expr);

julia> @constraint(model, expr == sum(exp.(x)))
expr - (0.0 + exp(x[2]) + exp(x[1])) = 0

julia> @objective(model, Min, sum(exp(x[i]) / expr for i in 1:2))
(exp(x[1]) / expr) + (exp(x[2]) / expr)
```

The reason JuMP does not perform common subexpression elimination automatically is for simplicity, and because there is a trade-off: for simple expressions, the extra complexity of detecting and merging common subexpressions may outweigh the cost of computing them independently. Instead, we leave it to the user to decide which expressions to extract as common subexpressions.

## 20.6 Automatic differentiation

JuMP computes first- and second-order derivatives using sparse reverse-mode automatic differentiation. For details, see [ReverseAD](#).

For a tutorial on how to construct and query the derivatives, see [Computing Hessians](#)

## 20.7 Nonlinear expressions in detail

Nonlinear expressions in JuMP are represented by a [NonlinearExpr](#) object.

### Constructors

Nonlinear expressions can be created using the [NonlinearExpr](#) constructors:

```
julia> model = Model();
julia> @variable(model, x);
julia> expr = NonlinearExpr(:sin, Any[x])
sin(x)
```

or via operator overloading:

```
julia> model = Model();
julia> @variable(model, x);
julia> expr = sin(x)
sin(x)
```

### Supported arguments

Nonlinear expressions can contain a mix of numbers, [AffExpr](#), [QuadExpr](#), and other [NonlinearExpr](#):

```
julia> model = Model();
julia> @variable(model, x);
julia> aff = x + 1;
julia> quad = x^2 + x;
julia> expr = cos(x) * sin(quad) + aff
(cos(x) * sin(x^2 + x)) + (x + 1)
```

### Supported operators

The list of supported operators may vary between solvers. Given an optimizer, query the list of supported operators using [MOI.ListOfSupportedNonlinearOperators](#):

```
julia> import Ipopt
julia> import MathOptInterface as MOI
julia> MOI.get(Ipopt.Optimizer(), MOI.ListOfSupportedNonlinearOperators())
85-element Vector{Symbol}:
:+
:-_
:abs
:sqrt
:cbrt
:abs2
:inv
:log
:log10
:log2
[]
:min
:max
:&&
:|||
:<=
:(==)
:>=
:<
:>
```

In some univariate cases, the operator is defined in `SpecialFunctions.jl`. To use these functions, you must explicitly import `SpecialFunctions.jl`

```
julia> import Ipopt
julia> op = MOI.get(Ipopt.Optimizer(), MOI.ListOfSupportedNonlinearOperators());
julia> :erfcx in op
true
julia> :dawson in op
true
julia> import SpecialFunctions
julia> model = Model();
julia> @variable(model, x)
x
julia> @expression(model, SpecialFunctions.erfcx(x))
erfcx(x)
julia> @expression(model, SpecialFunctions.dawson(x))
dawson(x)
```

## Limitations

Some nonlinear expressions cannot be created via operator overloading. For example, to minimize the likelihood of bugs in user-code, we have not overloaded comparisons such as `<` and  `$\geq$`  between JuMP objects:

```
julia> model = Model();
julia> @variable(model, x);
julia> x < 1
ERROR: Cannot evaluate `<` between a variable and a number.
[...]
```

Instead, wrap the expression in the `@expression` macro:

```
julia> model = Model();
julia> @variable(model, x);
julia> expr = @expression(model, x < 1)
x < 1
```

For technical reasons, other operators that are not overloaded include `||`, `&&`, and `ifelse`.

```
julia> model = Model();
julia> @variable(model, x);
julia> expr = @expression(model, ifelse(x < -1 || x >= 1, x^2, 0.0))
ifelse((x < -1) || (x >= 1), x^2, 0.0)
```

As an alternative, use the `JuMP.op_` functions, which fallback to the various comparison and logical operators:

```
julia> model = Model();
julia> @variable(model, x);
julia> expr = op_ifelse(
        op_or(op_strictly_less_than(x, -1), op_greater_than_or_equal_to(x, 1)),
        x^2,
        0.0,
    )
ifelse((x < -1) || (x >= 1), x^2, 0.0)
```

The available functions are:

## Fields

Each `NonlinearExpr` has two fields.

The `.head` field is a `Symbol` that represents the operator being called:

| JuMP function                            | Julia function          |
|------------------------------------------|-------------------------|
| <code>op_ifelse</code>                   | <code>ifelse</code>     |
| <code>op_and</code>                      | <code>&amp;&amp;</code> |
| <code>op_or</code>                       | <code>  </code>         |
| <code>op_greater_than_or_equal_to</code> | <code>&gt;=</code>      |
| <code>op_less_than_or_equal_to</code>    | <code>&lt;=</code>      |
| <code>op_equal_to</code>                 | <code>==</code>         |
| <code>op_strictly_greater_than</code>    | <code>&gt;</code>       |
| <code>op_strictly_less_than</code>       | <code>&lt;</code>       |

```
julia> expr.head
:sin
```

The `.args` field is a `Vector{Any}` containing the arguments to the operator:

```
julia> expr.args
1-element Vector{Any}:
 x
```

## Forcing nonlinear expressions

The JuMP macros and operator overloading will preferentially build affine ([GenericAffExpr](#)) and quadratic ([GenericQuadExpr](#)) expressions instead of [GenericNonlinearExpr](#). For example:

```
julia> model = Model();
julia> @variable(model, x);
julia> f = (x - 0.1)^2
x^2 - 0.2 x + 0.01000000000000002
julia> typeof(f)
QuadExpr (alias for GenericQuadExpr{Float64, GenericVariableRef{Float64}})
```

To override this behavior, use the `@force_nonlinear` macro:

```
julia> g = @force_nonlinear((x - 0.1)^2)
(x - 0.1) ^ 2
julia> typeof(g)
NonlinearExpr (alias for GenericNonlinearExpr{GenericVariableRef{Float64}})
```

### Warning

Use this macro only if necessary. See the docstring of `@force_nonlinear` for more details on when you should use it.

## 20.8 Function tracing

Nonlinear expressions can be constructed using *function tracing*. Function tracing is when you call a regular Julia function with JuMP variables as arguments and the function builds a nonlinear expression via operator overloading. For example:

```
julia> using JuMP

julia> model = Model();

julia> @variable(model, x[1:2]);

julia> f(x::Vector{VariableRef}) = 2 * sin(x[1]^2) + sqrt(x[2])
f (generic function with 1 method)

julia> y = f(x)
(2.0 * sin(x[1]^2)) + sqrt(x[2])

julia> typeof(y)
NonlinearExpr (alias for GenericNonlinearExpr{GenericVariableRef{Float64}})

julia> @objective(model, Max, f(x))
(2.0 * sin(x[1]^2)) + sqrt(x[2])
```

Function tracing supports functions which return vectors or arrays of `NonlinearExpr`:

```
julia> using JuMP

julia> model = Model();

julia> @variable(model, x[1:2]);

julia> f(x::Vector{VariableRef}) = sqrt.(x)
f (generic function with 1 method)

julia> y = f(x)
2-element Vector{NonlinearExpr}:
sqrt(x[1])
sqrt(x[2])

julia> typeof(y)
Vector{NonlinearExpr} (alias for Array{GenericNonlinearExpr{GenericVariableRef{Float64}}, 1})

julia> @constraint(model, f(x) .<= 2)
2-element Vector{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarNonlinearFunction,
    ↪ MathOptInterface.LessThan{Float64}}, ScalarShape}}:
sqrt(x[1]) - 2.0 ≤ 0
sqrt(x[2]) - 2.0 ≤ 0
```

```
julia> @objective(model, Max, sum(f(x)))
0.0 + sqrt(x[2]) + sqrt(x[1])
```

Because function tracing uses operator overloading, there are many functions for which it will not work. For example:

```
julia> using JuMP

julia> model = Model();

julia> @variable(model, x[1:2]);

julia> f(x::Vector{VariableRef}) = x[1] > 1 ? 0 : x[2]
f (generic function with 1 method)

julia> f(x)
ERROR: Cannot evaluate `>` between a variable and a number.
[...]
```

In these cases, you should define a [User-defined operator](#) using the `@operator` macro.

## 20.9 User-defined operators

In addition to a standard list of univariate and multivariate operators recognized by the `MOI.Nonlinear` sub-module, JuMP supports user-defined operators, which let you represent nonlinear functions that cannot (or should not) be traced, for example, because they rely on non-Julia subroutines.

### Warning

User-defined operators must return a scalar output. For a work-around, see [User-defined operators with vector outputs](#).

### Add an operator

Add a user-defined operator using the `@operator` macro:

```
julia> using JuMP

julia> square(x) = x^2
square (generic function with 1 method)

julia> f(x, y) = (x - 1)^2 + (y - 2)^2
f (generic function with 1 method)

julia> model = Model();

julia> @operator(model, op_square, 1, square)
NonlinearOperator(square, :op_square)
```

```
julia> @operator(model, op_f, 2, f)
NonlinearOperator(f, :op_f)

julia> @variable(model, x[1:2]);

julia> @objective(model, Min, op_f(x[1], op_square(x[2])))
op_f(x[1], op_square(x[2]))
```

The arguments to `@operator` are:

1. The model to which the operator is added.
2. A Julia symbol object which serves as the name of the user-defined operator in JuMP expressions. This name must not be the same as that of the function.
3. The number of scalar input arguments that the function takes.
4. A Julia method which computes the function.

### Warning

User-defined operators cannot be deleted.

You can obtain a reference to the operator using the `model[:key]` syntax:

```
julia> using JuMP

julia> square(x) = x^2
square (generic function with 1 method)

julia> model = Model();

julia> @operator(model, op_square, 1, square)
NonlinearOperator(square, :op_square)

julia> op_square_2 = model[:op_square]
NonlinearOperator(square, :op_square)
```

### Automatic differentiation

JuMP computes first- and second-order derivatives of expressions using `ReverseAD`, which implements sparse reverse-mode automatic differentiation. However, because `ReverseAD` requires the algebraic expression as input, JuMP cannot use `ReverseAD` to differentiate user-defined operators.

Instead, unless `Gradients and Hessians` are explicitly provided, user-defined operators must support automatic differentiation by `ForwardDiff.jl`.

The use of `ForwardDiff.jl` has two important implications:

1. ForwardDiff.jl supports only a limited subset of Julia. If you encounter an error adding the operator, see [Common mistakes when writing a user-defined operator](#).
2. Differentiating operators with many arguments is slow. In general, you should try to keep the number of arguments to less than 100, and ideally, to less than 10.

Because of the use of ForwardDiff, in most cases, you should prefer to use function tracing instead of defining a user-defined operator.

### Add an operator without macros

The `@operator` macro is syntactic sugar for `add_nonlinear_operator`. Thus, the non-macro version of the preceding example is:

```
julia> using JuMP

julia> square(x) = x^2
square (generic function with 1 method)

julia> f(x, y) = (x - 1)^2 + (y - 2)^2
f (generic function with 1 method)

julia> model = Model();

julia> op_square = add_nonlinear_operator(model, 1, square; name = :op_square)
NonlinearOperator(square, :op_square)

julia> model[:op_square] = op_square
NonlinearOperator(square, :op_square)

julia> op_f = add_nonlinear_operator(model, 2, f; name = :op_f)
NonlinearOperator(f, :op_f)

julia> model[:op_f] = op_f
NonlinearOperator(f, :op_f)

julia> @variable(model, x[1:2]);

julia> @objective(model, Min, op_f(x[1], op_square(x[2])))
op_f(x[1], op_square(x[2]))
```

### Operators with the same name as an existing function

A common error encountered is the following:

```
julia> using JuMP

julia> model = Model();

julia> f(x) = x^2
```

```
f (generic function with 1 method)

julia> @operator(model, f, l, f)
ERROR: Unable to add the nonlinear operator `:f` with the same name as
an existing function.
[...]
```

This error occurs because `@operator(model, f, l, f)` is equivalent to:

```
julia> f = add_nonlinear_operator(model, l, f; name = :f)
```

but `f` already exists as a Julia function.

If you evaluate the function without adding it as an operator, JuMP will trace the function using operator overloading:

```
julia> @variable(model, x);
julia> f(x)
x^2
```

To force JuMP to treat `f` as a user-defined operator and not trace it, add the operator using `add_nonlinear_operator` and define a new method which manually creates a `NonlinearExpr`:

```
julia> _ = add_nonlinear_operator(model, l, f; name = :f)
NonlinearOperator(f, :f)

julia> f(x::AbstractJuMPScalar) = NonlinearExpr(:f, Any[x])
f (generic function with 2 methods)

julia> @expression(model, log(f(x)))
log(f(x))
```

## Gradients and Hessians

By default, JuMP will use automatic differentiation to compute the gradient and Hessian of user-defined operators. If your function is not amenable to the default automatic differentiation, or you can compute analytic derivatives, you may pass additional arguments to `@operator` to compute the first- and second-derivatives.

### Tip

The tutorial [Automatic differentiation of user-defined operators](#) has examples of how to use third-party Julia packages to compute automatic derivatives.

## Univariate functions

For univariate functions, a gradient function  $\nabla f$  returns a number that represents the first-order derivative. You may, in addition, pass a third function which returns a number representing the second-order derivative:

```
julia> using JuMP

julia> f(x) = x^2
f (generic function with 1 method)

julia> ∇f(x) = 2x
∇f (generic function with 1 method)

julia> ∇²f(x) = 2
∇²f (generic function with 1 method)

julia> model = Model();

julia> @operator(model, op_f, 1, f, ∇f, ∇²f) # Providing ∇²f is optional
NonlinearOperator(f, :op_f)

julia> @variable(model, x)
x

julia> @objective(model, Min, op_f(x))
op_f(x)
```

### Multivariate functions

For multivariate functions, the gradient function  $\nabla f$  must take an `AbstractVector` as the first argument that is filled in-place. The Hessian function,  $\nabla^2 f$ , must take an `AbstractMatrix` as the first argument, the lower-triangular of which is filled in-place:

```
julia> using JuMP

julia> f(x...) = (1 - x[1])^2 + 100 * (x[2] - x[1]^2)^2
f (generic function with 1 method)

julia> function ∇f(g::AbstractVector{T}, x::T...) where {T}
    g[1] = 400 * x[1]^3 - 400 * x[1] * x[2] + 2 * x[1] - 2
    g[2] = 200 * (x[2] - x[1]^2)
    return
end
∇f (generic function with 1 method)

julia> function ∇²f(H::AbstractMatrix{T}, x::T...) where {T}
    H[1, 1] = 1200 * x[1]^2 - 400 * x[2] + 2
    # H[1, 2] = -400 * x[1] <-- Not needed. Fill the lower-triangular only.
    H[2, 1] = -400 * x[1]
    H[2, 2] = 200.0
    return
end
∇²f (generic function with 1 method)

julia> model = Model();
```

```
julia> @operator(model, rosenbrock, 2, f, ∇f, ∇²f) # Providing ∇²f is optional
NonlinearOperator(f, :rosenbrock)

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> @objective(model, Min, rosenbrock(x[1], x[2]))
rosenbrock(x[1], x[2])
```

You may assume the Hessian matrix  $H$  is initialized with zeros, and because  $H$  is symmetric, you need only to fill in the non-zero lower-triangular terms. The matrix type passed in as  $H$  depends on the automatic differentiation system, so make sure the first argument to the Hessian function supports an `AbstractMatrix` (it may be something other than `Matrix{Float64}`). Moreover, you may assume only that  $H$  supports `size(H)` and `setindex!`. Finally, the matrix is treated as dense, so the performance will be poor on functions with high-dimensional input.

### User-defined operators with vector inputs

User-defined operators which take vectors as input arguments (for example, `f(x::Vector)`) are *not* supported. Instead, use Julia's splatting syntax to create a function with scalar arguments. For example, instead of:

```
f(x::Vector) = sum(x[i]^i for i in 1:length(x))
```

define:

```
f(x...) = sum(x[i]^i for i in 1:length(x))
```

Another approach is to define the splatted function as an anonymous function:

```
julia> using JuMP

julia> model = Model();

julia> @variable(model, x[1:5])
5-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]
 x[4]
 x[5]

julia> f(x::Vector) = sum(x[i]^i for i in 1:length(x))
f (generic function with 1 method)

julia> @operator(model, op_f, 5, (x...) -> f(collect(x)))
NonlinearOperator(#6, :op_f)
```

```
julia> @objective(model, Min, op_f(x...))
op_f(x[1], x[2], x[3], x[4], x[5])
```

If the operator takes several vector inputs, write a function that takes the splatted arguments and reconstructs the required vector inputs:

```
julia> using JuMP

julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @variable(model, y[1:2]);

julia> @variable(model, z);

julia> f(x::Vector, y::Vector, z) = sum((x[i] * y[i])^z for i in 1:2)
f (generic function with 1 method)

julia> f(x, y, z)
((x[1]*y[1]) ^ z) + ((x[2]*y[2]) ^ z)

julia> f_splat(args...) = f(collect(args[1:2]), collect(args[3:4]), args[5])
f_splat (generic function with 1 method)

julia> f_splat(x..., y..., z)
((x[1]*y[1]) ^ z) + ((x[2]*y[2]) ^ z)

julia> @operator(model, op_f, 5, f_splat)
NonlinearOperator(f_splat, :op_f)

julia> @objective(model, Min, op_f(x..., y..., z))
op_f(x[1], x[2], y[1], y[2], z)
```

### Common mistakes when writing a user-defined operator

JuMP uses [ForwardDiff.jl](#) to compute the first-order derivatives of user-defined operators. ForwardDiff has a number of limitations that you should be aware of when writing user-defined operators.

The rest of this section provides debugging advice and explains some common mistakes.

#### Warning

Get an error like `No method matching Float64(::ForwardDiff.Dual)?` Read this section.

## Debugging

If you add an operator that does not support ForwardDiff, a long error message will be printed. You can review the stacktrace for more information, but it can often be hard to understand why and where your function is failing.

It may be helpful to debug the operator outside of JuMP as follows.

If the operator is univariate, do:

```
julia> import ForwardDiff

julia> my_operator(a) = a^2
my_operator (generic function with 1 method)

julia> ForwardDiff.derivative(my_operator, 1.0)
2.0
```

If the operator is multivariate, do:

```
julia> import ForwardDiff

julia> my_operator(a, b) = a^2 + b^2
my_operator (generic function with 1 method)

julia> ForwardDiff.gradient(x -> my_operator(x...), [1.0, 2.0])
2-element Vector{Float64}:
 2.0
 4.0
```

Note that even though the operator takes the splatted arguments, `ForwardDiff.gradient` requires a vector as input.

### Operator calls something unsupported by ForwardDiff

ForwardDiff works by overloading many Julia functions for a special type `ForwardDiff.Dual <: Real`. If your operator attempts to call a function for which an overload has not been defined, a `MethodError` will be thrown.

For example, your operator cannot call external C functions, or be the optimal objective value of a JuMP model.

```
julia> import ForwardDiff

julia> my_operator_bad(x) = @ccall sqrt(x::Cdouble)::Cdouble
my_operator_bad (generic function with 1 method)

julia> ForwardDiff.derivative(my_operator_bad, 1.0)
ERROR: MethodError: no method matching
→  Float64(::ForwardDiff.Dual{ForwardDiff.Tag{typeof(my_operator_bad), Float64}, Float64, 1})
[...]
```

Unfortunately, the list of calls supported by ForwardDiff is too large to enumerate what is not allowed, so the best advice is to try and see if it works.

### Operator does not accept splatted input

The operator takes `f(x::Vector)` as input, instead of the splatted `f(x...)`.

```
julia> import ForwardDiff

julia> my_operator_bad(x::Vector) = sum(x[i]^2 for i in eachindex(x))
my_operator_bad (generic function with 1 method)

julia> my_operator_good(x...) = sum(x[i]^2 for i in eachindex(x))
my_operator_good (generic function with 1 method)

julia> ForwardDiff.gradient(x -> my_operator_bad(x...), [1.0, 2.0])
ERROR: MethodError: no method matching
    ↪ my_operator_bad(::ForwardDiff.Dual{ForwardDiff.Tag{var"#5#6", Float64}, Float64, 2},
    ↪ ::ForwardDiff.Dual{ForwardDiff.Tag{var"#5#6", Float64}, Float64, 2})
    [...]

julia> ForwardDiff.gradient(x -> my_operator_good(x...), [1.0, 2.0])
2-element Vector{Float64}:
 2.0
 4.0
```

### Operator assumes `Float64` as input

The operator assumes `Float64` will be passed as input, but it must work for any generic `Real` type.

```
julia> import ForwardDiff

julia> my_operator_bad(x::Float64...) = sum(x[i]^2 for i in eachindex(x))
my_operator_bad (generic function with 1 method)

julia> my_operator_good(x::Real...) = sum(x[i]^2 for i in eachindex(x))
my_operator_good (generic function with 1 method)

julia> ForwardDiff.gradient(x -> my_operator_bad(x...), [1.0, 2.0])
ERROR: MethodError: no method matching
    ↪ my_operator_bad(::ForwardDiff.Dual{ForwardDiff.Tag{var"#5#6", Float64}, Float64, 2},
    ↪ ::ForwardDiff.Dual{ForwardDiff.Tag{var"#5#6", Float64}, Float64, 2})
    [...]

julia> ForwardDiff.gradient(x -> my_operator_good(x...), [1.0, 2.0])
2-element Vector{Float64}:
 2.0
 4.0
```

### Operator allocates `Float64` storage

The operator allocates temporary storage using `zeros(3)` or similar. This defaults to `Float64`, so use `zeros(T, 3)` instead.

```
julia> import ForwardDiff
```

```
julia> function my_operator_bad(x::Real...)
    # This line is problematic. zeros(n) is short for zeros(Float64, n)
    y = zeros(length(x))
    for i in eachindex(x)
        y[i] = x[i]^2
    end
    return sum(y)
end
my_operator_bad (generic function with 1 method)

julia> function my_operator_good(x::T...) where {T<:Real}
    y = zeros(T, length(x))
    for i in eachindex(x)
        y[i] = x[i]^2
    end
    return sum(y)
end
my_operator_good (generic function with 1 method)

julia> ForwardDiff.gradient(x -> my_operator_bad(x...), [1.0, 2.0])
ERROR: MethodError: no method matching Float64(::ForwardDiff.Dual{ForwardDiff.Tag{var"#1#2",
    ↪ Float64}, Float64, 2})
[...]

julia> ForwardDiff.gradient(x -> my_operator_good(x...), [1.0, 2.0])
2-element Vector{Float64}:
 2.0
 4.0
```

## Chapter 21

# Nonlinear Modeling (Legacy)

### Warning

This page describes the legacy nonlinear interface to JuMP. It has a number of quirks and limitations that prompted the development of a new nonlinear interface. The new interface is documented at [Nonlinear Modeling](#). This legacy interface will remain for all future v1.X releases of JuMP. The two nonlinear interfaces cannot be combined.

JuMP has support for general smooth nonlinear (convex and nonconvex) optimization problems. JuMP is able to provide exact, sparse second-order derivatives to solvers. This information can improve solver accuracy and performance.

There are three main changes to solve nonlinear programs in JuMP.

- Use `@NLobjective` instead of `@objective`
- Use `@NLconstraint` instead of `@constraint`
- Use `@NLexpression` instead of `@expression`

### Info

There are some restrictions on what syntax you can use in the `@NLxxx` macros. Make sure to read the [Syntax notes](#).

### 21.1 Set a nonlinear objective

Use `@NLobjective` to set a nonlinear objective.

```
julia> model = Model();  
julia> @variable(model, x[1:2]);  
julia> @NLobjective(model, Min, exp(x[1]) - sqrt(x[2]))
```

To modify a nonlinear objective, call `@NLobjective` again.

## 21.2 Add a nonlinear constraint

Use `@NLconstraint` to add a nonlinear constraint.

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @NLconstraint(model, exp(x[1]) <= 1)
exp(x[1]) - 1.0 ≤ 0

julia> @NLconstraint(model, [i = 1:2], x[i]^i >= i)
2-element Vector{NonlinearConstraintRef{ScalarShape}}:
x[1] ^ 1.0 - 1.0 ≥ 0
x[2] ^ 2.0 - 2.0 ≥ 0

julia> @NLconstraint(model, con[i = 1:2], prod(x[j] for j = 1:i) == i)
2-element Vector{NonlinearConstraintRef{ScalarShape}}:
(*)(x[1]) - 1.0 = 0
x[1] * x[2] - 2.0 = 0
```

### Info

You can only create nonlinear constraints with `<=`, `>=`, and `==`. More general Nonlinear-in-Set constraints are not supported.

Delete a nonlinear constraint using `delete`:

```
julia> delete(model, con[1])
```

## 21.3 Create a nonlinear expression

Use `@NLExpression` to create nonlinear expression objects. The syntax is identical to `@expression`, except that the expression can contain nonlinear terms.

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> expr = @NLExpression(model, exp(x[1]) + sqrt(x[2]))
subexpression[1]: exp(x[1]) + sqrt(x[2])

julia> my_anon_expr = @NLExpression(model, [i = 1:2], sin(x[i]))
2-element Vector{NonlinearExpression}:
subexpression[2]: sin(x[1])
subexpression[3]: sin(x[2])

julia> @NLExpression(model, my_expr[i = 1:2], sin(x[i]))
2-element Vector{NonlinearExpression}:
subexpression[4]: sin(x[1])
subexpression[5]: sin(x[2])
```

Nonlinear expression can be used in `@NLobjective`, `@NLconstraint`, and even nested in other `@NLexpressions`.

```
julia> @NLobjective(model, Min, expr^2 + 1)

julia> @NLconstraint(model, [i = 1:2], my_expr[i] <= i)
2-element Vector{NonlinearConstraintRef{ScalarShape}}:
 subexpression[4] - 1.0 ≤ 0
 subexpression[5] - 2.0 ≤ 0

julia> @NLexpression(model, nested[i = 1:2], sin(my_expr[i]))
2-element Vector{NonlinearExpression}:
 subexpression[6]: sin(subexpression[4])
 subexpression[7]: sin(subexpression[5])
```

Use `value` to query the value of a nonlinear expression:

```
julia> set_start_value(x[1], 1.0)

julia> value(start_value, nested[1])
0.7456241416655579

julia> sin(sin(1.0))
0.7456241416655579
```

## 21.4 Create a nonlinear parameter

For nonlinear models only, JuMP offers a syntax for explicit "parameter" objects, which are constants in the model that can be efficiently updated between solves.

Nonlinear parameters are declared by using the `@NLparameter` macro and may be indexed by arbitrary sets analogously to JuMP variables and expressions.

The initial value of the parameter must be provided on the right-hand side of the `==` sign.

```
julia> model = Model();

julia> @variable(model, x);

julia> @NLparameter(model, p[i = 1:2] == i)
2-element Vector{NonlinearParameter}:
 parameter[1] == 1.0
 parameter[2] == 2.0
```

Create anonymous parameters using the `value` keyword:

```
julia> anon_parameter = @NLparameter(model, value = 1)
parameter[3] == 1.0
```

**Info**

A parameter is not an optimization variable. It must be fixed to a value with `==`. If you want a parameter that is `<=` or `>=`, create a variable instead using `@variable`.

Use `value` and `set_value` to query or update the value of a parameter.

```
julia> value.(p)
2-element Vector{Float64}:
 1.0
 2.0

julia> set_value(p[2], 3.0)
3.0

julia> value.(p)
2-element Vector{Float64}:
 1.0
 3.0
```

Nonlinear parameters must be used *within nonlinear macros* only.

**When to use a parameter**

Nonlinear parameters are useful when solving nonlinear models in a sequence:

```
using JuMP, Ipopt
model = Model(Ipopt.Optimizer)
set_silent(model)
@variable(model, z)
@NLparameter(model, x == 1.0)
@NLobjective(model, Min, (z - x)^2)
optimize!(model)
@show value(z) # Equals 1.0.

# Now, update the value of x to solve a different problem.
set_value(x, 5.0)
optimize!(model)
@show value(z) # Equals 5.0
```

```
value(z) = 1.0
value(z) = 5.0
```

**Info**

Using nonlinear parameters can be faster than creating a new model from scratch with updated data because JuMP is able to avoid repeating a number of steps in processing the model before handing it off to the solver.

## 21.5 Syntax notes

The syntax accepted in nonlinear macros is more restricted than the syntax for linear and quadratic macros. We note some important points below.

### Scalar operations only

Except for the splatting syntax discussed below, all expressions must be simple scalar operations. You cannot use dot, matrix-vector products, vector slices, etc.

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @variable(model, y);

julia> c = [1, 2];

julia> @NLobjective(model, Min, c' * x + 3y)
ERROR: Unexpected array [1 2] in nonlinear expression. Nonlinear expressions may contain only
→ scalar expressions.
[...]
```

Translate vector operations into explicit sum() operations:

```
julia> @NLobjective(model, Min, sum(c[i] * x[i] for i = 1:2) + 3y)
```

Or use an @expression:

```
julia> @expression(model, expr, c' * x)
x[1] + 2 x[2]

julia> @NLobjective(model, Min, expr + 3y)
```

### Splatting

The `splatting operator ...` is recognized in a very restricted setting for expanding function arguments. The expression splatted can be *only* a symbol. More complex expressions are not recognized.

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> @NLconstraint(model, *(x...) <= 1.0)
x[1] * x[2] * x[3] - 1.0 ≤ 0

julia> @NLconstraint(model, *((x / 2)...)) <= 0.0
ERROR: Unsupported use of the splatting operator. JuMP supports splatting only symbols. For
→ example, `x...` is ok, but `(x + 1)...`, `[x; y]...` and `g(f(y)...)` are not.
```

## 21.6 User-defined Functions

JuMP natively supports the set of univariate and multivariate functions recognized by the MOI.Nonlinear submodule. In addition to this list of functions, it is possible to register custom *user-defined* nonlinear functions. User-defined functions can be used anywhere in `@NLobjective`, `@NLconstraint`, and `@NLexpression`.

JuMP will attempt to automatically register functions it detects in your nonlinear expressions, which usually means manually registering a function is not needed. Two exceptions are if you want to provide custom derivatives, or if the function is not available in the scope of the nonlinear expression.

### Warning

User-defined functions must return a scalar output. For a work-around, see [User-defined operators with vector outputs](#).

### Automatic differentiation

JuMP does not support black-box optimization, so all user-defined functions must provide derivatives in some form. Fortunately, JuMP supports **automatic differentiation of user-defined functions**, a feature to our knowledge not available in any comparable modeling systems.

### Info

Automatic differentiation is *not* finite differencing. JuMP's automatically computed derivatives are not subject to approximation error.

JuMP uses [ForwardDiff.jl](#) to perform automatic differentiation; see the [ForwardDiff.jl documentation](#) for a description of how to write a function suitable for automatic differentiation.

### Common mistakes when writing a user-defined function

### Warning

Get an error like `No method matching Float64(::ForwardDiff.Dual)?` Read this section, and see the guidelines at [ForwardDiff.jl](#).

The most common error is that your user-defined function is not generic with respect to the number type, that is, don't assume that the input to the function is `Float64`.

```
f(x::Float64) = 2 * x # This will not work.
f(x::Real)      = 2 * x # This is good.
f(x)           = 2 * x # This is also good.
```

Another reason you may encounter this error is if you create arrays inside your function which are `Float64`.

```
function bad_f(x...)
    y = zeros(length(x)) # This constructs an array of `Float64`!
    for i = 1:length(x)
        y[i] = x[i]^i
    end
    return sum(y)
end
```

```

end

function good_f(x::T...) where {T<:Real}
    y = zeros(T, length(x)) # Construct an array of type `T` instead!
    for i = 1:length(x)
        y[i] = x[i]^i
    end
    return sum(y)
end

```

## Register a function

To register a user-defined function with derivatives computed by automatic differentiation, use the `register` method as in the following example:

```

square(x) = x^2
f(x, y) = (x - 1)^2 + (y - 2)^2

model = Model()

register(model, :square, 1, square; autodiff = true)
register(model, :my_f, 2, f; autodiff = true)

@variable(model, x[1:2] >= 0.5)
@NLobjective(model, Min, my_f(x[1], square(x[2])))

```

The above code creates a JuMP model with the objective function  $(x[1] - 1)^2 + (x[2]^2 - 2)^2$ . The arguments to `register` are:

1. The model for which the functions are registered.
2. A Julia symbol object which serves as the name of the user-defined function in JuMP expressions.
3. The number of input arguments that the function takes.
4. The Julia method which computes the function
5. A flag to instruct JuMP to compute exact gradients automatically.

### Tip

The symbol `:my_f` doesn't have to match the name of the function `f`. However, it's more readable if it does. Make sure you use `my_f` and not `f` in the macros.

### Warning

User-defined functions cannot be re-registered and will not update if you modify the underlying Julia function. If you want to change a user-defined function between solves, rebuild the model or use a different name. To use a different name programmatically, see [Raw expression input](#).

## Register a function and gradient

Forward-mode automatic differentiation as implemented by ForwardDiff.jl has a computational cost that scales linearly with the number of input dimensions. As such, it is not the most efficient way to compute gradients of user-defined functions if the number of input arguments is large. In this case, users may want to provide their own routines for evaluating gradients.

### Univariate functions

For univariate functions, the gradient function  $\nabla f$  returns a number that represents the first-order derivative:

```
f(x) = x^2
∇f(x) = 2x
model = Model()
register(model, :my_square, 1, f, ∇f; autodiff = true)
@variable(model, x >= 0)
@NLobjective(model, Min, my_square(x))
```

If `autodiff = true`, JuMP will use automatic differentiation to compute the hessian.

### Multivariate functions

For multivariate functions, the gradient function  $\nabla f$  must take a gradient vector as the first argument that is filled in-place:

```
f(x, y) = (x - 1)^2 + (y - 2)^2
function ∇f(g::AbstractVector{T}, x::T, y::T) where {T}
    g[1] = 2 * (x - 1)
    g[2] = 2 * (y - 2)
    return
end

model = Model()
register(model, :my_square, 2, f, ∇f)
@variable(model, x[1:2] >= 0)
@NLobjective(model, Min, my_square(x[1], x[2]))
```

#### Warning

Make sure the first argument to  $\nabla f$  supports an `AbstractVector`, and do not assume the input is `Float64`.

## Register a function, gradient, and hessian

You can also register a function with the second-order derivative information, which is a scalar for univariate functions, and a symmetric matrix for multivariate functions.

### Univariate functions

Pass a function which returns a number representing the second-order derivative:

```
f(x) = x^2
∇f(x) = 2x
∇²f(x) = 2
model = Model()
register(model, :my_square, 1, f, ∇f, ∇²f)
@variable(model, x >= 0)
@NLobjective(model, Min, my_square(x))
```

### Multivariate functions

For multivariate functions, the hessian function  $\nabla^2 f$  must take an `AbstractMatrix` as the first argument, the lower-triangular of which is filled in-place:

```
f(x...) = (1 - x[1])^2 + 100 * (x[2] - x[1]^2)^2
function ∇f(g, x...)
    g[1] = 400 * x[1]^3 - 400 * x[1] * x[2] + 2 * x[1] - 2
    g[2] = 200 * (x[2] - x[1]^2)
    return
end
function ∇²f(H, x...)
    H[1, 1] = 1200 * x[1]^2 - 400 * x[2] + 2
    # H[1, 2] = -400 * x[1] <-- Not needed. Fill the lower-triangular only.
    H[2, 1] = -400 * x[1]
    H[2, 2] = 200.0
    return
end

model = Model()
register(model, :rosenbrock, 2, f, ∇f, ∇²f)
@variable(model, x[1:2])
@NLobjective(model, Min, rosenbrock(x[1], x[2]))
```

#### Warning

You may assume the Hessian matrix  $H$  is initialized with zeros, and because  $H$  is symmetric, you need only to fill in the non-zero of the lower-triangular terms. The matrix type passed in as  $H$  depends on the automatic differentiation system, so make sure the first argument to the Hessian function supports an `AbstractMatrix` (it may be something other than `Matrix{Float64}`). However, you may assume only that  $H$  supports `size(H)` and `setindex!`. Finally, the matrix is treated as dense, so the performance will be poor on functions with high-dimensional input.

### User-defined functions with vector inputs

User-defined functions which take vectors as input arguments (for example, `f(x::Vector)`) are *not* supported. Instead, use Julia's splatting syntax to create a function with scalar arguments. For example, instead of

```
f(x::Vector) = sum(x[i]^i for i in 1:length(x))
```

define:

```
f(x...) = sum(x[i]^i for i in 1:length(x))
```

This function `f` can be used in a JuMP model as follows:

```
model = Model()
@variable(model, x[1:5] >= 0)
f(x...) = sum(x[i]^i for i in 1:length(x))
register(model, :f, 5, f; autodiff = true)
@NLobjective(model, Min, f(x...))
```

### Tip

Make sure to read the syntax restrictions of [Splatting](#).

## 21.7 Factors affecting solution time

The execution time when solving a nonlinear programming problem can be divided into two parts, the time spent in the optimization algorithm (the solver) and the time spent evaluating the nonlinear functions and corresponding derivatives. Ipopt explicitly displays these two timings in its output, for example:

```
Total CPU secs in IPOPT (w/o function evaluations)    =      7.412
Total CPU secs in NLP function evaluations           =      2.083
```

For Ipopt in particular, one can improve the performance by installing advanced sparse linear algebra packages, see [Installation Guide](#). For other solvers, see their respective documentation for performance tips.

The function evaluation time, on the other hand, is the responsibility of the modeling language. JuMP computes derivatives by using reverse-mode automatic differentiation with graph coloring methods for exploiting sparsity of the Hessian matrix. As a conservative bound, JuMP's performance here currently may be expected to be within a factor of 5 of AMPL's. Our [paper in SIAM Review](#) has more details.

## 21.8 Querying derivatives from a JuMP model

For some advanced use cases, one may want to directly query the derivatives of a JuMP model instead of handing the problem off to a solver. Internally, JuMP implements the `MOI.AbstractNLPEvaluator` interface. To obtain an NLP evaluator object from a JuMP model, use `NLPEvaluator`. `index` returns the `MOI.VariableIndex` corresponding to a JuMP variable. `MOI.VariableIndex` itself is a type-safe wrapper for `Int64` (stored in the `.value` field.)

For example:

```
julia> raw_index(v::MOI.VariableIndex) = v.value
raw_index (generic function with 1 method)

julia> model = Model();

julia> @variable(model, x)
```

```

julia> @variable(model, y)
y

julia> @NLobjective(model, Min, sin(x) + sin(y))

julia> values = zeros(2)
2-element Vector{Float64}:
 0.0
 0.0

julia> x_index = raw_index(JuMP.index(x))
1

julia> y_index = raw_index(JuMP.index(y))
2

julia> values[x_index] = 2.0
2.0

julia> values[y_index] = 3.0
3.0

julia> d = NLPEvaluator(model)
Nonlinear.Evaluator with available features:
 * :Grad
 * :Jac
 * :JacVec
 * :Hess
 * :HessVec
 * :ExprGraph

julia> MOI.initialize(d, [:Grad])

julia> MOI.eval_objective(d, values)
1.0504174348855488

julia> sin(2.0) + sin(3.0)
1.0504174348855488

julia> ∇f = zeros(2)
2-element Vector{Float64}:
 0.0
 0.0

julia> MOI.eval_objective_gradient(d, ∇f, values)

julia> ∇f[x_index], ∇f[y_index]
(-0.4161468365471424, -0.9899924966004454)

julia> cos(2.0), cos(3.0)
(-0.4161468365471424, -0.9899924966004454)

```

Only nonlinear constraints (those added with `@NLconstraint`), and nonlinear objectives (added with `@NLobjective`) exist in the scope of the `NLPEvaluator`.

The `NLPEvaluator` does not evaluate derivatives of linear or quadratic constraints or objectives.

The `index` method applied to a nonlinear constraint reference object returns its index as a `MOI.Nonlinear.ConstraintIndex`. For example:

```
julia> model = Model();
julia> @variable(model, x);
julia> @NLconstraint(model, cons1, sin(x) <= 1);
julia> @NLconstraint(model, cons2, x + 5 == 10);
julia> typeof(cons1)
NonlinearConstraintRef{ScalarShape} (alias for ConstraintRef{GenericModel{Float64},
→ MathOptInterface.Nonlinear.ConstraintIndex, ScalarShape})
julia> index(cons1)
MathOptInterface.Nonlinear.ConstraintIndex(1)
julia> index(cons2)
MathOptInterface.Nonlinear.ConstraintIndex(2)
```

Note that for one-sided nonlinear constraints, JuMP subtracts any values on the right-hand side when computing expressions. In other words, one-sided nonlinear constraints are always transformed to have a right-hand side of zero.

This method of querying derivatives directly from a JuMP model is convenient for interacting with the model in a structured way, for example, for accessing derivatives of specific variables. For example, in statistical maximum likelihood estimation problems, one is often interested in the Hessian matrix at the optimal solution, which can be queried using the `NLPEvaluator`.

## 21.9 Raw expression input

### Warning

This section requires advanced knowledge of Julia's Expr. You should read the [Expressions and evaluation](#) section of the Julia documentation first.

In addition to the `@NLexpression`, `@NLobjective` and `@NLconstraint` macros, it is also possible to provide Julia Expr objects directly by using `add_nonlinear_expression`, `set_nonlinear_objective` and `add_nonlinear_constraint`.

This input form may be useful if the expressions are generated programmatically, or if you experience compilation issues with the macro input (see [Known performance issues](#) for more information).

### Add a nonlinear expression

Use `add_nonlinear_expression` to add a nonlinear expression to the model.

```
julia> model = Model();
julia> @variable(model, x)
x
```

```
julia> expr = :($(x) + sin($(x)^2))
:(x + sin(x ^ 2))

julia> expr_ref = add_nonlinear_expression(model, expr)
subexpression[1]: x + sin(x ^ 2.0)
```

This is equivalent to

```
julia> model = Model();

julia> @variable(model, x);

julia> expr_ref = @NLExpression(model, x + sin(x^2))
subexpression[1]: x + sin(x ^ 2.0)
```

### Note

You must interpolate the variables directly into the expression `expr`.

## Set the objective function

Use `set_nonlinear_objective` to set a nonlinear objective.

```
julia> model = Model();

julia> @variable(model, x);

julia> expr = :($(x) + $(x)^2)
:(x + x ^ 2)

julia> set_nonlinear_objective(model, MIN_SENSE, expr)
```

This is equivalent to

```
julia> model = Model();

julia> @variable(model, x);

julia> @NLobjective(model, Min, x + x^2)
```

### Note

You must use `MIN_SENSE` or `MAX_SENSE` instead of `Min` and `Max`.

## Add a constraint

Use `add_nonlinear_constraint` to add a nonlinear constraint.

```
julia> model = Model();
julia> @variable(model, x);
julia> expr = :($(x) + $(x)^2)
:(x + x ^ 2)
julia> add_nonlinear_constraint(model, :($(expr) <= 1))
(x + x ^ 2.0) - 1.0 ≤ 0
```

This is equivalent to

```
julia> model = Model();
julia> @variable(model, x);
julia> @NLconstraint(model, Min, x + x^2 <= 1)
(x + x ^ 2.0) - 1.0 ≤ 0
```

## More complicated examples

Raw expression input is most useful when the expressions are generated programmatically, often in conjunction with user-defined functions.

As an example, we construct a model with the nonlinear constraints  $f(x) \leq 1$ , where  $f(x) = x^2$  and  $f(x) = \sin(x)^2$ :

```
julia> function main(functions::Vector{Function})
    model = Model()
    @variable(model, x)
    for (i, f) in enumerate(functions)
        f_sym = Symbol("f_$(i)")
        register(model, f_sym, 1, f; autodiff = true)
        add_nonlinear_constraint(model, :($(f_sym)($x)) <= 1)
    end
    print(model)
    return
end
main (generic function with 1 method)

julia> main([x -> x^2, x -> sin(x)^2])
Feasibility
Subject to
f_1(x) - 1.0 ≤ 0
f_2(x) - 1.0 ≤ 0
```

As another example, we construct a model with the constraint  $x^2 + \sin(x)^2 \leq 1$ :

```
julia> function main(functions::Vector{Function})
    model = Model()
    @variable(model, x)
```

```

expr = Expr(:call, :+)
for (i, f) in enumerate(functions)
    f_sym = Symbol("f_$(i)")
    register(model, f_sym, 1, f; autodiff = true)
    push!(expr.args, :($(f_sym)($(x))))
end
add_nonlinear_constraint(model, :($(expr) <= 1))
print(model)
return
end
main (generic function with 1 method)

julia> main([x -> x^2, x -> sin(x)^2])
Feasibility
Subject to
(f_1(x) + f_2(x)) - 1.0 ≤ 0

```

### Registered functions with a variable number of arguments

User defined functions require a fixed number of input arguments. However, sometimes you will want to use a registered function like:

```
julia> f(x...) = sum(exp(x[i]^2) for i in 1:length(x));
```

with different numbers of arguments.

The solution is to register the same function `f` for each unique number of input arguments, making sure to use a unique name each time. For example:

```

julia> A = [[1], [1, 2], [2, 3, 4], [1, 3, 4, 5]];

julia> model = Model();

julia> @variable(model, x[1:5]);

julia> funcs = Set{Symbol}();

julia> for a in A
    key = Symbol("f$(length(a))")
    if !(key in funcs)
        push!(funcs, key)
        register(model, key, length(a), f; autodiff = true)
    end
    add_nonlinear_constraint(model, :($key($(x[a]...)) <= 1))
end

julia> print(model)
Feasibility
Subject to
f1(x[1]) - 1.0 ≤ 0
f2(x[1], x[2]) - 1.0 ≤ 0
f3(x[2], x[3], x[4]) - 1.0 ≤ 0
f4(x[1], x[3], x[4], x[5]) - 1.0 ≤ 0

```

## 21.10 Known performance issues

The macro-based input to JuMP's nonlinear interface can cause a performance issue if you:

1. write a macro with a large number (hundreds) of terms
2. call that macro from within a function instead of from the top-level in global scope.

The first issue does not depend on the number of resulting terms in the mathematical expression, but rather the number of terms in the Julia Expr representation of that expression. For example, the expression `sum(x[i] for i in 1:1_000_000)` contains one million mathematical terms, but the Expr representation is just a single sum.

The most common cause, other than a lot of tedious typing, is if you write a program that automatically writes a JuMP model as a text file, which you later execute. One example is [MINLPlib.jl](#) which automatically transpiled models in the GAMS scalar format into JuMP examples.

As a rule of thumb, if you are writing programs to automatically generate expressions for the JuMP macros, you should target the [Raw expression input](#) instead. For more information, read [MathOptInterface Issue#1997](#).

## **Part IV**

### **API Reference**

## Chapter 22

# Docstrings

### 22.1 JuMP

#### JuMP

This page lists the public API of JuMP.

##### Info

This page is an unstructured list of the JuMP API. For a more structured overview, read the Manual or Tutorial parts of this documentation.

Load all of the public the API into the current scope with:

```
using JuMP
```

Alternatively, load only the module with:

```
import JuMP
```

and then prefix all calls with JuMP. to create JuMP.<NAME>.

#### @build\_constraint

JuMP.@build\_constraint – Macro.

```
@build_constraint(constraint_expr)
```

Constructs a ScalarConstraint or VectorConstraint using the same machinery as [@constraint](#) but without adding the constraint to a model.

Constraints using broadcast operators like `x .<= 1` are also supported and will create arrays of ScalarConstraint or VectorConstraint.

#### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> @build_constraint(2x >= 1)
ScalarConstraint{AffExpr, MathOptInterface.GreaterThan{Float64}}(2 x,
→ MathOptInterface.GreaterThan{Float64}(1.0))
```

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> @build_constraint(x .>= 0)
2-element Vector{ScalarConstraint{AffExpr, MathOptInterface.GreaterThan{Float64}}}:
 ScalarConstraint{AffExpr, MathOptInterface.GreaterThan{Float64}}(x[1],
← MathOptInterface.GreaterThan{Float64}(-0.0))
 ScalarConstraint{AffExpr, MathOptInterface.GreaterThan{Float64}}(x[2],
← MathOptInterface.GreaterThan{Float64}(-0.0))
```

`source`

### `@constraint`

JuMP.`@constraint` – Macro.

```
@constraint(model, expr, args...; kwargs...)
@constraint(model, [index_sets...], expr, args...; kwargs...)
@constraint(model, name, expr, args...; kwargs...)
@constraint(model, name[index_sets...], expr, args...; kwargs...)
```

Add a constraint described by the expression `expr`.

The `name` argument is optional. If index sets are passed, a container is built and the constraint may depend on the indices of the index sets.

The expression `expr` may be one of following forms:

- `func in set`, constraining the function `func` to belong to the set `set`, which is either a [MOI.AbstractSet](#) or one of the JuMP shortcuts like [SecondOrderCone](#) or [PSDCone](#)
- `a <op> b`, where `<op>` is one of `==`, `≥`, `>=`, `≤`, `<=`
- `l <= f <= u` or `u >= f >= l`, constraining the expression `f` to lie between `l` and `u`
- `f(x) ⊥ x`, which defines a complementarity constraint
- `z --> {expr}`, which defines an indicator constraint that activates when `z` is 1
- `!z --> {expr}`, which defines an indicator constraint that activates when `z` is 0
- `z <--> {expr}`, which defines a reified constraint
- `expr := rhs`, which defines a Boolean equality constraint

Broadcasted comparison operators like `.==` are also supported for the case when the left- and right-hand sides of the comparison operator are arrays.

JuMP extensions may additionally provide support for constraint expressions which are not listed here.

### Keyword arguments

- `base_name`: sets the name prefix used to generate constraint names. It corresponds to the constraint name for scalar constraints, otherwise, the constraint names are set to `base_name[...]` for each index ....
- `container = :Auto`: force the container type by passing `container = Array,`  
`container = DenseAxisArray, container = SparseAxisArray`, or any another container type which is supported by a JuMP extension.
- `set_string_name::Bool = true`: control whether to set the `MOI.ConstraintName` attribute. Passing `set_string_name = false` can improve performance.

Other keyword arguments may be supported by JuMP extensions.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> @variable(model, z, Bin);

julia> @constraint(model, x in SecondOrderCone())
[x[1], x[2], x[3]] ∈ MathOptInterface.SecondOrderCone(3)

julia> @constraint(model, [i in 1:3], x[i] == i)
3-element Vector{ConstraintRef{Model},
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64}},
    ↪ MathOptInterface.EqualTo{Float64}}, ScalarShape}:
x[1] = 1
x[2] = 2
x[3] = 3

julia> @constraint(model, x .== [1, 2, 3])
3-element Vector{ConstraintRef{Model},
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64}},
    ↪ MathOptInterface.EqualTo{Float64}}, ScalarShape}:
x[1] = 1
x[2] = 2
x[3] = 3

julia> @constraint(model, con_name, 1 <= x[1] + x[2] <= 3)
con_name : x[1] + x[2] ∈ [1, 3]

julia> @constraint(model, con_perp[i in 1:3], x[i] - 1 ⊥ x[i])
3-element Vector{ConstraintRef{Model},
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.VectorAffineFunction{Float64}},
    ↪ MathOptInterface.Complements}, VectorShape}:
con_perp[1] : [x[1] - 1, x[1]] ∈ MathOptInterface.Complements(2)
con_perp[2] : [x[2] - 1, x[2]] ∈ MathOptInterface.Complements(2)
```

```
con_perp[3] : [x[3] - 1, x[3]] ∈ MathOptInterface.Complements(2)

julia> @constraint(model, z --> {x[1] >= 0})
z --> {x[1] ≥ 0}

julia> @constraint(model, !z --> {2 * x[2] <= 3})
!z --> {2 * x[2] ≤ 3}
```

**source****@constraints**

JuMP.@constraints – Macro.

```
@constraints(model, args...)
```

Adds groups of constraints at once, in the same fashion as the `@constraint` macro.

The model must be the first argument, and multiple constraints can be added on multiple lines wrapped in a `begin ... end` block.

The macro returns a tuple containing the constraints that were defined.

**Example**

```
julia> model = Model();

julia> @variable(model, w);

julia> @variable(model, x);

julia> @variable(model, y);

julia> @variable(model, z[1:3]);

julia> @constraints(model, begin
           x >= 1
           y - w <= 2
           sum_to_one[i=1:3], z[i] + y == 1
         end);

julia> print(model)
Feasibility
Subject to
  sum_to_one[1] : y + z[1] = 1
  sum_to_one[2] : y + z[2] = 1
  sum_to_one[3] : y + z[3] = 1
  x ≥ 1
  -w + y ≤ 2
```

**source**

**@expression**

JuMP.**@expression** – Macro.

```
@expression(model::GenericModel, expression)
@expression(model::GenericModel, [index_sets...], expression)
@expression(model::GenericModel, name, expression)
@expression(model::GenericModel, name[index_sets...], expression)
```

Efficiently builds and returns an expression.

The name argument is optional. If index sets are passed, a container is built and the expression may depend on the indices of the index sets.

**Keyword arguments**

- `container = :Auto`: force the container type by passing `container = Array`, `container = DenseAxisArray`, `container = SparseAxisArray`, or any another container type which is supported by a JuMP extension.

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:5]);

julia> @expression(model, shared, sum(i * x[i] for i in 1:5))
x[1] + 2 x[2] + 3 x[3] + 4 x[4] + 5 x[5]

julia> shared
x[1] + 2 x[2] + 3 x[3] + 4 x[4] + 5 x[5]
```

In the same way as `@variable`, the second argument may define index sets, and those indices can be used in the construction of the expressions:

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> @expression(model, expr[i = 1:3], i * sum(x[j] for j in 1:3))
3-element Vector{AffExpr}:
 x[1] + x[2] + x[3]
 2 x[1] + 2 x[2] + 2 x[3]
 3 x[1] + 3 x[2] + 3 x[3]
```

Anonymous syntax is also supported:

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> expr = @expression(model, [i in 1:3], i * sum(x[j] for j in 1:3))
```

```
3-element Vector{AffExpr}:
x[1] + x[2] + x[3]
2 x[1] + 2 x[2] + 2 x[3]
3 x[1] + 3 x[2] + 3 x[3]
```

`source`

### `@expressions`

JuMP.`@expressions` – Macro.

```
@expressions(model, args...)
```

Adds multiple expressions to model at once, in the same fashion as the `@expression` macro.

The model must be the first argument, and multiple expressions can be added on multiple lines wrapped in a `begin ... end` block.

The macro returns a tuple containing the expressions that were defined.

#### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @variable(model, y);

julia> @variable(model, z[1:2]);

julia> a = [4, 5];

julia> @expressions(model, begin
           my_expr, x^2 + y^2
           my_expr_1[i = 1:2], a[i] - z[i]
         end)
(x^2 + y^2, AffExpr[-z[1] + 4, -z[2] + 5])
```

`source`

### `@force_nonlinear`

JuMP.`@force_nonlinear` – Macro.

```
@force_nonlinear(expr)
```

Change the parsing of `expr` to construct `GenericNonlinearExpr` instead of `GenericAffExpr` or `GenericQuadExpr`.

This macro works by walking `expr` and substituting all calls to `+`, `-`, `*`, `/`, and `^` in favor of ones that construct `GenericNonlinearExpr`.

This macro will error if the resulting expression does not produce a `GenericNonlinearExpr` because, for example, it is used on an expression that does not use the basic arithmetic operators.

### When to use this macro

In most cases, you should not use this macro.

Use this macro only if the intended output type is a `GenericNonlinearExpr` and the regular macro calls destroy problem structure, or in rare cases, if the regular macro calls introduce a large amount of intermediate variables, for example, because they promote types to a common quadratic expression.

### Example

#### Use-case one: preserve problem structure.

```
julia> model = Model();

julia> @variable(model, x);

julia> @expression(model, (x - 0.1)^2)
x^2 - 0.2 x + 0.01000000000000002

julia> @expression(model, @force_nonlinear((x - 0.1)^2))
(x - 0.1) ^ 2

julia> (x - 0.1)^2
x^2 - 0.2 x + 0.01000000000000002

julia> @force_nonlinear((x - 0.1)^2)
(x - 0.1) ^ 2
```

#### Use-case two: reduce allocations

In this example, we know that  $x * 2.0 * (1 + x) * x$  is going to construct a nonlinear expression.

However, the default parsing first constructs:

- the `GenericAffExpr`  $a = x * 2.0$ ,
- another `GenericAffExpr`  $b = 1 + x$
- the `GenericQuadExpr`  $c = a * b$
- a `GenericNonlinearExpr`  $*(c, x)$

In contrast, the modified parsing constructs:

- the `GenericNonlinearExpr`  $a = \text{GenericNonlinearExpr}(:+, 1, x)$
- the `GenericNonlinearExpr`  $\text{GenericNonlinearExpr}(:*, x, 2.0, a, x)$

This results in significantly fewer allocations.

```
julia> model = Model();

julia> @variable(model, x);

julia> @expression(model, x * 2.0 * (1 + x) * x)
```

```
(2 x2 + 2 x) * x

julia> @expression(model, @force_nonlinear(x * 2.0 * (1 + x) * x))
x * 2.0 * (1 + x) * x

julia> @allocated @expression(model, x * 2.0 * (1 + x) * x)
3584

julia> @allocated @expression(model, @force_nonlinear(x * 2.0 * (1 + x) * x))
672
```

`source`

### **@objective**

JuMP.`@objective` – Macro.

```
@objective(model::GenericModel, sense, func)
```

Set the objective sense to `sense` and objective function to `func`.

The objective sense can be either Min, Max, MOI.MIN\_SENSE, MOI.MAX\_SENSE or MOI.FEASIBILITY\_SENSE. In order to set the sense programmatically, that is, when `sense` is a variable whose value is the sense, one of the three MOI.OptimizationSense values must be used.

#### **Example**

Minimize the value of the variable `x`, do:

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @objective(model, Min, x)
x
```

Maximize the value of the affine expression  $2x - 1$ :

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @objective(model, Max, 2x - 1)
2 x - 1
```

Set the objective sense programmatically:

```
julia> model = Model();

julia> @variable(model, x)
x

julia> sense = MIN_SENSE
MIN_SENSE::OptimizationSense = 0

julia> @objective(model, sense, x^2 - 2x + 1)
x^2 - 2 x + 1
```

`source`

### @operator

JuMP.`@operator` – Macro.

```
@operator(model, operator, dim, f[, ∇f[, ∇²f]])
```

Add the nonlinear operator `operator` in `model` with `dim` arguments, and create a new `NonlinearOperator` object called `operator` in the current scope.

The function `f` evaluates the operator and must return a scalar.

The optional function `∇f` evaluates the first derivative, and the optional function `∇²f` evaluates the second derivative.

`∇²f` may be provided only if `∇f` is also provided.

#### Univariate syntax

If `dim == 1`, then the method signatures of each function must be:

- `f(::T)::T where {T<:Real}`
- `∇f(::T)::T where {T<:Real}`
- `∇²f(::T)::T where {T<:Real}`

#### Multivariate syntax

If `dim > 1`, then the method signatures of each function must be:

- `f(x::T...)::T where {T<:Real}`
- `∇f(g::AbstractVector{T}, x::T...)::Nothing where {T<:Real}`
- `∇²f(H::AbstractMatrix{T}, x::T...)::Nothing where {T<:Real}`

Where the gradient vector `g` and Hessian matrix `H` are filled in-place. For the Hessian, you must fill in the non-zero lower-triangular entries only. Setting an off-diagonal upper-triangular element may error.

#### Example

```

julia> model = Model();

julia> @variable(model, x)
x

julia> f(x::Float64) = x^2
f (generic function with 1 method)

julia> ∇f(x::Float64) = 2 * x
∇f (generic function with 1 method)

julia> ∇²f(x::Float64) = 2.0
∇²f (generic function with 1 method)

julia> @operator(model, op_f, 1, f, ∇f, ∇²f)
NonlinearOperator(f, :op_f)

julia> @objective(model, Min, op_f(x))
op_f(x)

julia> op_f(2.0)
4.0

julia> model[:op_f]
NonlinearOperator(f, :op_f)

julia> model[:op_f](x)
op_f(x)

```

### Non-macro version

This macro is provided as helpful syntax that matches the style of the rest of the JuMP macros. However, you may also add operators outside the macro using `add_nonlinear_operator`. For example:

```

julia> model = Model();

julia> f(x) = x^2
f (generic function with 1 method)

julia> @operator(model, op_f, 1, f)
NonlinearOperator(f, :op_f)

```

is equivalent to

```

julia> model = Model();

julia> f(x) = x^2
f (generic function with 1 method)

julia> op_f = model[:op_f] = add_nonlinear_operator(model, 1, f; name = :op_f)
NonlinearOperator(f, :op_f)

```

[source](#)

**@variable**

JuMP.@variable – Macro.

```
@variable(model, expr, args..., kw_args...)
```

Add a variable to the model `model` described by the expression `expr`, the positional arguments `args` and the keyword arguments `kw_args`.

**Anonymous and named variables**

`expr` must be one of the forms:

- Omitted, like `@variable(model)`, which creates an anonymous variable
- A single symbol like `@variable(model, x)`
- A container expression like `@variable(model, x[i=1:3])`
- An anonymous container expression like `@variable(model, [i=1:3])`

**Bounds**

In addition, the expression can have bounds, such as:

- `@variable(model, x >= 0)`
- `@variable(model, x <= 0)`
- `@variable(model, x == 0)`
- `@variable(model, 0 <= x <= 1)`

and bounds can depend on the indices of the container expressions:

- `@variable(model, -i <= x[i=1:3] <= i)`

**Sets**

You can explicitly specify the set to which the variable belongs:

- `@variable(model, x in MOI.Interval(0.0, 1.0))`

For more information on this syntax, read [Variables constrained on creation](#).

**Positional arguments**

The recognized positional arguments in `args` are the following:

- `Bin`: restricts the variable to the `MOI.ZeroOne` set, that is,  $\{0, 1\}$ . For example, `@variable(model, x, Bin)`. Note: you cannot use `@variable(model, Bin)`, use the `binary` keyword instead.
- `Int`: restricts the variable to the set of integers, that is, ..., -2, -1, 0, 1, 2, ... For example, `@variable(model, x, Int)`. Note: you cannot use `@variable(model, Int)`, use the `integer` keyword instead.
- `Symmetric`: Only available when creating a square matrix of variables, that is when `expr` is of the form `varname[1:n,1:n]` or `varname[i=1:n,j=1:n]`, it creates a symmetric matrix of variables.
- `PSD`: A restrictive extension to `Symmetric` which constraints a square matrix of variables to `Symmetric` and constrains to be positive semidefinite.

### Keyword arguments

Four keyword arguments are useful in all cases:

- `base_name`: Sets the name prefix used to generate variable names. It corresponds to the variable name for scalar variable, otherwise, the variable names are set to `base_name[...]` for each index ... of the axes axes.
- `start::Float64`: specify the value passed to `set_start_value` for each variable
- `container`: specify the container type. See [Forcing the container type](#) for more information.
- `set_string_name::Bool = true`: control whether to set the `MOI.VariableName` attribute. Passing `set_string_name = false` can improve performance.

Other keyword arguments are needed to disambiguate situations with anonymous variables:

- `lower_bound::Float64`: an alternative to `x >= lb`, sets the value of the variable lower bound.
- `upper_bound::Float64`: an alternative to `x <= ub`, sets the value of the variable upper bound.
- `binary::Bool`: an alternative to passing `Bin`, sets whether the variable is binary or not.
- `integer::Bool`: an alternative to passing `Int`, sets whether the variable is integer or not.
- `set::MOI.AbstractSet`: an alternative to using `x in set`
- `variable_type`: used by JuMP extensions. See [Extend @variable](#) for more information.

### Example

The following are equivalent ways of creating a variable `x` of name `x` with lower bound 0:

```
julia> model = Model();
julia> @variable(model, x >= 0)
x
```

```
julia> model = Model();
julia> @variable(model, x, lower_bound = 0)
x
```

```
julia> model = Model();
julia> x = @variable(model, base_name = "x", lower_bound = 0)
x
```

Other examples:

```
julia> model = Model();
julia> @variable(model, x[i=1:3] <= i, Int, start = sqrt(i), lower_bound = -i)
3-element Vector{VariableRef}:
 x[1]
 x[2]
```

```
x[3]

julia> @variable(model, y[i=1:3], container = DenseAxisArray, set = MOI.ZeroOne())
1-dimensional DenseAxisArray{VariableRef,1,...} with index sets:
    Dimension 1, Base.OneTo(3)
And data, a 3-element Vector{VariableRef}:
y[1]
y[2]
y[3]

julia> @variable(model, z[i=1:3], set_string_name = false)
3-element Vector{VariableRef}:
_ [7]
_ [8]
_ [9]
```

[source](#)**@variables**

JuMP.@variables – Macro.

`@variables(model, args...)`

Adds multiple variables to model at once, in the same fashion as the [@variable](#) macro.

The model must be the first argument, and multiple variables can be added on multiple lines wrapped in a `begin ... end` block.

The macro returns a tuple containing the variables that were defined.

**Example**

```
julia> model = Model();

julia> @variables(model, begin
           x
           y[i = 1:2] >= 0, (start = i)
           z, Bin, (start = 0, base_name = "Z")
       end)
(x, VariableRef[y[1], y[2]], Z)
```

**Note**

Keyword arguments must be contained within parentheses (refer to the example above).

[source](#)**add\_bridge**

JuMP.add\_bridge – Function.

```
add_bridge(
    model::GenericModel{T},
    BT::Type{<:MOI.Bridges.AbstractBridge};
    coefficient_type::Type{S} = T,
) where {T,S}
```

Add  $BT\{T\}$  to the list of bridges that can be used to transform unsupported constraints into an equivalent formulation using only constraints supported by the optimizer.

See also: [remove\\_bridge](#).

### Example

```
julia> model = Model();

julia> add_bridge(model, MOI.Bridges.Constraint.SOCToNonConvexQuadBridge)

julia> add_bridge(
        model,
        MOI.Bridges.Constraint.NumberConversionBridge;
        coefficient_type = Complex{Float64}
    )
```

[source](#)

### add\_constraint

JuMP.add\_constraint - Function.

```
add_constraint(
    model::GenericModel,
    con::AbstractConstraint,
    name::String= "",
)
```

This method should only be implemented by developers creating JuMP extensions. It should never be called by users of JuMP.

[source](#)

### add\_nonlinear\_operator

JuMP.add\_nonlinear\_operator - Function.

```
add_nonlinear_operator(
    model::Model,
    dim::Int,
    f::Function,
    [∇f::Function,]
    [∇²f::Function];
    [name::Symbol = Symbol(f),]
)
```

Add a new nonlinear operator with `dim` input arguments to `model` and associate it with the name `name`.

The function `f` evaluates the operator and must return a scalar.

The optional function `∇f` evaluates the first derivative, and the optional function `∇²f` evaluates the second derivative.

`∇²f` may be provided only if `∇f` is also provided.

### Univariate syntax

If `dim == 1`, then the method signatures of each function must be:

- `f(::T)::T where {T<:Real}`
- `∇f(::T)::T where {T<:Real}`
- `∇²f(::T)::T where {T<:Real}`

### Multivariate syntax

If `dim > 1`, then the method signatures of each function must be:

- `f(x::T...)::T where {T<:Real}`
- `∇f(g::AbstractVector{T}, x::T...)::Nothing where {T<:Real}`
- `∇²f(H::AbstractMatrix{T}, x::T...)::Nothing where {T<:Real}`

Where the gradient vector `g` and Hessian matrix `H` are filled in-place. For the Hessian, you must fill in the non-zero lower-triangular entries only. Setting an off-diagonal upper-triangular element may error.

### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> f(x::Float64) = x^2
f (generic function with 1 method)

julia> ∇f(x::Float64) = 2 * x
∇f (generic function with 1 method)

julia> ∇²f(x::Float64) = 2.0
∇²f (generic function with 1 method)

julia> op_f = add_nonlinear_operator(model, 1, f, ∇f, ∇²f)
NonlinearOperator(f, :f)

julia> @objective(model, Min, op_f(x))
f(x)

julia> op_f(2.0)
4.0
```

[source](#)

**add\_to\_expression!**

JuMP.add\_to\_expression! – Function.

```
add_to_expression!(expression, terms...)
```

Updates expression in-place to expression + (\*)(terms...).

This is typically much more efficient than expression += (\*)(terms...) because it avoids the temporary allocation of the right-hand side term.

For example, add\_to\_expression!(expression, a, b) produces the same result as expression += a\*b, and add\_to\_expression!(expression, a) produces the same result as expression += a.

**When to implement**

Only a few methods are defined, mostly for internal use, and only for the cases when:

1. they can be implemented efficiently
2. expression is capable of storing the result. For example, add\_to\_expression!(:AffExpr, ::GenericVariableRef, ::GenericVariableRef) is not defined because a GenericAffExpr cannot store the product of two variables.

**Example**

```
julia> model = Model();
julia> @variable(model, x)
x

julia> expr = 2 + x
x + 2

julia> add_to_expression!(expr, 3, x)
4 x + 2

julia> expr
4 x + 2
```

```
julia> model = Model();
julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> @expression(model, ex1, sum(x))
x[1] + x[2]

julia> @expression(model, ex2, 2 * sum(x))
2 x[1] + 2 x[2]

julia> add_to_expression!(ex1, ex2)
```

```
3 x[1] + 3 x[2]

julia> ex1
3 x[1] + 3 x[2]

julia> ex2
2 x[1] + 2 x[2]
```

`source`

### `add_to_function_constant`

JuMP.`add_to_function_constant` - Function.

```
add_to_function_constant(constraint::ConstraintRef, value)
```

Add `value` to the function constant term of constraint.

Note that for scalar constraints, JuMP will aggregate all constant terms onto the right-hand side of the constraint so instead of modifying the function, the set will be translated by `-value`. For example, given a constraint  $2x \leq 3$ , `add_to_function_constant(c, 4)` will modify it to  $2x \leq -1$ .

#### Example

For scalar constraints, the set is translated by `-value`:

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, con, 0 <= 2x - 1 <= 2)
con : 2 x ∈ [1, 3]

julia> add_to_function_constant(con, 4)

julia> con
con : 2 x ∈ [-3, -1]
```

For vector constraints, the constant is added to the function:

```
julia> model = Model();

julia> @variable(model, x);

julia> @variable(model, y);

julia> @constraint(model, con, [x + y, x, y] in SecondOrderCone())
con : [x + y, x, y] ∈ MathOptInterface.SecondOrderCone(3)

julia> add_to_function_constant(con, [1, 2, 2])

julia> con
con : [x + y + 1, x + 2, y + 2] ∈ MathOptInterface.SecondOrderCone(3)
```

```
source

add_variable
JuMP.add_variable - Function.
```

```
add_variable(m::GenericModel, v::AbstractVariable, name::String = "")
```

This method should only be implemented by developers creating JuMP extensions. It should never be called by users of JuMP.

```
source

all_constraints
JuMP.all_constraints - Function.
```

```
all_constraints(model::GenericModel, function_type, set_type)::Vector{<:ConstraintRef}
```

Return a list of all constraints currently in the model where the function has type `function_type` and the set has type `set_type`. The constraints are ordered by creation time.

See also [list\\_of\\_constraint\\_types](#) and [num\\_constraints](#).

### Example

```
julia> model = Model();

julia> @variable(model, x >= 0, Bin);

julia> @constraint(model, 2x <= 1);

julia> all_constraints(model, VariableRef, MOI.GreaterThan{Float64})
1-element Vector{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    ↪ MathOptInterface.GreaterThan{Float64}}, ScalarShape}}:
    x ≥ 0

julia> all_constraints(model, VariableRef, MOI.ZeroOne)
1-element Vector{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne},
    ↪ ScalarShape}}:
    x binary

julia> all_constraints(model, AffExpr, MOI.LessThan{Float64})
1-element Vector{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↪ MathOptInterface.LessThan{Float64}}, ScalarShape}}:
    2 x ≤ 1
```

```
source
```

```
all_constraints(
    model::GenericModel,
    include_variable_in_set_constraints::Bool,
)::Vector{ConstraintRef}
```

Return a list of all constraints in `model`.

If `include_variable_in_set_constraints == true`, then `VariableRef` constraints such as `VariableRef-in-Integer` are included. To return only the structural constraints (for example, the rows in the constraint matrix of a linear program), pass `include_variable_in_set_constraints = false`.

### Example

```
julia> model = Model();

julia> @variable(model, x >= 0, Int);

julia> @constraint(model, 2x <= 1);

julia> @NLconstraint(model, x^2 <= 1);

julia> all_constraints(model; include_variable_in_set_constraints = true)
4-element Vector{ConstraintRef}:
 2 x ≤ 1
 x ≥ 0
 x integer
 x ^ 2.0 - 1.0 ≤ 0

julia> all_constraints(model; include_variable_in_set_constraints = false)
2-element Vector{ConstraintRef}:
 2 x ≤ 1
 x ^ 2.0 - 1.0 ≤ 0
```

### Performance considerations

Note that this function is type-unstable because it returns an abstractly typed vector. If performance is a problem, consider using `list_of_constraint_types` and a function barrier. See the [Performance tips for extensions](#) section of the documentation for more details.

`source`

### all\_variables

`JuMP.all_variables` – Function.

```
all_variables(model)::GenericModel{T})::Vector{GenericVariableRef{T}} where {T}
```

Returns a list of all variables currently in the model. The variables are ordered by creation time.

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @variable(model, y);

julia> all_variables(model)
2-element Vector{VariableRef}:
 x
 y
```

`source`

#### **anonymous\_name**

JuMP.`anonymous_name` – Function.

```
anonymous_name(::MIME, x::AbstractVariableRef)
```

The name to use for an anonymous variable x when printing.

#### **Example**

```
julia> model = Model();

julia> x = @variable(model);

julia> anonymous_name(MIME("text/plain"), x)
"_[1]"
```

`source`

#### **assert\_is\_solved\_and\_feasible**

JuMP.`assert_is_solved_and_feasible` – Function.

```
assert_is_solved_and_feasible(model::GenericModel; kwargs...)
```

A function calls `is_solved_and_feasible` and, if the return is false, errors with an informative error message describing the state of the solver.

#### **Keyword arguments**

See `is_solved_and_feasible` for a description of all keyword arguments.

#### **Example**

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);
```

```
julia> is_solved_and_feasible(model)
false

julia> assert_is_solved_and_feasible(model)
ERROR: The model was not solved correctly. Here is a summary of the solution to help debug why
↳ this happened:

* Solver : Ipopt

* Status
  Result count      : 0
  Termination status : OPTIMIZE_NOT_CALLED
  Message from the solver:
  "optimize not called"

* Candidate solution (result #1)
  Primal status     : NO_SOLUTION
  Dual status       : NO_SOLUTION

* Work counters

Stacktrace:
[...]
```

`source`

### backend

JuMP.backend – Function.

```
backend(model::GenericModel)
```

Return the lower-level MathOptInterface model that sits underneath JuMP. This model depends on which operating mode JuMP is in (see `mode`).

- If JuMP is in DIRECT mode (that is, the model was created using `direct_model`), the backend will be the optimizer passed to `direct_model`.
- If JuMP is in MANUAL or AUTOMATIC mode, the backend is a MOI.Utilities.CachingOptimizer.

Use `index` to get the index of a variable or constraint in the backend model.

#### Warning

This function should only be used by advanced users looking to access low-level MathOptInterface or solver-specific functionality.

#### Notes

If JuMP is not in DIRECT mode, the type returned by `backend` may change between any JuMP releases. Therefore, only use the public API exposed by MathOptInterface, and do not access internal fields. If you

require access to the innermost optimizer, see [unsafe\\_backend](#). Alternatively, use [direct\\_model](#) to create a JuMP model in DIRECT mode.

See also: [unsafe\\_backend](#).

### Example

```
julia> import HiGHS

julia> model = direct_model(HiGHS.Optimizer());

julia> set_silent(model)

julia> @variable(model, x >= 0)
x

julia> highs = backend(model)
A HiGHS model with 1 columns and 0 rows.

julia> index(x)
MOI.VariableIndex(1)
```

[source](#)

### barrier\_iterations

JuMP.barrier\_iterations – Function.

```
barrier_iterations(model::GenericModel)
```

If available, returns the cumulative number of barrier iterations during the most-recent optimization (the [MOI.BarrierIterations](#) attribute).

Throws a [MOI.GetAttributeNotAllowed](#) error if the attribute is not implemented by the solver.

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> optimize!(model)

julia> barrier_iterations(model)
0
```

[source](#)

### bridge\_constraints

JuMP.bridge\_constraints – Function.

```
bridge_constraints(model::GenericModel)
```

When in direct mode, return false.

When in manual or automatic mode, return a Bool indicating whether the optimizer is set and unsupported constraints are automatically bridged to equivalent supported constraints when an appropriate transformation is available.

### Example

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> bridge_constraints(model)
true

julia> model = Model(Ipopt.Optimizer; add_bridges = false);

julia> bridge_constraints(model)
false
```

`source`

### build\_constraint

JuMP.build\_constraint – Function.

```
build_constraint(error_fn::Function, func, set, args...; kwargs...)
```

This method should only be implemented by developers creating JuMP extensions. It should never be called by users of JuMP.

`source`

### build\_variable

JuMP.build\_variable – Function.

```
build_variable(
    error_fn::Function,
    info::VariableInfo,
    args...;
    kwargs...,
)
```

Return a new `AbstractVariable` object.

This method should only be implemented by developers creating JuMP extensions. It should never be called by users of JuMP.

### Arguments

- `error_fn`: a function to call instead of `error`. `error_fn` annotates the error message with additional information for the user.
- `info`: an instance of `VariableInfo`. This has a variety of fields relating to the variable such as `info.lower_bound` and `info.binary`.
- `args`: optional additional positional arguments for extending the `@variable` macro.
- `kwargs`: optional keyword arguments for extending the `@variable` macro.

See also: `@variable`

#### Warning

Extensions should define a method with ONE positional argument to dispatch the call to a different method. Creating an extension that relies on multiple positional arguments leads to `MethodErrors` if the user passes the arguments in the wrong order.

#### Example

```
@variable(model, x, Foo)
```

will call

```
build_variable(error_fn::Function, info::VariableInfo, ::Type{Foo})
```

Passing special-case positional arguments such as `Bin`, `Int`, and `PSD` is okay, along with keyword arguments:

```
@variable(model, x, Int, Foo(), mykwarg = true)
# or
@variable(model, x, Foo(), Int, mykwarg = true)
```

will call

```
build_variable(error_fn::Function, info::VariableInfo, ::Foo; mykwarg)
```

and `info.integer` will be `true`.

Note that the order of the positional arguments does not matter.

`source`

#### callback\_node\_status

JuMP.`callback_node_status` – Function.

```
callback_node_status(cb_data, model::GenericModel)
```

Return an `MOI.CallbackNodeStatusCode` enum, indicating if the current primal solution available from `callback_value` is integer feasible.

### Example

```
julia> import Gurobi

julia> model = Model(Gurobi.Optimizer);

julia> set_silent(model)

julia> @variable(model, x <= 10, Int);

julia> @objective(model, Max, x);

julia> function my_callback_function(cb_data, cb_where)
           status = callback_node_status(cb_data, model)
           if status == MOI.CALLBACK_NODE_STATUS_INTEGER
               println("Status is: ", status)
           end
           return
       end
my_callback_function (generic function with 1 method)

julia> set_attribute(model, Gurobi.CallbackFunction(), my_callback_function)

julia> optimize!(model)
Status is: CALLBACK_NODE_STATUS_INTEGER
```

`source`

### `callback_value`

`JuMP.callback_value` - Function.

```
callback_value(cb_data, x::GenericVariableRef)
callback_value(cb_data, x::Union{GenericAffExpr, GenericQuadExpr})
```

Return the primal solution of `x` inside a callback.

`cb_data` is the argument to the callback function, and the type is dependent on the solver.

Use `callback_node_status` to check whether a solution is available.

### Example

```
julia> import Gurobi

julia> model = Model(Gurobi.Optimizer);

julia> set_silent(model)

julia> @variable(model, x <= 10, Int);
```

```
julia> @objective(model, Max, x);

julia> function my_callback_function(cb_data, cb_where)
    status = callback_node_status(cb_data, model)
    if status == MOI.CALLBACK_NODE_STATUS_INTEGER
        Gurobi.load_callback_variable_primal(cb_data, cb_where)
        println("Solution is: ", callback_value(cb_data, x))
    end
    return
end
my_callback_function (generic function with 1 method)

julia> set_attribute(model, Gurobi.CallbackFunction(), my_callback_function)

julia> optimize!(model)
Solution is: 10.0
```

**source****check\_belongs\_to\_model**

JuMP.check\_belongs\_to\_model - Function.

```
check_belongs_to_model(x::AbstractJuMPScalar, model::AbstractModel)
check_belongs_to_model(x::AbstractConstraint, model::AbstractModel)
```

Throw `VariableNotOwned` if the `owner_model` of `x` is not `model`.**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> check_belongs_to_model(x, model)

julia> model_2 = Model();

julia> check_belongs_to_model(x, model_2)
ERROR: VariableNotOwned{VariableRef}(x): the variable x cannot be used in this model because
it belongs to a different model.
[...]
```

**source****coefficient**

JuMP.coefficient - Function.

```
coefficient(v1::GenericVariableRef{T}, v2::GenericVariableRef{T}) where {T}
```

Return `one(T)` if `v1 == v2` and `zero(T)` otherwise.

This is a fallback for other `coefficient` methods to simplify code in which the expression may be a single variable.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> coefficient(x[1], x[1])
1.0

julia> coefficient(x[1], x[2])
0.0
```

`source`

```
coefficient(a::GenericAffExpr{C,V}, v::V) where {C,V}
```

Return the coefficient associated with variable `v` in the affine expression `a`.

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> expr = 2.0 * x + 1.0;

julia> coefficient(expr, x)
2.0
```

`source`

```
coefficient(a::GenericQuadExpr{C,V}, v1::V, v2::V) where {C,V}
```

Return the coefficient associated with the term `v1 * v2` in the quadratic expression `a`.

Note that `coefficient(a, v1, v2)` is the same as `coefficient(a, v2, v1)`.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> expr = 2.0 * x[1] * x[2];

julia> coefficient(expr, x[1], x[2])
2.0
```

```
julia> coefficient(expr, x[2], x[1])
2.0
```

```
julia> coefficient(expr, x[1], x[1])
0.0
```

`source`

```
coefficient(a::GenericQuadExpr{C,V}, v::V) where {C,V}
```

Return the coefficient associated with variable `v` in the affine component of `a`.

### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> expr = 2.0 * x^2 + 3.0 * x;
julia> coefficient(expr, x)
3.0
```

`source`

`compute_conflict!`

`JuMP.compute_conflict!` – Function.

```
compute_conflict!(model::GenericModel)
```

Compute a conflict if the model is infeasible.

The conflict is also called the Irreducible Infeasible Subsystem (IIS).

If an optimizer has not been set yet (see `set_optimizer`), a `NoOptimizer` error is thrown.

The status of the conflict can be checked with the `MOI.ConflictStatus` model attribute. Then, the status for each constraint can be queried with the `MOI.ConstraintConflictStatus` attribute.

See also: `copy_conflict`

### Example

```
julia> using JuMP
julia> model = Model(Gurobi.Optimizer);
julia> set_silent(model)
julia> @variable(model, x >= 0);
```

```
julia> @constraint(model, c1, x >= 2);

julia> @constraint(model, c2, x <= 1);

julia> optimize!(model)

julia> compute_conflict!(model)

julia> get_attribute(model, MOI.ConflictStatus())
CONFLICT_FOUND::ConflictStatusCode = 3
```

**source****constant**

JuMP.constant – Function.

```
constant(aff::GenericAffExpr{C,V})::C
```

Return the constant of the affine expression.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> aff = 2.0 * x + 3.0;

julia> constant(aff)
3.0
```

**source**

```
constant(quad::GenericQuadExpr{C,V})::C
```

Return the constant of the quadratic expression.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> quad = 2.0 * x^2 + 3.0;

julia> constant(quad)
3.0
```

**source**

**constraint\_by\_name**

JuMP.constraint\_by\_name – Function.

```
constraint_by_name(model::AbstractModel, name::String, [F, S])::Union{ConstraintRef,Nothing}
```

Return the reference of the constraint with name attribute name or Nothing if no constraint has this name attribute.

Throws an error if several constraints have name as their name attribute.

If F and S are provided, this method additionally throws an error if the constraint is not an F-in-S constraint where F is either the JuMP or MOI type of the function and S is the MOI type of the set.

Providing F and S is recommended if you know the type of the function and set since its returned type can be inferred while for the method above (that is, without F and S), the exact return type of the constraint index cannot be inferred.

**Example**

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @constraint(model, con, x^2 == 1)
con : x^2 = 1

julia> constraint_by_name(model, "kon")

julia> constraint_by_name(model, "con")
con : x^2 = 1

julia> constraint_by_name(model, "con", AffExpr, MOI.EqualTo{Float64})

julia> constraint_by_name(model, "con", QuadExpr, MOI.EqualTo{Float64})
con : x^2 = 1
```

[source](#)

**constraint\_object**

JuMP.constraint\_object – Function.

```
constraint_object(con_ref::ConstraintRef)
```

Return the underlying constraint data for the constraint referenced by con\_ref.

**Example**

A scalar constraint:

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, c, 2x <= 1)
c : 2 x ≤ 1

julia> object = constraint_object(c)
ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(2 x,
↪ MathOptInterface.LessThan{Float64}(1.0))

julia> typeof(object)
ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}};

julia> object.func
2 x

julia> object.set
MathOptInterface.LessThan{Float64}(1.0)
```

A vector constraint:

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> @constraint(model, c, x in SecondOrderCone())
c : [x[1], x[2], x[3]] ∈ MathOptInterface.SecondOrderCone(3)

julia> object = constraint_object(c)
VectorConstraint{VariableRef, MathOptInterface.SecondOrderCone, VectorShape}(VariableRef[x[1],
↪ x[2], x[3]], MathOptInterface.SecondOrderCone(3), VectorShape())

julia> typeof(object)
VectorConstraint{VariableRef, MathOptInterface.SecondOrderCone, VectorShape}

julia> object.func
3-element Vector{VariableRef}:
x[1]
x[2]
x[3]

julia> object.set
MathOptInterface.SecondOrderCone(3)
```

[source](#)

### constraint\_ref\_with\_index

JuMP.constraint\_ref\_with\_index - Function.

```
constraint_ref_with_index(model::AbstractModel, index::MOI.ConstraintIndex)
```

Return a ConstraintRef of model corresponding to index.

This function is a helper function used internally by JuMP and some JuMP extensions. It should not need to be called in user-code.

`source`

### `constraint_string`

JuMP.constraint\_string – Function.

```
constraint_string(
    mode::MIME,
    ref::ConstraintRef;
    in_math_mode::Bool = false,
)
```

Return a string representation of the constraint ref, given the mode.

#### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, c, 2 * x <= 1);

julia> constraint_string(MIME("text/plain"), c)
"c : 2 x ≤ 1"
```

`source`

### `constraints_string`

JuMP.constraints\_string – Function.

```
constraints_string(mode, model::AbstractModel)::Vector{String}
```

Return a list of Strings describing each constraint of the model.

#### Example

```
julia> model = Model();

julia> @variable(model, x >= 0);

julia> @constraint(model, c, 2 * x <= 1);

julia> constraints_string(MIME("text/plain"), model)
2-element Vector{String}:
 "c : 2 x ≤ 1"
 "x ≥ 0"
```

`source`

**copy\_conflict**

JuMP.copy\_conflict - Function.

```
copy_conflict(model::GenericModel)
```

Return a copy of the current conflict for the model model and a `GenericReferenceMap` that can be used to obtain the variable and constraint reference of the new model corresponding to a given model's reference.

This is a convenience function that provides a filtering function for `copy_model`.

**Note**

Model copy is not supported in DIRECT mode, that is, when a model is constructed using the `direct_model` constructor instead of the `Model` constructor. Moreover, independently on whether an optimizer was provided at model construction, the new model will have no optimizer, that is, an optimizer will have to be provided to the new model in the `optimize!` call.

**Example**

In the following example, a model model is constructed with a variable x and two constraints c1 and c2. This model has no solution, as the two constraints are mutually exclusive. The solver is asked to compute a conflict with `compute_conflict!`. The parts of model participating in the conflict are then copied into a model `iis_model`.

```
julia> using JuMP

julia> import Gurobi

julia> model = Model(Gurobi.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0)
x

julia> @constraint(model, c1, x >= 2)
c1 : x ≥ 2

julia> @constraint(model, c2, x <= 1)
c2 : x ≤ 1

julia> optimize!(model)

julia> compute_conflict!(model)

julia> if get_attribute(model, MOI.ConflictStatus()) == MOI.CONFLICT_FOUND
           iis_model, reference_map = copy_conflict(model)
           print(iis_model)
       end
Feasibility
Subject to
c1 : x ≥ 2
c2 : x ≤ 1
```

[source](#)

**copy\_extension\_data**

JuMP.copy\_extension\_data - Function.

```
copy_extension_data(data, new_model::AbstractModel, model::AbstractModel)
```

Return a copy of the extension data data of the model model to the extension data of the new model new\_model.

A method should be added for any JuMP extension storing data in the ext field.

This method should only be implemented by developers creating JuMP extensions. It should never be called by users of JuMP.

**Warning**

Do not engage in type piracy by implementing this method for types of data that you did not define! JuMP extensions should store types that they define in model.ext, rather than regular Julia types.

[source](#)

**copy\_model**

JuMP.copy\_model - Function.

```
copy_model(model::GenericModel; filter_constraints::Union{Nothing, Function}=nothing)
```

Return a copy of the model model and a `GenericReferenceMap` that can be used to obtain the variable and constraint reference of the new model corresponding to a given model's reference. A `Base.copy(::AbstractModel)` method has also been implemented, it is similar to `copy_model` but does not return the reference map.

If the `filter_constraints` argument is given, only the constraints for which this function returns true will be copied. This function is given a constraint reference as argument.

**Note**

Model copy is not supported in DIRECT mode, that is, when a model is constructed using the `direct_model` constructor instead of the `Model` constructor. Moreover, independently on whether an optimizer was provided at model construction, the new model will have no optimizer, that is, an optimizer will have to be provided to the new model in the `optimize!` call.

**Example**

In the following example, a model `model` is constructed with a variable `x` and a constraint `cref`. It is then copied into a model `new_model` with the new references assigned to `x_new` and `cref_new`.

```
julia> model = Model();
julia> @variable(model, x)
x
julia> @constraint(model, cref, x == 2)
```

```
cref : x = 2

julia> new_model, reference_map = copy_model(model);

julia> x_new = reference_map[x]
x

julia> cref_new = reference_map[cref]
cref : x = 2
```

`source`

### `delete`

JuMP.`delete` - Function.

```
delete(model::GenericModel, con_ref::ConstraintRef)
```

Delete the constraint associated with `constraint_ref` from the model `model`.

Note that `delete` does not unregister the name from the model, so adding a new constraint of the same name will throw an error. Use `unregister` to unregister the name after deletion.

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, c, 2x <= 1)
c : 2 x ≤ 1

julia> delete(model, c)

julia> unregister(model, :c)

julia> print(model)
Feasibility
Subject to

julia> model[:c]
ERROR: KeyError: key :c not found
Stacktrace:
[...]
```

`source`

```
delete(model::GenericModel, con_refs::Vector{<:ConstraintRef})
```

Delete the constraints associated with `con_refs` from the model `model`.

Solvers may implement specialized methods for deleting multiple constraints of the same concrete type. These methods may be more efficient than repeatedly calling the single constraint delete method.

See also: [unregister](#)

### Example

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> @constraint(model, c, 2 * x .≤ 1)
3-element Vector{ConstraintRef{Model},
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    ↪ MathOptInterface.LessThan{Float64}}, ScalarShape}:
c : 2 x[1] ≤ 1
c : 2 x[2] ≤ 1
c : 2 x[3] ≤ 1

julia> delete(model, c)

julia> unregister(model, :c)

julia> print(model)
Feasibility
Subject to

julia> model[:c]
ERROR: KeyError: key :c not found
Stacktrace:
[...]
```

[source](#)

```
delete(model::GenericModel, variable_ref::GenericVariableRef)
```

Delete the variable associated with `variable_ref` from the model `model`.

Note that `delete` does not unregister the name from the model, so adding a new variable of the same name will throw an error. Use [unregister](#) to unregister the name after deletion.

### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> delete(model, x)

julia> unregister(model, :x)

julia> print(model)
Feasibility
Subject to
```

```
julia> model[:x]
ERROR: KeyError: key :x not found
Stacktrace:
[...]
```

source

```
delete(model::GenericModel, variable_refs::Vector{<:GenericVariableRef})
```

Delete the variables associated with `variable_refs` from the model `model`. Solvers may implement methods for deleting multiple variables that are more efficient than repeatedly calling the single variable delete method.

See also: [unregister](#)

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> delete(model, x)

julia> unregister(model, :x)

julia> print(model)
Feasibility
Subject to

julia> model[:x]
ERROR: KeyError: key :x not found
Stacktrace:
[...]
```

source

### `delete_lower_bound`

JuMP.`delete_lower_bound` – Function.

```
delete_lower_bound(v::GenericVariableRef)
```

Delete the lower bound constraint of a variable.

See also [LowerBoundRef](#), [has\\_lower\\_bound](#), [lower\\_bound](#), [set\\_lower\\_bound](#).

### Example

```
julia> model = Model();
julia> @variable(model, x >= 1.0);
julia> has_lower_bound(x)
true
julia> delete_lower_bound(x)
julia> has_lower_bound(x)
false
```

[source](#)

### **delete\_upper\_bound**

JuMP.delete\_upper\_bound – Function.

```
delete_upper_bound(v::GenericVariableRef)
```

Delete the upper bound constraint of a variable.

Errors if one does not exist.

See also [UpperBoundRef](#), [has\\_upper\\_bound](#), [upper\\_bound](#), [set\\_upper\\_bound](#).

#### **Example**

```
julia> model = Model();
julia> @variable(model, x <= 1.0);
julia> has_upper_bound(x)
true
julia> delete_upper_bound(x)
julia> has_upper_bound(x)
false
```

[source](#)

### **direct\_generic\_model**

JuMP.direct\_generic\_model – Function.

```
direct_generic_model(
    value_type::Type{T},
    backend::MOI.ModelLike;
) where {T<:Real}
```

Return a new JuMP model using `backend` to store the model and solve it.

As opposed to the `Model` constructor, no cache of the model is stored outside of `backend` and no bridges are automatically applied to `backend`.

### Notes

The absence of a cache reduces the memory footprint but, it is important to bear in mind the following implications of creating models using this *direct* mode:

- When `backend` does not support an operation, such as modifying constraints or adding variables/constraints after solving, an error is thrown. For models created using the `Model` constructor, such situations can be dealt with by storing the modifications in a cache and loading them into the optimizer when `optimize!` is called.
- No constraint bridging is supported by default.
- The optimizer used cannot be changed the model is constructed.
- The model created cannot be copied.

`source`

```
direct_generic_model(::Type{T}, factory::MOI.OptimizerWithAttributes)
```

Create a `direct_generic_model` using `factory`, a `MOI.OptimizerWithAttributes` object created by `optimizer_with_attributes`.

### Example

```
julia> import HiGHS

julia> optimizer = optimizer_with_attributes(
           HiGHS.Optimizer,
           "presolve" => "off",
           MOI.Silent() => true,
       );

julia> model = direct_generic_model(Float64, optimizer)
A JuMP Model
├ mode: DIRECT
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none
```

is equivalent to:

```
julia> import HiGHS

julia> model = direct_generic_model(Float64, HiGHS.Optimizer())
A JuMP Model
├ mode: DIRECT
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
└ num_variables: 0
```

```
| num_constraints: 0
└ Names registered in the model: none

julia> set_attribute(model, "presolve", "off")

julia> set_attribute(model, MOI.Silent(), true)
```

**source****direct\_model**

JuMP.direct\_model - Function.

```
direct_model(backend::MOI.ModelLike)
```

Return a new JuMP model using `backend` to store the model and solve it.

As opposed to the `Model` constructor, no cache of the model is stored outside of `backend` and no bridges are automatically applied to `backend`.

**Notes**

The absence of a cache reduces the memory footprint but, it is important to bear in mind the following implications of creating models using this *direct* mode:

- When `backend` does not support an operation, such as modifying constraints or adding variables/constraints after solving, an error is thrown. For models created using the `Model` constructor, such situations can be dealt with by storing the modifications in a cache and loading them into the optimizer when `optimize!` is called.
- No constraint bridging is supported by default.
- The optimizer used cannot be changed the model is constructed.
- The model created cannot be copied.

**source**

```
direct_model(factory::MOI.OptimizerWithAttributes)
```

Create a `direct_model` using `factory`, a `MOI.OptimizerWithAttributes` object created by `optimizer_with_attributes`.

**Example**

```
julia> import HiGHS

julia> optimizer = optimizer_with_attributes(
        HiGHS.Optimizer,
        "presolve" => "off",
        MOI.Silent() => true,
    );

julia> model = direct_model(optimizer)
```

```
A JuMP Model
├ mode: DIRECT
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none
```

is equivalent to:

```
julia> import HiGHS

julia> model = direct_model(HiGHS.Optimizer())
A JuMP Model
├ mode: DIRECT
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> set_attribute(model, "presolve", "off")

julia> set_attribute(model, MOI.Silent(), true)
```

`source`

### `drop_zeros!`

JuMP.`drop_zeros!` – Function.

```
drop_zeros!(expr::GenericAffExpr)
```

Remove terms in the affine expression with 0 coefficients.

#### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> expr = x[1] + x[2];

julia> add_to_expression!(expr, -1.0, x[1])
0 x[1] + x[2]

julia> drop_zeros!(expr)

julia> expr
x[2]
```

`source`

```
drop_zeros!(expr::GenericQuadExpr)
```

Remove terms in the quadratic expression with 0 coefficients.

### Example

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> expr = x[1]^2 + x[2]^2;
julia> add_to_expression!(expr, -1.0, x[1], x[1])
0 x[1]^2 + x[2]^2
julia> drop_zeros!(expr)
julia> expr
x[2]^2
```

`source`

### dual

JuMP.dual – Function.

```
dual(con_ref::ConstraintRef; result::Int = 1)
```

Return the dual value of constraint `con_ref` associated with result index `result` of the most-recent solution returned by the solver.

Use `has_duals` to check if a result exists before asking for values.

See also: `result_count`, `shadow_price`.

### Example

```
julia> import HiGHS
julia> model = Model(HiGHS.Optimizer);
julia> set_silent(model)
julia> @variable(model, x);
julia> @constraint(model, c, x <= 1)
c : x ≤ 1
julia> @objective(model, Max, 2 * x + 1);
julia> optimize!(model)
```

```
julia> has_duals(model)
true

julia> dual(c)
-2.0
```

[source](#)

### dual\_objective\_value

JuMP.dual\_objective\_value – Function.

```
dual_objective_value(model::GenericModel; result::Int = 1)
```

Return the value of the objective of the dual problem associated with result index result of the most-recent solution returned by the solver.

Throws MOI.UnsupportedAttribute{MOI.DualObjectiveValue} if the solver does not support this attribute.

This function is equivalent to querying the [MOI.DualObjectiveValue](#) attribute.

See also: [result\\_count](#).

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 1);

julia> @objective(model, Min, 2 * x + 1);

julia> optimize!(model)

julia> dual_objective_value(model)
3.0

julia> dual_objective_value(model; result = 2)
ERROR: Result index of attribute MathOptInterface.DualObjectiveValue(2) out of bounds. There are
→ currently 1 solution(s) in the model.
Stacktrace:
[...]
```

[source](#)

### dual\_shape

JuMP.dual\_shape – Function.

```
dual_shape(shape::AbstractShape)::AbstractShape
```

Returns the shape of the dual space of the space of objects of shape `shape`. By default, the `dual_shape` of a shape is itself. See the examples section below for an example for which this is not the case.

### Example

Consider polynomial constraints for which the dual is moment constraints and moment constraints for which the dual is polynomial constraints. Shapes for polynomials can be defined as follows:

```
struct Polynomial
    coefficients::Vector{Float64}
    monomials::Vector{Monomial}
end
struct PolynomialShape <: AbstractShape
    monomials::Vector{Monomial}
end
JuMP.reshape_vector(x::Vector, shape::PolynomialShape) = Polynomial(x, shape.monomials)
```

and a shape for moments can be defined as follows:

```
struct Moments
    coefficients::Vector{Float64}
    monomials::Vector{Monomial}
end
struct MomentsShape <: AbstractShape
    monomials::Vector{Monomial}
end
JuMP.reshape_vector(x::Vector, shape::MomentsShape) = Moments(x, shape.monomials)
```

Then `dual_shape` allows the definition of the shape of the dual of polynomial and moment constraints:

```
dual_shape(shape::PolynomialShape) = MomentsShape(shape.monomials)
dual_shape(shape::MomentsShape) = PolynomialShape(shape.monomials)
```

`source`

`dual_start_value`

JuMP.`dual_start_value` – Function.

```
dual_start_value(con_ref::ConstraintRef)
```

Return the dual start value (MOI attribute `ConstraintDualStart`) of the constraint `con_ref`.

If no dual start value has been set, `dual_start_value` will return nothing.

See also [set\\_dual\\_start\\_value](#).

### Example

```
julia> model = Model();

julia> @variable(model, x, start = 2.0);

julia> @constraint(model, c, [2x] in Nonnegatives())
c : [2 x] ∈ Nonnegatives()

julia> set_dual_start_value(c, [0.0])

julia> dual_start_value(c)
1-element Vector{Float64}:
 0.0

julia> set_dual_start_value(c, nothing)

julia> dual_start_value(c)
```

**source****dual\_status**

JuMP.dual\_status - Function.

```
dual_status(model::GenericModel; result::Int = 1)
```

Return a MOI.ResultStatusCode describing the status of the most recent dual solution of the solver (that is, the MOI.DualStatus attribute) associated with the result index `result`.

See also: `result_count`.

**Example**

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> dual_status(model; result = 2)
NO_SOLUTION::ResultStatusCode = 0
```

**source****error\_if\_direct\_mode**

JuMP.error\_if\_direct\_mode - Function.

```
error_if_direct_mode(model::GenericModel, func::Symbol)
```

Errors if `model` is in direct mode during a call from the function named `func`.

Used internally within JuMP, or by JuMP extensions who do not want to support models in direct mode.

**Example**

```
julia> import HiGHS

julia> model = direct_model(HiGHS.Optimizer());

julia> error_if_direct_mode(model, :foo)
ERROR: The `foo` function is not supported in DIRECT mode.
Stacktrace:
[...]
```

source

**fix**

JuMP.fix – Function.

```
fix(v::GenericVariableRef, value::Number; force::Bool = false)
```

Fix a variable to a value. Update the fixing constraint if one exists, otherwise create a new one.

If the variable already has variable bounds and force=false, calling fix will throw an error. If force=true, existing variable bounds will be deleted, and the fixing constraint will be added. Note a variable will have no bounds after a call to `unfix`.

See also `FixRef`, `is_fixed`, `fix_value`, `unfix`.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> is_fixed(x)
false

julia> fix(x, 1.0)

julia> is_fixed(x)
true
```

```
julia> model = Model();

julia> @variable(model, 0 <= x <= 1);

julia> is_fixed(x)
false

julia> fix(x, 1.0; force = true)

julia> is_fixed(x)
true
```

```
source

fix_discrete_variables
JuMP.fix_discrete_variables - Function.
```

```
fix_discrete_variables([var_value::Function = value,] model::GenericModel)
```

Modifies `model` to convert all binary and integer variables to continuous variables with fixed bounds of `var_value(x)`.

### Return

Returns a function that can be called without any arguments to restore the original model. The behavior of this function is undefined if additional changes are made to the affected variables in the meantime.

### Notes

- An error is thrown if semi-continuous or semi-integer constraints are present (support may be added for these in the future).
- All other constraints are ignored (left in place). This includes discrete constraints like SOS and indicator constraints.

### Example

```
julia> model = Model();
julia> @variable(model, x, Bin, start = 1);
julia> @variable(model, 1 <= y <= 10, Int, start = 2);
julia> @objective(model, Min, x + y);
julia> undo_relax = fix_discrete_variables(start_value, model);

julia> print(model)
Min x + y
Subject to
x = 1
y = 2

julia> undo_relax()

julia> print(model)
Min x + y
Subject to
y ≥ 1
y ≤ 10
y integer
x binary
```

```
source
```

**fix\_value**

JuMP.fix\_value – Function.

```
fix_value(v::GenericVariableRef)
```

Return the value to which a variable is fixed.

Error if one does not exist.

See also [FixRef](#), [is\\_fixed](#), [fix](#), [unfix](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x == 1);

julia> fix_value(x)
1.0
```

[source](#)

**flatten!**

JuMP.flatten! – Function.

```
flatten!(expr::GenericNonlinearExpr)
```

Flatten a nonlinear expression in-place by lifting nested + and \* nodes into a single n-ary operation.

**Motivation**

Nonlinear expressions created using operator overloading can be deeply nested and unbalanced. For example, `prod(x for i in 1:4)` creates `*(x, *(x, *(x, x)))` instead of the more preferable `*(x, x, x, x)`.

**Example**

```
julia> model = Model();

julia> @variable(model, x)
x

julia> y = prod(x for i in 1:4)
((x^2) * x) * x

julia> flatten!(y)
(x^2) * x * x

julia> flatten!(sin(prod(x for i in 1:4)))
sin((x^2) * x * x)
```

[source](#)

**function\_string**

JuMP.function\_string - Function.

```
function_string(
    mode::MIME,
    func::Union{JuMP.AbstractJuMPScalar,Vector{<:JuMP.AbstractJuMPScalar}},
)
```

Return a String representing the function func using print mode mode.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> function_string(MIME("text/plain"), 2 * x + 1)
"2 x + 1"
```

source

**get\_attribute**

JuMP.get\_attribute - Function.

```
get_attribute(model::GenericModel, attr::MOI.AbstractModelAttribute)
get_attribute(x::GenericVariableRef, attr::MOI.AbstractVariableAttribute)
get_attribute(cr::ConstraintRef, attr::MOI.AbstractConstraintAttribute)
```

Get the value of a solver-specific attribute attr.

This is equivalent to calling `MOI.get` with the associated MOI model and, for variables and constraints, with the associated `MOI.VariableIndex` or `MOI.ConstraintIndex`.

**Example**

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @constraint(model, c, 2 * x <= 1)
c : 2 x ≤ 1

julia> get_attribute(model, MOI.Name())
""

julia> get_attribute(x, MOI.VariableName())
"x"

julia> get_attribute(c, MOI.ConstraintName())
"c"
```

```
source

get_attribute(
    model::Union{GenericModel, MOI.OptimizerWithAttributes},
    attr::Union{AbstractString, MOI.AbstractOptimizerAttribute},
)
```

Get the value of a solver-specific attribute attr.

This is equivalent to calling `MOI.get` with the associated MOI model.

If attr is an `AbstractString`, it is converted to `MOI.RawOptimizerAttribute`.

### Example

```
julia> import HiGHS

julia> opt = optimizer_with_attributes(HiGHS.Optimizer, "output_flag" => true);

julia> model = Model(opt);

julia> get_attribute(model, "output_flag")
true

julia> get_attribute(model, MOI.RawOptimizerAttribute("output_flag"))
true

julia> get_attribute(opt, "output_flag")
true

julia> get_attribute(opt, MOI.RawOptimizerAttribute("output_flag"))
true
```

source

### has\_duals

`JuMP.has_duals` – Function.

```
has_duals(model::GenericModel; result::Int = 1)
```

Return `true` if the solver has a dual solution in result index `result` available to query, otherwise return `false`.

See also `dual`, `shadow_price`, and `result_count`.

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)
```

```
julia> @variable(model, x);

julia> @constraint(model, c, x <= 1)
c : x ≤ 1

julia> @objective(model, Max, 2 * x + 1);

julia> has_duals(model)
false

julia> optimize!(model)

julia> has_duals(model)
true
```

**source****has\_lower\_bound**

JuMP.has\_lower\_bound - Function.

```
has_lower_bound(v::GenericVariableRef)
```

Return true if v has a lower bound. If true, the lower bound can be queried with [lower\\_bound](#).

See also [LowerBoundRef](#), [lower\\_bound](#), [set\\_lower\\_bound](#), [delete\\_lower\\_bound](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x >= 1.0);

julia> has_lower_bound(x)
true
```

**source****has\_start\_value**

JuMP.has\_start\_value - Function.

```
has_start_value(variable::AbstractVariableRef)
```

Return true if the variable has a start value set, otherwise return false.

See also: [start\\_value](#), [set\\_start\\_value](#).

**Example**

```
julia> model = Model();
julia> @variable(model, x, start = 1.5);
julia> @variable(model, y);
julia> has_start_value(x)
true
julia> has_start_value(y)
false
julia> start_value(x)
1.5
julia> set_start_value(y, 2.0)
julia> has_start_value(y)
true
julia> start_value(y)
2.0
```

[source](#)**has\_upper\_bound**

JuMP.has\_upper\_bound – Function.

```
has_upper_bound(v::GenericVariableRef)
```

Return true if v has a upper bound. If true, the upper bound can be queried with [upper\\_bound](#).

See also [UpperBoundRef](#), [upper\\_bound](#), [set\\_upper\\_bound](#), [delete\\_upper\\_bound](#).

**Example**

```
julia> model = Model();
julia> @variable(model, x <= 1.0);
julia> has_upper_bound(x)
true
```

[source](#)**has\_values**

JuMP.has\_values – Function.

```
has_values(model::GenericModel; result::Int = 1)
```

Return true if the solver has a primal solution in result index result available to query, otherwise return false.

See also [value](#) and [result\\_count](#).

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x);

julia> @constraint(model, c, x <= 1)
c : x ≤ 1

julia> @objective(model, Max, 2 * x + 1);

julia> has_values(model)
false

julia> optimize!(model)

julia> has_values(model)
true
```

[source](#)

### in\_set\_string

JuMP.in\_set\_string - Function.

```
in_set_string(mode::MIME, set)
```

Return a String representing the membership to the set set using print mode mode.

### Extensions

JuMP extensions may extend this method for new set types to improve the legibility of their printing.

### Example

```
julia> in_set_string(MIME("text/plain"), MOI.Interval(1.0, 2.0))
"∈ [1, 2]"
```

[source](#)

**index**

JuMP.index – Function.

```
index(cr::ConstraintRef)::MOI.ConstraintIndex
```

Return the index of the constraint that corresponds to cr in the MOI backend.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, c, x >= 0);

julia> index(c)
MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
→ MathOptInterface.GreaterThan{Float64}}(1)
```

**source**

```
index(v::GenericVariableRef)::MOI.VariableIndex
```

Return the index of the variable that corresponds to v in the MOI backend.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> index(x)
MOI.VariableIndex(1)
```

**source****is\_binary**

JuMP.is\_binary – Function.

```
is_binary(v::GenericVariableRef)
```

Return true if v is constrained to be binary.

See also [BinaryRef](#), [set\\_binary](#), [unset\\_binary](#).

**Example**

```
julia> model = Model();
julia> @variable(model, x, Bin);
julia> is_binary(x)
true
```

[source](#)

### is\_fixed

JuMP.is\_fixed – Function.

```
is_fixed(v::GenericVariableRef)
```

Return true if v is a fixed variable. If true, the fixed value can be queried with [fix\\_value](#).

See also [FixRef](#), [fix\\_value](#), [fix](#), [unfix](#).

### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> is_fixed(x)
false
julia> fix(x, 1.0)
julia> is_fixed(x)
true
```

[source](#)

### is\_integer

JuMP.is\_integer – Function.

```
is_integer(v::GenericVariableRef)
```

Return true if v is constrained to be integer.

See also [IntegerRef](#), [set\\_integer](#), [unset\\_integer](#).

### Example

```
julia> model = Model();
julia> @variable(model, x);
```

```
julia> is_integer(x)
false

julia> set_integer(x)

julia> is_integer(x)
true
```

`source`

### `is_parameter`

JuMP.`is_parameter` - Function.

```
is_parameter(x::GenericVariableRef)::Bool
```

Return true if x is constrained to be a parameter.

See also [ParameterRef](#), [set\\_parameter\\_value](#), [parameter\\_value](#).

### `Example`

```
julia> model = Model();

julia> @variable(model, p in Parameter(2))
p

julia> is_parameter(p)
true

julia> @variable(model, x)
x

julia> is_parameter(x)
false
```

`source`

### `is_solved_and_feasible`

JuMP.`is_solved_and_feasible` - Function.

```
is_solved_and_feasible(
    model::GenericModel;
    allow_local::Bool = true,
    allow_almost::Bool = false,
    dual::Bool = false,
    result::Int = 1,
)
```

Return true if:

- the `termination_status` is one of:
  - `OPTIMAL` (the solver found a global optimum)
  - `LOCALLY_SOLVED` (the solver found a local optimum, which may also be the global optimum, but the solver could not prove so).
- the `primal_status` of the result index `result` is `FEASIBLE_POINT`.

This function is conservative, in that it returns `false` for situations like the solver terminating with a feasible solution due to a time limit.

If this function returns `false`, use `termination_status`, `result_count`, `primal_status` and `dual_status` to understand what solutions are available (if any).

See also: `assert_is_solved_and_feasible`.

#### **Keyword arguments**

##### **allow\_local**

If `allow_local = false`, then this function returns `true` only if the `termination_status` is `OPTIMAL`.

##### **allow\_almost**

If `allow_almost = true`, then the `termination_status` may additionally be `ALMOST_OPTIMAL` or `ALMOST_LOCALLY_SOLVED` (`allow_local`), and the `primal_status` and `dual_status` may additionally be `NEARLY_FEASIBLE_POINT`.

##### **dual**

If `dual`, additionally check that an optimal dual solution is available via `dual_status`. The `allow_` keywords control both the primal and dual solutions.

##### **result**

The index of the result to query. This value is passed to the `result` keyword arguments of `primal_status` and `dual_status`.

#### **Example**

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> is_solved_and_feasible(model)
false

julia> is_solved_and_feasible(
           model;
           allow_almost = true,
           dual = true,
           result = 2,
       )
false
```

[source](#)

**is\_valid**

JuMP.is\_valid - Function.

```
is_valid(model::GenericModel, con_ref::ConstraintRef{<:AbstractModel})
```

Return true if con\_ref refers to a valid constraint in model.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, c, 2 * x <= 1);

julia> is_valid(model, c)
true

julia> model_2 = Model();

julia> is_valid(model_2, c)
false
```

source

```
is_valid(model::GenericModel, variable_ref::GenericVariableRef)
```

Return true if variable refers to a valid variable in model.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> is_valid(model, x)
true

julia> model_2 = Model();

julia> is_valid(model_2, x)
false
```

source

**isequal\_canonical**

JuMP.isequal\_canonical - Function.

```
isequal_canonical(
    x::T,
    y::T
) where {T<:AbstractJuMPScalar, AbstractArray{<:AbstractJuMPScalar}}
```

Return `true` if `x` is equal to `y` after dropping zeros and disregarding the order.

This method is mainly useful for testing, because fallbacks like `x == y` do not account for valid mathematical comparisons like `x[1] + 0 * x[2] + 1 == x[1] + 1`.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> a = x[1] + 1.0
x[1] + 1

julia> b = x[1] + x[2] + 1.0
x[1] + x[2] + 1

julia> add_to_expression!(b, -1.0, x[2])
x[1] + 0 * x[2] + 1

julia> a == b
false

julia> isequal_canonical(a, b)
true
```

`source`

### jump\_function

`JuMP.jump_function` – Function.

```
jump_function(model::AbstractModel, x::MOI.AbstractFunction)
```

Given an `MathOptInterface` object `x`, return the JuMP equivalent.

See also: [moi\\_function](#).

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> f = 2.0 * index(x) + 1.0
1.0 + 2.0 MOI.VariableIndex(1)
```

```
julia> jump_function(model, f)
2 x + 1
```

[source](#)

### jump\_function\_type

JuMP.jump\_function\_type – Function.

```
jump_function_type(model::AbstractModel, ::Type{T}) where {T}
```

Given an MathOptInterface object type T, return the JuMP equivalent.

See also: [moi\\_function\\_type](#).

### Example

```
julia> model = Model();

julia> jump_function_type(model, MOI.ScalarAffineFunction{Float64})
AffExpr (alias for GenericAffExpr{Float64, GenericVariableRef{Float64}})
```

[source](#)

### latex\_formulation

JuMP.latex\_formulation – Function.

```
latex_formulation(model::AbstractModel)
```

Wrap model in a type so that it can be pretty-printed as text/latex in a notebook like IJulia, or in Documenter.

To render the model, end the cell with `latex_formulation(model)`, or call `display(latex_formulation(model))` in to force the display of the model from inside a function.

[source](#)

### linear\_terms

JuMP.linear\_terms – Function.

```
linear_terms(aff::GenericAffExpr{C,V})
```

Provides an iterator over coefficient-variable tuples (`a_i::C, x_i::V`) in the linear part of the affine expression.

[source](#)

```
linear_terms(quad::GenericQuadExpr{C,V})
```

Provides an iterator over tuples (coefficient::C, variable::V) in the linear part of the quadratic expression.

[source](#)

### `list_of_constraint_types`

JuMP.list\_of\_constraint\_types - Function.

```
list_of_constraint_types(model::GenericModel)::Vector{Tuple{Type,Type}}
```

Return a list of tuples of the form (F, S) where F is a JuMP function type and S is an MOI set type such that `all_constraints(model, F, S)` returns a nonempty list.

#### Example

```
julia> model = Model();
julia> @variable(model, x >= 0, Bin);
julia> @constraint(model, 2x <= 1);
julia> list_of_constraint_types(model)
3-element Vector{Tuple{Type, Type}}:
 (AffExpr, MathOptInterface.LessThan{Float64})
 (VariableRef, MathOptInterface.GreaterThan{Float64})
 (VariableRef, MathOptInterface.ZeroOne)
```

### Performance considerations

Iterating over the list of function and set types is a type-unstable operation. Consider using a function barrier. See the [Performance tips for extensions](#) section of the documentation for more details.

[source](#)

### `lower_bound`

JuMP.lower\_bound - Function.

```
lower_bound(v::GenericVariableRef)
```

Return the lower bound of a variable. Error if one does not exist.

See also [LowerBoundRef](#), [has\\_lower\\_bound](#), [set\\_lower\\_bound](#), [delete\\_lower\\_bound](#).

#### Example

```
julia> model = Model();
julia> @variable(model, x >= 1.0);
julia> lower_bound(x)
1.0
```

`source`

### `lp_matrix_data`

JuMP.`lp_matrix_data` - Function.

```
lp_matrix_data(model::GenericModel{T})
```

Given a JuMP model of a linear program, return an `LPMATRIXDATA{T}` struct storing data for an equivalent linear program in the form:

$$\begin{aligned} \min & c^\top x + c_0 \\ \text{s.t. } & b_l \leq Ax \leq b_u \\ & x_l \leq x \leq x_u \end{aligned}$$

where elements in `x` may be continuous, integer, or binary variables.

### Fields

The struct returned by `lp_matrix_data` has the fields:

- `A`: `SparseArrays.SparseMatrixCSC{T, Int}`: the constraint matrix in sparse matrix form.
- `b_lower`: `Vector{T}`: the dense vector of row lower bounds. If missing, the value of `typemin(T)` is used.
- `b_upper`: `Vector{T}`: the dense vector of row upper bounds. If missing, the value of `typemax(T)` is used.
- `x_lower`: `Vector{T}`: the dense vector of variable lower bounds. If missing, the value of `typemin(T)` is used.
- `x_upper`: `Vector{T}`: the dense vector of variable upper bounds. If missing, the value of `typemax(T)` is used.
- `c`: `Vector{T}`: the dense vector of linear objective coefficients
- `c_offset`: `T`: the constant term in the objective function.
- `sense`: `MOI.OptimizationSense`: the objective sense of the model.
- `integers`: `Vector{Int}`: the sorted list of column indices that are integer variables.
- `binaries`: `Vector{Int}`: the sorted list of column indices that are binary variables.
- `variables`: `Vector{GenericVariableRef{T}}`: a vector of `GenericVariableRef`, corresponding to order of the columns in the matrix form.
- `affine_constraints`: `Vector{ConstraintRef}`: a vector of `ConstraintRef`, corresponding to the order of rows in the matrix form.

### Limitations

The models supported by `lp_matrix_data` are intentionally limited to linear programs.

### Example

```
julia> model = Model();  
  
julia> @variable(model, x[1:2] >= 0);  
  
julia> @constraint(model, x[1] + 2 * x[2] <= 1);  
  
julia> @objective(model, Max, x[2]);  
  
julia> data = lp_matrix_data(model);  
  
julia> data.A  
1×2 SparseArrays.SparseMatrixCSC{Float64, Int64} with 2 stored entries:  
 1.0  2.0  
  
julia> data.b_lower  
1-element Vector{Float64}:  
 -Inf  
  
julia> data.b_upper  
1-element Vector{Float64}:  
 1.0  
  
julia> data.x_lower  
2-element Vector{Float64}:  
 0.0  
 0.0  
  
julia> data.x_upper  
2-element Vector{Float64}:  
 Inf  
 Inf  
  
julia> data.c  
2-element Vector{Float64}:  
 0.0  
 1.0  
  
julia> data.c_offset  
0.0  
  
julia> data.sense  
MAX_SENSE::OptimizationSense = 1
```

`source`

### `lp_sensitivity_report`

`JuMP.lp_sensitivity_report` - Function.

```
lp_sensitivity_report(model::GenericModel{T}; atol::T =
    Base.rtoldefault(T))::SensitivityReport{T} where {T}
```

Given a linear program model with a current optimal basis, return a `SensitivityReport` object, which maps:

- Every variable reference to a tuple `(d_lo, d_hi)::Tuple{T,T}`, explaining how much the objective coefficient of the corresponding variable can change by, such that the original basis remains optimal.
- Every constraint reference to a tuple `(d_lo, d_hi)::Tuple{T,T}`, explaining how much the right-hand side of the corresponding constraint can change by, such that the basis remains optimal.

Both tuples are relative, rather than absolute. So given a objective coefficient of 1.0 and a tuple (-0.5, 0.5), the objective coefficient can range between 1.0 - 0.5 an 1.0 + 0.5.

`atol` is the primal/dual optimality tolerance, and should match the tolerance of the solver used to compute the basis.

Note: interval constraints are NOT supported.

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, -1 <= x <= 2)
x

julia> @objective(model, Min, x)
x

julia> optimize!(model)

julia> report = lp_sensitivity_report(model; atol = 1e-7);

julia> dx_lo, dx_hi = report[x]
(-1.0, Inf)

julia> println(
        "The objective coefficient of `x` can decrease by $dx_lo or " *
        "increase by $dx_hi."
    )
The objective coefficient of `x` can decrease by -1.0 or increase by Inf.

julia> dRHS_lo, dRHS_hi = report[LowerBoundRef(x)]
(-Inf, 3.0)

julia> println(
        "The lower bound of `x` can decrease by $dRHS_lo or increase " *
        "by $dRHS_hi."
    )
The lower bound of `x` can decrease by -Inf or increase by 3.0.
```

`source`

### `map_coefficients`

JuMP.`map_coefficients` – Function.

```
map_coefficients(f::Function, a::GenericAffExpr)
```

Apply `f` to the coefficients and constant term of an `GenericAffExpr` `a` and return a new expression.

See also: `map_coefficients_inplace!`

#### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> a = GenericAffExpr(1.0, x => 1.0)
x + 1
julia> map_coefficients(c -> 2 * c, a)
2 x + 2
julia> a
x + 1
```

`source`

```
map_coefficients(f::Function, a::GenericQuadExpr)
```

Apply `f` to the coefficients and constant term of an `GenericQuadExpr` `a` and return a new expression.

See also: `map_coefficients_inplace!`

#### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> a = @expression(model, x^2 + x + 1)
x^2 + x + 1
julia> map_coefficients(c -> 2 * c, a)
2 x^2 + 2 x + 2
julia> a
x^2 + x + 1
```

`source`

**map\_coefficients\_inplace!**

JuMP.map\_coefficients\_inplace! – Function.

```
map_coefficients_inplace!(f::Function, a::GenericAffExpr)
```

Apply `f` to the coefficients and constant term of an `GenericAffExpr` `a` and update them in-place.

See also: [map\\_coefficients](#)

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> a = GenericAffExpr(1.0, x => 1.0)
x + 1

julia> map_coefficients_inplace!(c -> 2 * c, a)
2 x + 2

julia> a
2 x + 2
```

[source](#)

```
map_coefficients_inplace!(f::Function, a::GenericQuadExpr)
```

Apply `f` to the coefficients and constant term of an `GenericQuadExpr` `a` and update them in-place.

See also: [map\\_coefficients](#)

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> a = @expression(model, x^2 + x + 1)
x^2 + x + 1

julia> map_coefficients_inplace!(c -> 2 * c, a)
2 x^2 + 2 x + 2

julia> a
2 x^2 + 2 x + 2
```

[source](#)

**mode**

JuMP.mode – Function.

```
mode(model::GenericModel)
```

Return the [ModelMode](#) of model.

**Example**

```
julia> model = Model();
julia> mode(model)
AUTOMATIC::ModelMode = 0
```

[source](#)

**model\_convert**

JuMP.model\_convert – Function.

```
model_convert(
    model::AbstractModel,
    rhs::Union{
        AbstractConstraint,
        Number,
        AbstractJuMPScalar,
        MOI.AbstractSet,
    },
)
```

Convert the coefficients and constants of functions and sets in the rhs to the coefficient type `value_type(typeof(model))`.

**Purpose**

Creating and adding a constraint is a two-step process. The first step calls `build_constraint`, and the result of that is passed to `add_constraint`.

However, because `build_constraint` does not take the model as an argument, the coefficients and constants of the function or set might be different than `value_type(typeof(model))`.

Therefore, the result of `build_constraint` is converted in a call to `model_convert` before the result is passed to `add_constraint`.

[source](#)

**model\_string**

JuMP.model\_string – Function.

```
model_string(mode::MIME, model::AbstractModel)
```

Return a String representation of model given the mode.

### Example

```
julia> model = Model();

julia> @variable(model, x >= 0);

julia> print(model_string(MIME("text/plain"), model))
Feasibility
Subject to
  x ≥ 0
```

[source](#)

### moi\_function

JuMP.moi\_function - Function.

```
moi_function(x::AbstractJuMPScalar)
moi_function(x::AbstractArray{<:AbstractJuMPScalar})
```

Given a JuMP object x, return the MathOptInterface equivalent.

See also: [jump\\_function](#).

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> f = 2.0 * x + 1.0
2 x + 1

julia> moi_function(f)
1.0 + 2.0 MOI.VariableIndex(1)
```

[source](#)

### moi\_function\_type

JuMP.moi\_function\_type - Function.

```
moi_function_type(::Type{T}) where {T}
```

Given a JuMP object type T, return the MathOptInterface equivalent.

See also: [jump\\_function\\_type](#).

### Example

```
julia> moi_function_type(AffExpr)
MathOptInterface.ScalarAffineFunction{Float64}
```

[source](#)

### moi\_set

JuMP.moi\_set – Function.

```
moi_set(constraint::AbstractConstraint)
```

Return the set of the constraint constraint in the function-in-set form as a MathOptInterface.AbstractSet.

```
moi_set(s::AbstractVectorSet, dim::Int)
```

Returns the MOI set of dimension dim corresponding to the JuMP set s.

```
moi_set(s::AbstractScalarSet)
```

Returns the MOI set corresponding to the JuMP set s.

[source](#)

### name

JuMP.name – Function.

```
name(con_ref::ConstraintRef)
```

Get a constraint's name attribute.

### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> @constraint(model, c, [2x] in Nonnegatives())
c : [2 x] ∈ Nonnegatives()
julia> name(c)
"c"
```

[source](#)

```
name(v::GenericVariableRef)::String
```

Get a variable's name attribute.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> name(x[1])
"x[1]"
```

source

```
name(model::AbstractModel)
```

Return the `MOI.Name` attribute of `model`'s `backend`, or a default if empty.

### Example

```
julia> model = Model();

julia> name(model)
"A JuMP Model"
```

source

### node\_count

`JuMP.node_count` – Function.

```
node_count(model::GenericModel)
```

If available, returns the total number of branch-and-bound nodes explored during the most recent optimization in a Mixed Integer Program (the `MOI.NodeCount` attribute).

Throws a `MOI.GetAttributeNotAllowed` error if the attribute is not implemented by the solver.

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)
```

```
julia> optimize!(model)

julia> node_count(model)
0
```

[source](#)

### normalized\_coefficient

JuMP.normalized\_coefficient - Function.

```
normalized_coefficient(
    constraint::ConstraintRef,
    variable::GenericVariableRef,
)
```

Return the coefficient associated with `variable` in `constraint` after JuMP has normalized the constraint into its standard form.

See also [set\\_normalized\\_coefficient](#).

#### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @constraint(model, con, 2x + 3x <= 2)
con : 5 x ≤ 2

julia> normalized_coefficient(con, x)
5.0

julia> @constraint(model, con_vec, [x, 2x + 1, 3] >= 0)
con_vec : [x, 2 x + 1, 3] ∈ Nonnegatives()

julia> normalized_coefficient(con_vec, x)
2-element Vector{Tuple{Int64, Float64}}:
 (1, 1.0)
 (2, 2.0)
```

[source](#)

```
normalized_coefficient(
    constraint::ConstraintRef,
    variable_1::GenericVariableRef,
    variable_2::GenericVariableRef,
)
```

Return the quadratic coefficient associated with `variable_1` and `variable_2` in `constraint` after JuMP has normalized the constraint into its standard form.

See also [set\\_normalized\\_coefficient](#).

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @constraint(model, con, 2x[1]^2 + 3 * x[1] * x[2] + x[2] <= 2)
con : 2 x[1]^2 + 3 x[1]*x[2] + x[2] ≤ 2

julia> normalized_coefficient(con, x[1], x[1])
2.0

julia> normalized_coefficient(con, x[1], x[2])
3.0

julia> @constraint(model, con_vec, x.^2 <= [1, 2])
con_vec : [x[1]^2 - 1, x[2]^2 - 2] ∈ Nonpositives()

julia> normalized_coefficient(con_vec, x[1], x[1])
1-element Vector{Tuple{Int64, Float64}}:
(1, 1.0)

julia> normalized_coefficient(con_vec, x[1], x[2])
Tuple{Int64, Float64}[]
```

[source](#)

### normalized\_rhs

JuMP.normalized\_rhs – Function.

```
normalized_rhs(constraint::ConstraintRef)
```

Return the right-hand side term of constraint after JuMP has converted the constraint into its normalized form.

See also [set\\_normalized\\_rhs](#).

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, con, 2x + 1 <= 2)
con : 2 x ≤ 1

julia> normalized_rhs(con)
1.0
```

[source](#)

**num\_constraints**

JuMP.num\_constraints - Function.

```
num_constraints(model::GenericModel, function_type, set_type)::Int64
```

Return the number of constraints currently in the model where the function has type `function_type` and the set has type `set_type`.

See also [list\\_of\\_constraint\\_types](#) and [all\\_constraints](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x >= 0, Bin);

julia> @variable(model, y);

julia> @constraint(model, y in MOI.GreaterThan(1.0));

julia> @constraint(model, y <= 1.0);

julia> @constraint(model, 2x <= 1);

julia> num_constraints(model, VariableRef, MOI.GreaterThan{Float64})
2

julia> num_constraints(model, VariableRef, MOI.ZeroOne)
1

julia> num_constraints(model, AffExpr, MOI.LessThan{Float64})
2
```

**source**

```
num_constraints(model::GenericModel; count_variable_in_set_constraints::Bool)
```

Return the number of constraints in `model`.

If `count_variable_in_set_constraints == true`, then `VariableRef` constraints such as `VariableRef-in-Integer` are included. To count only the number of structural constraints (for example, the rows in the constraint matrix of a linear program), pass `count_variable_in_set_constraints = false`.

**Example**

```
julia> model = Model();

julia> @variable(model, x >= 0, Int);

julia> @constraint(model, 2x <= 1);

julia> num_constraints(model; count_variable_in_set_constraints = true)
```

```
3

julia> num_constraints(model; count_variable_in_set_constraints = false)
1
```

[source](#)

### **num\_variables**

JuMP.num\_variables – Function.

```
num_variables(model::GenericModel)::Int64
```

Returns number of variables in model.

#### **Example**

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> num_variables(model)
2
```

[source](#)

### **object\_dictionary**

JuMP.object\_dictionary – Function.

```
object_dictionary(model::GenericModel)
```

Return the dictionary that maps the symbol name of a variable, constraint, or expression to the corresponding object.

Objects are registered to a specific symbol in the macros. For example, `@variable(model, x[1:2, 1:2])` registers the array of variables `x` to the symbol `:x`.

This method should be defined for any subtype of `AbstractModel`.

See also: [unregister](#).

#### **Example**

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> object_dictionary(model)
Dict{Symbol, Any} with 1 entry:
:x => VariableRef[x[1], x[2]]
```

[source](#)

**objective\_bound**

JuMP.objective\_bound – Function.

```
objective_bound(model::GenericModel)
```

Return the best known bound on the optimal objective value after a call to `optimize!(model)`.

For scalar-valued objectives, this function returns a `Float64`. For vector-valued objectives, it returns a `Vector{Float64}`.

In the case of a vector-valued objective, this returns the *ideal point*, that is, the point obtained if each objective was optimized independently.

This function is equivalent to querying the `MOI.ObjectiveBound` attribute.

**Example**

```
julia> import HiGHS
julia> model = Model(HiGHS.Optimizer);
julia> set_silent(model)
julia> @variable(model, x >= 1, Int);
julia> @objective(model, Min, 2 * x + 1);
julia> optimize!(model)
julia> objective_bound(model)
3.0
```

`source`

**objective\_function**

JuMP.objective\_function – Function.

```
objective_function(
    model::GenericModel,
    ::Type{F} = objective_function_type(model),
) where {F}
```

Return an object of type `F` representing the objective function.

Errors if the objective is not convertible to type `F`.

This function is equivalent to querying the `MOI.ObjectiveFunction{F}` attribute.

**Example**

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @objective(model, Min, 2x + 1)
2 x + 1

julia> objective_function(model, AffExpr)
2 x + 1

julia> objective_function(model, QuadExpr)
2 x + 1

julia> typeof(objective_function(model, QuadExpr))
QuadExpr (alias for GenericQuadExpr{Float64, GenericVariableRef{Float64}})
```

We see with the last two commands that even if the objective function is affine, as it is convertible to a quadratic function, it can be queried as a quadratic function and the result is quadratic.

However, it is not convertible to a variable:

```
julia> objective_function(model, VariableRef)
ERROR: InexactError: convert(MathOptInterface.VariableIndex, 1.0 + 2.0 MOI.VariableIndex(1))
[...]
```

`source`

`objective_function_string`  
`JuMP.objective_function_string - Function.`

```
objective_function_string(mode, model::AbstractModel)::String
```

Return a `String` describing the objective function of the model.

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @objective(model, Min, 2 * x);

julia> objective_function_string(MIME("text/plain"), model)
"2 x"
```

`source`

**objective\_function\_type**

JuMP.objective\_function\_type - Function.

```
objective_function_type(model::GenericModel)::AbstractJuMPScalar
```

Return the type of the objective function.

This function is equivalent to querying the `MOI.ObjectiveFunctionType` attribute.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> @objective(model, Min, 2 * x + 1);

julia> objective_function_type(model)
AffExpr (alias for GenericAffExpr{Float64, GenericVariableRef{Float64}})
```

`source`

**objective\_sense**

JuMP.objective\_sense - Function.

```
objective_sense(model::GenericModel)::MOI.OptimizationSense
```

Return the objective sense.

This function is equivalent to querying the `MOI.ObjectiveSense` attribute.

**Example**

```
julia> model = Model();

julia> objective_sense(model)
FEASIBILITY_SENSE::OptimizationSense = 2

julia> @variable(model, x);

julia> @objective(model, Max, x)

julia> objective_sense(model)
MAX_SENSE::OptimizationSense = 1
```

`source`

**objective\_value**

JuMP.objective\_value - Function.

```
objective_value(model::GenericModel; result::Int = 1)
```

Return the objective value associated with result index `result` of the most-recent solution returned by the solver.

For scalar-valued objectives, this function returns a `Float64`. For vector-valued objectives, it returns a `Vector{Float64}`.

This function is equivalent to querying the `MOI.ObjectiveValue` attribute.

See also: `result_count`.

**Example**

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 1);

julia> @objective(model, Min, 2 * x + 1);

julia> optimize!(model)

julia> objective_value(model)
3.0

julia> objective_value(model; result = 2)
ERROR: Result index of attribute MathOptInterface.ObjectiveValue(2) out of bounds. There are
↳ currently 1 solution(s) in the model.
Stacktrace:
[...]
```

`source`

**op\_ifelse**

JuMP.op\_ifelse - Function.

```
op_ifelse(a, x, y)
```

A function that falls back to `ifelse(a, x, y)`, but when called with a JuMP variables or expression in the first argument, returns a `GenericNonlinearExpr`.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> op_ifelse(true, 1.0, 2.0)
1.0

julia> op_ifelse(x, 1.0, 2.0)
ifelse(x, 1.0, 2.0)

julia> op_ifelse(true, x, 2.0)
x
```

`source`

### `op_string`

JuMP.`op_string` - Function.

```
op_string(mime::MIME, x::GenericNonlinearExpr, ::Val{op}) where {op}
```

Return the string that should be printed for the operator `op` when `function_string` is called with `mime` and `x`.

### **Example**

```
julia> model = Model();

julia> @variable(model, x[1:2], Bin);

julia> f = @expression(model, x[1] || x[2]);

julia> op_string(MIME("text/plain"), f, Val(:||))
"||"
```

`source`

### `operator_to_set`

JuMP.`operator_to_set` - Function.

```
operator_to_set(error_fn::Function, ::Val{sense_symbol})
```

Converts a sense symbol to a set set such that `@constraint(model, func sense_symbol 0)` is equivalent to `@constraint(model, func in set)` for any `func::AbstractJuMPScalar`.

### **Example**

Once a custom set is defined you can directly create a JuMP constraint with it:

```
julia> struct CustomSet{T} <: MOI.AbstractScalarSet
    value::T
end

julia> Base.copy(x::CustomSet) = CustomSet(x.value)

julia> model = Model();

julia> @variable(model, x)
x

julia> cref = @constraint(model, x in CustomSet(1.0))
x ∈ CustomSet{Float64}(1.0)
```

However, there might be an appropriate sign that could be used in order to provide a more convenient syntax:

```
julia> JuMP.operator_to_set(::Function, ::Val{:[]}) = CustomSet(0.0)

julia> MOIU.supports_shift_constant(::Type{<:CustomSet}) = true

julia> MOIU.shift_constant(set::CustomSet, value) = CustomSet(set.value + value)

julia> cref = @constraint(model, x [] 1)
x ∈ CustomSet{Float64}(1.0)
```

Note that the whole function is first moved to the right-hand side, then the sign is transformed into a set with zero constant and finally the constant is moved to the set with MOIU.shift\_constant.

`source`

### `operator_warn`

JuMP.`operator_warn` – Function.

```
operator_warn(model::AbstractModel)
operator_warn(model::GenericModel)
```

This function is called on the model whenever two affine expressions are added together without using `destructive_add!`, and at least one of the two expressions has more than 50 terms.

For the case of `Model`, if this function is called more than 20,000 times then a warning is generated once.

This method should only be implemented by developers creating JuMP extensions. It should never be called by users of JuMP.

`source`

### `optimize!`

JuMP.`optimize!` – Function.

```
optimize!(
    model::GenericModel,
    ignore_optimize_hook = (model.optimize_hook === nothing),
    kwargs...,
)
```

Optimize the model.

If an optimizer has not been set yet (see `set_optimizer`), a `NoOptimizer` error is thrown.

If `ignore_optimize_hook == true`, the optimize hook is ignored and the model is solved as if the hook was not set. Keyword arguments `kwargs` are passed to the `optimize_hook`. An error is thrown if `optimize_hook` is nothing and keyword arguments are provided.

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> function my_optimize_hook(model; foo)
           println("Hook called with foo = ", foo)
           return optimize!(model; ignore_optimize_hook = true)
       end
my_optimize_hook (generic function with 1 method)

julia> set_optimize_hook(model, my_optimize_hook)
my_optimize_hook (generic function with 1 method)

julia> optimize!(model; foo = 2)
Hook called with foo = 2
```

`source`

### optimizer\_index

JuMP.optimizer\_index - Function.

```
optimizer_index(x::GenericVariableRef)::MOI.VariableIndex
optimizer_index(x::ConstraintRef{<:GenericModel})::MOI.ConstraintIndex
```

Return the variable or constraint index that corresponds to `x` in the associated model `unsafe_backend(owner_model(x))`.

This function should be used with `unsafe_backend`.

As a safer alternative, use `backend` and `index`. See the docstrings of `backend` and `unsafe_backend` for more details.

### Throws

- Throws `NoOptimizer` if no optimizer is set.

- Throws an `ErrorException` if the optimizer is set but is not attached.
- Throws an `ErrorException` if the index is bridged.

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0)
x

julia> MOI.Utilities.attach_optimizer(model)

julia> highs = unsafe_backend(model)
A HiGHS model with 1 columns and 0 rows.

julia> optimizer_index(x)
MOI.VariableIndex(1)
```

[source](#)

### optimizer\_with\_attributes

JuMP.`optimizer_with_attributes` – Function.

```
optimizer_with_attributes(optimizer_constructor, attrs::Pair...)
```

Groups an optimizer constructor with the list of attributes `attrs`. Note that it is equivalent to `MOI.OptimizerWithAttributes`.

When provided to the `Model` constructor or to `set_optimizer`, it creates an optimizer by calling `optimizer_constructor()`, and then sets the attributes using `set_attribute`.

See also: [set\\_attribute](#), [get\\_attribute](#).

### Note

The string names of the attributes are specific to each solver. One should consult the solver's documentation to find the attributes of interest.

### Example

```
julia> import HiGHS

julia> optimizer = optimizer_with_attributes(
        HiGHS.Optimizer, "presolve" => "off", MOI.Silent() => true,
    );

julia> model = Model(optimizer);
```

is equivalent to:

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_attribute(model, "presolve", "off")

julia> set_attribute(model, MOI.Silent(), true)
```

**source****owner\_model**

JuMP.owner\_model - Function.

```
owner_model(s::AbstractJuMPScalar)
```

Return the model owning the scalar s.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> owner_model(x) === model
true
```

**source****parameter\_value**

JuMP.parameter\_value - Function.

```
parameter_value(x::GenericVariableRef)
```

Return the value of the parameter x.

Errors if x is not a parameter.

See also [ParameterRef](#), [is\\_parameter](#), [set\\_parameter\\_value](#).

**Example**

```
julia> model = Model();

julia> @variable(model, p in Parameter(2))
p

julia> parameter_value(p)
2.0
```

```
julia> set_parameter_value(p, 2.5)

julia> parameter_value(p)
2.5
```

[source](#)

### parse\_constraint

JuMP.parse\_constraint – Function.

```
parse_constraint(error_fn::Function, expr::Expr)
```

The entry-point for all constraint-related parsing.

#### Arguments

- The error\_fn function is passed everywhere to provide better error messages
  - expr comes from the @constraint macro. There are two possibilities:
    - @constraint(model, expr)
    - @constraint(model, name[args], expr)
- In both cases, expr is the main component of the constraint.

#### Supported syntax

JuMP currently supports the following expr objects:

- $\text{lhs} \leq \text{rhs}$
- $\text{lhs} == \text{rhs}$
- $\text{lhs} \geq \text{rhs}$
- $\text{l} \leq \text{body} \leq \text{u}$
- $\text{u} \geq \text{body} \geq \text{l}$
- $\text{lhs} \perp \text{rhs}$
- $\text{lhs} \in \text{rhs}$
- $\text{z} \dashrightarrow \{\text{constraint}\}$
- $!\text{z} \dashrightarrow \{\text{constraint}\}$
- $\text{z} \dashleftarrow\text{-} \dashrightarrow \{\text{constraint}\}$
- $!\text{z} \dashleftarrow\text{-} \dashrightarrow \{\text{constraint}\}$
- $\text{z} \Rightarrow \{\text{constraint}\}$
- $!\text{z} \Rightarrow \{\text{constraint}\}$

as well as all broadcasted variants.

#### Extensions

The infrastructure behind parse\_constraint is extendable. See [parse\\_constraint\\_head](#) and [parse\\_constraint\\_call](#) for details.

[source](#)

**parse\_constraint\_call**

JuMP.parse\_constraint\_call - Function.

```
parse_constraint_call(
    error_fn::Function,
    is_vectorized::Bool,
    ::Val{op},
    args...,
)
```

Implement this method to intercept the parsing of a :call expression with operator op.

**Warning**

Extending the constraint macro at parse time is an advanced operation and has the potential to interfere with existing JuMP syntax. Please discuss with the [developer chatroom](#) before publishing any code that implements these methods.

**Arguments**

- `error_fn`: a function that accepts a String and throws the string as an error, along with some descriptive information of the macro from which it was thrown.
- `is_vectorized`: a boolean to indicate if `op` should be broadcast or not
- `op`: the first element of the `.args` field of the `Expr` to intercept
- `args...:` the `.args` field of the `Expr`.

**Returns**

This function must return:

- `parse_code::Expr`: an expression containing any setup or rewriting code that needs to be called before `build_constraint`
- `build_code::Expr`: an expression that calls `build_constraint()` or `build_constraint.( )` depending on `is_vectorized`.

See also: [parse\\_constraint\\_head](#), [build\\_constraint](#)

**source**

```
parse_constraint_call(
    error_fn::Function,
    vectorized::Bool,
    ::Val{op},
    lhs,
    rhs,
) where {op}
```

Fallback handler for binary operators. These might be infix operators like `@constraint(model, lhs op rhs)`, or normal operators like `@constraint(model, op(lhs, rhs))`.

In both cases, we rewrite as `lhs - rhs` in `operator_to_set(error_fn, op)`.

See [operator\\_to\\_set](#) for details.

[source](#)

### `parse_constraint_head`

JuMP.`parse_constraint_head` – Function.

```
parse_constraint_head(error_fn::Function, ::Val{head}, args...)
```

Implement this method to intercept the parsing of an expression with head `head`.

#### Warning

Extending the constraint macro at parse time is an advanced operation and has the potential to interfere with existing JuMP syntax. Please discuss with the [developer chatroom](#) before publishing any code that implements these methods.

#### Arguments

- `error_fn`: a function that accepts a String and throws the string as an error, along with some descriptive information of the macro from which it was thrown.
- `head`: the `.head` field of the `Expr` to intercept
- `args...`: the `.args` field of the `Expr`.

#### Returns

This function must return:

- `is_vectorized::Bool`: whether the expression represents a broadcasted expression like `x .<= 1`
- `parse_code::Expr`: an expression containing any setup or rewriting code that needs to be called before `build_constraint`
- `build_code::Expr`: an expression that calls `build_constraint()` or `build_constraint.(` depending on `is_vectorized`.

#### Existing implementations

JuMP currently implements:

- `::Val{:call}`, which forwards calls to [parse\\_constraint\\_call](#)
- `::Val{:comparison}`, which handles the special case of `l <= body <= u`.

See also: [parse\\_constraint\\_call](#), [build\\_constraint](#)

[source](#)

### `parse_one_operator_variable`

JuMP.`parse_one_operator_variable` – Function.

```
parse_one_operator_variable(
    error_fn::Function,
    info_expr::VariableInfoExpr,
    sense::Val{S},
    value,
) where {S}
```

Update infoexpr for a variable expression in the @variable macro of the form variable name S value.

`source`

### `parse_ternary_variable`

JuMP.parse\_ternary\_variable - Function.

```
parse_ternary_variable(error_fn, info_expr, lhs_sense, lhs, rhs_sense, rhs)
```

A hook for JuMP extensions to intercept the parsing of a :comparison expression, which has the form lhs lhs\_sense variable rhs\_sense rhs.

`source`

### `parse_variable`

JuMP.parse\_variable - Function.

```
parse_variable(error_fn::Function, ::VariableInfoExpr, args...)
```

A hook for extensions to intercept the parsing of inequality constraints in the `@variable` macro.

`source`

### `primal_feasibility_report`

JuMP.primal\_feasibility\_report - Function.

```
primal_feasibility_report(
    model::GenericModel{T},
    point::AbstractDict{GenericVariableRef{T},T} = _last_primal_solution(model),
    atol::T = zero(T),
    skip_missing::Bool = false,
)::Dict{Any,T}
```

Given a dictionary point, which maps variables to primal values, return a dictionary whose keys are the constraints with an infeasibility greater than the supplied tolerance atol. The value corresponding to each key is the respective infeasibility. Infeasibility is defined as the distance between the primal value of the constraint (see MOI.ConstraintPrimal) and the nearest point by Euclidean distance in the corresponding set.

### Notes

- If `skip_missing = true`, constraints containing variables that are not in `point` will be ignored.
- If `skip_missing = false` and a partial primal solution is provided, an error will be thrown.
- If no `point` is provided, the primal solution from the last time the model was solved is used.

**Example**

```
julia> model = Model();
julia> @variable(model, 0.5 <= x <= 1);
julia> primal_feasibility_report(model, Dict(x => 0.2))
Dict{Any, Float64} with 1 entry:
  x ≥ 0.5 => 0.3
```

`source`

```
primal_feasibility_report(
    point::Function,
    model::GenericModel{T};
    atol::T = zero(T),
    skip_missing::Bool = false,
) where {T}
```

A form of `primal_feasibility_report` where a function is passed as the first argument instead of a dictionary as the second argument.

**Example**

```
julia> model = Model();
julia> @variable(model, 0.5 <= x <= 1, start = 1.3);
julia> primal_feasibility_report(model) do v
           return start_value(v)
       end
Dict{Any, Float64} with 1 entry:
  x ≤ 1 => 0.3
```

`source`**primal\_status**

JuMP.primal\_status - Function.

```
primal_status(model::GenericModel; result::Int = 1)
```

Return a `MOI.ResultStatusCode` describing the status of the most recent primal solution of the solver (that is, the `MOI.PrimalStatus` attribute) associated with the result index `result`.

See also: `result_count`.

**Example**

```
julia> import Ipopt  
  
julia> model = Model(Ipopt.Optimizer);  
  
julia> primal_status(model; result = 2)  
NO_SOLUTION::ResultStatusCode = 0
```

source

**print\_active\_bridges**

JuMP.print\_active\_bridges – Function.

```
print_active_bridges([io::IO = stdout,] model::GenericModel)
```

Print a list of the variable, constraint, and objective bridges that are currently used in the model.

source

```
print_active_bridges([io::IO = stdout,] model::GenericModel, ::Type{F}) where {F}
```

Print a list of bridges required for an objective function of type F.

source

```
print_active_bridges(  
    [io::IO = stdout,]  
    model::GenericModel,  
    F::Type,  
    S::Type{<:MOI.AbstractSet},  
)
```

Print a list of bridges required for a constraint of type F-in-S.

source

```
print_active_bridges(  
    [io::IO = stdout,]  
    model::GenericModel,  
    S::Type{<:MOI.AbstractSet},  
)
```

Print a list of bridges required to add a variable constrained to the set S.

source

**print\_bridge\_graph**

JuMP.print\_bridge\_graph – Function.

```
print_bridge_graph([io::IO,] model::GenericModel)
```

Print the hyper-graph containing all variable, constraint, and objective types that could be obtained by bridging the variables, constraints, and objectives that are present in the model.

**Warning**

This function is intended for advanced users. If you want to see only the bridges that are currently used, use `print_active_bridges` instead.

**Explanation of output**

Each node in the hyper-graph corresponds to a variable, constraint, or objective type.

- Variable nodes are indicated by [ ]
- Constraint nodes are indicated by ( )
- Objective nodes are indicated by | |

The number inside each pair of brackets is an index of the node in the hyper-graph.

Note that this hyper-graph is the full list of possible transformations. When the bridged model is created, we select the shortest hyper-path(s) from this graph, so many nodes may be un-used.

For more information, see Legat, B., Dowson, O., Garcia, J., and Lubin, M. (2020). "MathOptInterface: a data structure for mathematical optimization problems." URL: <https://arxiv.org/abs/2002.03447>

`source`

**quad\_terms**

JuMP.quad\_terms – Function.

```
quad_terms(quad::GenericQuadExpr{C,V})
```

Provides an iterator over tuples (`coefficient::C, var_1::V, var_2::V`) in the quadratic part of the quadratic expression.

`source`

**raw\_status**

JuMP.raw\_status – Function.

```
raw_status(model::GenericModel)
```

Return the reason why the solver stopped in its own words (that is, the `MathOptInterface` model attribute `MOI.RawStatusString`).

### Example

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> raw_status(model)
"optimize not called"
```

`source`

`read_from_file`  
`JuMP.read_from_file` - Function.

```
read_from_file(
    filename::String;
    format::MOI.FileFormats.FileFormat = MOI.FileFormats FORMAT_AUTOMATIC,
    kwargs...,
)
```

Return a JuMP model read from `filename` in the format `format`.

If the `filename` ends in `.gz`, it will be uncompressed using GZip. If the `filename` ends in `.bz2`, it will be uncompressed using BZip2.

Other `kwargs` are passed to the `Model` constructor of the chosen format.

`source`

`reduced_cost`  
`JuMP.reduced_cost` - Function.

```
reduced_cost(x::GenericVariableRef{T})::T where {T}
```

Return the reduced cost associated with variable `x`.

One interpretation of the reduced cost is that it is the change in the objective from an infinitesimal relaxation of the variable bounds.

This method is equivalent to querying the shadow price of the active variable bound (if one exists and is active).

See also: [shadow\\_price](#).

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x <= 1);

julia> @objective(model, Max, 2 * x + 1);

julia> optimize!(model)

julia> has_duals(model)
true

julia> reduced_cost(x)
2.0
```

[source](#)

### relative\_gap

JuMP.relative\_gap - Function.

```
relative_gap(model::GenericModel)
```

Return the final relative optimality gap after a call to `optimize!(model)`.

Exact value depends upon implementation of `MOI.RelativeGap` by the particular solver used for optimization.

This function is equivalent to querying the `MOI.RelativeGap` attribute.

#### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 1, Int);

julia> @objective(model, Min, 2 * x + 1);

julia> optimize!(model)

julia> relative_gap(model)
0.0
```

[source](#)

**relax\_integrality**

JuMP.`relax_integrality` – Function.

```
relax_integrality(model::GenericModel)
```

Modifies model to "relax" all binary and integrality constraints on variables. Specifically,

- Binary constraints are deleted, and variable bounds are tightened if necessary to ensure the variable is constrained to the interval  $[0, 1]$ .
- Integrality constraints are deleted without modifying variable bounds.
- An error is thrown if semi-continuous or semi-integer constraints are present (support may be added for these in the future).
- All other constraints are ignored (left in place). This includes discrete constraints like SOS and indicator constraints.

Returns a function that can be called without any arguments to restore the original model. The behavior of this function is undefined if additional changes are made to the affected variables in the meantime.

**Example**

```
julia> model = Model();
julia> @variable(model, x, Bin);
julia> @variable(model, 1 <= y <= 10, Int);
julia> @objective(model, Min, x + y);
julia> undo_relax = relax_integrality(model);

julia> print(model)
Min x + y
Subject to
x ≥ 0
y ≥ 1
x ≤ 1
y ≤ 10

julia> undo_relax()

julia> print(model)
Min x + y
Subject to
y ≥ 1
y ≤ 10
y integer
x binary
```

[source](#)

**relax\_with\_penalty!**

JuMP.`relax_with_penalty!` – Function.

```
relax_with_penalty!
    model::GenericModel{T},
    [penalties::Dict{ConstraintRef,T}];
    [default::Union{Nothing,Real} = nothing,]
) where {T}
```

Destructively modify the model in-place to create a penalized relaxation of the constraints.

**Warning**

This is a destructive routine that modifies the model in-place. If you don't want to modify the original model, use `copy_model` to create a copy before calling `relax_with_penalty!`.

**Reformulation**

See `MOI.Utilities.ScalarPenaltyRelaxation` for details of the reformulation.

For each constraint  $c_i$ , the penalty passed to `MOI.Utilities.ScalarPenaltyRelaxation` is `get(penalties, ci, default)`. If the value is nothing, because  $c_i$  does not exist in `penalties` and `default = nothing`, then the constraint is skipped.

**Return value**

This function returns a `Dict{ConstraintRef,AffExpr}` that maps each constraint index to the corresponding  $y + z$  as an `AffExpr`. In an optimal solution, query the value of these functions to compute the violation of each constraint.

**Relax a subset of constraints**

To relax a subset of constraints, pass a `penalties` dictionary and set `default = nothing`.

**Example**

```
julia> function new_model()
    model = Model()
    @variable(model, x)
    @objective(model, Max, 2x + 1)
    @constraint(model, c1, 2x - 1 <= -2)
    @constraint(model, c2, 3x >= 0)
    return model
end
new_model (generic function with 1 method)

julia> model_1 = new_model();

julia> penalty_map = relax_with_penalty!(model_1; default = 2.0);

julia> penalty_map[model_1[:c1]]
_[3]

julia> penalty_map[model_1[:c2]]
_[2]
```

```

julia> print(model_1)
Max 2 x - 2 _[2] - 2 _[3] + 1
Subject to
c2 : 3 x + _[2] ≥ 0
c1 : 2 x - _[3] ≤ -1
_[2] ≥ 0
_[3] ≥ 0

julia> model_2 = new_model();

julia> relax_with_penalty!(model_2, Dict(model_2[:c2] => 3.0))
Dict{ConstraintRef{Model,
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64}},
    ↪ MathOptInterface.GreaterThan{Float64}}, ScalarShape}, AffExpr} with 1 entry:
c2 : 3 x + _[2] ≥ 0 => _[2]

julia> print(model_2)
Max 2 x - 3 _[2] + 1
Subject to
c2 : 3 x + _[2] ≥ 0
c1 : 2 x ≤ -1
_[2] ≥ 0

```

`source`**`remove_bridge`**JuMP.`remove_bridge` – Function.

```

remove_bridge(
    model::GenericModel{S},
    BT::Type{<:MOI.Bridges.AbstractBridge};
    coefficient_type::Type{T} = S,
) where {S,T}

```

Remove `BT{T}` from the list of bridges that can be used to transform unsupported constraints into an equivalent formulation using only constraints supported by the optimizer.

See also: [add\\_bridge](#).

**Example**

```

julia> model = Model();

julia> add_bridge(model, MOI.Bridges.Constraint.SOCToNonConvexQuadBridge)

julia> remove_bridge(model, MOI.Bridges.Constraint.SOCToNonConvexQuadBridge)

julia> add_bridge(
        model,
        MOI.Bridges.Constraint.NumberConversionBridge;
        coefficient_type = Complex{Float64},

```

```

)
julia> remove_bridge(
    model,
    MOI.Bridges.Constraint.NumberConversionBridge;
    coefficient_type = Complex{Float64},
)

```

[source](#)**reshape\_set**

JuMP.reshape\_set - Function.

```
reshape_set(vectorized_set::MOI.AbstractSet, shape::AbstractShape)
```

Return a set in its original shape `shape` given its vectorized form `vectorized_form`.

**Example**

Given a `SymmetricMatrixShape` of vectorized form [1, 2, 3] in `MOI.PositiveSemidefiniteConeTriangle(2)`, the following code returns the set of the original constraint `Symmetric(Matrix[1 2; 2 3])` in `PSDCones()`:

```
julia> reshape_set(MOI.PositiveSemidefiniteConeTriangle(2), SymmetricMatrixShape(2))
PSDCones()
```

[source](#)**reshape\_vector**

JuMP.reshape\_vector - Function.

```
reshape_vector(vectorized_form::Vector, shape::AbstractShape)
```

Return an object in its original shape `shape` given its vectorized form `vectorized_form`.

**Example**

Given a `SymmetricMatrixShape` of vectorized form [1, 2, 3], the following code returns the matrix `Symmetric(Matrix[1 2; 2 3])`:

```
julia> reshape_vector([1, 2, 3], SymmetricMatrixShape(2))
2×2 LinearAlgebra.Symmetric{Int64, Matrix{Int64}}:
 1  2
 2  3
```

[source](#)

**result\_count**

JuMP.result\_count - Function.

```
result_count(model::GenericModel)
```

Return the number of results available to query after a call to [optimize!](#).

**Example**

```
julia> import Ipopt
julia> model = Model(Ipopt.Optimizer);
julia> result_count(model)
0
```

[source](#)

**reverse\_sense**

JuMP.reverse\_sense - Function.

```
reverse_sense(::Val{T}) where {T}
```

Given an (in)equality symbol T, return a new Val object with the opposite (in)equality symbol.

This function is intended for use in JuMP extensions.

**Example**

```
julia> reverse_sense(Val(:>=))
Val{:<=}()
```

[source](#)

**set\_attribute**

JuMP.set\_attribute - Function.

```
set_attribute(model::GenericModel, attr::MOI.AbstractModelAttribute, value)
set_attribute(x::GenericVariableRef, attr::MOI.AbstractVariableAttribute, value)
set_attribute(cr::ConstraintRef, attr::MOI.AbstractConstraintAttribute, value)
```

Set the value of a solver-specific attribute attr to value.

This is equivalent to calling [MOI.set](#) with the associated MOI model and, for variables and constraints, with the associated [MOI.VariableIndex](#) or [MOI.ConstraintIndex](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @constraint(model, c, 2 * x <= 1)
c : 2 x ≤ 1

julia> set_attribute(model, MOI.Name(), "model_new")

julia> set_attribute(x, MOI.VariableName(), "x_new")

julia> set_attribute(c, MOI.ConstraintName(), "c_new")
```

**source**

```
set_attribute(
    model::Union{GenericModel,MOI.OptimizerWithAttributes},
    attr::Union{AbstractString,MOI.AbstractOptimizerAttribute},
    value,
)
```

Set the value of a solver-specific attribute `attr` to `value`.

This is equivalent to calling `MOI.set` with the associated MOI model.

If `attr` is an `AbstractString`, it is converted to `MOI.RawOptimizerAttribute`.

### Example

```
julia> import HiGHS

julia> opt = optimizer_with_attributes(HiGHS.Optimizer, "output_flag" => false);

julia> model = Model(opt);

julia> set_attribute(model, "output_flag", false)

julia> set_attribute(model, MOI.RawOptimizerAttribute("output_flag"), true)

julia> set_attribute(opt, "output_flag", true)

julia> set_attribute(opt, MOI.RawOptimizerAttribute("output_flag"), false)
```

**source**

### `set_attributes`

JuMP.`set_attributes` – Function.

```
set_attributes(
    destination::Union{
```

```

    GenericModel,
    MOI.OptimizerWithAttributes,
    GenericVariableRef,
    ConstraintRef,
),
pairs::Pair...,
)

```

Given a list of attribute => value pairs, calls `set_attribute(destination, attribute, value)` for each pair.

See also: [set\\_attribute](#), [get\\_attribute](#).

### Example

```

julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> set_attributes(model, "tol" => 1e-4, "max_iter" => 100)

```

is equivalent to:

```

julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> set_attribute(model, "tol", 1e-4)

julia> set_attribute(model, "max_iter", 100)

```

`source`

### set\_binary

JuMP.set\_binary – Function.

```
set_binary(v::GenericVariableRef)
```

Add a constraint on the variable `v` that it must take values in the set  $\{0, 1\}$ .

See also [BinaryRef](#), [is\\_binary](#), [unset\\_binary](#).

### Example

```

julia> model = Model();

julia> @variable(model, x);

julia> is_binary(x)
false

```

```
julia> set_binary(x)
```

```
julia> is_binary(x)
true
```

[source](#)

### set\_dual\_start\_value

JuMP.set\_dual\_start\_value - Function.

```
set_dual_start_value(con_ref::ConstraintRef, value)
```

Set the dual start value (MOI attribute ConstraintDualStart) of the constraint con\_ref to value.

To remove a dual start value set it to nothing.

See also [dual\\_start\\_value](#).

#### Example

```
julia> model = Model();

julia> @variable(model, x, start = 2.0);

julia> @constraint(model, c, [2x] in Nonnegatives())
c : [2 x] ∈ Nonnegatives()

julia> set_dual_start_value(c, [0.0])

julia> dual_start_value(c)
1-element Vector{Float64}:
 0.0

julia> set_dual_start_value(c, nothing)

julia> dual_start_value(c)
```

[source](#)

### set\_integer

JuMP.set\_integer - Function.

```
set_integer(variable_ref::GenericVariableRef)
```

Add an integrality constraint on the variable variable\_ref.

See also [IntegerRef](#), [is\\_integer](#), [unset\\_integer](#).

#### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> is_integer(x)
false

julia> set_integer(x)

julia> is_integer(x)
true
```

`source`

### `set_lower_bound`

JuMP.`set_lower_bound` – Function.

```
set_lower_bound(v::GenericVariableRef, lower::Number)
```

Set the lower bound of a variable. If one does not exist, create a new lower bound constraint.

See also [LowerBoundRef](#), [has\\_lower\\_bound](#), [lower\\_bound](#), [delete\\_lower\\_bound](#).

### **Example**

```
julia> model = Model();

julia> @variable(model, x >= 1.0);

julia> lower_bound(x)
1.0

julia> set_lower_bound(x, 2.0)

julia> lower_bound(x)
2.0
```

`source`

### `set_name`

JuMP.`set_name` – Function.

```
set_name(con_ref::ConstraintRef, s::AbstractString)
```

Set a constraint's name attribute.

### **Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, c, [2x] in Nonnegatives())
c : [2 x] ∈ Nonnegatives()

julia> set_name(c, "my_constraint")

julia> name(c)
"my_constraint"

julia> c
my_constraint : [2 x] ∈ Nonnegatives()
```

**source**

```
set_name(v::GenericVariableRef, s::AbstractString)
```

Set a variable's name attribute.

### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> set_name(x, "x_foo")

julia> x
x_foo

julia> name(x)
"x_foo"
```

**source**

### `set_normalized_coefficient`

JuMP.`set_normalized_coefficient` – Function.

```
set_normalized_coefficient(
    constraint::ConstraintRef,
    variable::GenericVariableRef,
    value::Number,
)
```

Set the coefficient of variable in the constraint constraint to value.

Note that prior to this step, JuMP will aggregate multiple terms containing the same variable. For example, given a constraint  $2x + 3x \leq 2$ , `set_normalized_coefficient(con, x, 4)` will create the constraint  $4x \leq 2$ .

### Example

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @constraint(model, con, 2x + 3x <= 2)
con : 5 x ≤ 2

julia> set_normalized_coefficient(con, x, 4)

julia> con
con : 4 x ≤ 2
```

`source`

```
set_normalized_coefficient(
    constraints::AbstractVector{<:ConstraintRef},
    variables::AbstractVector{<:GenericVariableRef},
    values::AbstractVector{<:Number},
)
```

Set multiple coefficient of variables in the constraints constraints to values.

Note that prior to this step, JuMP will aggregate multiple terms containing the same variable. For example, given a constraint  $2x + 3x \leq 2$ , `set_normalized_coefficient(con, [x], [4])` will create the constraint  $4x \leq 2$ .

### Example

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> @constraint(model, con, 2x + 3x + 4y <= 2)
con : 5 x + 4 y ≤ 2

julia> set_normalized_coefficient([con, con], [x, y], [6, 7])

julia> con
con : 6 x + 7 y ≤ 2
```

`source`

```
set_normalized_coefficient(
    con_ref::ConstraintRef,
    variable::AbstractVariableRef,
    new_coefficients::Vector{Tuple{Int64,T}},
)
```

Set the coefficients of `variable` in the constraint `con_ref` to `new_coefficients`, where each element in `new_coefficients` is a tuple which maps the row to a new coefficient.

Note that prior to this step, during constraint creation, JuMP will aggregate multiple terms containing the same variable.

### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @constraint(model, con, [2x + 3x, 4x] in MOI.Nonnegatives(2))
con : [5 x, 4 x] ∈ MathOptInterface.Nonnegatives(2)

julia> set_normalized_coefficient(con, x, [(1, 2.0), (2, 5.0)])

julia> con
con : [2 x, 5 x] ∈ MathOptInterface.Nonnegatives(2)
```

`source`

```
set_normalized_coefficient(
    constraint::ConstraintRef,
    variable_1::GenericVariableRef,
    variable_2::GenericVariableRef,
    value::Number,
)
```

Set the quadratic coefficient associated with `variable_1` and `variable_2` in the constraint `constraint` to `value`.

Note that prior to this step, JuMP will aggregate multiple terms containing the same variable. For example, given a constraint  $2x^2 + 3x^2 \leq 2$ , `set_normalized_coefficient(con, x, 4)` will create the constraint  $4x^2 \leq 2$ .

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @constraint(model, con, 2x[1]^2 + 3 * x[1] * x[2] + x[2] <= 2)
con : 2 x[1]^2 + 3 x[1]*x[2] + x[2] ≤ 2

julia> set_normalized_coefficient(con, x[1], x[1], 4)
```

```
julia> set_normalized_coefficient(con, x[1], x[2], 5)

julia> con
con : 4 x[1]^2 + 5 x[1]*x[2] + x[2] ≤ 2
```

`source`

```
set_normalized_coefficient(
    constraints::AbstractVector{<:ConstraintRef},
    variables_1::AbstractVector{<:GenericVariableRef},
    variables_2::AbstractVector{<:GenericVariableRef},
    values::AbstractVector{<:Number},
)
```

Set multiple quadratic coefficients associated with `variables_1` and `variables_2` in the constraints `constraints` to `values`.

Note that prior to this step, JuMP will aggregate multiple terms containing the same variable. For example, given a constraint  $2x^2 + 3x^2 \leq 2$ , `set_normalized_coefficient(con, [x], [x], [4])` will create the constraint  $4x^2 \leq 2$ .

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @constraint(model, con, 2x[1]^2 + 3 * x[1] * x[2] + x[2] ≤ 2)
con : 2 x[1]^2 + 3 x[1]*x[2] + x[2] ≤ 2

julia> set_normalized_coefficient([con, con], [x[1], x[1]], [x[1], x[2]], [4, 5])

julia> con
con : 4 x[1]^2 + 5 x[1]*x[2] + x[2] ≤ 2
```

`source`

### set\_normalized\_rhs

JuMP.`set_normalized_rhs` – Function.

```
set_normalized_rhs(constraint::ConstraintRef, value::Number)
```

Set the right-hand side term of `constraint` to `value`.

Note that prior to this step, JuMP will aggregate all constant terms onto the right-hand side of the constraint. For example, given a constraint  $2x + 1 \leq 2$ , `set_normalized_rhs(con, 4)` will create the constraint  $2x \leq 4$ , not  $2x + 1 \leq 4$ .

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, con, 2x + 1 <= 2)
con : 2 x ≤ 1

julia> set_normalized_rhs(con, 4)

julia> con
con : 2 x ≤ 4
```

```
source

set_normalized_rhs(
    constraints::AbstractVector{<:ConstraintRef},
    values::AbstractVector{<:Number}
)
```

Set the right-hand side terms of all constraints to values.

Note that prior to this step, JuMP will aggregate all constant terms onto the right-hand side of the constraint. For example, given a constraint  $2x + 1 \leq 2$ , `set_normalized_rhs([con], [4])` will create the constraint  $2x \leq 4$ , not  $2x + 1 \leq 4$ .

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, con1, 2x + 1 <= 2)
con1 : 2 x ≤ 1

julia> @constraint(model, con2, 3x + 2 <= 4)
con2 : 3 x ≤ 2

julia> set_normalized_rhs([con1, con2], [4, 5])

julia> con1
con1 : 2 x ≤ 4

julia> con2
con2 : 3 x ≤ 5
```

```
source

set_objective

JuMP.set_objective - Function.
```

```
set_objective(model::AbstractModel, sense::MOI.OptimizationSense, func)
```

The functional equivalent of the `@objective` macro.

Sets the objective sense and objective function simultaneously, and is equivalent to calling `set_objective_sense` and `set_objective_function` separately.

### Example

```
julia> model = Model();
julia> @variable(model, x)
x
julia> set_objective(model, MIN_SENSE, x)
```

`source`

### set\_objective\_coefficient

JuMP.set\_objective\_coefficient - Function.

```
set_objective_coefficient(
    model::GenericModel,
    variable::GenericVariableRef,
    coefficient::Real,
)
```

Set the linear objective coefficient associated with `variable` to `coefficient`.

Note: this function will throw an error if a nonlinear objective is set.

### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> @objective(model, Min, 2x + 1)
2 x + 1
julia> set_objective_coefficient(model, x, 3)
julia> objective_function(model)
3 x + 1
```

`source`

```
set_objective_coefficient(
    model::GenericModel,
    variables::Vector{<:GenericVariableRef},
    coefficients::Vector{<:Real},
)
```

Set multiple linear objective coefficients associated with variables to coefficients, in a single call.

Note: this function will throw an error if a nonlinear objective is set.

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @variable(model, y);

julia> @objective(model, Min, 3x + 2y + 1)
3 x + 2 y + 1

julia> set_objective_coefficient(model, [x, y], [5, 4])

julia> objective_function(model)
5 x + 4 y + 1
```

### source

```
set_objective_coefficient(
    model::GenericModel{T},
    variable_1::GenericVariableRef{T},
    variable_2::GenericVariableRef{T},
    coefficient::Real,
) where {T}
```

Set the quadratic objective coefficient associated with variable\_1 and variable\_2 to coefficient.

Note: this function will throw an error if a nonlinear objective is set.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @objective(model, Min, x[1]^2 + x[1] * x[2])
x[1]^2 + x[1]*x[2]

julia> set_objective_coefficient(model, x[1], x[1], 2)

julia> set_objective_coefficient(model, x[1], x[2], 3)

julia> objective_function(model)
2 x[1]^2 + 3 x[1]*x[2]
```

```
source
```

```
set_objective_coefficient(
    model::GenericModel{T},
    variables_1::AbstractVector{<:GenericVariableRef{T}},
    variables_2::AbstractVector{<:GenericVariableRef{T}},
    coefficients::AbstractVector{<:Real},
) where {T}
```

Set multiple quadratic objective coefficients associated with `variables_1` and `variables_2` to `coefficients`, in a single call.

Note: this function will throw an error if a nonlinear objective is set.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @objective(model, Min, x[1]^2 + x[1] * x[2])
x[1]^2 + x[1]*x[2]

julia> set_objective_coefficient(model, [x[1], x[1]], [x[1], x[2]], [2, 3])

julia> objective_function(model)
2 x[1]^2 + 3 x[1]*x[2]
```

```
source
```

### set\_objective\_function

JuMP.set\_objective\_function - Function.

```
set_objective_function(model::GenericModel, func::MOI.AbstractFunction)
set_objective_function(model::GenericModel, func::AbstractJuMPScalar)
set_objective_function(model::GenericModel, func::Real)
set_objective_function(model::GenericModel, func::Vector{<:AbstractJuMPScalar})
```

Sets the objective function of the model to the given function.

See `set_objective_sense` to set the objective sense.

These are low-level functions; the recommended way to set the objective is with the `@objective` macro.

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @objective(model, Min, x);
```

```
julia> objective_function(model)
x

julia> set_objective_function(model, 2 * x + 1)

julia> objective_function(model)
2 x + 1
```

[source](#)**set\_objective\_sense**

JuMP.set\_objective\_sense – Function.

```
set_objective_sense(model::GenericModel, sense::MOI.OptimizationSense)
```

Sets the objective sense of the model to the given sense.

See [set\\_objective\\_function](#) to set the objective function.

These are low-level functions; the recommended way to set the objective is with the [@objective](#) macro.

**Example**

```
julia> model = Model();

julia> objective_sense(model)
FEASIBILITY_SENSE::OptimizationSense = 2

julia> set_objective_sense(model, MOI.MAX_SENSE)

julia> objective_sense(model)
MAX_SENSE::OptimizationSense = 1
```

[source](#)**set\_optimize\_hook**

JuMP.set\_optimize\_hook – Function.

```
set_optimize_hook(model::GenericModel, f::Union{Function,Nothing})
```

Set the function `f` as the optimize hook for `model`.

`f` should have a signature `f(model::GenericModel; kwargs...)`, where the `kwargs` are those passed to [optimize!](#).

**Notes**

- The optimize hook should generally modify the model, or some external state in some way, and then call `optimize!(model; ignore_optimize_hook = true)` to optimize the problem, bypassing the hook.

- Use `set_optimize_hook(model, nothing)` to unset an optimize hook.

### Example

```
julia> model = Model();

julia> function my_hook(model::Model; kwargs...)
    println(kwargs)
    println("Calling with `ignore_optimize_hook = true`")
    optimize!(model; ignore_optimize_hook = true)
    return
end
my_hook (generic function with 1 method)

julia> set_optimize_hook(model, my_hook)
my_hook (generic function with 1 method)

julia> optimize!(model; test_arg = true)
Base.Pairs{Symbol, Bool, Tuple{Symbol}, @NamedTuple{test_arg::Bool}}(:test_arg => 1)
Calling with `ignore_optimize_hook = true`
ERROR: NoOptimizer()
[...]
```

[source](#)

### set\_optimizer

JuMP.set\_optimizer - Function.

```
set_optimizer(
    model::GenericModel,
    optimizer_factory;
    add_bridges::Bool = true,
)
```

Creates an empty `MathOptInterface.AbstractOptimizer` instance by calling `optimizer_factory()` and sets it as the optimizer of `model`. Specifically, `optimizer_factory` must be callable with zero arguments and return an empty `MathOptInterface.AbstractOptimizer`.

If `add_bridges` is true, constraints and objectives that are not supported by the optimizer are automatically bridged to equivalent supported formulation. Passing `add_bridges = false` can improve performance if the solver natively supports all of the elements in `model`.

See [set\\_attribute](#) for setting solver-specific parameters of the optimizer.

### Example

```
julia> import HiGHS

julia> model = Model();

julia> set_optimizer(model, () -> HiGHS.Optimizer())

julia> set_optimizer(model, HiGHS.Optimizer; add_bridges = false)
```

[source](#)

### set\_parameter\_value

JuMP.set\_parameter\_value - Function.

```
set_parameter_value(x::GenericVariableRef, value)
```

Update the parameter constraint on the variable x to value.

Errors if x is not a parameter.

See also [ParameterRef](#), [is\\_parameter](#), [parameter\\_value](#).

#### Example

```
julia> model = Model();

julia> @variable(model, p in Parameter(2))
p

julia> parameter_value(p)
2.0

julia> set_parameter_value(p, 2.5)

julia> parameter_value(p)
2.5
```

[source](#)

### set\_silent

JuMP.set\_silent - Function.

```
set_silent(model::GenericModel)
```

Takes precedence over any other attribute controlling verbosity and requires the solver to produce no output.

See also: [unset\\_silent](#).

#### Example

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> set_silent(model)

julia> get_attribute(model, MOI.Silent())
true
```

```
julia> unset_silent(model)

julia> get_attribute(model, MOI.Silent())
false
```

[source](#)

### **set\_start\_value**

JuMP.set\_start\_value - Function.

```
set_start_value(con_ref::ConstraintRef, value)
```

Set the primal start value ([MOI.ConstraintPrimalStart](#)) of the constraint `con_ref` to `value`.

To remove a primal start value set it to nothing.

See also [start\\_value](#).

#### **Example**

```
julia> model = Model();

julia> @variable(model, x, start = 2.0);

julia> @constraint(model, c, [2x] in Nonnegatives())
c : [2 x] ∈ Nonnegatives()

julia> set_start_value(c, [4.0])

julia> start_value(c)
1-element Vector{Float64}:
 4.0

julia> set_start_value(c, nothing)

julia> start_value(c)
```

[source](#)

```
set_start_value(variable::GenericVariableRef, value::Union{Real,Nothing})
```

Set the start value ([MOI.VariablePrimalStart](#)) of the variable to `value`.

Pass nothing to unset the start value.

Note: VariablePrimalStarts are sometimes called "MIP-starts" or "warmstarts".

See also: [has\\_start\\_value](#), [start\\_value](#).

#### **Example**

```
julia> model = Model();

julia> @variable(model, x, start = 1.5);

julia> @variable(model, y);

julia> has_start_value(x)
true

julia> has_start_value(y)
false

julia> start_value(x)
1.5

julia> set_start_value(x, nothing)

julia> has_start_value(x)
false

julia> set_start_value(y, 2.0)

julia> has_start_value(y)
true

julia> start_value(y)
2.0
```

[source](#)

### `set_start_values`

JuMP.`set_start_values` – Function.

```
set_start_values(
    model::GenericModel;
    variable_primal_start::Union{Nothing,Function} = value,
    constraint_primal_start::Union{Nothing,Function} = value,
    constraint_dual_start::Union{Nothing,Function} = dual,
    nonlinear_dual_start::Union{Nothing,Function} = nonlinear_dual_start_value,
)
```

Set the primal and dual starting values in `model` using the functions provided.

If any keyword argument is `nothing`, the corresponding start value is skipped.

If the optimizer does not support setting the starting value, the value will be skipped.

#### `variable_primal_start`

This function controls the primal starting solution for the variables. It is equivalent to calling `set_start_value` for each variable, or setting the `MOI.VariablePrimalStart` attribute.

If it is a function, it must have the form `variable_primal_start(x::VariableRef)` that maps each variable `x` to the starting primal value.

The default is `value`.

#### **constraint\_primal\_start**

This function controls the primal starting solution for the constraints. It is equivalent to calling `set_start_value` for each constraint, or setting the `MOI.ConstraintPrimalStart` attribute.

If it is a function, it must have the form `constraint_primal_start(ci::ConstraintRef)` that maps each constraint `ci` to the starting primal value.

The default is `value`.

#### **constraint\_dual\_start**

This function controls the dual starting solution for the constraints. It is equivalent to calling `set_dual_start_value` for each constraint, or setting the `MOI.ConstraintDualStart` attribute.

If it is a function, it must have the form `constraint_dual_start(ci::ConstraintRef)` that maps each constraint `ci` to the starting dual value.

The default is `dual`.

#### **nonlinear\_dual\_start**

This function controls the dual starting solution for the nonlinear constraints. It is equivalent to calling `set_nonlinear_dual_start_value`.

If it is a function, it must have the form `nonlinear_dual_start(model::GenericModel)` that returns a vector corresponding to the dual start of the constraints.

The default is `nonlinear_dual_start_value`.

#### **source**

#### **set\_string\_names\_on\_creation**

JuMP.`set_string_names_on_creation` - Function.

```
set_string_names_on_creation(model::GenericModel, value::Bool)
```

Set the default argument of the `set_string_name` keyword in the `@variable` and `@constraint` macros to `value`.

The `set_string_name` keyword is used to determine whether to assign String names to all variables and constraints in `model`.

By default, `value` is true. However, for larger models calling `set_string_names_on_creation(model, false)` can improve performance at the cost of reducing the readability of printing and solver log messages.

#### **Example**

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_string_names_on_creation(model)
true

julia> set_string_names_on_creation(model, false)
```

```
julia> set_string_names_on_creation(model)
false
```

[source](#)

### set\_time\_limit\_sec

JuMP.set\_time\_limit\_sec - Function.

```
set_time_limit_sec(model::GenericModel, limit::Float64)
```

Set the time limit (in seconds) of the solver.

Can be unset using `unset_time_limit_sec` or with `limit` set to nothing.

See also: `unset_time_limit_sec`, `time_limit_sec`.

#### Example

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> time_limit_sec(model)

julia> set_time_limit_sec(model, 60.0)

julia> time_limit_sec(model)
60.0

julia> unset_time_limit_sec(model)

julia> time_limit_sec(model)
```

[source](#)

### set\_upper\_bound

JuMP.set\_upper\_bound - Function.

```
set_upper_bound(v::GenericVariableRef, upper::Number)
```

Set the upper bound of a variable. If one does not exist, create an upper bound constraint.

See also `UpperBoundRef`, `has_upper_bound`, `upper_bound`, `delete_upper_bound`.

#### Example

```
julia> model = Model();
julia> @variable(model, x <= 1.0);
julia> upper_bound(x)
1.0
julia> set_upper_bound(x, 2.0)
julia> upper_bound(x)
2.0
```

[source](#)

### shadow\_price

JuMP.shadow\_price – Function.

```
shadow_price(con_ref::ConstraintRef)
```

Return the change in the objective from an infinitesimal relaxation of the constraint.

The shadow price is computed from `dual` and can be queried only when `has_duals` is true and the objective sense is `MIN_SENSE` or `MAX_SENSE` (not `FEASIBILITY_SENSE`).

See also `reduced_cost`.

#### Comparison to dual

The shadow prices differ at most in sign from the dual value depending on the objective sense. The differences are summarized in the table:

|               | Min | Max |
|---------------|-----|-----|
| $f(x) \leq b$ | +1  | -1  |
| $f(x) \geq b$ | -1  | +1  |

#### Notes

- The function simply translates signs from `dual` and does not validate the conditions needed to guarantee the sensitivity interpretation of the shadow price. The caller is responsible, for example, for checking whether the solver converged to an optimal primal-dual pair or a proof of infeasibility.
- The computation is based on the current objective sense of the model. If this has changed since the last solve, the results will be incorrect.
- Relaxation of equality constraints (and hence the shadow price) is defined based on which sense of the equality constraint is active.

#### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x);

julia> @constraint(model, c, x <= 1)
c : x ≤ 1

julia> @objective(model, Max, 2 * x + 1);

julia> optimize!(model)

julia> has_duals(model)
true

julia> shadow_price(c)
2.0
```

**source****shape**

JuMP.shape – Function.

```
shape(c::AbstractConstraint)::AbstractShape
```

Return the shape of the constraint c.

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> c = @constraint(model, x[2] <= 1);

julia> shape(constraint_object(c))
ScalarShape()

julia> d = @constraint(model, x in SOS1());

julia> shape(constraint_object(d))
VectorShape()
```

**source****show\_backend\_summary**

JuMP.show\_backend\_summary – Function.

```
show_backend_summary(io::IO, model::GenericModel)
```

Print a summary of the optimizer backing model.

### Extensions

AbstractModels should implement this method.

### Example

```
julia> model = Model();

julia> show_backend_summary(stdout, model)
Model mode: AUTOMATIC
CachingOptimizer state: NO_OPTIMIZER
Solver name: No optimizer attached.
```

[source](#)

### show\_constraints\_summary

JuMP.show\_constraints\_summary - Function.

```
show_constraints_summary(io::IO, model::AbstractModel)
```

Write to io a summary of the number of constraints.

### Extensions

AbstractModels should implement this method.

### Example

```
julia> model = Model();

julia> @variable(model, x >= 0);

julia> show_constraints_summary(stdout, model)
`VariableRef`-in-`MathOptInterface.GreaterThan{Float64}`: 1 constraint
```

[source](#)

### show\_objective\_function\_summary

JuMP.show\_objective\_function\_summary - Function.

```
show_objective_function_summary(io::IO, model::AbstractModel)
```

Write to io a summary of the objective function type.

**Extensions**

AbstractModels should implement this method.

**Example**

```
julia> model = Model();
julia> show_objective_function_summary(stdout, model)
Objective function type: AffExpr
```

[source](#)

**simplex\_iterations**

JuMP.simplex\_iterations – Function.

```
simplex_iterations(model::GenericModel)
```

If available, returns the cumulative number of simplex iterations during the most-recent optimization (the `MOI.SimplexIterations` attribute).

Throws a `MOI.GetAttributeNotAllowed` error if the attribute is not implemented by the solver.

**Example**

```
julia> import HiGHS
julia> model = Model(HiGHS.Optimizer);
julia> set_silent(model)
julia> optimize!(model)
julia> simplex_iterations(model)
0
```

[source](#)

**solution\_summary**

JuMP.solution\_summary – Function.

```
solution_summary(model::GenericModel; result::Int = 1, verbose::Bool = false)
```

Return a struct that can be used print a summary of the solution in result `result`.

If `verbose=true`, write out the primal solution for every variable and the dual solution for every constraint, excluding those with empty names.

**Example**

When called at the REPL, the summary is automatically printed:

```
julia> model = Model();

julia> solution_summary(model)
* Solver : No optimizer attached.

* Status
  Result count      : 0
  Termination status : OPTIMIZE_NOT_CALLED
  Message from the solver:
    "optimize not called"

* Candidate solution (result #1)
  Primal status      : NO_SOLUTION
  Dual status        : NO_SOLUTION

* Work counters
```

Use `print` to force the printing of the summary from inside a function:

```
julia> model = Model();

julia> function foo(model)
           print(solution_summary(model))
           return
       end
foo (generic function with 1 method)

julia> foo(model)
* Solver : No optimizer attached.

* Status
  Result count      : 0
  Termination status : OPTIMIZE_NOT_CALLED
  Message from the solver:
    "optimize not called"

* Candidate solution (result #1)
  Primal status      : NO_SOLUTION
  Dual status        : NO_SOLUTION

* Work counters
```

`source`

### solve\_time

`JuMP.solve_time` – Function.

```
solve_time(model::GenericModel)
```

If available, returns the solve time in wall-clock seconds reported by the solver (the `MOI.SolveTimeSec` attribute).

Throws a `MOI.GetAttributeNotAllowed` error if the attribute is not implemented by the solver.

### Example

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> optimize!(model)

julia> solve_time(model)
1.0488089174032211e-5
```

[source](#)

### solver\_name

`JuMP.solver_name` – Function.

```
solver_name(model::GenericModel)
```

If available, returns the `MOI.SolverName` property of the underlying optimizer.

Returns "No optimizer attached." in AUTOMATIC or MANUAL modes when no optimizer is attached.

Returns "SolverName() attribute not implemented by the optimizer." if the attribute is not implemented.

### Example

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> solver_name(model)
"Ipopt"

julia> model = Model();

julia> solver_name(model)
"No optimizer attached."

julia> model = Model(MOI.FileFormats.MPS.Model);

julia> solver_name(model)
"SolverName() attribute not implemented by the optimizer."
```

[source](#)

**start\_value**

JuMP.start\_value – Function.

```
start_value(con_ref::ConstraintRef)
```

Return the primal start value ([MOI.ConstraintPrimalStart](#)) of the constraint `con_ref`.

If no primal start value has been set, `start_value` will return nothing.

See also [set\\_start\\_value](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x, start = 2.0);

julia> @constraint(model, c, [2x] in Nonnegatives())
c : [2 x] ∈ Nonnegatives()

julia> set_start_value(c, [4.0])

julia> start_value(c)
1-element Vector{Float64}:
 4.0

julia> set_start_value(c, nothing)

julia> start_value(c)
```

**source**

```
start_value(v::GenericVariableRef)
```

Return the start value ([MOI.VariablePrimalStart](#)) of the variable `v`.

Note: VariablePrimalStarts are sometimes called "MIP-starts" or "warmstarts".

See also: [has\\_start\\_value](#), [set\\_start\\_value](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x, start = 1.5);

julia> @variable(model, y);

julia> has_start_value(x)
true

julia> has_start_value(y)
false
```

```
julia> start_value(x)
1.5

julia> set_start_value(y, 2.0)

julia> has_start_value(y)
true

julia> start_value(y)
2.0
```

[source](#)

### termination\_status

JuMP.termination\_status - Function.

```
termination_status(model::GenericModel)
```

Return a [MOI.TerminationStatusCode](#) describing why the solver stopped (that is, the [MOI.TerminationStatus](#) attribute).

#### Example

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> termination_status(model)
OPTIMIZE_NOT_CALLED::TerminationStatusCode = 0
```

[source](#)

### time\_limit\_sec

JuMP.time\_limit\_sec - Function.

```
time_limit_sec(model::GenericModel)
```

Return the time limit (in seconds) of the model.

Returns nothing if unset.

See also: [set\\_time\\_limit\\_sec](#), [unset\\_time\\_limit\\_sec](#).

#### Example

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> time_limit_sec(model)

julia> set_time_limit_sec(model, 60.0)

julia> time_limit_sec(model)
60.0

julia> unset_time_limit_sec(model)

julia> time_limit_sec(model)
```

**source****triangle\_vec**

JuMP.triangle\_vec – Function.

```
triangle_vec(matrix::Matrix)
```

Return the upper triangle of a matrix concatenated into a vector in the order required by JuMP and MathOptInterface for Triangle sets.

**Example**

```
julia> model = Model();

julia> @variable(model, X[1:3, 1:3], Symmetric);

julia> @variable(model, t)
t

julia> @constraint(model, [t; triangle_vec(X)] in MOI.RootDetConeTriangle(3))
[t, X[1,1], X[1,2], X[2,2], X[1,3], X[2,3], X[3,3]] ∈ MathOptInterface.RootDetConeTriangle(3)
```

**source****unfix**

JuMP.unfix – Function.

```
unfix(v::GenericVariableRef)
```

Delete the fixing constraint of a variable.

Error if one does not exist.

See also [FixRef](#), [is\\_fixed](#), [fix\\_value](#), [fix](#).

### Example

```
julia> model = Model();

julia> @variable(model, x == 1);

julia> is_fixed(x)
true

julia> unfix(x)

julia> is_fixed(x)
false
```

[source](#)

### unregister

JuMP.unregister – Function.

```
unregister(model::GenericModel, key::Symbol)
```

Unregister the name key from model so that a new variable, constraint, or expression can be created with the same key.

Note that this will not delete the object model[key]; it will just remove the reference at model[key]. To delete the object, use [delete](#) as well.

See also: [delete](#), [object\\_dictionary](#).

### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, x)
ERROR: An object of name x is already attached to this model. If this
      is intended, consider using the anonymous construction syntax, for example,
      `x = @variable(model, [1:N], ...)` where the name of the object does
      not appear inside the macro.

Alternatively, use `unregister(model, :x)` to first unregister
the existing name from the model. Note that this will not delete the
object; it will just remove the reference at `model[:x]`.

Stacktrace:
[...]

julia> num_variables(model)
1
```

```
julia> unregister(model, :x)

julia> @variable(model, x)
x

julia> num_variables(model)
2
```

[source](#)

### unsafe\_backend

JuMP.unsafe\_backend – Function.

```
unsafe_backend(model::GenericModel)
```

Return the innermost optimizer associated with the JuMP model `model`.

**This function should only be used by advanced users looking to access low-level solver-specific functionality. It has a high-risk of incorrect usage. We strongly suggest you use the alternative suggested below.**

See also: [backend](#).

To obtain the index of a variable or constraint in the unsafe backend, use [optimizer\\_index](#).

### Unsafe behavior

This function is unsafe for two main reasons.

First, the formulation and order of variables and constraints in the unsafe backend may be different to the variables and constraints in `model`. This can happen because of bridges, or because the solver requires the variables or constraints in a specific order. In addition, the variable or constraint index returned by [index](#) at the JuMP level may be different to the index of the corresponding variable or constraint in the unsafe\_backend. There is no solution to this. Use the alternative suggested below instead.

Second, the unsafe\_backend may be empty, or lack some modifications made to the JuMP model. Thus, before calling unsafe\_backend you should first call [MOI.Utilities.attach\\_optimizer](#) to ensure that the backend is synchronized with the JuMP model.

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer)
A JuMP Model
├ solver: HiGHS
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
├ num_constraints: 0
└ Names registered in the model: none

julia> MOI.Utilities.attach_optimizer(model)

julia> inner = unsafe_backend(model)
A HiGHS model with 0 columns and 0 rows.
```

Moreover, if you modify the JuMP model, the reference you have to the backend (that is, `inner` in the example above) may be out-dated, and you should call `MOI.Utilities.attach_optimizer` again.

This function is also unsafe in the reverse direction: if you modify the unsafe backend, for example, by adding a new constraint to `inner`, the changes may be silently discarded by JuMP when the JuMP model is modified or solved.

### Alternative

Instead of `unsafe_backend`, create a model using `direct_model` and call `backend` instead.

For example, instead of:

```
julia> import HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> set_silent(model)

julia> @variable(model, x >= 0)
x

julia> MOI.Utilities.attach_optimizer(model)

julia> highs = unsafe_backend(model)
A HiGHS model with 1 columns and 0 rows.

julia> optimizer_index(x)
MOI.VariableIndex(1)
```

Use:

```
julia> import HiGHS

julia> model = direct_model(HiGHS.Optimizer());

julia> set_silent(model)

julia> @variable(model, x >= 0)
x

julia> highs = backend(model) # No need to call `attach_optimizer`.
A HiGHS model with 1 columns and 0 rows.

julia> index(x)
MOI.VariableIndex(1)
```

`source`

### unset\_binary

JuMP.`unset_binary` – Function.

```
unset_binary(variable_ref::GenericVariableRef)
```

Remove the binary constraint on the variable `variable_ref`.

See also [BinaryRef](#), [is\\_binary](#), [set\\_binary](#).

### Example

```
julia> model = Model();

julia> @variable(model, x, Bin);

julia> is_binary(x)
true

julia> unset_binary(x)

julia> is_binary(x)
false
```

`source`

### unset\_integer

`JuMP.unset_integer` – Function.

```
unset_integer(variable_ref::GenericVariableRef)
```

Remove the integrality constraint on the variable `variable_ref`.

Errors if one does not exist.

See also [IntegerRef](#), [is\\_integer](#), [set\\_integer](#).

### Example

```
julia> model = Model();

julia> @variable(model, x, Int);

julia> is_integer(x)
true

julia> unset_integer(x)

julia> is_integer(x)
false
```

`source`

**unset\_silent**

JuMP.unset\_silent - Function.

```
unset_silent(model::GenericModel)
```

Neutralize the effect of the `set_silent` function and let the solver attributes control the verbosity.

See also: `set_silent`.

**Example**

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> set_silent(model)

julia> get_attribute(model, MOI.Silent())
true

julia> unset_silent(model)

julia> get_attribute(model, MOI.Silent())
false
```

[source](#)

**unset\_time\_limit\_sec**

JuMP.unset\_time\_limit\_sec - Function.

```
unset_time_limit_sec(model::GenericModel)
```

Unset the time limit of the solver.

See also: `set_time_limit_sec`, `time_limit_sec`.

**Example**

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> time_limit_sec(model)

julia> set_time_limit_sec(model, 60.0)

julia> time_limit_sec(model)
60.0

julia> unset_time_limit_sec(model)

julia> time_limit_sec(model)
```

`source`

### **upper\_bound**

JuMP.`upper_bound` – Function.

```
upper_bound(v::GenericVariableRef)
```

Return the upper bound of a variable.

Error if one does not exist.

See also [UpperBoundRef](#), [has\\_upper\\_bound](#), [set\\_upper\\_bound](#), [delete\\_upper\\_bound](#).

### **Example**

```
julia> model = Model();
julia> @variable(model, x <= 1.0);
julia> upper_bound(x)
1.0
```

`source`

### **value**

JuMP.`value` – Function.

```
value(con_ref::ConstraintRef; result::Int = 1)
```

Return the primal value of constraint `con_ref` associated with result index `result` of the most-recent solution returned by the solver.

That is, if `con_ref` is the reference of a constraint func-in-set, it returns the value of `func` evaluated at the value of the variables (given by [value\(::GenericVariableRef\)](#)).

Use [has\\_values](#) to check if a result exists before asking for values.

See also: [result\\_count](#).

### **Note**

For scalar constraints, the constant is moved to the set so it is not taken into account in the primal value of the constraint. For instance, the constraint `@constraint(model, 2x + 3y + 1 == 5)` is transformed into `2x + 3y`-in-MOI.EqualTo(4) so the value returned by this function is the evaluation of `2x + 3y`.

`source`

```
value(var_value::Function, con_ref::ConstraintRef)
```

Evaluate the primal value of the constraint `con_ref` using `var_value(v)` as the value for each variable `v`.

`source`

```
value(v::GenericVariableRef; result = 1)
```

Return the value of variable v associated with result index result of the most-recent returned by the solver.

Use [has\\_values](#) to check if a result exists before asking for values.

See also: [result\\_count](#).

[source](#)

```
value(var_value::Function, v::GenericVariableRef)
```

Evaluate the value of the variable v as var\_value(v).

[source](#)

```
value(var_value::Function, ex::GenericAffExpr)
```

Evaluate ex using var\_value(v) as the value for each variable v.

[source](#)

```
value(v::GenericAffExpr; result::Int = 1)
```

Return the value of the GenericAffExpr v associated with result index result of the most-recent solution returned by the solver.

See also: [result\\_count](#).

[source](#)

```
value(var_value::Function, ex::GenericQuadExpr)
```

Evaluate ex using var\_value(v) as the value for each variable v.

[source](#)

```
value(v::GenericQuadExpr; result::Int = 1)
```

Return the value of the GenericQuadExpr v associated with result index result of the most-recent solution returned by the solver.

Replaces getvalue for most use cases.

See also: [result\\_count](#).

[source](#)

```
value(p::NonlinearParameter)
```

Return the current value stored in the nonlinear parameter p.

### Example

```
julia> model = Model();
julia> @NLparameter(model, p == 10)
p == 10.0
julia> value(p)
10.0
```

[source](#)

```
value(ex::NonlinearExpression; result::Int = 1)
```

Return the value of the NonlinearExpression ex associated with result index result of the most-recent solution returned by the solver.

See also: [result\\_count](#).

[source](#)

```
value(var_value::Function, ex::NonlinearExpression)
```

Evaluate ex using var\_value(v) as the value for each variable v.

[source](#)

```
value(c::NonlinearConstraintRef; result::Int = 1)
```

Return the value of the NonlinearConstraintRef c associated with result index result of the most-recent solution returned by the solver.

See also: [result\\_count](#).

[source](#)

```
value(var_value::Function, c::NonlinearConstraintRef)
```

Evaluate c using var\_value(v) as the value for each variable v.

[source](#)

### value\_type

JuMP.value\_type – Function.

```
value_type(::Type{<:Union{AbstractModel,AbstractVariableRef}})
```

Return the return type of `value` for variables of that model. It defaults to `Float64` if it is not implemented.

### Example

```
julia> value_type(GenericModel{BigFloat})
BigFloat
```

source

### variable\_by\_name

JuMP.variable\_by\_name - Function.

```
variable_by_name(
    model::AbstractModel,
    name::String,
)::Union{AbstractVariableRef,Nothing}
```

Returns the reference of the variable with name attribute `name` or `Nothing` if no variable has this name attribute. Throws an error if several variables have `name` as their name attribute.

### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> variable_by_name(model, "x")
x

julia> @variable(model, base_name="x")
x

julia> variable_by_name(model, "x")
ERROR: Multiple variables have the name x.
Stacktrace:
[1] error(::String) at ./error.jl:33
[2] get(::MOIU.Model{Float64}, ::Type{MathOptInterface.VariableIndex}, ::String) at
  ↪ /home/blegat/.julia/dev/MathOptInterface/src/Utilities/model.jl:222
[3] get at /home/blegat/.julia/dev/MathOptInterface/src/Utilities/universalfallback.jl:201
  ↪ [inlined]
[4]
  ↪ get(::MathOptInterface.Utilities.CachingOptimizer{MathOptInterface.AbstractOptimizer,MathOptInterface.Utility
  ↪ ::Type{MathOptInterface.VariableIndex}, ::String}) at
  ↪ /home/blegat/.julia/dev/MathOptInterface/src/Utilities/cachingoptimizer.jl:490
[5] variable_by_name(::GenericModel, ::String) at
  ↪ /home/blegat/.julia/dev/JuMP/src/variables.jl:268
[6] top-level scope at none:0

julia> var = @variable(model, base_name="y")
y
```

```
julia> variable_by_name(model, "y")
y

julia> set_name(var, "z")

julia> variable_by_name(model, "y")

julia> variable_by_name(model, "z")
z

julia> @variable(model, u[1:2])
2-element Vector{VariableRef}:
 u[1]
 u[2]

julia> variable_by_name(model, "u[2]")
u[2]
```

`source`**variable\_ref\_type**

JuMP.variable\_ref\_type - Function.

```
variable_ref_type(::Union{F, Type{F}}) where {F}
```

A helper function used internally by JuMP and some JuMP extensions. Returns the variable type associated with the model or expression type F.

`source`**vectorize**

JuMP.vectorize - Function.

```
vectorize(matrix::AbstractMatrix, ::Shape)
```

Convert the matrix into a vector according to Shape.

`source`**write\_to\_file**

JuMP.write\_to\_file - Function.

```
write_to_file(
    model::GenericModel,
    filename::String;
    format::MOI.FileFormats.FileFormat = MOI.FileFormats FORMAT_AUTOMATIC,
    kwargs...,
)
```

Write the JuMP model `model` to `filename` in the format `format`.

If the `filename` ends in `.gz`, it will be compressed using GZip. If the `filename` ends in `.bz2`, it will be compressed using BZip2.

Other kwargs are passed to the `Model` constructor of the chosen format.

`source`

### **AbstractConstraint**

JuMP.`AbstractConstraint` – Type.

```
abstract type AbstractConstraint
```

An abstract base type for all constraint types. `AbstractConstraints` store the function and set directly, unlike `ConstraintRefs` that are merely references to constraints stored in a model. `AbstractConstraints` do not need to be attached to a model.

`source`

### **AbstractJuMPScalar**

JuMP.`AbstractJuMPScalar` – Type.

```
AbstractJuMPScalar <: MutableArithmetics.AbstractMutable
```

Abstract base type for all scalar types

The subtyping of `AbstractMutable` will allow calls of some `Base` functions to be redirected to a method in `MA` that handles type promotion more carefully (for example the promotion in sparse matrix products in `SparseArrays` usually does not work for JuMP types) and exploits the mutability of `AffExpr` and `QuadExpr`.

`source`

### **AbstractModel**

JuMP.`AbstractModel` – Type.

```
AbstractModel
```

An abstract type that should be subtyped for users creating JuMP extensions.

`source`

### **AbstractScalarSet**

JuMP.`AbstractScalarSet` – Type.

```
AbstractScalarSet
```

An abstract type for defining new scalar sets in JuMP.

Implement `moi_set(::AbstractScalarSet)` to convert the type into an MOI set.

See also: [moi\\_set](#).

[source](#)

### **AbstractShape**

JuMP.`AbstractShape` – Type.

`AbstractShape`

Abstract vectorizable shape. Given a flat vector form of an object of shape `shape`, the original object can be obtained by [reshape\\_vector](#).

[source](#)

### **AbstractVariable**

JuMP.`AbstractVariable` – Type.

`AbstractVariable`

Variable returned by [build\\_variable](#). It represents a variable that has not been added yet to any model. It can be added to a given model with [add\\_variable](#).

[source](#)

### **AbstractVariableRef**

JuMP.`AbstractVariableRef` – Type.

`AbstractVariableRef`

Variable returned by [add\\_variable](#). Affine (resp. quadratic) operations with variables of type `V<:AbstractVariableRef` and coefficients of type `T` create a `GenericAffExpr{T,V}` (resp. `GenericQuadExpr{T,V}`).

[source](#)

### **AbstractVectorSet**

JuMP.`AbstractVectorSet` – Type.

`AbstractVectorSet`

An abstract type for defining new sets in JuMP.

Implement `moi_set(::AbstractVectorSet, dim::Int)` to convert the type into an MOI set.

See also: [moi\\_set](#).

[source](#)

**AffExpr**

JuMP.AffExpr – Type.

```
AffExpr
```

Alias for GenericAffExpr{Float64,VariableRef}, the specific [GenericAffExpr](#) used by JuMP.

[source](#)

**ArrayShape**

JuMP.ArrayShape – Type.

```
ArrayShape{N}(dims::NTuple{N,Int}) where {N}
```

An [AbstractShape](#) that represents array-valued constraints.

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:2, 1:3]);

julia> c = @constraint(model, x >= 0, Nonnegatives())
[x[1,1]  x[1,2]  x[1,3]
 x[2,1]  x[2,2]  x[2,3]] ∈ Nonnegatives()

julia> shape(constraint_object(c))
ArrayShape{2}((2, 3))
```

[source](#)

**BinaryRef**

JuMP.BinaryRef – Function.

```
BinaryRef(v::GenericVariableRef)
```

Return a constraint reference to the constraint constraining v to be binary. Errors if one does not exist.

See also [is\\_binary](#), [set\\_binary](#), [unset\\_binary](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x, Bin);

julia> BinaryRef(x)
x binary
```

[source](#)

**BridgeableConstraint**

JuMP.BridgeableConstraint - Type.

```
BridgeableConstraint(
    constraint::C,
    bridge_type::B;
    coefficient_type::Type{T} = Float64,
) where {C<:AbstractConstraint,B<:Type{<:MOI.Bridges.AbstractBridge},T}
```

An `AbstractConstraint` representinng that constraint that can be bridged by the bridge of type `bridge_type{coefficient_type}`.

Adding a `BridgeableConstraint` to a model is equivalent to:

```
add_bridge(model, bridge_type; coefficient_type = coefficient_type)
add_constraint(model, constraint)
```

**Example**

Given a new scalar set type `CustomSet` with a bridge `CustomBridge` that can bridge F-in-CustomSet constraints, when the user does:

```
model = Model()
@variable(model, x)
@constraint(model, x + 1 in CustomSet())
optimize!(model)
```

with an optimizer that does not support F-in-CustomSet constraints, the constraint will not be bridged unless they first call `add_bridge(model, CustomBridge)`.

In order to automatically add the `CustomBridge` to any model to which an F-in-CustomSet is added, add the following method:

```
function JuMP.build_constraint(
    error_fn::Function,
    func::AbstractJuMPScalar,
    set::CustomSet,
)
    constraint = ScalarConstraint(func, set)
    return BridgeableConstraint(constraint, CustomBridge)
end
```

**Note**

JuMP extensions should extend `JuMP.build_constraint` only if they also defined `CustomSet`, for three reasons:

1. It is problematic if multiple extensions overload the same JuMP method.
2. A missing method will not inform the users that they forgot to load the extension module defining the `build_constraint` method.
3. Defining a method where neither the function nor any of the argument types are defined in the package is called *type piracy* and is discouraged in the Julia style guide.

`source`

**ComplexPlane**

JuMP.ComplexPlane - Type.

```
ComplexPlane
```

Complex plane object that can be used to create a complex variable in the `@variable` macro.

**Example**

Consider the following example:

```
julia> model = Model();

julia> @variable(model, x in ComplexPlane())
real(x) + imag(x) im

julia> all_variables(model)
2-element Vector{VariableRef}:
 real(x)
 imag(x)
```

We see in the output of the last command that two real variables were created. The Julia variable `x` binds to an affine expression in terms of these two variables that parametrize the complex plane.

`source`

**ComplexVariable**

JuMP.ComplexVariable - Type.

```
ComplexVariable{S,T,U,V} <: AbstractVariable
```

A struct used when adding complex variables.

See also: `ComplexPlane`.

`source`

**ConstraintNotOwned**

JuMP.ConstraintNotOwned - Type.

```
struct ConstraintNotOwned{C<:ConstraintRef} <: Exception
    constraint_ref::C
end
```

An error thrown when the constraint `constraint_ref` was used in a model different to `owner_model(constraint_ref)`.

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, c, x >= 0)
c : x ≥ 0

julia> model_new = Model();

julia> MOI.get(model_new, MOI.ConstraintName(), c)
ERROR: ConstraintNotOwned{ConstraintRef{Model,
    MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
    MathOptInterface.GreaterThan{Float64}}, ScalarShape}}(c : x ≥ 0)
Stacktrace:
[...]
```

[source](#)**ConstraintRef**

JuMP.ConstraintRef – Type.

[ConstraintRef](#)

Holds a reference to the model and the corresponding MOI.ConstraintIndex.

[source](#)**FixRef**

JuMP.FixRef – Function.

[FixRef\(v::GenericVariableRef\)](#)

Return a constraint reference to the constraint fixing the value of v.

Errors if one does not exist.

See also [is\\_fixed](#), [fix\\_value](#), [fix](#), [unfix](#).**Example**

```
julia> model = Model();

julia> @variable(model, x == 1);

julia> FixRef(x)
x = 1
```

[source](#)

**GenericAffExpr**

JuMP.GenericAffExpr – Type.

```
mutable struct GenericAffExpr{CoefType,VarType} <: AbstractJuMPScalar
    constant::CoefType
    terms::OrderedDict{VarType,CoefType}
end
```

An expression type representing an affine expression of the form:  $\sum a_i x_i + c$ .

**Fields**

- `.constant`: the constant  $c$  in the expression.
- `.terms`: an `OrderedDict`, with keys of `VarType` and values of `CoefType` describing the sparse vector  $a$ .

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> expr = x[2] + 3.0 * x[1] + 4.0
x[2] + 3 x[1] + 4

julia> expr.constant
4.0

julia> expr.terms
OrderedCollections.OrderedDict{VariableRef, Float64} with 2 entries:
x[2] => 1.0
x[1] => 3.0
```

[source](#)

**GenericModel**

JuMP.GenericModel – Type.

```
GenericModel{T}(
    [optimizer_factory;]
    add_bridges::Bool = true,
) where {T<:Real}
```

Create a new instance of a JuMP model.

If `optimizer_factory` is provided, the model is initialized with the optimizer returned by `MOI.instantiate(optimizer_factory)`.

If `optimizer_factory` is not provided, use `set_optimizer` to set the optimizer before calling `optimize!`.

If `add_bridges`, JuMP adds a `MOI.Bridges.LazyBridgeOptimizer` to automatically reformulate the problem into a form supported by the optimizer.

### **Value type T**

Passing a type other than `Float64` as the value type `T` is an advanced operation. The value type must match that expected by the chosen optimizer. Consult the optimizers documentation for details.

If not documented, assume that the optimizer supports only `Float64`.

Choosing an unsupported value type will throw an `MOI.UnsupportedConstraint` or an `MOI.UnsupportedAttribute` error, the timing of which (during the model construction or during a call to `optimize!`) depends on how the solver is interfaced to JuMP.

### **Example**

```
julia> model = GenericModel{BigFloat}();
julia> typeof(model)
GenericModel{BigFloat}
```

`source`

### **GenericNonlinearExpr**

JuMP.`GenericNonlinearExpr` – Type.

```
GenericNonlinearExpr{V}(head::Symbol, args::Vector{Any})
GenericNonlinearExpr{V}(head::Symbol, args::Any...)
```

The scalar-valued nonlinear function `head(args...)`, represented as a symbolic expression tree, with the call operator `head` and ordered arguments in `args`.

`V` is the type of `AbstractVariableRef` present in the expression, and is used to help dispatch JuMP extensions.

#### **head**

The `head::Symbol` must be an operator supported by the model.

The default list of supported univariate operators is given by:

- `MOI.Nonlinear.DEFAULT_UNIVARIATE_OPERATORS`

and the default list of supported multivariate operators is given by:

- `MOI.Nonlinear.DEFAULT_MULTIVARIATE_OPERATORS`

Additional operators can be add using `@operator`.

See the full list of operators supported by a `MOI.ModelLike` by querying the `MOI.ListOfSupportedNonlinearOperators` attribute.

#### **args**

The vector `args` contains the arguments to the nonlinear function. If the operator is univariate, it must contain one element. Otherwise, it may contain multiple elements.

Given a subtype of `AbstractVariableRef`, `V`, for `GenericNonlinearExpr{V}`, each element must be one of the following:

- A constant value of type `<:Real`
- A `V`
- A `GenericAffExpr{T,V}`
- A `GenericQuadExpr{T,V}`
- A `GenericNonlinearExpr{V}`

where `T<:Real` and `T == value_type(V)`.

### Unsupported operators

If the optimizer does not support head, an `MOI.UnsupportedNonlinearOperator` error will be thrown.

There is no guarantee about when this error will be thrown; it may be thrown when the function is first added to the model, or it may be thrown when `optimize!` is called.

### Example

To represent the function  $f(x) = \sin(x)^2$ , do:

```
julia> model = Model();
julia> @variable(model, x)
x

julia> f = sin(x)^2
sin(x) ^ 2.0

julia> f = GenericNonlinearExpr{VariableRef}(
           :^,
           GenericNonlinearExpr{VariableRef}(:sin, x),
           2.0,
           )
sin(x) ^ 2.0
```

`source`

### GenericQuadExpr

`JuMP.GenericQuadExpr` – Type.

```
mutable struct GenericQuadExpr{CoefType,VarType} <: AbstractJuMPScalar
    aff::GenericAffExpr{CoefType,VarType}
    terms::OrderedDict{UnorderedPair{VarType}, CoefType}
end
```

An expression type representing an quadratic expression of the form:  $\sum q_{i,j}x_i x_j + \sum a_i x_i + c$ .

### Fields

- `.aff`: an `GenericAffExpr` representing the affine portion of the expression.

- `.terms`: an `OrderedDict`, with keys of `UnorderedPair{VarType}` and values of `CoeffType`, describing the sparse list of terms `q`.

### Example

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> expr = 2.0 * x[1]^2 + x[1] * x[2] + 3.0 * x[1] + 4.0
2 x[1]^2 + x[1]*x[2] + 3 x[1] + 4

julia> expr.aff
3 x[1] + 4

julia> expr.terms
OrderedCollections.OrderedDict{UnorderedPair{VariableRef}, Float64} with 2 entries:
  UnorderedPair{VariableRef}(x[1], x[1]) => 2.0
  UnorderedPair{VariableRef}(x[1], x[2]) => 1.0
```

`source`

### GenericReferenceMap

JuMP.`GenericReferenceMap` – Type.

```
GenericReferenceMap{T}
```

Mapping between variable and constraint reference of a model and its copy. The reference of the copied model can be obtained by indexing the map with the reference of the corresponding reference of the original model.

`source`

### GenericVariableRef

JuMP.`GenericVariableRef` – Type.

```
GenericVariableRef{T} <: AbstractVariableRef
```

Holds a reference to the model and the corresponding MOI.VariableIndex.

`source`

### GreaterThanZero

JuMP.`GreaterThanZero` – Type.

```
GreaterThanZero()
```

A struct used to intercept when  $\geq$  or  $\geq$  is used in a macro via `operator_to_set`.

This struct is not the same as `Nonnegatives` so that we can disambiguate  $x \geq y$  and  $x - y$  in `Nonnegatives()`.

This struct is not intended for general usage, but it may be useful to some JuMP extensions.

### Example

```
julia> operator_to_set(error, Val(:>=))
GreaterThanZero()
```

`source`

### HermitianMatrixAdjointShape

JuMP.HermitianMatrixAdjointShape – Type.

```
HermitianMatrixAdjointShape(side_dimension)
```

The `dual_shape` of `HermitianMatrixShape`.

This shape is not intended for regular use.

`source`

### HermitianMatrixShape

JuMP.HermitianMatrixShape – Type.

```
HermitianMatrixShape(
    side_dimension::Int;
    needs_adjoint_dual::Bool = false,
)
```

The shape object for a Hermitian square matrix of `side_dimension` rows and columns.

The vectorized form corresponds to `MOI.HermitianPositiveSemidefiniteConeTriangle`.

#### needs\_adjoint\_dual

By default, the `dual_shape` of `HermitianMatrixShape` is also `HermitianMatrixShape`. This is true for cases such as a `LinearAlgebra.Hermitian` matrix in `HermitianPSDCone`.

However, JuMP also supports `LinearAlgebra.Hermitian` matrix in `Zeros`, which is interpreted as an element-wise equality constraint. By exploiting symmetry, we pass only the upper triangle of the equality constraints. This works for the primal, but it leads to a factor of 2 difference in the off-diagonal dual elements. (The dual value of the  $(i, j)$  element in the triangle formulation should be divided by 2 when spread across the  $(i, j)$  and  $(j, i)$  elements in the square matrix formulation.) If the constraint has this dual inconsistency, set `needs_adjoint_dual = true`.

`source`

**HermitianMatrixSpace**

JuMP.HermitianMatrixSpace – Type.

```
HermitianMatrixSpace()
```

Use in the `@variable` macro to constrain a matrix of variables to be hermitian.

**Example**

```
julia> model = Model();

julia> @variable(model, Q[1:2, 1:2] in HermitianMatrixSpace())
2×2 LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef},
                           Matrix{GenericAffExpr{ComplexF64, VariableRef}}}:
  real(Q[1,1])           real(Q[1,2]) + imag(Q[1,2]) im
  real(Q[1,2]) - imag(Q[1,2]) im  real(Q[2,2])
```

`source`

**HermitianPSDCone**

JuMP.HermitianPSDCone – Type.

```
HermitianPSDCone
```

Hermitian positive semidefinite cone object that can be used to create a Hermitian positive semidefinite square matrix in the `@variable` and `@constraint` macros.

**Example**

Consider the following example:

```
julia> model = Model();

julia> @variable(model, H[1:3, 1:3] in HermitianPSDCone())
3×3 LinearAlgebra.Hermitian{GenericAffExpr{ComplexF64, VariableRef},
                           Matrix{GenericAffExpr{ComplexF64, VariableRef}}}:
  real(H[1,1])           ..  real(H[1,3]) + imag(H[1,3]) im
  real(H[1,2]) - imag(H[1,2]) im  real(H[2,3]) + imag(H[2,3]) im
  real(H[1,3]) - imag(H[1,3]) im  real(H[3,3])

julia> all_variables(model)
9-element Vector{VariableRef}:
  real(H[1,1])
  real(H[1,2])
  real(H[2,2])
  real(H[1,3])
  real(H[2,3])
  real(H[3,3])
  imag(H[1,2])
  imag(H[1,3])
```

```
    imag(H[2,3])

julia> all_constraints(model, Vector{VariableRef},
    ↪ MOI.HermitianPositiveSemidefiniteConeTriangle)
1-element Vector{ConstraintRef{Model},
    ↪ MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.HermitianPositiveSemidefiniteConeTriangle}}:
 [real(H[1,1]), real(H[1,2]), real(H[2,2]), real(H[1,3]), real(H[2,3]), real(H[3,3]),
    ↪ imag(H[1,2]), imag(H[1,3]), imag(H[2,3])] ∈
    ↪ MathOptInterface.HermitianPositiveSemidefiniteConeTriangle(3)
```

We see in the output of the last commands that 9 real variables were created. The matrix H constrains affine expressions in terms of these 9 variables that parametrize a Hermitian matrix.

[source](#)

### **IntegerRef**

JuMP.IntegerRef – Function.

```
IntegerRef(v::GenericVariableRef)
```

Return a constraint reference to the constraint constraining v to be integer.

Errors if one does not exist.

See also [is\\_integer](#), [set\\_integer](#), [unset\\_integer](#).

#### **Example**

```
julia> model = Model();
julia> @variable(model, x, Int);
julia> IntegerRef(x)
x integer
```

[source](#)

### **LPMATRIXDATA**

JuMP.LPMATRIXDATA – Type.

```
LPMATRIXDATA{T}
```

The struct returned by [lp\\_matrix\\_data](#). See [lp\\_matrix\\_data](#) for a description of the public fields.

[source](#)

**LessThanZero**

JuMP.LessThanZero - Type.

```
GreaterThanZero()
```

A struct used to intercept when `<=` or  `$\leq$`  is used in a macro via `operator_to_set`.

This struct is not the same as `Nonpositives` so that we can disambiguate `x <= y` and `x - y` in `Nonpositives()`.

This struct is not intended for general usage, but it may be useful to some JuMP extensions.

**Example**

```
julia> operator_to_set(error, Val(:<=))
LessThanZero()
```

`source`

**LinearTermIterator**

JuMP.LinearTermIterator - Type.

```
LinearTermIterator{GAE<:GenericAffExpr}
```

A struct that implements the `iterate` protocol in order to iterate over tuples of (`coefficient`, `variable`) in the `GenericAffExpr`.

`source`

**LowerBoundRef**

JuMP.LowerBoundRef - Function.

```
LowerBoundRef(v::GenericVariableRef)
```

Return a constraint reference to the lower bound constraint of `v`.

Errors if one does not exist.

See also `has_lower_bound`, `lower_bound`, `set_lower_bound`, `delete_lower_bound`.

**Example**

```
julia> model = Model();
julia> @variable(model, x >= 1.0);
julia> LowerBoundRef(x)
x ≥ 1
```

`source`

**Model**

JuMP.Model – Type.

```
Model([optimizer_factory;] add_bridges::Bool = true)
```

Create a new instance of a JuMP model.

If `optimizer_factory` is provided, the model is initialized with the optimizer returned by `MOI.instantiate(optimizer_factory)`.

If `optimizer_factory` is not provided, use `set_optimizer` to set the optimizer before calling `optimize!`.

If `add_bridges`, JuMP adds a `MOI.Bridges.LazyBridgeOptimizer` to automatically reformulate the problem into a form supported by the optimizer.

**Example**

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> solver_name(model)
"Ipopt"

julia> import HiGHS

julia> import MultiObjectiveAlgorithms as MOA

julia> model = Model(() -> MOA.Optimizer(HiGHS.Optimizer); add_bridges = false);
```

[source](#)

**ModelMode**

JuMP.ModelMode – Type.

```
ModelMode
```

An enum to describe the state of the CachingOptimizer inside a JuMP model.

See also: `mode`.

**Values**

Possible values are:

`AUTOMATIC` : `moi_backend` field holds a CachingOptimizer in AUTOMATIC mode.

`MANUAL` : `moi_backend` field holds a CachingOptimizer in MANUAL mode.

`DIRECT` : `moi_backend` field holds an AbstractOptimizer. No extra copy of the model is stored. The `moi_backend` must support `add_constraint` etc.

[source](#)

**NLPEvaluator**

JuMP.NLPEvaluator - Function.

```
NLPEvaluator(
    model::Model,
    _differentiation_backend::MOI.Nonlinear.AbstractAutomaticDifferentiation =
        MOI.Nonlinear.SparseReverseMode(),
)
```

Return an `MOI.AbstractNLPEvaluator` constructed from `model`

**Warning**

Before using, you must initialize the evaluator using `MOI.initialize`.

**Experimental**

These features may change or be removed in any future version of JuMP.

Pass `_differentiation_backend` to specify the differentiation backend used to compute derivatives.

`source`

**NoOptimizer**

JuMP.NoOptimizer - Type.

```
struct NoOptimizer <: Exception end
```

An error thrown when no optimizer is set and one is required.

The optimizer can be provided to the `Model` constructor or by calling `set_optimizer`.

**Example**

```
julia> model = Model();
julia> optimize!(model)
ERROR: NoOptimizer()
Stacktrace:
[...]
```

`source`

**NonlinearExpr**

JuMP.NonlinearExpr - Type.

```
NonlinearExpr
```

Alias for `GenericNonlinearExpr{VariableRef}`, the specific `GenericNonlinearExpr` used by JuMP.

`source`

**NonlinearOperator**

JuMP.NonlinearOperator – Type.

```
NonlinearOperator(func::Function, head::Symbol)
```

A callable struct (functor) representing a function named head.

When called with `AbstractJuMPScalars`s, the struct returns a `GenericNonlinearExpr`.

When called with non-JuMP types, the struct returns the evaluation of `func(args...)`.

Unless head is special-cased by the optimizer, the operator must have already been added to the model using `add_nonlinear_operator` or `@operator`.

**Example**

```
julia> model = Model();

julia> @variable(model, x)
x

julia> f(x::Float64) = x^2
f (generic function with 1 method)

julia> ∇f(x::Float64) = 2 * x
∇f (generic function with 1 method)

julia> ∇²f(x::Float64) = 2.0
∇²f (generic function with 1 method)

julia> @operator(model, op_f, 1, f, ∇f, ∇²f)
NonlinearOperator(f, :op_f)

julia> bar = NonlinearOperator(f, :op_f)
NonlinearOperator(f, :op_f)

julia> @objective(model, Min, bar(x))
op_f(x)

julia> bar(2.0)
4.0
```

[source](#)

**Nonnegatives**

JuMP.Nonnegatives – Type.

```
Nonnegatives()
```

The JuMP equivalent of the `MOI.Nonnegatives` set, in which the dimension is inferred from the corresponding function.

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
x[1]
x[2]

julia> @constraint(model, x in Nonnegatives())
[x[1], x[2]] ∈ Nonnegatives()

julia> A = [1 2; 3 4];

julia> b = [5, 6];

julia> @constraint(model, A * x >= b)
[x[1] + 2 x[2] - 5, 3 x[1] + 4 x[2] - 6] ∈ Nonnegatives()
```

`source`**Nonpositives**

JuMP.Nonpositives – Type.

```
Nonpositives()
```

The JuMP equivalent of the `MOI.Nonnegatives` set, in which the dimension is inferred from the corresponding function.

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
x[1]
x[2]

julia> @constraint(model, x in Nonpositives())
[x[1], x[2]] ∈ Nonpositives()

julia> A = [1 2; 3 4];

julia> b = [5, 6];

julia> @constraint(model, A * x <= b)
[x[1] + 2 x[2] - 5, 3 x[1] + 4 x[2] - 6] ∈ Nonpositives()
```

`source`

**OptimizationSense**

JuMP.OptimizationSense – Type.

```
OptimizationSense
```

An enum for the value of the [ObjectiveSense](#) attribute.

**Values**

Possible values are:

- [MIN\\_SENSE](#): the goal is to minimize the objective function
- [MAX\\_SENSE](#): the goal is to maximize the objective function
- [FEASIBILITY\\_SENSE](#): the model does not have an objective function

[source](#)

**OptimizeNotCalled**

JuMP.OptimizeNotCalled – Type.

```
struct OptimizeNotCalled <: Exception end
```

An error thrown when a result attribute cannot be queried before [optimize!](#) is called.

**Example**

```
julia> import Ipopt
julia> model = Model(Ipopt.Optimizer);
julia> objective_value(model)
ERROR: OptimizeNotCalled()
Stacktrace:
[...]
```

[source](#)

**PSDCone**

JuMP.PSDCone – Type.

```
PSDCone
```

Positive semidefinite cone object that can be used to constrain a square matrix to be positive semidefinite in the [@constraint](#) macro.

If the matrix has type [Symmetric](#) then the columns vectorization (the vector obtained by concatenating the columns) of its upper triangular part is constrained to belong to the [MOI.PositiveSemidefiniteConeTriangle](#)

set, otherwise its column vectorization is constrained to belong to the `MOI.PositiveSemidefiniteConeSquare` set.

### Example

Non-symmetric case:

```
julia> model = Model();

julia> @variable(model, x);

julia> a = [x 2x; 2x x];

julia> b = [1 2; 2 4];

julia> cref = @constraint(model, a >= b, PSDCone())
[x - 1    2 x - 2
 2 x - 2  x - 4] ∈ PSDCone()

julia> jump_function(constraint_object(cref))
4-element Vector{AffExpr}:
 x - 1
 2 x - 2
 2 x - 2
 x - 4

julia> moi_set(constraint_object(cref))
MathOptInterface.PositiveSemidefiniteConeSquare(2)
```

Symmetric case:

```
julia> using LinearAlgebra # For Symmetric

julia> model = Model();

julia> @variable(model, x);

julia> a = [x 2x; 2x x];

julia> b = [1 2; 2 4];

julia> cref = @constraint(model, Symmetric(a - b) in PSDCone())
[x - 1  2 x - 2
   ..      x - 4] ∈ PSDCone()

julia> jump_function(constraint_object(cref))
3-element Vector{AffExpr}:
 x - 1
 2 x - 2
 x - 4

julia> moi_set(constraint_object(cref))
MathOptInterface.PositiveSemidefiniteConeTriangle(2)
```

[source](#)

**Parameter**

JuMP.Parameter – Type.

```
Parameter(value)
```

A short-cut for the [MOI.Parameter](#) set.

**Example**

```
julia> model = Model();

julia> @variable(model, x in Parameter(2))
x

julia> print(model)
Feasibility
Subject to
  x ∈ MathOptInterface.Parameter{Float64}(2.0)
```

[source](#)

**ParameterRef**

JuMP.ParameterRef – Function.

```
ParameterRef(x::GenericVariableRef)
```

Return a constraint reference to the constraint constraining x to be a parameter.

Errors if one does not exist.

See also [is\\_parameter](#), [set\\_parameter\\_value](#), [parameter\\_value](#).

**Example**

```
julia> model = Model();

julia> @variable(model, p in Parameter(2))
p

julia> ParameterRef(p)
p ∈ MathOptInterface.Parameter{Float64}(2.0)

julia> @variable(model, x);

julia> ParameterRef(x)
ERROR: Variable x is not a parameter.
Stacktrace:
[...]
```

[source](#)

**QuadExpr**

JuMP.QuadExpr – Type.

`QuadExpr`

An alias for GenericQuadExpr{Float64, VariableRef}, the specific [GenericQuadExpr](#) used by JuMP.

`source`**QuadTermIterator**

JuMP.QuadTermIterator – Type.

`QuadTermIterator{GQE<: GenericQuadExpr}`

A struct that implements the `iterate` protocol in order to iterate over tuples of (`coefficient`, `variable`, `variable`) in the `GenericQuadExpr`.

`source`**ReferenceMap**

JuMP.ReferenceMap – Type.

`GenericReferenceMap{T}`

Mapping between variable and constraint reference of a model and its copy. The reference of the copied model can be obtained by indexing the map with the reference of the corresponding reference of the original model.

`source`**ResultStatusCode**

JuMP.ResultStatusCode – Type.

`ResultStatusCode`

An Enum of possible values for the [PrimalStatus](#) and [DualStatus](#) attributes.

The values indicate how to interpret the result vector.

**Values**

Possible values are:

- [NO\\_SOLUTION](#): the result vector is empty.
- [FEASIBLE\\_POINT](#): the result vector is a feasible point.

- `NEARLY_FEASIBLE_POINT`: the result vector is feasible if some constraint tolerances are relaxed.
- `INFEASIBLE_POINT`: the result vector is an infeasible point.
- `INFEASIBILITY_CERTIFICATE`: the result vector is an infeasibility certificate. If the PrimalStatus is `INFEASIBILITY_CERTIFICATE`, then the primal result vector is a certificate of dual infeasibility. If the DualStatus is `INFEASIBILITY_CERTIFICATE`, then the dual result vector is a proof of primal infeasibility.
- `NEARLY_INFEASIBILITY_CERTIFICATE`: the result satisfies a relaxed criterion for a certificate of infeasibility.
- `REDUCTION_CERTIFICATE`: the result vector is an ill-posed certificate; see [this article](#) for details. If the PrimalStatus is `REDUCTION_CERTIFICATE`, then the primal result vector is a proof that the dual problem is ill-posed. If the DualStatus is `REDUCTION_CERTIFICATE`, then the dual result vector is a proof that the primal is ill-posed.
- `NEARLY_REDUCTION_CERTIFICATE`: the result satisfies a relaxed criterion for an ill-posed certificate.
- `UNKNOWN_RESULT_STATUS`: the result vector contains a solution with an unknown interpretation.
- `OTHER_RESULT_STATUS`: the result vector contains a solution with an interpretation not covered by one of the statuses defined above

`source`**RotatedSecondOrderCone**

JuMP.RotatedSecondOrderCone – Type.

RotatedSecondOrderCone

Rotated second order cone object that can be used to constrain the square of the euclidean norm of a vector  $x$  to be less than or equal to  $2tu$  where  $t$  and  $u$  are nonnegative scalars.

This is a shortcut for the `MOI.RotatedSecondOrderCone` set.

**Example**

The following constrains  $\|(x - 1, x - 2)\|_2^2 \leq 2tx$  and  $t, x \geq 0$ :

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @variable(model, t)
t

julia> @constraint(model, [t, x, x-1, x-2] in RotatedSecondOrderCone())
[t, x, x - 1, x - 2] ∈ MathOptInterface.RotatedSecondOrderCone(4)
```

`source`

**SOS1**

JuMP.SOS1 – Type.

```
SOS1(weights = Real[])
```

The SOS1 (Special Ordered Set of Type 1) set constrains a vector  $x$  to the set where at most one variable can take a non-zero value, and all other elements are zero.

The weights vector, if specified, induces an ordering of the variables; as such, it should contain unique values. The weights vector must have the same number of elements as the vector  $x$ , and the element  $\text{weights}[i]$  corresponds to element  $x[i]$ . If not provided, the weights vector defaults to  $\text{weights}[i] = i$ .

This is a shortcut for the [MOI.SOS1](#) set.

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:3] in SOS1([4.1, 3.2, 5.0]))
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]

julia> print(model)
Feasibility
Subject to
 [x[1], x[2], x[3]] ∈ MathOptInterface.SOS1{Float64}([4.1, 3.2, 5.0])
```

[source](#)

**SOS2**

JuMP.SOS2 – Type.

```
SOS2(weights = Real[])
```

The SOS2 (Special Ordered Set of Type 2) set constrains a vector  $x$  to the set where at most two variables can take a non-zero value, and all other elements are zero. In addition, the two non-zero values must be consecutive given the ordering of the  $x$  vector induced by weights.

The weights vector, if specified, induces an ordering of the variables; as such, it must contain unique values. The weights vector must have the same number of elements as the vector  $x$ , and the element  $\text{weights}[i]$  corresponds to element  $x[i]$ . If not provided, the weights vector defaults to  $\text{weights}[i] = i$ .

This is a shortcut for the [MOI.SOS2](#) set.

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:3] in SOS2([4.1, 3.2, 5.0]))
3-element Vector{VariableRef}:
 x[1]
 x[2]
 x[3]

julia> print(model)
Feasibility
Subject to
 [x[1], x[2], x[3]] ∈ MathOptInterface.SOS2{Float64}([4.1, 3.2, 5.0])
```

[source](#)

## ScalarConstraint

JuMP.ScalarConstraint – Type.

```
struct ScalarConstraint
```

The data for a scalar constraint.

See also the [documentation](#) on JuMP's representation of constraints for more background.

### Fields

- `.func`: field contains a JuMP object representing the function
- `.set`: field contains the MOI set

### Example

A scalar constraint:

```
julia> model = Model();

julia> @variable(model, x);

julia> @constraint(model, c, 2x <= 1)
c : 2 x ≤ 1

julia> object = constraint_object(c)
ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}(2 x,
    ↳ MathOptInterface.LessThan{Float64}(1.0))

julia> typeof(object)
ScalarConstraint{AffExpr, MathOptInterface.LessThan{Float64}}

julia> object.func
2 x

julia> object.set
MathOptInterface.LessThan{Float64}(1.0)
```

[source](#)**ScalarShape**

JuMP.ScalarShape - Type.

`ScalarShape()`

An [AbstractShape](#) that represents scalar constraints.

**Example**

```
julia> model = Model();
julia> @variable(model, x[1:2]);
julia> c = @constraint(model, x[2] <= 1);
julia> shape(constraint_object(c))
ScalarShape()
```

[source](#)**ScalarVariable**

JuMP.ScalarVariable - Type.

`ScalarVariable{S,T,U,V} <: AbstractVariable`

A struct used when adding variables.

See also: [add\\_variable](#).

[source](#)**SecondOrderCone**

JuMP.SecondOrderCone - Type.

`SecondOrderCone`

Second order cone object that can be used to constrain the euclidean norm of a vector  $x$  to be less than or equal to a nonnegative scalar  $t$ .

This is a shortcut for the [MOI.SecondOrderCone](#) set.

**Example**

The following constrains  $\|(x - 1, x - 2)\|_2 \leq t$  and  $t \geq 0$ :

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, t)
t

julia> @constraint(model, [t, x-1, x-2] in SecondOrderCone())
[t, x - 1, x - 2] ∈ MathOptInterface.SecondOrderCone(3)
```

`source`

### Semicontinuous

JuMP.Semicontinuous – Type.

```
Semicontinuous(lower, upper)
```

A short-cut for the [MOI.Semicontinuous](#) set.

This short-cut is useful because it automatically promotes lower and upper to the same type, and converts them into the element type supported by the JuMP model.

#### Example

```
julia> model = Model();

julia> @variable(model, x in Semicontinuous(1, 2))
x

julia> print(model)
Feasibility
Subject to
x ∈ MathOptInterface.Semicontinuous{Int64}(1, 2)
```

`source`

### Semiinteger

JuMP.Semiinteger – Type.

```
Semiinteger(lower, upper)
```

A short-cut for the [MOI.Semiinteger](#) set.

This short-cut is useful because it automatically promotes lower and upper to the same type, and converts them into the element type supported by the JuMP model.

#### Example

```
julia> model = Model();

julia> @variable(model, x in Semiinteger(3, 5))
x

julia> print(model)
Feasibility
Subject to
x ∈ MathOptInterface.Semiinteger{Int64}(3, 5)
```

[source](#)

### SensitivityReport

JuMP.SensitivityReport - Type.

```
SensitivityReport
```

See [lp\\_sensitivity\\_report](#).

[source](#)

### SkewSymmetricMatrixShape

JuMP.SkewSymmetricMatrixShape - Type.

```
SkewSymmetricMatrixShape
```

Shape object for a skew symmetric square matrix of `side_dimension` rows and columns. The vectorized form contains the entries of the upper-right triangular part of the matrix (without the diagonal) given column by column (or equivalently, the entries of the lower-left triangular part given row by row). The diagonal is zero.

[source](#)

### SkewSymmetricMatrixSpace

JuMP.SkewSymmetricMatrixSpace - Type.

```
SkewSymmetricMatrixSpace()
```

Use in the `@variable` macro to constrain a matrix of variables to be skew-symmetric.

#### Example

```
julia> model = Model();

julia> @variable(model, Q[1:2, 1:2] in SkewSymmetricMatrixSpace())
2×2 Matrix{AffExpr}:
 0           Q[1,2]
 -Q[1,2]     0
```

[source](#)

### SkipModelConvertScalarSetWrapper

JuMP.SkipModelConvertScalarSetWrapper – Type.

```
SkipModelConvertScalarSetWrapper(set::MOI.AbstractScalarSet)
```

JuMP uses `model_convert` to automatically promote `MOI.AbstractScalarSet` sets to the same `value_type` as the model.

In cases where this is undesirable, wrap the set in `SkipModelConvertScalarSetWrapper` to pass the set un-changed to the solver.

#### Warning

This struct is intended for use internally by JuMP extensions. You should not need to use it in regular JuMP code.

### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> @constraint(model, x in MOI.EqualTo(1 // 2))
x = 0.5
julia> @constraint(model, x in SkipModelConvertScalarSetWrapper(MOI.EqualTo(1 // 2)))
x = 1//2
```

[source](#)

### SquareMatrixShape

JuMP.SquareMatrixShape – Type.

```
SquareMatrixShape
```

Shape object for a square matrix of `side_dimension` rows and columns. The vectorized form contains the entries of the matrix given column by column (or equivalently, the entries of the lower-left triangular part given row by row).

[source](#)

### SymmetricMatrixAdjointShape

JuMP.SymmetricMatrixAdjointShape – Type.

```
SymmetricMatrixAdjointShape(side_dimension)
```

The `dual_shape` of `SymmetricMatrixShape`.

This shape is not intended for regular use.

`source`

### SymmetricMatrixShape

JuMP.SymmetricMatrixShape – Type.

```
SymmetricMatrixShape(
    side_dimension::Int,
    needs_adjoint_dual::Bool = false,
)
```

The shape object for a symmetric square matrix of `side_dimension` rows and columns.

The vectorized form contains the entries of the upper-right triangular part of the matrix given column by column (or equivalently, the entries of the lower-left triangular part given row by row).

#### needs\_adjoint\_dual

By default, the `dual_shape` of `SymmetricMatrixShape` is also `SymmetricMatrixShape`. This is true for cases such as a `LinearAlgebra.Symmetric` matrix in `PSDCone`.

However, JuMP also supports `LinearAlgebra.Symmetric` matrix in `Zeros`, which is interpreted as an element-wise equality constraint. By exploiting symmetry, we pass only the upper triangle of the equality constraints. This works for the primal, but it leads to a factor of 2 difference in the off-diagonal dual elements. (The dual value of the  $(i, j)$  element in the triangle formulation should be divided by 2 when spread across the  $(i, j)$  and  $(j, i)$  elements in the square matrix formulation.) If the constraint has this dual inconsistency, set `needs_adjoint_dual = true`.

`source`

### SymmetricMatrixSpace

JuMP.SymmetricMatrixSpace – Type.

```
SymmetricMatrixSpace()
```

Use in the `@variable` macro to constrain a matrix of variables to be symmetric.

#### Example

```
julia> model = Model();

julia> @variable(model, Q[1:2, 1:2] in SymmetricMatrixSpace())
2×2 LinearAlgebra.Symmetric{VariableRef, Matrix{VariableRef}}:
 Q[1,1]  Q[1,2]
 Q[1,2]  Q[2,2]
```

`source`

**TerminationStatusCode**

JuMP.TerminationStatusCode – Type.

```
TerminationStatusCode
```

An Enum of possible values for the TerminationStatus attribute. This attribute is meant to explain the reason why the optimizer stopped executing in the most recent call to [optimize!](#).

**Values**

Possible values are:

- [OPTIMIZE\\_NOT\\_CALLED](#): The algorithm has not started.
- [OPTIMAL](#): The algorithm found a globally optimal solution.
- [INFEASIBLE](#): The algorithm concluded that no feasible solution exists.
- [DUAL\\_INFEASIBLE](#): The algorithm concluded that no dual bound exists for the problem. If, additionally, a feasible (primal) solution is known to exist, this status typically implies that the problem is unbounded, with some technical exceptions.
- [LOCALLY\\_SOLVED](#): The algorithm converged to a stationary point, local optimal solution, could not find directions for improvement, or otherwise completed its search without global guarantees.
- [LOCALLY\\_INFEASIBLE](#): The algorithm converged to an infeasible point or otherwise completed its search without finding a feasible solution, without guarantees that no feasible solution exists.
- [INFEASIBLE\\_OR\\_UNBOUNDED](#): The algorithm stopped because it decided that the problem is infeasible or unbounded; this occasionally happens during MIP presolve.
- [ALMOST\\_OPTIMAL](#): The algorithm found a globally optimal solution to relaxed tolerances.
- [ALMOST\\_INFEASIBLE](#): The algorithm concluded that no feasible solution exists within relaxed tolerances.
- [ALMOST\\_DUAL\\_INFEASIBLE](#): The algorithm concluded that no dual bound exists for the problem within relaxed tolerances.
- [ALMOST\\_LOCALLY\\_SOLVED](#): The algorithm converged to a stationary point, local optimal solution, or could not find directions for improvement within relaxed tolerances.
- [ITERATION\\_LIMIT](#): An iterative algorithm stopped after conducting the maximum number of iterations.
- [TIME\\_LIMIT](#): The algorithm stopped after a user-specified computation time.
- [NODE\\_LIMIT](#): A branch-and-bound algorithm stopped because it explored a maximum number of nodes in the branch-and-bound tree.
- [SOLUTION\\_LIMIT](#): The algorithm stopped because it found the required number of solutions. This is often used in MIPs to get the solver to return the first feasible solution it encounters.
- [MEMORY\\_LIMIT](#): The algorithm stopped because it ran out of memory.
- [OBJECTIVE\\_LIMIT](#): The algorithm stopped because it found a solution better than a minimum limit set by the user.
- [NORM\\_LIMIT](#): The algorithm stopped because the norm of an iterate became too large.
- [OTHER\\_LIMIT](#): The algorithm stopped due to a limit not covered by one of the \_LIMIT\_ statuses above.
- [SLOW\\_PROGRESS](#): The algorithm stopped because it was unable to continue making progress towards the solution.

- [NUMERICAL\\_ERROR](#): The algorithm stopped because it encountered unrecoverable numerical error.
- [INVALID\\_MODEL](#): The algorithm stopped because the model is invalid.
- [INVALID\\_OPTION](#): The algorithm stopped because it was provided an invalid option.
- [INTERRUPTED](#): The algorithm stopped because of an interrupt signal.
- [OTHER\\_ERROR](#): The algorithm stopped because of an error not covered by one of the statuses defined above.

`source`

### UnorderedPair

JuMP.UnorderedPair – Type.

```
UnorderedPair(a::T, b::T)
```

A wrapper type used by [GenericQuadExpr](#) with fields `.a` and `.b`.

#### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> expr = 2.0 * x[1] * x[2]
2 x[1]*x[2]

julia> expr.terms
OrderedCollections.OrderedDict{UnorderedPair{VariableRef}, Float64} with 1 entry:
    UnorderedPair{VariableRef}(x[1], x[2]) => 2.0
```

`source`

### UpperBoundRef

JuMP.UpperBoundRef – Function.

```
UpperBoundRef(v::GenericVariableRef)
```

Return a constraint reference to the upper bound constraint of `v`.

Errors if one does not exist.

See also [has\\_upper\\_bound](#), [upper\\_bound](#), [set\\_upper\\_bound](#), [delete\\_upper\\_bound](#).

#### Example

```
julia> model = Model();

julia> @variable(model, x <= 1.0);

julia> UpperBoundRef(x)
x ≤ 1
```

[source](#)

### **VariableConstrainedOnCreation**

JuMP.VariableConstrainedOnCreation - Type.

```
VariableConstrainedOnCreation <: AbstractVariable
```

Variable scalar\_variables constrained to belong to set.

Adding this variable can be understood as doing:

```
function JuMP.add_variable(
    model::GenericModel,
    variable::VariableConstrainedOnCreation,
    names,
)
    var_ref = add_variable(model, variable.scalar_variable, name)
    add_constraint(model, VectorConstraint(var_ref, variable.set))
    return var_ref
end
```

but adds the variables with MOI.add\_constrained\_variable(model, variable.set) instead.

[source](#)

### **VariableInfo**

JuMP.VariableInfo - Type.

```
VariableInfo{S,T,U,V}
```

A struct by JuMP internally when creating variables. This may also be used by JuMP extensions to create new types of variables.

See also: [ScalarVariable](#).

[source](#)

### **VariableNotOwned**

JuMP.VariableNotOwned - Type.

```
struct VariableNotOwned{V<:AbstractVariableRef} <: Exception
    variable::V
end
```

The variable variable was used in a model different to owner\_model(variable).

[source](#)

**VariableRef**

JuMP.VariableRef – Type.

```
GenericVariableRef{T} <: AbstractVariableRef
```

Holds a reference to the model and the corresponding MOI.VariableIndex.

[source](#)

**VariablesConstrainedOnCreation**

JuMP.VariablesConstrainedOnCreation – Type.

```
VariablesConstrainedOnCreation <: AbstractVariable
```

Vector of variables scalar\_variables constrained to belong to set. Adding this variable can be thought as doing:

```
function JuMP.add_variable(
    model::GenericModel,
    variable::VariablesConstrainedOnCreation,
    names,
)
    v_names = vectorize(names, variable.shape)
    var_refs = add_variable.(model, variable.scalar_variables, v_names)
    add_constraint(model, VectorConstraint(var_refs, variable.set))
    return reshape_vector(var_refs, variable.shape)
end
```

but adds the variables with MOI.add\_constrained\_variables(model, variable.set) instead. See [the MOI documentation](#) for the difference between adding the variables with MOI.add\_constrained\_variables and adding them with MOI.add\_variables and adding the constraint separately.

[source](#)

**VectorConstraint**

JuMP.VectorConstraint – Type.

```
struct VectorConstraint
```

The data for a vector constraint.

See also the [documentation](#) on JuMP's representation of constraints.

**Fields**

- func: field contains a JuMP object representing the function
- set: field contains the MOI set.

- `shape`: field contains an `AbstractShape` matching the form in which the constraint was constructed (for example, by using matrices or flat vectors).

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:3]);

julia> @constraint(model, c, x in SecondOrderCone())
c : [x[1], x[2], x[3]] ∈ MathOptInterface.SecondOrderCone(3)

julia> object = constraint_object(c)
VectorConstraint{VariableRef, MathOptInterface.SecondOrderCone, VectorShape}(VariableRef[x[1],
← x[2], x[3]], MathOptInterface.SecondOrderCone(3), VectorShape())

julia> typeof(object)
VectorConstraint{VariableRef, MathOptInterface.SecondOrderCone, VectorShape}

julia> object.func
3-element Vector{VariableRef}:
x[1]
x[2]
x[3]

julia> object.set
MathOptInterface.SecondOrderCone(3)

julia> object.shape
VectorShape()
```

**source****VectorShape**

JuMP.VectorShape - Type.

```
VectorShape()
```

An `AbstractShape` that represents vector-valued constraints.**Example**

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> c = @constraint(model, x in SOS1());

julia> shape(constraint_object(c))
VectorShape()
```

**source**

**Zeros**

JuMP.Zeros – Type.

```
Zeros()
```

The JuMP equivalent of the `MOI.Zeros` set, in which the dimension is inferred from the corresponding function.

**Example**

```
julia> model = Model();

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> @constraint(model, x in Zeros())
[x[1], x[2]] ∈ Zeros()

julia> A = [1 2; 3 4];

julia> b = [5, 6];

julia> @constraint(model, A * x == b)
[x[1] + 2 x[2] - 5, 3 x[1] + 4 x[2] - 6] ∈ Zeros()
```

[source](#)

**ALMOST\_DUAL\_INFEASIBLE**

JuMP.ALMOST\_DUAL\_INFEASIBLE – Constant.

```
ALMOST_DUAL_INFEASIBLE::TerminationStatusCode
```

An instance of the `TerminationStatusCode` enum.

`ALMOST_DUAL_INFEASIBLE`: The algorithm concluded that no dual bound exists for the problem within relaxed tolerances.

[source](#)

**ALMOST\_INFEASIBLE**

JuMP.ALMOST\_INFEASIBLE – Constant.

```
ALMOST_INFEASIBLE::TerminationStatusCode
```

An instance of the `TerminationStatusCode` enum.

`ALMOST_INFEASIBLE`: The algorithm concluded that no feasible solution exists within relaxed tolerances.

[source](#)

**ALMOST\_LOCALLY\_SOLVED**

JuMP.ALMOST\_LOCALLY\_SOLVED – Constant.

```
ALMOST_LOCALLY_SOLVED::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

ALMOST\_LOCALLY\_SOLVED: The algorithm converged to a stationary point, local optimal solution, or could not find directions for improvement within relaxed tolerances.

[source](#)

**ALMOST\_OPTIMAL**

JuMP.ALMOST\_OPTIMAL – Constant.

```
ALMOST_OPTIMAL::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

ALMOST\_OPTIMAL: The algorithm found a globally optimal solution to relaxed tolerances.

[source](#)

**AUTOMATIC**

JuMP.AUTOMATIC – Constant.

moi\_backend field holds a CachingOptimizer in AUTOMATIC mode.

[source](#)

**DIRECT**

JuMP.DIRECT – Constant.

moi\_backend field holds an AbstractOptimizer. No extra copy of the model is stored. The moi\_backend must support add\_constraint etc.

[source](#)

**DUAL\_INFEASIBLE**

JuMP.DUAL\_INFEASIBLE – Constant.

```
DUAL_INFEASIBLE::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

DUAL\_INFEASIBLE: The algorithm concluded that no dual bound exists for the problem. If, additionally, a feasible (primal) solution is known to exist, this status typically implies that the problem is unbounded, with some technical exceptions.

[source](#)

**FEASIBILITY\_SENSE**

JuMP.FEASIBILITY\_SENSE – Constant.

```
FEASIBILITY_SENSE::OptimizationSense
```

An instance of the [OptimizationSense](#) enum.

FEASIBILITY\_SENSE: the model does not have an objective function

[source](#)

**FEASIBLE\_POINT**

JuMP.FEASIBLE\_POINT – Constant.

```
FEASIBLE_POINT::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

FEASIBLE\_POINT: the result vector is a feasible point.

[source](#)

**INFEASIBILITY\_CERTIFICATE**

JuMP.INFEASIBILITY\_CERTIFICATE – Constant.

```
INFEASIBILITY_CERTIFICATE::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

INFEASIBILITY\_CERTIFICATE: the result vector is an infeasibility certificate. If the PrimalStatus is INFEASIBILITY\_CERTIFICATE, then the primal result vector is a certificate of dual infeasibility. If the DualStatus is INFEASIBILITY\_CERTIFICATE, then the dual result vector is a proof of primal infeasibility.

[source](#)

**INFEASIBLE**

JuMP.INFEASIBLE – Constant.

```
INFEASIBLE::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

INFEASIBLE: The algorithm concluded that no feasible solution exists.

[source](#)

**INFEASIBLE\_OR\_UNBOUNDED**

JuMP.INFEASIBLE\_OR\_UNBOUNDED – Constant.

**INFEASIBLE\_OR\_UNBOUNDED::TerminationStatusCode**

An instance of the [TerminationStatusCode](#) enum.

INFEASIBLE\_OR\_UNBOUNDED: The algorithm stopped because it decided that the problem is infeasible or unbounded; this occasionally happens during MIP presolve.

[source](#)

**INFEASIBLE\_POINT**

JuMP.INFEASIBLE\_POINT – Constant.

**INFEASIBLE\_POINT::ResultStatusCode**

An instance of the [ResultStatusCode](#) enum.

INFEASIBLE\_POINT: the result vector is an infeasible point.

[source](#)

**INTERRUPTED**

JuMP.INTERRUPTED – Constant.

**INTERRUPTED::TerminationStatusCode**

An instance of the [TerminationStatusCode](#) enum.

INTERRUPTED: The algorithm stopped because of an interrupt signal.

[source](#)

**INVALID\_MODEL**

JuMP.INVALID\_MODEL – Constant.

**INVALID\_MODEL::TerminationStatusCode**

An instance of the [TerminationStatusCode](#) enum.

INVALID\_MODEL: The algorithm stopped because the model is invalid.

[source](#)

**INVALID\_OPTION**

JuMP.INVALID\_OPTION – Constant.

**INVALID\_OPTION**:  
:TerminationStatusCodeAn instance of the [TerminationStatusCode](#) enum.

INVALID\_OPTION: The algorithm stopped because it was provided an invalid option.

[source](#)**ITERATION\_LIMIT**

JuMP.ITERATION\_LIMIT – Constant.

**ITERATION\_LIMIT**:  
:TerminationStatusCodeAn instance of the [TerminationStatusCode](#) enum.

ITERATION\_LIMIT: An iterative algorithm stopped after conducting the maximum number of iterations.

[source](#)**LOCALLY\_INFEASIBLE**

JuMP.LOCALLY\_INFEASIBLE – Constant.

**LOCALLY\_INFEASIBLE**:  
:TerminationStatusCodeAn instance of the [TerminationStatusCode](#) enum.

LOCALLY\_INFEASIBLE: The algorithm converged to an infeasible point or otherwise completed its search without finding a feasible solution, without guarantees that no feasible solution exists.

[source](#)**LOCALLY\_SOLVED**

JuMP.LOCALLY\_SOLVED – Constant.

**LOCALLY\_SOLVED**:  
:TerminationStatusCodeAn instance of the [TerminationStatusCode](#) enum.

LOCALLY\_SOLVED: The algorithm converged to a stationary point, local optimal solution, could not find directions for improvement, or otherwise completed its search without global guarantees.

[source](#)

**MANUAL**

JuMP.MANUAL – Constant.

moi\_backend field holds a CachingOptimizer in MANUAL mode.

[source](#)

**MAX\_SENSE**

JuMP.MAX\_SENSE – Constant.

MAX\_SENSE::[OptimizationSense](#)

An instance of the [OptimizationSense](#) enum.

MAX\_SENSE: the goal is to maximize the objective function

[source](#)

**MEMORY\_LIMIT**

JuMP.MEMORY\_LIMIT – Constant.

MEMORY\_LIMIT::[TerminationStatusCode](#)

An instance of the [TerminationStatusCode](#) enum.

MEMORY\_LIMIT: The algorithm stopped because it ran out of memory.

[source](#)

**MIN\_SENSE**

JuMP.MIN\_SENSE – Constant.

MIN\_SENSE::[OptimizationSense](#)

An instance of the [OptimizationSense](#) enum.

MIN\_SENSE: the goal is to minimize the objective function

[source](#)

**NEARLY\_FEASIBLE\_POINT**

JuMP.NEARLY\_FEASIBLE\_POINT – Constant.

NEARLY\_FEASIBLE\_POINT::[ResultStatusCode](#)

An instance of the [ResultStatusCode](#) enum.

NEARLY\_FEASIBLE\_POINT: the result vector is feasible if some constraint tolerances are relaxed.

[source](#)

**NEARLY\_INFEASIBILITY\_CERTIFICATE**

JuMP.NEARLY\_INFEASIBILITY\_CERTIFICATE – Constant.

```
NEARLY_INFEASIBILITY_CERTIFICATE::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

NEARLY\_INFEASIBILITY\_CERTIFICATE: the result satisfies a relaxed criterion for a certificate of infeasibility.

[source](#)

**NEARLY\_REDUCTION\_CERTIFICATE**

JuMP.NEARLY\_REDUCTION\_CERTIFICATE – Constant.

```
NEARLY_REDUCTION_CERTIFICATE::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

NEARLY\_REDUCTION\_CERTIFICATE: the result satisfies a relaxed criterion for an ill-posed certificate.

[source](#)

**NODE\_LIMIT**

JuMP.NODE\_LIMIT – Constant.

```
NODE_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

NODE\_LIMIT: A branch-and-bound algorithm stopped because it explored a maximum number of nodes in the branch-and-bound tree.

[source](#)

**NORM\_LIMIT**

JuMP.NORM\_LIMIT – Constant.

```
NORM_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

NORM\_LIMIT: The algorithm stopped because the norm of an iterate became too large.

[source](#)

**NO\_SOLUTION**

JuMP.NO\_SOLUTION – Constant.

```
NO_SOLUTION::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

NO\_SOLUTION: the result vector is empty.

[source](#)

**NUMERICAL\_ERROR**

JuMP.NUMERICAL\_ERROR – Constant.

```
NUMERICAL_ERROR::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

NUMERICAL\_ERROR: The algorithm stopped because it encountered unrecoverable numerical error.

[source](#)

**OBJECTIVE\_LIMIT**

JuMP.OBJECTIVE\_LIMIT – Constant.

```
OBJECTIVE_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

OBJECTIVE\_LIMIT: The algorithm stopped because it found a solution better than a minimum limit set by the user.

[source](#)

**OPTIMAL**

JuMP.OPTIMAL – Constant.

```
OPTIMAL::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

OPTIMAL: The algorithm found a globally optimal solution.

[source](#)

**OPTIMIZE\_NOT\_CALLED**

JuMP.OPTIMIZE\_NOT\_CALLED – Constant.

```
OPTIMIZE_NOT_CALLED::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

OPTIMIZE\_NOT\_CALLED: The algorithm has not started.

[source](#)

**OTHER\_ERROR**

JuMP.OTHER\_ERROR – Constant.

```
OTHER_ERROR::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

OTHER\_ERROR: The algorithm stopped because of an error not covered by one of the statuses defined above.

[source](#)

**OTHER\_LIMIT**

JuMP.OTHER\_LIMIT – Constant.

```
OTHER_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

OTHER\_LIMIT: The algorithm stopped due to a limit not covered by one of the \_LIMIT\_ statuses above.

[source](#)

**OTHER\_RESULT\_STATUS**

JuMP.OTHER\_RESULT\_STATUS – Constant.

```
OTHER_RESULT_STATUS::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

OTHER\_RESULT\_STATUS: the result vector contains a solution with an interpretation not covered by one of the statuses defined above

[source](#)

**REDUCTION\_CERTIFICATE**

JuMP.REDUCTION\_CERTIFICATE – Constant.

**REDUCTION\_CERTIFICATE**: :ResultStatusCode

An instance of the [ResultStatusCode](#) enum.

**REDUCTION\_CERTIFICATE**: the result vector is an ill-posed certificate; see [this article](#) for details. If the PrimalStatus is REDUCTION\_CERTIFICATE, then the primal result vector is a proof that the dual problem is ill-posed. If the DualStatus is REDUCTION\_CERTIFICATE, then the dual result vector is a proof that the primal is ill-posed.

[source](#)**SLOW\_PROGRESS**

JuMP.SLOW\_PROGRESS – Constant.

**SLOW\_PROGRESS**: :TerminationStatusCode

An instance of the [TerminationStatusCode](#) enum.

**SLOW\_PROGRESS**: The algorithm stopped because it was unable to continue making progress towards the solution.

[source](#)**SOLUTION\_LIMIT**

JuMP.SOLUTION\_LIMIT – Constant.

**SOLUTION\_LIMIT**: :TerminationStatusCode

An instance of the [TerminationStatusCode](#) enum.

**SOLUTION\_LIMIT**: The algorithm stopped because it found the required number of solutions. This is often used in MIPs to get the solver to return the first feasible solution it encounters.

[source](#)**TIME\_LIMIT**

JuMP.TIME\_LIMIT – Constant.

**TIME\_LIMIT**: :TerminationStatusCode

An instance of the [TerminationStatusCode](#) enum.

**TIME\_LIMIT**: The algorithm stopped after a user-specified computation time.

[source](#)

**UNKNOWN\_RESULT\_STATUS**

JuMP.UNKNOWN\_RESULT\_STATUS - Constant.

```
UNKNOWN_RESULT_STATUS::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

**UNKNOWN\_RESULT\_STATUS:** the result vector contains a solution with an unknown interpretation.

[source](#)

**op\_and**

JuMP.op\_and - Constant.

```
op_and(x, y)
```

A function that falls back to `x & y`, but when called with JuMP variables or expressions, returns a [GenericNonlinearExpr](#).

**Example**

```
julia> model = Model();
julia> @variable(model, x);
julia> op_and(true, false)
false
julia> op_and(true, x)
true && x
```

[source](#)

**op\_equal\_to**

JuMP.op\_equal\_to - Constant.

```
op_equal_to(x, y)
```

A function that falls back to `x == y`, but when called with JuMP variables or expressions, returns a [GenericNonlinearExpr](#).

**Example**

```
julia> model = Model();
julia> @variable(model, x);
julia> op_equal_to(2, 2)
true
```

```
julia> op_equal_to(x, 2)
x == 2
```

`source`

### `op_greater_than_or_equal_to`

JuMP.`op_greater_than_or_equal_to` - Constant.

```
op_greater_than_or_equal_to(x, y)
```

A function that falls back to  $x \geq y$ , but when called with JuMP variables or expressions, returns a [GenericNonlinearExpr](#).

#### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> op_greater_than_or_equal_to(2, 2)
true
julia> op_greater_than_or_equal_to(x, 2)
x >= 2
```

`source`

### `op_less_than_or_equal_to`

JuMP.`op_less_than_or_equal_to` - Constant.

```
op_less_than_or_equal_to(x, y)
```

A function that falls back to  $x \leq y$ , but when called with JuMP variables or expressions, returns a [GenericNonlinearExpr](#).

#### Example

```
julia> model = Model();
julia> @variable(model, x);
julia> op_less_than_or_equal_to(2, 2)
true
julia> op_less_than_or_equal_to(x, 2)
x <= 2
```

`source`

**op\_or**

JuMP.op\_or - Constant.

```
op_or(x, y)
```

A function that falls back to  $x \mid y$ , but when called with JuMP variables or expressions, returns a [GenericNonlinearExpr](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> op_or(true, false)
true

julia> op_or(true, x)
true || x
```

`source`

**op\_strictly\_greater\_than**

JuMP.op\_strictly\_greater\_than - Constant.

```
op_strictly_greater_than(x, y)
```

A function that falls back to  $x > y$ , but when called with JuMP variables or expressions, returns a [GenericNonlinearExpr](#).

**Example**

```
julia> model = Model();

julia> @variable(model, x);

julia> op_strictly_greater_than(1, 2)
false

julia> op_strictly_greater_than(x, 2)
x > 2
```

`source`

**op\_strictly\_less\_than**

JuMP.op\_strictly\_less\_than - Constant.

```
op_strictly_less_than(x, y)
```

A function that falls back to  $x < y$ , but when called with JuMP variables or expressions, returns a [GenericNonlinearExpr](#).

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> op_strictly_less_than(1, 2)
true

julia> op_strictly_less_than(x, 2)
x < 2
```

[source](#)

### Base.empty!(::GenericModel)

Base.empty! – Method.

```
empty!(model::GenericModel)::GenericModel
```

Empty the model, that is, remove all variables, constraints and model attributes but not optimizer attributes. Always return the argument.

Note: removes extensions data.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> isempty(model)
false

julia> empty!(model)
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> print(model)
Feasibility
Subject to

julia> isempty(model)
true
```

[source](#)

**Baseisempty(::GenericModel)**

Baseisempty – Method.

```
isempty(model::GenericModel)
```

Verifies whether the model is empty, that is, whether the MOI backend is empty and whether the model is in the same state as at its creation, apart from optimizer attributes.

**Example**

```
julia> model = Model();
julia> isempty(model)
true

julia> @variable(model, x[1:2]);

julia> isempty(model)
false
```

[source](#)

**Base.copy(::AbstractModel)**

Base.copy – Method.

```
copy(model::AbstractModel)
```

Return a copy of the model model. It is similar to [copy\\_model](#) except that it does not return the mapping between the references of model and its copy.

**Note**

Model copy is not supported in DIRECT mode, that is, when a model is constructed using the [direct\\_model](#) constructor instead of the [Model](#) constructor. Moreover, independently on whether an optimizer was provided at model construction, the new model will have no optimizer, that is, an optimizer will have to be provided to the new model in the [optimize!](#) call.

**Example**

In the following example, a model model is constructed with a variable x and a constraint cref. It is then copied into a model new\_model with the new references assigned to x\_new and cref\_new.

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @constraint(model, cref, x == 2)
cref : x = 2
```

```
julia> new_model = copy(model);  
  
julia> x_new = model[:x]  
x  
  
julia> cref_new = model[:cref]  
cref : x = 2
```

`source`

`Base.write(::IO, ::GenericModel; ::MOI.FileFormats.FileFormat)`

`Base.write` - Method.

```
Base.write(  
    io::IO,  
    model::GenericModel;  
    format::MOI.FileFormats.FileFormat = MOI.FileFormats FORMAT_MOF,  
    kwargs...  
)
```

Write the JuMP model `model` to `io` in the format `format`.

Other `kwargs` are passed to the `Model` constructor of the chosen format.

`source`

`MOI.Utilities.reset_optimizer(::GenericModel)`

`MathOptInterface.Utilities.reset_optimizer` - Method.

```
MOIU.reset_optimizer(model::GenericModel)
```

Call `MOIU.reset_optimizer` on the backend of `model`.

Cannot be called in direct mode.

`source`

`MOI.Utilities.drop_optimizer(::GenericModel)`

`MathOptInterface.Utilities.drop_optimizer` - Method.

```
MOIU.drop_optimizer(model::GenericModel)
```

Call `MOIU.drop_optimizer` on the backend of `model`.

Cannot be called in direct mode.

`source`

```
MOI.Utilities.attach_optimizer(::GenericModel)
MathOptInterface.Utilities.attach_optimizer - Method.
```

```
MOIU.attach_optimizer(model::GenericModel)
```

Call MOIU.attach\_optimizer on the backend of model.

Cannot be called in direct mode.

`source`

### **@NLconstraint**

JuMP.@NLconstraint - Macro.

```
@NLconstraint(model::GenericModel, expr)
```

Add a constraint described by the nonlinear expression expr. See also [@constraint](#).

#### Compat

This macro is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#). In most cases, you can replace @NLconstraint with [@constraint](#).

#### Example

```
julia> model = Model();
julia> @variable(model, x)
x

julia> @NLconstraint(model, sin(x) <= 1)
sin(x) - 1.0 ≤ 0

julia> @NLconstraint(model, [i = 1:3], sin(i * x) <= 1 / i)
3-element Vector{NonlinearConstraintRef{ScalarShape}}:
 (sin(1.0 * x) - 1.0 / 1.0) - 0.0 ≤ 0
 (sin(2.0 * x) - 1.0 / 2.0) - 0.0 ≤ 0
 (sin(3.0 * x) - 1.0 / 3.0) - 0.0 ≤ 0
```

`source`

### **@NLconstraints**

JuMP.@NLconstraints - Macro.

```
@NLconstraints(model, args...)
```

Adds multiple nonlinear constraints to model at once, in the same fashion as the `@NLconstraint` macro.

The model must be the first argument, and multiple constraints can be added on multiple lines wrapped in a `begin ... end` block.

The macro returns a tuple containing the constraints that were defined.

### Compat

This macro is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#). In most cases, you can replace `@NLconstraints` with `@constraints`.

### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @variable(model, y);

julia> @variable(model, t);

julia> @variable(model, z[1:2]);

julia> a = [4, 5];

julia> @NLconstraints(model, begin
           t >= sqrt(x^2 + y^2)
           [i = 1:2], z[i] <= log(a[i])
         end)
((t - sqrt(x ^ 2.0 + y ^ 2.0)) - 0.0 ≥ 0, NonlinearConstraintRef{ScalarShape}[(z[1] - log(4.0))
→ - 0.0 ≤ 0, (z[2] - log(5.0)) - 0.0 ≤ 0])
```

[source](#)

### `@NExpression`

JuMP.`@NExpression` – Macro.

```
@NExpression(args...)
```

Efficiently build a nonlinear expression which can then be inserted in other nonlinear constraints and the objective. See also `[@expression]`.

### Compat

This macro is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#). In most cases, you can replace `@NExpression` with `@expression`.

### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @variable(model, y)
y

julia> @NLexpression(model, my_expr, sin(x)^2 + cos(x^2))
subexpression[1]: sin(x) ^ 2.0 + cos(x ^ 2.0)

julia> @NLconstraint(model, my_expr + y >= 5)
(subexpression[1] + y) - 5.0 ≥ 0

julia> @NLobjective(model, Min, my_expr)
```

Indexing over sets and anonymous expressions are also supported:

```
julia> @NLexpression(model, my_expr_1[i=1:3], sin(i * x))
3-element Vector{NonlinearExpression}:
 subexpression[2]: sin(1.0 * x)
 subexpression[3]: sin(2.0 * x)
 subexpression[4]: sin(3.0 * x)

julia> my_expr_2 = @NLexpression(model, log(1 + sum(exp(my_expr_1[i]) for i in 1:2)))
subexpression[5]: log(1.0 + (exp(subexpression[2]) + exp(subexpression[3])))
```

`source`

### @NLexpressions

JuMP.@NLexpressions – Macro.

```
@NLexpressions(model, args...)
```

Adds multiple nonlinear expressions to model at once, in the same fashion as the `@NLexpression` macro.

The model must be the first argument, and multiple expressions can be added on multiple lines wrapped in a `begin ... end` block.

The macro returns a tuple containing the expressions that were defined.

#### Compat

This macro is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#). In most cases, you can replace `@NLexpressions` with `@expressions`.

#### Example

```
julia> model = Model();

julia> @variable(model, x);

julia> @variable(model, y);

julia> @variable(model, z[1:2]);

julia> a = [4, 5];

julia> @NLexpressions(model, begin
           my_expr, sqrt(x^2 + y^2)
           my_expr_1[i = 1:2], log(a[i]) - z[i]
         end)
(subexpression[1]: sqrt(x ^ 2.0 + y ^ 2.0), NonlinearExpression[subexpression[2]: log(4.0) -
→ z[1], subexpression[3]: log(5.0) - z[2]])
```

**source****@NLobjective**

JuMP.@NLobjective - Macro.

```
@NLobjective(model, sense, expression)
```

Add a nonlinear objective to `model` with optimization sense `sense`. `sense` must be `Max` or `Min`.

**Compat**

This macro is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#). In most cases, you can replace `@NLobjective` with `@objective`.

**Example**

```
julia> model = Model();

julia> @variable(model, x)
x

julia> @NLobjective(model, Max, 2x + 1 + sin(x))

julia> print(model)
Max 2.0 * x + 1.0 + sin(x)
Subject to
```

**source****@NLparameter**

JuMP.@NLparameter - Macro.

```
@NLparameter(model, param == value)
```

Create and return a nonlinear parameter `param` attached to the model `model` with initial value set to `value`. Nonlinear parameters may be used only in nonlinear expressions.

### Example

```
julia> model = Model();

julia> @NLparameter(model, x == 10)
x == 10.0

julia> value(x)
10.0
```

```
@NLparameter(model, value = param_value)
```

Create and return an anonymous nonlinear parameter `param` attached to the model `model` with initial value set to `param_value`. Nonlinear parameters may be used only in nonlinear expressions.

### Example

```
julia> model = Model();

julia> x = @NLparameter(model, value = 10)
parameter[1] == 10.0

julia> value(x)
10.0
```

```
@NLparameter(model, param_collection[...] == value_expr)
```

Create and return a collection of nonlinear parameters `param_collection` attached to the model `model` with initial value set to `value_expr` (may depend on index sets). Uses the same syntax for specifying index sets as [@variable](#).

### Example

```
julia> model = Model();

julia> @NLparameter(model, y[i = 1:3] == 2 * i)
3-element Vector{NonlinearParameter}:
 parameter[1] == 2.0
 parameter[2] == 4.0
 parameter[3] == 6.0

julia> value(y[2])
4.0
```

```
@NLparameter(model, [...] == value_expr)
```

Create and return an anonymous collection of nonlinear parameters attached to the model `model` with initial value set to `value_expr` (may depend on index sets). Uses the same syntax for specifying index sets as [@variable](#).

### Compat

This macro is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#). In most cases, you can replace a call like `@NLparameter(model, p == value)` with `@variable(model, p in Parameter(value))`.

### Example

```
julia> model = Model();  
  
julia> y = @NLparameter(model, [i = 1:3] == 2 * i)  
3-element Vector{NonlinearParameter}:  
parameter[1] == 2.0  
parameter[2] == 4.0  
parameter[3] == 6.0  
  
julia> value(y[2])  
4.0
```

[source](#)

### @NLparameters

JuMP.`@NLparameters` – Macro.

```
@NLparameters(model, args...)
```

Create and return multiple nonlinear parameters attached to model `model`, in the same fashion as [@NLparameter](#) macro.

The model must be the first argument, and multiple parameters can be added on multiple lines wrapped in a `begin ... end` block. Distinct parameters need to be placed on separate lines as in the following example.

The macro returns a tuple containing the parameters that were defined.

**Compat**

This macro is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#). In most cases, you can replace a call like

```
@NLparameters(model, begin
    p == value
end)
```

with

```
@variables(model, begin
    p in Parameter(value)
end)
```

**Example**

```
julia> model = Model();

julia> @NLparameters(model, begin
           x == 10
           b == 156
       end);

julia> value(x)
10.0
```

`source`

**add\_nonlinear\_constraint**

JuMP.add\_nonlinear\_constraint - Function.

```
add_nonlinear_constraint(model::Model, expr::Expr)
```

Add a nonlinear constraint described by the Julia expression `ex` to `model`.

This function is most useful if the expression `ex` is generated programmatically, and you cannot use `@NLconstraint`.

**Compat**

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

**Notes**

- You must interpolate the variables directly into the expression `expr`.

**Example**

```
julia> model = Model();  
  
julia> @variable(model, x);  
  
julia> add_nonlinear_constraint(model, :($x) + $(x)^2 <= 1))  
(x + x ^ 2.0) - 1.0 ≤ 0
```

source

**add\_nonlinear\_expression**

JuMP.add\_nonlinear\_expression - Function.

```
add_nonlinear_expression(model::Model, expr::Expr)
```

Add a nonlinear expression `expr` to `model`.

This function is most useful if the expression `expr` is generated programmatically, and you cannot use [@NLExpression](#).

**Compat**

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

**Notes**

- You must interpolate the variables directly into the expression `expr`.

**Example**

```
julia> model = Model();  
  
julia> @variable(model, x);  
  
julia> add_nonlinear_expression(model, :($x) + $(x)^2))  
subexpression[1]: x + x ^ 2.0
```

source

**add\_nonlinear\_parameter**

JuMP.add\_nonlinear\_parameter - Function.

```
add_nonlinear_parameter(model::Model, value::Real)
```

Add an anonymous parameter to the model.

### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

[source](#)

### all\_nonlinear\_constraints

JuMP.all\_nonlinear\_constraints – Function.

```
all_nonlinear_constraints(model::GenericModel)
```

Return a vector of all nonlinear constraint references in the model in the order they were added to the model.

### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

This function returns only the constraints added with `@NLconstraint` and `add_nonlinear_constraint`. It does not return `GenericNonlinearExpr` constraints.

[source](#)

### get\_optimizer\_attribute

JuMP.get\_optimizer\_attribute – Function.

```
get_optimizer_attribute(
    model::Union{GenericModel, MOI.OptimizerWithAttributes},
    attr::Union{AbstractString, MOI.AbstractOptimizerAttribute},
)
```

Return the value associated with the solver-specific attribute `attr`.

If `attr` is an `AbstractString`, this is equivalent to `get_optimizer_attribute(model, MOI.RawOptimizerAttribute(name))`.

### Compat

This method will remain in all v1.X releases of JuMP, but it may be removed in a future v2.0 release. We recommend using `get_attribute` instead.

See also: [set\\_optimizer\\_attribute](#), [set\\_optimizer\\_attributes](#).

### Example

```
julia> import Ipopt
julia> model = Model(Ipopt.Optimizer);
julia> get_optimizer_attribute(model, MOI.Silent())
false
```

[source](#)**nonlinear\_constraint\_string**

JuMP.nonlinear\_constraint\_string - Function.

```
nonlinear_constraint_string(
    model::GenericModel,
    mode::MIME,
    c::_NonlinearConstraint,
)
```

Return a string representation of the nonlinear constraint `c` belonging to `model`, given the `mode`.

**Compat**

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

[source](#)**nonlinear\_dual\_start\_value**

JuMP.nonlinear\_dual\_start\_value - Function.

```
nonlinear_dual_start_value(model::Model)
```

Return the current value of the MOI attribute `MOI.NLPBlockDualStart`.

**Compat**

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

[source](#)**nonlinear\_expr\_string**

JuMP.nonlinear\_expr\_string - Function.

```
nonlinear_expr_string(
    model::GenericModel,
    mode::MIME,
    c::MOI.Nonlinear.Expression,
)
```

Return a string representation of the nonlinear expression `c` belonging to `model`, given the `mode`.

### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

[source](#)

### nonlinear\_model

JuMP.`nonlinear_model` – Function.

```
nonlinear_model(
    model::GenericModel;
    force::Bool = false,
)::Union{MOI.Nonlinear.Model,Nothing}
```

If `model` has nonlinear components, return a `MOI.Nonlinear.Model`, otherwise return nothing.

If `force`, always return a `MOI.Nonlinear.Model`, and if one does not exist for the model, create an empty one.

### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

[source](#)

### num\_nonlinear\_constraints

JuMP.`num_nonlinear_constraints` – Function.

```
num_nonlinear_constraints(model::GenericModel)
```

Returns the number of nonlinear constraints associated with the `model`.

### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

This function counts only the constraints added with `@NLconstraint` and `add_nonlinear_constraint`. It does not count `GenericNonlinearExpr` constraints.

```
source

register

JuMP.register - Function.
```

```
register(
    model::Model,
    op::Symbol,
    dimension::Integer,
    f::Function;
    autodiff::Bool = false,
)
```

Register the user-defined function `f` that takes `dimension` arguments in `model` as the symbol `op`.

The function `f` must support all subtypes of `Real` as arguments. Do not assume that the inputs are `Float64`.

### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

### Notes

- For this method, you must explicitly set `autodiff = true`, because no user-provided gradient function  $\nabla f$  is given.
- Second-derivative information is only computed if `dimension == 1`.
- `op` does not have to be the same symbol as `f`, but it is generally more readable if it is.

### Example

```
julia> model = Model();

julia> @variable(model, x)
x

julia> f(x::T) where {T<:Real} = x^2
f (generic function with 1 method)

julia> register(model, :foo, 1, f; autodiff = true)

julia> @NLobjective(model, Min, foo(x))
```

```
julia> model = Model();

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
```

```
x[1]
x[2]

julia> g(x::T, y::T) where {T<:Real} = x * y
g (generic function with 1 method)

julia> register(model, :g, 2, g; autodiff = true)

julia> @NLobjective(model, Min, g(x[1], x[2]))
```

`source`

```
register(
    model::Model,
    s::Symbol,
    dimension::Integer,
    f::Function,
    ∇f::Function;
    autodiff::Bool = false,
)
```

Register the user-defined function `f` that takes `dimension` arguments in `model` as the symbol `s`. In addition, provide a gradient function `∇f`.

The functions `f` and `∇f` must support all subtypes of `Real` as arguments. Do not assume that the inputs are `Float64`.

### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

### Notes

- If the function `f` is univariate (that is, `dimension == 1`), `∇f` must return a number which represents the first-order derivative of the function `f`.
- If the function `f` is multi-variate, `∇f` must have a signature matching `∇f(g::AbstractVector{T}, args::T...)` where `{T<:Real}`, where the first argument is a vector `g` that is modified in-place with the gradient.
- If `autodiff = true` and `dimension == 1`, use automatic differentiation to compute the second-order derivative information. If `autodiff = false`, only first-order derivative information will be used.
- `s` does not have to be the same symbol as `f`, but it is generally more readable if it is.

### Example

```
julia> model = Model();

julia> @variable(model, x)
x
```

```
julia> f(x::T) where {T<:Real} = x^2
f (generic function with 1 method)

julia> ∇f(x::T) where {T<:Real} = 2 * x
∇f (generic function with 1 method)

julia> register(model, :foo, 1, f, ∇f; autodiff = true)

julia> @NLobjective(model, Min, foo(x))
```

```
julia> model = Model();

julia> @variable(model, x[1:2])
2-element Vector{VariableRef}:
 x[1]
 x[2]

julia> g(x::T, y::T) where {T<:Real} = x * y
g (generic function with 1 method)

julia> function ∇g(g::AbstractVector{T}, x::T, y::T) where {T<:Real}
    g[1] = y
    g[2] = x
    return
end
∇g (generic function with 1 method)

julia> register(model, :g, 2, g, ∇g)

julia> @NLobjective(model, Min, g(x[1], x[2]))
```

`source`

```
register(
    model::Model,
    s::Symbol,
    dimension::Integer,
    f::Function,
    ∇f::Function,
    ∇²f::Function,
)
```

Register the user-defined function `f` that takes `dimension` arguments in `model` as the symbol `s`. In addition, provide a gradient function `∇f` and a hessian function `∇²f`.

`∇f` and `∇²f` must return numbers corresponding to the first- and second-order derivatives of the function `f` respectively.

### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

**Notes**

- Because automatic differentiation is not used, you can assume the inputs are all `Float64`.
- This method will throw an error if `dimension > 1`.
- `s` does not have to be the same symbol as `f`, but it is generally more readable if it is.

**Example**

```
julia> model = Model();

julia> @variable(model, x)
x

julia> f(x::Float64) = x^2
f (generic function with 1 method)

julia> ∇f(x::Float64) = 2 * x
∇f (generic function with 1 method)

julia> ∇²f(x::Float64) = 2.0
∇²f (generic function with 1 method)

julia> register(model, :foo, 1, f, ∇f, ∇²f)

julia> @NLobjective(model, Min, foo(x))
```

`source`

`set_nonlinear_dual_start_value`  
`JuMP.set_nonlinear_dual_start_value` - Function.

```
set_nonlinear_dual_start_value(
    model::Model,
    start::Union{Nothing,Vector{Float64}},
)
```

Set the value of the MOI attribute `MOI.NLPBlockDualStart`.

**Compat**

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

The start vector corresponds to the Lagrangian duals of the nonlinear constraints, in the order given by `all_nonlinear_constraints`. That is, you must pass a single start vector corresponding to all of the nonlinear constraints in a single function call; you cannot set the dual start value of nonlinear constraints one-by-one. The example below demonstrates how to use `all_nonlinear_constraints` to create a mapping between the nonlinear constraint references and the start vector.

Pass nothing to unset a previous start.

### Example

```
julia> model = Model();

julia> @variable(model, x[1:2]);

julia> nl1 = @NLconstraint(model, x[1] <= sqrt(x[2]));

julia> nl2 = @NLconstraint(model, x[1] >= exp(x[2]));

julia> start = Dict(nl1 => -1.0, nl2 => 1.0);

julia> start_vector = [start[con] for con in all_nonlinear_constraints(model)]
2-element Vector{Float64}:
-1.0
1.0

julia> set_nonlinear_dual_start_value(model, start_vector)

julia> nonlinear_dual_start_value(model)
2-element Vector{Float64}:
-1.0
1.0
```

[source](#)

### set\_nonlinear\_objective

JuMP.set\_nonlinear\_objective - Function.

```
set_nonlinear_objective(
    model::Model,
    sense::MOI.OptimizationSense,
    expr::Expr,
)
```

Set the nonlinear objective of `model` to the expression `expr`, with the optimization sense `sense`.

This function is most useful if the expression `expr` is generated programmatically, and you cannot use `@NLobjective`.

#### Compat

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

#### Notes

- You must interpolate the variables directly into the expression `expr`.
- You must use `MIN_SENSE` or `MAX_SENSE` instead of `Min` and `Max`.

**Example**

```
julia> model = Model();
julia> @variable(model, x);
julia> set_nonlinear_objective(model, MIN_SENSE, :($x + $(x)^2))
```

**source****set\_normalized\_coefficients**

JuMP.set\_normalized\_coefficients - Function.

```
set_normalized_coefficients(
    constraint::ConstraintRef{<:AbstractModel,<:MOI.ConstraintIndex{F}},
    variable::AbstractVariableRef,
    new_coefficients::Vector{Tuple{Int64,T}},
) where {T,F<:Union{MOI.VectorAffineFunction{T},MOI.VectorQuadraticFunction{T}}}
```

A deprecated method that now redirects to [set\\_normalized\\_coefficient](#).

**source****set\_optimizer\_attribute**

JuMP.set\_optimizer\_attribute - Function.

```
set_optimizer_attribute(
    model::Union{GenericModel,MOI.OptimizerWithAttributes},
    attr::Union{AbstractString,MOI.AbstractOptimizerAttribute},
    value,
)
```

Set the solver-specific attribute `attr` in `model` to `value`.

If `attr` is an `AbstractString`, this is equivalent to `set_optimizer_attribute(model, MOI.RawOptimizerAttribute(name), value)`.

**Compat**

This method will remain in all v1.X releases of JuMP, but it may be removed in a future v2.0 release.  
We recommend using [set\\_attribute](#) instead.

See also: [set\\_optimizer\\_attributes](#), [get\\_optimizer\\_attribute](#).

**Example**

```
julia> model = Model();
julia> set_optimizer_attribute(model, MOI.Silent(), true)
```

```
source

set_optimizer_attributes

JuMP.set_optimizer_attributes - Function.
```

```
set_optimizer_attributes(
    model::Union{GenericModel, MOI.OptimizerWithAttributes},
    pairs::Pair...
)
```

Given a list of attribute => value pairs, calls `set_optimizer_attribute(model, attribute, value)` for each pair.

### Compat

This method will remain in all v1.X releases of JuMP, but it may be removed in a future v2.0 release.  
We recommend using `set_attributes` instead.

See also: `set_optimizer_attribute`, `get_optimizer_attribute`.

### Example

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> set_optimizer_attributes(model, "tol" => 1e-4, "max_iter" => 100)
```

is equivalent to:

```
julia> import Ipopt

julia> model = Model(Ipopt.Optimizer);

julia> set_optimizer_attribute(model, "tol", 1e-4)

julia> set_optimizer_attribute(model, "max_iter", 100)
```

```
source

set_value

JuMP.set_value - Function.
```

```
set_value(p::NonlinearParameter, v::Number)
```

Store the value `v` in the nonlinear parameter `p`.

**Compat**

This function is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

**Example**

```
julia> model = Model();  
  
julia> @NLparameter(model, p == 0)  
p == 0.0  
  
julia> set_value(p, 5)  
5  
  
julia> value(p)  
5.0
```

[source](#)

**NonlinearConstraintIndex**

JuMP.NonlinearConstraintIndex - Type.

```
ConstraintIndex
```

An index to a nonlinear constraint that is returned by [add\\_constraint](#).

Given `data::Model` and `c::ConstraintIndex`, use `data[c]` to retrieve the corresponding [Constraint](#).

[source](#)

**NonlinearConstraintRef**

JuMP.NonlinearConstraintRef - Type.

```
NonlinearConstraintRef
```

**Compat**

This type is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

[source](#)

**NonlinearExpression**

JuMP.NonlinearExpression - Type.

```
NonlinearExpression <: AbstractJuMPScalar
```

A struct to represent a nonlinear expression.

Create an expression using [@NLexpression](#).

#### Compat

This type is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

[source](#)

#### NonlinearParameter

JuMP.NonlinearParameter – Type.

```
NonlinearParameter <: AbstractJuMPScalar
```

A struct to represent a nonlinear parameter.

Create a parameter using [@NLparameter](#).

#### Compat

This type is part of the legacy nonlinear interface. Consider using the new nonlinear interface documented in [Nonlinear Modeling](#).

[source](#)

## 22.2 JuMP.Containers

### JuMP.Containers

This page lists the public API of JuMP.Containers.

#### Info

This page is an unstructured list of the JuMP.Containers API. For a more structured overview, read the Manual or Tutorial parts of this documentation.

Load all of the public the API into the current scope with:

```
using JuMP.Containers
```

Alternatively, load only the module with:

```
import JuMP.Containers
```

and then prefix all calls with JuMP.Containers. to create JuMP.Containers.<NAME>.

### DenseAxisArray

JuMP.Containers.DenseAxisArray - Type.

```
DenseAxisArray(data::Array{T, N}, axes...) where {T, N}
```

Construct a JuMP array with the underlying data specified by the data array and the given axes. Exactly N axes must be provided, and their lengths must match size(data) in the corresponding dimensions.

#### Example

```
julia> array = Containers.DenseAxisArray([1 2; 3 4], [:a, :b], 2:3)
2-dimensional DenseAxisArray{Int64,2,...} with index sets:
    Dimension 1, [:a, :b]
    Dimension 2, 2:3
And data, a 2x2 Matrix{Int64}:
 1  2
 3  4

julia> array[:b, 3]
4
```

[source](#)

```
DenseAxisArray{T}(undef, axes...) where T
```

Construct an uninitialized DenseAxisArray with element-type T indexed over the given axes.

#### Example

```
julia> array = Containers.DenseAxisArray{Float64}(undef, [:a, :b], 1:2);

julia> fill!(array, 1.0)
2-dimensional DenseAxisArray{Float64,2,...} with index sets:
    Dimension 1, [:a, :b]
    Dimension 2, 1:2
And data, a 2x2 Matrix{Float64}:
 1.0  1.0
 1.0  1.0

julia> array[:a, 2] = 5.0
5.0

julia> array[:a, 2]
5.0
```

```
julia> array
2-dimensional DenseAxisArray{Float64,2,...} with index sets:
    Dimension 1, [:a, :b]
    Dimension 2, 1:2
And data, a 2x2 Matrix{Float64}:
1.0  5.0
1.0  1.0
```

[source](#)**SparseAxisArray**

JuMP.Containers.SparseAxisArray – Type.

```
struct SparseAxisArray{T,N,K<:NTuple{N, Any}} <: AbstractArray{T,N}
    data::OrderedCollections.OrderedDict{K,T}
end
```

N-dimensional array with elements of type T where only a subset of the entries are defined. The entries with indices `idx = (i1, i2, ..., iN)` in `keys(data)` has value `data[idx]`.

Note that, as opposed to `SparseArrays.AbstractSparseArray`, the missing entries are not assumed to be `zero(T)`, they are simply not part of the array. This means that the result of `map(f, sa::SparseAxisArray)` or `f.(sa::SparseAxisArray)` has the same sparsity structure as `sa`, even if `f(zero(T))` is not zero.

**Example**

```
julia> using OrderedCollections: OrderedDict

julia> dict = OrderedDict((:a, 2) => 1.0, (:a, 3) => 2.0, (:b, 3) => 3.0)
OrderedDict{Tuple{Symbol, Int64}, Float64} with 3 entries:
    (:a, 2) => 1.0
    (:a, 3) => 2.0
    (:b, 3) => 3.0

julia> array = Containers.SparseAxisArray(dict)
SparseAxisArray{Float64, 2, Tuple{Symbol, Int64}} with 3 entries:
    [a, 2]   = 1.0
    [a, 3]   = 2.0
    [b, 3]   = 3.0

julia> array[:b, 3]
3.0
```

[source](#)**Containers.@container**

JuMP.Containers.@container – Macro.

```
@container([i=..., j=..., ...], expr[], container = :Auto)
```

Create a container with indices `i`, `j`, ... and values given by `expr` that may depend on the value of the indices.

```
@container(ref[i=..., j=..., ...], expr[], container = :Auto))
```

Same as above but the container is assigned to the variable of name `ref`.

The type of container can be controlled by the `container` keyword.

#### Note

When the index set is explicitly given as `1:n` for any expression `n`, it is transformed to `Base.OneTo(n)` before being given to `container`.

#### Example

```
julia> Containers.@container([i = 1:3, j = 1:3], i + j)
3x3 Matrix{Int64}:
 2  3  4
 3  4  5
 4  5  6

julia> I = 1:3
1:3

julia> Containers.@container(x[i = I, j = I], i + j);

julia> x
2-dimensional DenseAxisArray{Int64,2,...} with index sets:
  Dimension 1, 1:3
  Dimension 2, 1:3
And data, a 3x3 Matrix{Int64}:
 2  3  4
 3  4  5
 4  5  6

julia> Containers.@container([i = 2:3, j = 1:3], i + j)
2-dimensional DenseAxisArray{Int64,2,...} with index sets:
  Dimension 1, 2:3
  Dimension 2, Base.OneTo(3)
And data, a 2x3 Matrix{Int64}:
 3  4  5
 4  5  6

julia> Containers.@container([i = 1:3, j = 1:3; i <= j], i + j)
SparseAxisArray{Int64, 2, Tuple{Int64, Int64}} with 6 entries:
 [1, 1]  =  2
 [1, 2]  =  3
 [1, 3]  =  4
 [2, 2]  =  4
```

```
[2, 3] = 5
[3, 3] = 6
```

[source](#)

### Containers.container

JuMP.Containers.container – Function.

```
container(f::Function, indices[], ::Type{C} = AutoContainerType], names])
```

Create a container of type C with index names names, indices indices and values at given indices given by f.

If the method with names is not specialized on Type{C}, it falls back to calling container(f, indices, c) for backwards compatibility with containers not supporting index names.

#### Example

```
julia> Containers.container((i, j) -> i + j, Containers.vectorized_product(Base.OneTo(3),
    ↪ Base.OneTo(3)))
3x3 Matrix{Int64}:
 2  3  4
 3  4  5
 4  5  6

julia> Containers.container((i, j) -> i + j, Containers.vectorized_product(1:3, 1:3))
2-dimensional DenseAxisArray{Int64,2,...} with index sets:
  Dimension 1, 1:3
  Dimension 2, 1:3
And data, a 3x3 Matrix{Int64}:
 2  3  4
 3  4  5
 4  5  6

julia> Containers.container((i, j) -> i + j, Containers.vectorized_product(2:3, Base.OneTo(3)))
2-dimensional DenseAxisArray{Int64,2,...} with index sets:
  Dimension 1, 2:3
  Dimension 2, Base.OneTo(3)
And data, a 2x3 Matrix{Int64}:
 3  4  5
 4  5  6

julia> Containers.container((i, j) -> i + j, Containers.nested(() -> 1:3, i -> i:3, condition =
    ↪ (i, j) -> isodd(i) || isodd(j)))
SparseAxisArray{Int64, 2, Tuple{Int64, Int64}} with 5 entries:
 [1, 1] = 2
 [1, 2] = 3
 [1, 3] = 4
 [2, 3] = 5
 [3, 3] = 6
```

[source](#)

**Containers.rowtable**

JuMP.Containers.rowtable - Function.

```
rowtable([f::Function=identity,] x; [header::Vector{Symbol} = Symbol[]])
```

Applies the function `f` to all elements of the variable container `x`, returning the result as a Vector of NamedTuples, where `header` is a vector containing the corresponding axis names.

If `x` is an N-dimensional array, there must be `N+1` names, so that the last name corresponds to the result of `f(x[i])`.

If `header` is left empty, then the default header is `[:x1, :x2, ..., :xN, :y]`.

**Info**

A Vector of NamedTuples implements the [Tables.jl](#) interface, and so the result can be used as input for any function that consumes a 'Tables.jl' compatible source.

**Example**

```
julia> model = Model();

julia> @variable(model, x[i=1:2, j=i:2] >= 0, start = i+j);

julia> Containers.rowtable(start_value, x; header = [:i, :j, :start])
3-element Vector{@NamedTuple{i::Int64, j::Int64, start::Float64}}:
 (i = 1, j = 1, start = 2.0)
 (i = 1, j = 2, start = 3.0)
 (i = 2, j = 2, start = 4.0)

julia> Containers.rowtable(x)
3-element Vector{@NamedTuple{x1::Int64, x2::Int64, y::VariableRef}}:
 (x1 = 1, x2 = 1, y = x[1,1])
 (x1 = 1, x2 = 2, y = x[1,2])
 (x1 = 2, x2 = 2, y = x[2,2])
```

[source](#)

**Containers.default\_container**

JuMP.Containers.default\_container - Function.

```
default_container(indices)
```

If `indices` is a [NestedIterator](#), return a [SparseAxisArray](#). Otherwise, `indices` should be a [VectorizedProductIterator](#) and the function returns [Array](#) if all iterators of the product are `Base.OneTo` and returns [DenseAxisArray](#) otherwise.

[source](#)

**Containers.nested**

JuMP.Containers.nested – Function.

```
nested(iterators...; condition = (args...) -> true)
```

Create a [NestedIterator](#).**Example**

```
julia> iterator = Containers.nested(
    () -> 1:2,
    (i,) -> ["A", "B"];
    condition = (i, j) -> isodd(i) || j == "B",
);
julia> collect(iterator)
3-element Vector{Tuple{Int64, String}}:
 (1, "A")
 (1, "B")
 (2, "B")
```

[source](#)**Containers.vectorized\_product**

JuMP.Containers.vectorized\_product – Function.

```
vectorized_product(iterators...)
```

Created a [VectorizedProductIterator](#).**Example**

```
julia> iterator = Containers.vectorized_product(1:2, ["A", "B"]);
julia> collect(iterator)
2×2 Matrix{Tuple{Int64, String}}:
 (1, "A")  (1, "B")
 (2, "A")  (2, "B")
```

[source](#)**Containers.build\_error\_fn**

JuMP.Containers.build\_error\_fn – Function.

```
build_error_fn(macro_name, args, source)
```

Return a function that can be used in place of Base.error, but which additionally prints the macro from which it was called.

`source`

### `Containers.parse_macro_arguments`

JuMP.Containers.parse\_macro\_arguments – Function.

```
parse_macro_arguments(
    error_fn::Function,
    args;
    valid_kwargs::Union{Nothing,Vector{Symbol}} = nothing,
    num_positional_args::Union{Nothing,Int,UnitRange{Int}} = nothing,
)
```

Returns a `Tuple{Vector{Any}, Dict{Symbol, Any}}` containing the ordered positional arguments and a dictionary mapping the keyword arguments.

This specially handles the distinction of `@foo(key = value)` and `@foo(; key = value)` in macros.

An error is thrown if multiple keyword arguments are passed with the same key.

If `valid_kwargs` is a `Vector{Symbol}`, an error is thrown if a keyword is not in `valid_kwargs`.

If `num_positional_args` is not `nothing`, an error is thrown if the number of positional arguments is not in `num_positional_args`.

`source`

### `Containers.parse_ref_sets`

JuMP.Containers.parse\_ref\_sets – Function.

```
parse_ref_sets(
    error_fn::Function,
    expr;
    invalid_index_variables::Vector{Symbol} = Symbol[],
)
```

Helper function for macros to construct container objects.

#### Warning

This function is for advanced users implementing JuMP extensions. See [container\\_code](#) for more details.

#### Arguments

- `error_fn`: a function that takes a `String` and throws an error, potentially annotating the input string with extra information such as from which macro it was thrown from. Use `error` if you do not want a modified error message.

- expr: an Expr that specifies the container, for example, `:x[i = 1:3, [:red, :blue], k = S; i + k <= 6]`

### Returns

1. name: the name of the container, if given, otherwise nothing
2. index\_vars: a Vector{Any} of names for the index variables, for example, `[:i, gensym(), :k]`. These may also be expressions, like `:((i, j))` from a call like `:(x[(i, j) in S])`.
3. indices: an iterator over the indices, for example, `Containers.NestedIterator`

### Example

See `container_code` for a worked example.

`source`

### Containers.build\_name\_expr

JuMP.Containers.build\_name\_expr – Function.

```
build_name_expr(
    name::Union{Symbol,Nothing},
    index_vars::Vector,
    kwargs::Dict{Symbol,Any},
)
```

Returns an expression for the name of a container element, where name and index\_vars are the values returned by `parse_ref_sets` and kwargs is the dictionary returned by `parse_macro_arguments`.

This assumes that the key in kwargs used to over-ride the name choice is `:base_name`.

### Example

```
julia> Containers.build_name_expr(:x, [:i, :j], Dict{Symbol,Any}())
:(string("x", "[", string($(Expr(:escape, :i))), ",", string($(Expr(:escape, :j))), "]"))

julia> Containers.build_name_expr(nothing, [:i, :j], Dict{Symbol,Any}())
""

julia> Containers.build_name_expr(:y, [:i, :j], Dict{Symbol,Any}(:base_name => "y"))
:(string("y", "[", string($(Expr(:escape, :i))), ",", string($(Expr(:escape, :j))), "]"))
```

`source`

### Containers.add\_additional\_args

JuMP.Containers.add\_additional\_args – Function.

```
add_additional_args(
    call::Expr,
    args::Vector,
    kwargs::Dict{Symbol,Any};
    kwarg_exclude::Vector{Symbol} = Symbol[],
)
```

Add the positional arguments args to the function call expression call, escaping each argument expression.

This function is able to incorporate additional positional arguments to calls that already have keyword arguments.

`source`

### `Containers.container_code`

JuMP.`Containers.container_code` – Function.

```
container_code(
    index_vars::Vector{Any},
    indices::Expr,
    code,
    requested_container::Union{Symbol, Expr, Dict{Symbol, Any}},
)
```

Used in macros to construct a call to `container`. This should be used in conjunction with `parse_ref_sets`.

#### Arguments

- `index_vars::Vector{Any}`: a vector of names for the indices of the container. These may also be expressions, like `:(i, j)` from a call like `:(x[(i, j) in S])`.
- `indices::Expr`: an expression that evaluates to an iterator of the indices.
- `code`: an expression or literal constant for the value to be stored in the container as a function of the named `index_vars`.
- `requested_container`: passed to the third argument of `container`. For built-in JuMP types, choose one of `:Array`, `:DenseAxisArray`, `:SparseAxisArray`, or `:Auto`. For a user-defined container, this expression must evaluate to the correct type. You may also pass the `kwargs` dictionary from `parse_macro_arguments`.

#### Warning

In most cases, you should `esc(code)` before passing it to `container_code`.

#### Example

```
julia> macro foo(ref_sets, code)
    name, index_vars, indices =
        Containers.parse_ref_sets(error, ref_sets)
    @assert name !== nothing # Anonymous container not supported
    container =
        Containers.container_code(index_vars, indices, esc(code), :Auto)
    return quote
        $(esc(name)) = $container
    end
end
@foo (macro with 1 method)

julia> @foo(x[i=1:2, j=["A", "B"]], j^i);
```

```
julia> x
2-dimensional DenseAxisArray{String,2,...} with index sets:
    Dimension 1, Base.OneTo(2)
    Dimension 2, ["A", "B"]
And data, a 2x2 Matrix{String}:
"A"      "B"
"AA"     "BB"
```

**source****Containers.AutoContainerType**

JuMP.Containers.AutoContainerType – Type.

```
AutoContainerType
```

Pass AutoContainerType to [container](#) to let the container type be chosen based on the type of the indices using [default\\_container](#).

**source****Containers.NestedIterator**

JuMP.Containers.NestedIterator – Type.

```
struct NestedIterator{T}
    iterators::T # Tuple of functions
    condition::Function
end
```

Iterators over the tuples that are produced by a nested for loop.

Construct a NestedIterator using [nested](#).

**Example**

```
julia> iterators = (() -> 1:2, (i,) -> ["A", "B"]);

julia> condition = (i, j) -> isodd(i) || j == "B";

julia> x = Containers.NestedIterator(iterators, condition);

julia> for (i, j) in x
        println((i, j))
    end
(1, "A")
(1, "B")
(2, "B")
```

is the same as

```
julia> for i in iterators[1]()
    for j in iterators[2](i)
        if condition(i, j)
            println((i, j))
        end
    end
end
(1, "A")
(1, "B")
(2, "B")
```

source

### Containers.VectorizedProductIterator

JuMP.Containers.VectorizedProductIterator - Type.

```
struct VectorizedProductIterator{T}
    prod::Iterators.ProductIterator{T}
end
```

A wrapper type for Iterators.ProductIterator that discards shape information and returns a Vector.

Construct a VectorizedProductIterator using [vectorized\\_product](#).

source

## **Part V**

### **Background Information**

## Chapter 23

# Algebraic modeling languages

JuMP is an algebraic modeling language for mathematical optimization written in the [Julia language](#). In this page, we explain what an algebraic modeling language actually is.

### 23.1 What is an algebraic modeling language?

If you have taken a class in mixed-integer linear programming, you will have seen a formulation like:

$$\begin{aligned} \min \quad & c^\top x \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \\ & x_i \in \mathbb{Z}, \quad \forall i \in \mathcal{I} \end{aligned}$$

where  $c$ ,  $A$ , and  $b$  are appropriately sized vectors and matrices of data, and  $\mathcal{I}$  denotes the set of variables that are integer.

Solvers expect problems in a *standard form* like this because it limits the types of constraints that they need to consider. This makes writing a solver much easier.

#### What is a solver?

A solver is a software package that computes solutions to one or more classes of problems.

For example, [HiGHS](#) is a solver for linear programming (LP) and mixed integer programming (MIP) problems. It incorporates algorithms such as the simplex method and the interior-point method.

JuMP currently supports a number of open-source and commercial solvers, which can be viewed in the [Supported-solvers](#) table.

Despite the textbook view of a linear program, you probably formulated problems algebraically like so:

$$\begin{aligned}
 & \max \sum_{i=1}^n c_i x_i \\
 \text{s.t. } & \sum_{i=1}^n w_i x_i \leq b \\
 & x_i \geq 0 \quad \forall i = 1, \dots, n \\
 & x_i \in \mathbb{Z} \quad \forall i = 1, \dots, n.
 \end{aligned}$$

**Info**

Do you recognize this formulation? It's the knapsack problem.

Users prefer to write problems in *algebraic form* because it is more convenient. For example, we used  $\leq b$ , even though the standard form only supported constraints of the form  $Ax = b$ .

We could convert our knapsack problem into the standard form by adding a new slack variable  $x_0$ :

$$\begin{aligned}
 & \max \sum_{i=1}^n c_i x_i \\
 \text{s.t. } & x_0 + \sum_{i=1}^n w_i x_i = b \\
 & x_i \geq 0 \quad \forall i = 0, \dots, n \\
 & x_i \in \mathbb{Z} \quad \forall i = 1, \dots, n.
 \end{aligned}$$

However, as models get more complicated, this manual conversion becomes more and more error-prone.

An algebraic modeling language is a tool that simplifies the translation between the algebraic form of the modeler, and the standard form of the solver.

Each algebraic modeling language has two main parts:

1. A domain specific language for the user to write down problems in algebraic form.
2. A converter from the algebraic form into a standard form supported by the solver (and back again).

Part 2 is less trivial than it might seem, because each solver has a unique application programming interface (API) and data structure for representing optimization models and obtaining results.

JuMP uses the [MathOptInterface.jl](#) package to abstract these differences between solvers.

### What is MathOptInterface?

MathOptInterface (MOI) is an abstraction layer designed to provide an interface to mathematical optimization solvers so that users do not need to understand multiple solver-specific APIs. MOI can be used directly, or through a higher-level modeling interface like JuMP.

There are three main parts to MathOptInterface:

1. A solver-independent API that abstracts concepts such as adding and deleting variables and constraints, setting and getting parameters, and querying results. For more information on the MathOptInterface API, read the [documentation](#).
2. An automatic rewriting system based on equivalent formulations of a constraint. For more information on this rewriting system, read the [LazyBridgeOptimizer](#) section of the manual, and our [paper on arXiv](#).
3. Utilities for managing how and when models are copied to solvers. For more information on this, read the [CachingOptimizer](#) section of the manual.

## 23.2 From user to solver

This section provides a brief summary of the steps that happen in order to translate the model that the user writes into a model that the solver understands.

### Step I: writing in algebraic form

JuMP provides the first part of an algebraic modeling language using the `@variable`, `@objective`, and `@constraint` macros.

For example, here's how we write the knapsack problem in JuMP:

```
julia> using JuMP, HiGHS

julia> function algebraic_knapsack(c, w, b)
    n = length(c)
    model = Model(HiGHS.Optimizer)
    set_silent(model)
    @variable(model, x[1:n] >= 0, Int)
    @objective(model, Max, sum(c[i] * x[i] for i = 1:n))
    @constraint(model, sum(w[i] * x[i] for i = 1:n) <= b)
    optimize!(model)
    if termination_status(model) != OPTIMAL
        error("Not solved correctly")
    end
    return value.(x)
end
algebraic_knapsack (generic function with 1 method)

julia> algebraic_knapsack([1, 2], [0.5, 0.5], 1.25)
2-element Vector{Float64}:
 0.0
 2.0
```

This formulation is compact, and it closely matches the algebraic formulation of the model we wrote out above.

### Step II: algebraic to functional

For the next step, JuMP's macros re-write the variables and constraints into a functional form. Here's what the JuMP code looks like after this step:

```
julia> using JuMP, HiGHS

julia> function nonalgebraic_knapsack(c, w, b)
```

```

n = length(c)
model = Model(HiGHS.Optimizer)
set_silent(model)
x = [VariableRef(model) for i = 1:n]
for i = 1:n
    set_lower_bound(x[i], 0)
    set_integer(x[i])
    set_name(x[i], "x[$i]")
end
obj = AffExpr(0.0)
for i = 1:n
    add_to_expression!(obj, c[i], x[i])
end
set_objective(model, MAX_SENSE, obj)
lhs = AffExpr(0.0)
for i = 1:n
    add_to_expression!(lhs, w[i], x[i])
end
con = build_constraint(error, lhs, MOI.LessThan(b))
add_constraint(model, con)
optimize!(model)
if termination_status(model) != OPTIMAL
    error("Not solved correctly")
end
return value.(x)
end
nonalgebraic_knapsack (generic function with 1 method)

julia> nonalgebraic_knapsack([1, 2], [0.5, 0.5], 1.25)
2-element Vector{Float64}:
 0.0
 2.0

```

Hopefully you agree that the macro version is much easier to read.

### Part III: JuMP to MathOptInterface

In the third step, JuMP converts the functional form of the problem, that is, `nonalgebraic_knapsack`, into the `MathOptInterface` API:

```

julia> import MathOptInterface as MOI

julia> import HiGHS

julia> function mathoptinterface_knapsack(optimizer, c, w, b)
    n = length(c)
    model = MOI.instantiate(optimizer)
    MOI.set(model, MOI.Silent(), true)
    x = MOI.add_variables(model, n)
    for i in 1:n
        MOI.add_constraint(model, x[i], MOI.GreaterThan(0.0))
        MOI.add_constraint(model, x[i], MOI.Integer())
        MOI.set(model, MOI.VariableName(), x[i], "x[$i]")
    end
end

```

```

MOI.set(model, MOI.ObjectiveSense(), MOI.MAX_SENSE)
obj = MOI.ScalarAffineFunction(MOI.ScalarAffineTerm.(c, x), 0.0)
MOI.set(model, MOI.ObjectiveFunction{typeof(obj)}(), obj)
MOI.add_constraint(
    model,
    MOI.ScalarAffineFunction(MOI.ScalarAffineTerm.(w, x), 0.0),
    MOI.LessThan(b),
)
MOI.optimize!(model)
if MOI.get(model, MOI.TerminationStatus()) != MOI.OPTIMAL
    error("Not solved correctly")
end
return MOI.get.(model, MOI.VariablePrimal()), x
end
mathoptinterface_knapsack (generic function with 1 method)

julia> mathoptinterface_knapsack(HiGHS.Optimizer, [1.0, 2.0], [0.5, 0.5], 1.25)
2-element Vector{Float64}:
 0.0
 2.0

```

The code is becoming more verbose and looking less like the mathematical formulation that we started with.

#### Step IV: MathOptInterface to HiGHS

As a final step, the `HiGHS.jl` package converts the MathOptInterface form, that is, `mathoptinterface_knapsack`, into a HiGHS-specific API:

```

julia> using HiGHS

julia> function highs_knapsack(c, w, b)
    n = length(c)
    model = Highs_create()
    Highs_setBoolOptionValue(model, "output_flag", false)
    for i in 1:n
        Highs_addCol(model, c[i], 0.0, Inf, 0, C_NULL, C_NULL)
        Highs_changeColIntegrality(model, i-1, 1)
    end
    Highs_changeObjectiveSense(model, -1)
    Highs_addRow(
        model,
        -Inf,
        b,
        Cint(length(w)),
        collect(Cint(0):Cint(n-1)),
        w,
    )
    Highs_run(model)
    if Highs_getModelStatus(model) != kHighsModelStatusOptimal
        error("Not solved correctly")
    end
    x = fill(NaN, 2)
    Highs_getSolution(model, x, C_NULL, C_NULL, C_NULL)
    Highs_destroy(model)
end

```

```
    return x
end
highs_knapsack (generic function with 1 method)

julia> highs_knapsack([1.0, 2.0], [0.5, 0.5], 1.25)
2-element Vector{Float64}:
 0.0
 2.0
```

We've now gone from a algebraic model that looked identical to the mathematical model we started with, to a verbose function that uses HiGHS-specific functionality.

The difference between `algebraic_knapsack` and `highs_knapsack` highlights the benefit that algebraic modeling languages provide to users. Moreover, if we used a different solver, the solver-specific function would be entirely different. A key benefit of an algebraic modeling language is that you can change the solver without needing to rewrite the model.

## Chapter 24

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## **Part VI**

### **Developer Docs**

# Chapter 25

## Contributing

### 25.1 How to contribute to JuMP

Welcome, this document explains some ways you can contribute to JuMP.

#### Code of Conduct

This project and everyone participating in it is governed by the [JuMP Code of Conduct](#). By participating, you are expected to uphold this code.

#### Join the community forum

First up, join the [community forum](#).

The forum is a good place to ask questions about how to use JuMP. You can also use the forum to discuss possible feature requests and bugs before raising a GitHub issue (more on this below).

Aside from asking questions, the easiest way you can contribute to JuMP is to help answer questions on the forum.

#### Join the developer chatroom

If you're interested in contributing code to JuMP, the next place to join is the [developer chatroom](#). Let us know what you have in mind, and we can point you in the right direction.

#### Improve the documentation

Chances are, if you asked (or answered) a question on the community forum, then it is a sign that the [documentation](#) could be improved. Moreover, since it is your question, you are probably the best-placed person to improve it.

The docs are written in Markdown and are built using [Documenter.jl](#). You can find the source of all the docs [here](#).

If your change is small (like fixing typos, or one or two sentence corrections), the easiest way to do this is via GitHub's online editor. (GitHub has [help](#) on how to do this.)

If your change is larger, or touches multiple files, you will need to make the change locally and then use Git to submit a pull request. (See [Contribute code to JuMP](#) below for more on this.)

**Tip**

If you need any help, come join the [developer chatroom](#) and we will walk you through the process.

**File a bug report**

Another way to contribute to JuMP is to file [bug reports](#).

Make sure you read the info in the box where you write the body of the issue before posting. You can also find a copy of that info [here](#).

**Tip**

If you're unsure whether you have a real bug, post on the [community forum](#) first. Someone will either help you fix the problem, or let you know the most appropriate place to open a bug report.

**Contribute code to JuMP**

Finally, you can also contribute code to JuMP.

**Warning**

If you do not have experience with Git, GitHub, and Julia development, the first steps can be a little daunting. However, there are lots of tutorials available online, including these for:

- [GitHub](#)
- [Git and GitHub](#)
- [Git](#)
- [Julia package development](#)

If you need any help, come join the [developer chatroom](#) and we will walk you through the process.

Once you are familiar with Git and GitHub, the workflow for contributing code to JuMP is similar to the following:

**Step 1: decide what to work on**

The first step is to find an [open issue](#) (or open a new one) for the problem you want to solve. Then, *before* spending too much time on it, discuss what you are planning to do in the issue to see if other contributors are fine with your proposed changes. Getting feedback early can improve code quality, and avoid time spent writing code that does not get merged into JuMP.

**Tip**

At this point, remember to be patient and polite; you may get a *lot* of comments on your issue. However, do not be afraid. Comments mean that people are willing to help you improve the code that you are contributing to JuMP.

**Step 2: fork JuMP**

Go to <https://github.com/jump-dev/JuMP.jl> and click the "Fork" button in the top-right corner. This will create a copy of JuMP under your GitHub account.

### Step 3: install JuMP locally

Open Julia and run:

```
] dev JuMP
```

This will download the JuMP Git repository to `~/.julia/dev/JuMP`. If you're on Windows, this will be `C:\\\\Users\\\\<my_name>\\\\.julia\\\\dev\\\\JuMP`.

#### Warning

`]` command means "first type `]` to enter the Julia pkg mode, then type the rest. Don't copy-paste the code directly.

### Step 4: checkout a new branch

#### Note

In the following, replace any instance of `GITHUB_ACCOUNT` with your GitHub user name.

The next step is to checkout a development branch. In a terminal (or command prompt on Windows), run:

```
$ cd ~/.julia/dev/JuMP  
$ git remote add GITHUB_ACCOUNT https://github.com/GITHUB_ACCOUNT/JuMP.jl.git  
$ git checkout master  
$ git pull  
$ git checkout -b my_new_branch
```

#### Tip

Lines starting with `$` mean "run these in a terminal (command prompt on Windows)."

### Step 5: make changes

Now make any changes to the source code inside the `~/.julia/dev/JuMP` directory.

Make sure you:

- Follow the [Style guide](#) and run [JuliaFormatter](#)
- Add tests and documentation for any changes or new features

#### Tip

When you change the source code, you'll need to restart Julia for the changes to take effect. This is a pain, so install [Revise.jl](#).

### Step 6a: test your code changes

To test that your changes work, run the JuMP test-suite by opening Julia and running:

```
cd("~/julia/dev/JuMP")
] activate .
] test
```

#### Warning

Running the tests might take a long time (~10-15 minutes).

#### Tip

If you're using Revise.jl, you can also run the tests by calling `include`:

```
include("test/runtests.jl")
```

This can be faster if you want to re-run the tests multiple times.

### Step 6b: test your documentation changes

Open Julia, then run:

```
cd("~/julia/dev/JuMP/docs")
] activate .
include("src/make.jl")
```

#### Warning

Building the documentation might take a long time (~10 minutes).

#### Tip

If there's a problem with the tests that you don't know how to fix, don't worry. Continue to step 5, and one of the JuMP contributors will comment on your pull request telling you how to fix things.

### Step 7: make a pull request

Once you've made changes, you're ready to push the changes to GitHub. Run:

```
$ cd ~/julia/dev/JuMP
$ git add .
$ git commit -m "A descriptive message of the changes"
$ git push -u GITHUB_ACCOUNT my_new_branch
```

Then go to <https://github.com/jump-dev/JuMP.jl> and follow the instructions that pop up to open a pull request.

#### **Step 8: respond to comments**

At this point, remember to be patient and polite; you may get a *lot* of comments on your pull request. However, do not be afraid. A lot of comments means that people are willing to help you improve the code that you are contributing to JuMP.

To respond to the comments, go back to step 5, make any changes, test the changes in step 6, and then make a new commit in step 7. Your PR will automatically update.

#### **Step 9: cleaning up**

Once the PR is merged, clean-up your Git repository ready for the next contribution.

```
$ cd ~/.julia/dev/JuMP  
$ git checkout master  
$ git pull
```

#### **Note**

If you have suggestions to improve this guide, please make a pull request. It's particularly helpful if you do this after your first pull request because you'll know all the parts that could be explained better.

# Chapter 26

## Extensions

### 26.1 Extensions

JuMP provides a variety of ways to extend the basic modeling functionality.

#### Tip

This documentation in this section is still a work-in-progress. The best place to look for ideas and help when writing a new JuMP extension are existing JuMP extensions. Examples include:

- [BilevelJuMP.jl](#)
- [Coluna.jl](#)
- [InfiniteOpt.jl](#)
- [Plasmo.jl](#)
- [PolyJuMP.jl](#)
- [SDDP.jl](#)
- [StochasticPrograms.jl](#)
- [SumOfSquares.jl](#)
- [vOptGeneric.jl](#)

### Compatibility

When writing JuMP extensions, you should carefully consider the compatibility guarantees that JuMP makes. In particular:

- All functions, structs, and constants which do not begin with an underscore (\_) are public. These are always safe to use, and they should all have corresponding documentation.
- All identifiers beginning with an underscore (\_) are private. These are not safe to use, because they may break in any JuMP release, including patch releases.

- Unless explicitly mentioned in the documentation, all fields of a struct are private. These are not safe to use, because they may break in any JuMP release, including patch releases. An example of a field which is safe to use is the `model.ext` extension dictionary, which is documented in [The extension dictionary](#).

In general, we strongly encourage you to use only the public API of JuMP. If you are missing a feature, please open a GitHub issue.

However, if you *do* use the private API (for example, because your feature request has not been implemented yet), then you must carefully restrict the versions of JuMP that your package is compatible with in the `Project.toml` file. The easiest way to do this is via the [hyphen specifiers](#). For example, if your package supports all JuMP versions between v1.0.0 and v1.1.1, do:

```
JuMP = "1.0.0 - 1.1.1"
```

Then, whenever JuMP releases a new version, you should check if your package is still compatible and update the bound accordingly.

### Define a new set

To define a new set for JuMP, subtype `MOI.AbstractScalarSet` or `MOI.AbstractVectorSet` and implement `Base.copy` for the set.

```
julia> struct NewMOIVectorSet <: MOI.AbstractVectorSet
           dimension::Int
       end

julia> Base.copy(x::NewMOIVectorSet) = x

julia> model = Model();

julia> @variable(model, x[1:2]);

julia> @constraint(model, x in NewMOIVectorSet(2))
[x[1], x[2]] ∈ NewMOIVectorSet(2)
```

However, for vector-sets, this requires the user to specify the `dimension` argument to their set, even though we could infer it from the length of `x`!

You can make a more user-friendly set by subtyping `AbstractVectorSet` and implementing `moi_set`.

```
julia> struct NewVectorSet <: JuMP.AbstractVectorSet end

julia> JuMP.moi_set(::NewVectorSet, dim::Int) = NewMOIVectorSet(dim)

julia> @constraint(model, x in NewVectorSet())
[x[1], x[2]] ∈ NewMOIVectorSet(2)
```

### Extend `@variable`

Just as `Bin` and `Int` create binary and integer variables, you can extend the `@variable` macro to create new types of variables. Here is an explanation by example, where we create a `AddTwice` type, that creates a tuple of two JuMP variables instead of a single variable.

First, create a new struct. This can be anything. Our struct holds a `VariableInfo` object that stores bound information, and whether the variable is binary or integer.

```
julia> struct AddTwice
    info::JuMP.VariableInfo
end
```

Second, implement `build_variable`, which takes `::Type{AddTwice}` as an argument, and returns an instance of `AddTwice`. Note that you can also receive keyword arguments.

```
julia> function JuMP.build_variable(
    _err::Function,
    info::JuMP.VariableInfo,
    ::Type{AddTwice};
    kwargs...
)
    println("Can also use $kwargs here.")
    return AddTwice(info)
end
```

Third, implement `add_variable`, which takes the instance of `AddTwice` from the previous step, and returns something. Typically, you will want to call `add_variable` here. For example, our `AddTwice` call is going to add two JuMP variables.

```
julia> function JuMP.add_variable(
    model::JuMP.Model,
    duplicate::AddTwice,
    name::String,
)
    a = JuMP.add_variable(
        model,
        JuMP.ScalarVariable(duplicate.info),
        "$(name)_a",
    )
    b = JuMP.add_variable(
        model,
        JuMP.ScalarVariable(duplicate.info),
        "$(name)_b",
    )
    return (a, b)
end
```

Now `AddTwice` can be passed to `@variable` similar to `Bin` or `Int`, or through the `variable_type` keyword. However, now it adds two variables instead of one.

```
julia> model = Model();

julia> @variable(model, x[i=1:2], variable_type = AddTwice, kw = i)
Can also use Base.Pairs(:kw => 1) here.
Can also use Base.Pairs(:kw => 2) here.
2-element Vector{Tuple{VariableRef, VariableRef}}:
 (x[1]_a, x[1]_b)
```

```
(x[2]_a, x[2]_b)

julia> num_variables(model)
4

julia> first(x[1])
x[1]_a

julia> last(x[2])
x[2]_b
```

## Extend @constraint

The `@constraint` macro has three steps that can be intercepted and extended: parse time, build time, and add time.

### Parse

To extend the `@constraint` macro at parse time, implement one of the following methods:

- `parse_constraint_head`
- `parse_constraint_call`

#### Warning

Extending the constraint macro at parse time is an advanced operation and has the potential to interfere with existing JuMP syntax. Please discuss with the [developer chatroom](#) before publishing any code that implements these methods.

`parse_constraint_head` should be implemented to intercept an expression based on the `.head` field of `Base.Expr`. For example:

```
julia> using JuMP

julia> const MutableArithmetics = JuMP._MA;

julia> model = Model(); @variable(model, x);

julia> function JuMP.parse_constraint_head(
    error_fn::Function,
    ::Val{:==},
    lhs,
    rhs,
)
    println("Rewriting = as ==")
    new_lhs, parse_code = MutableArithmetics.rewrite(lhs)
    build_code = :(
        build_constraint($(error_fn), $(new_lhs), MOI.EqualTo($(rhs)))
    )
    return false, parse_code, build_code
end
```

```

end

julia> @constraint(model, x + x == 1.0)
Rewriting == as ==
2 x = 1

```

`parse_constraint_call` should be implemented to intercept an expression of the form `Expr(:call, op, args...)`. For example:

```

julia> using JuMP

julia> const MutableArithmetics = JuMP._MA;

julia> model = Model(); @variable(model, x);

julia> function JuMP.parse_constraint_call(
    error_fn::Function,
    is_vectorized::Bool,
    ::Val{:my_equal_to},
    lhs,
    rhs,
)
    println("Rewriting my_equal_to to ==")
    new_lhs, parse_code = MutableArithmetics.rewrite(lhs)
    build_code = if is_vectorized
        :(build_constraint($(error_fn), $(new_lhs), MOI.EqualTo($(rhs)))
    )
    else
        :(build_constraint.($(error_fn), $(new_lhs), MOI.EqualTo($(rhs))))
    end
    return parse_code, build_code
end

julia> @constraint(model, my_equal_to(x + x, 1.0))
Rewriting my_equal_to to ==
2 x = 1

```

### Tip

When parsing a constraint you can recurse into sub-constraint (for example, the `{expr}` in `z -> {x <= 1}`) by calling `parse_constraint`.

To prevent JuMP from promoting the set to the same value type as the model, use [SkipModelConvertScalarSetWrapper](#).

### Build

To extend the `@constraint` macro at build time, implement a new `build_constraint` method.

This may mean implementing a method for a specific function or set created at parse time, or it may mean implementing a method which handles additional positional arguments.

`build_constraint` must return an `AbstractConstraint`, which can either be an `AbstractConstraint` already supported by JuMP, for example, `ScalarConstraint` or `VectorConstraint`, or a custom `AbstractConstraint` with a corresponding `add_constraint` method (see [Add](#)).

**Tip**

The easiest way to extend `@constraint` is via an additional positional argument to `build_constraint`.

Here is an example of adding extra arguments to `build_constraint`:

```
julia> model = Model(); @variable(model, x);

julia> struct MyConstrType end

julia> function JuMP.build_constraint(
    error_fn::Function,
    f::JuMP.GenericAffExpr,
    set::MOI.EqualTo,
    extra::Type{MyConstrType};
    d = 0,
)
    new_set = MOI.LessThan(set.value + d)
    return JuMP.build_constraint(error_fn, f, new_set)
end

julia> @constraint(model, my_con, x == 0, MyConstrType, d = 2)
my_con : x ≤ 2
```

**Note**

Only a single positional argument can be given to a particular constraint. Extensions that seek to pass multiple arguments (for example, Foo and Bar) should combine them into one argument type (for example, FooBar).

**Add**

`build_constraint` returns an `AbstractConstraint` object. To extend `@constraint` at add time, define a subtype of `AbstractConstraint`, implement `build_constraint` to return an instance of the new type, and then implement `add_constraint`.

Here is an example:

```
julia> model = Model(); @variable(model, x);

julia> struct MyTag
    name::String
end

julia> struct MyConstraint{S} <: AbstractConstraint
    name::String
    f::AffExpr
    s::S
end

julia> function JuMP.build_constraint(
    error_fn::Function,
```

```

        f::AffExpr,
        set::MOI.AbstractScalarSet,
        extra::MyTag,
    )
    return MyConstraint(extra.name, f, set)
end

julia> function JuMP.add_constraint(
    model::Model,
    con::MyConstraint,
    name::String,
)
    return add_constraint(
        model,
        ScalarConstraint(con.f, con.s),
        "$(con.name)[$(name)]",
    )
end

julia> @constraint(model, my_con, 2x <= 1, MyTag("my_prefix"))
my_prefix[my_con] : 2 x - 1 ≤ 0

```

## The extension dictionary

Every JuMP model has a field `.ext::Dict{Symbol,Any}` that can be used by extensions. This is useful if your extensions to `@variable` and `@constraint` need to store information between calls.

The most common way to initialize a model with information in the `.ext` dictionary is to provide a new constructor:

```

julia> function MyModel()
    model = Model()
    model.ext[:MyModel] = 1
    return model
end

MyModel (generic function with 1 method)

julia> model = MyModel()
A JuMP Model
├ solver: none
├ objective_sense: FEASIBILITY_SENSE
├ num_variables: 0
└ num_constraints: 0
└ Names registered in the model: none

julia> model.ext
Dict{Symbol, Any} with 1 entry:
:MyModel => 1

```

If you define extension data, implement `copy_extension_data` to support `copy_model`.

## Defining new JuMP models

If extending individual calls to `@variable` and `@constraint` is not sufficient, it is possible to implement a new model via a subtype of `AbstractModel`. You can also define new `AbstractVariableRef`s to create different types of JuMP variables.

### Warning

Extending JuMP in this manner is an advanced operation. We strongly encourage you to consider how you can use the methods mentioned in the previous sections to achieve your aims instead of defining new model and variable types. Consult the [developer chatroom](#) before starting work on this.

If you define new types, you will need to implement a considerable number of methods, and doing so will require a detailed understanding of the JuMP internals. Therefore, the list of methods to implement is currently undocumented.

The easiest way to extend JuMP by defining a new model type is to follow an existing example. A simple example to follow is the `JuMPExtension` module in the JuMP test suite. The best example of an external JuMP extension that implements an `AbstractModel` is `InfiniteOpt.jl`.

## Testing JuMP extensions

The JuMP test suite contains a large number of tests for JuMP extensions. You can run these tests by copying the MIT-licensed `Kokako.jl` file in the JuMP tests into your `/test` folder, and then adding this snippet to your `/test/runtests.jl` file:

```
using MyJuMPExtension
import JuMP
include("Kokako.jl")
const MODULES_TO_TEST = Kokako.include_modules_to_test(JuMP)
Kokako.run_tests(
    MODULES_TO_TEST,
    MyJuMPExtension.MyModel,
    MyJuMPExtension.MyVariableRef;
    test_prefix = "test_extension_",
)
```

## Set an optimize! hook

Some extensions require modification to the problem after the user has finished constructing the problem, but before `optimize!` is called. For these situations, JuMP provides `set_optimize_hook`, which lets you intercept the `optimize!` call.

Here's a simple example of adding an optimize hook that extends `optimize!` to take a keyword argument `silent`:

```
julia> using JuMP, HiGHS

julia> model = Model(HiGHS.Optimizer);

julia> @variable(model, x >= 1.5, Int);

julia> @objective(model, Min, x);
```

```

julia> function silent_hook(model; silent::Bool)
    if silent
        set_silent(model)
    else
        unset_silent(model)
    end
    ## Make sure you set ignore_optimize_hook = true, or we'll
    ## recursively enter the optimize hook!
    return optimize!(model; ignore_optimize_hook = true)
end
silent_hook (generic function with 1 method)

julia> set_optimize_hook(model, silent_hook)
silent_hook (generic function with 1 method)

julia> optimize!(model; silent = true)

julia> optimize!(model; silent = false)
Coefficient ranges:
  Cost  [1e-00, 1e+00]
  Bound [2e+00, 2e+00]
Assessing feasibility of MIP using primal feasibility and integrality tolerance of      1e-06
Solution has          num       max       sum
Col    infeasibilities   0         0         0
Integer infeasibilities   0         0         0
Row    infeasibilities   0         0         0
Row    residuals         0         0         0
Presolving model
0 rows, 0 cols, 0 nonzeros  0s
0 rows, 0 cols, 0 nonzeros  0s
Presolve: Optimal

      Nodes      |      B&B Tree      |          Objective Bounds      |      Dynamic
→ Constraints |          Work
      Proc. InQueue | Leaves Expl. | BestBound      BestSol
→ Confl. | LpIters     Time
      0         0         0     0.00%    2
→ 0         0         0.0s

Solving report
  Status      Optimal
  Primal bound  2
  Dual bound   2
  Gap          0% (tolerance: 0.01%)
  Solution status feasible
                2 (objective)
                0 (bound viol.)
                0 (int. viol.)
                0 (row viol.)
  Timing      0.00 (total)
                0.00 (presolve)
                0.00 (postsolve)
  Nodes       0

```

```

LP iterations      0 (total)
                  0 (strong br.)
                  0 (separation)
                  0 (heuristics)

```

### Creating new container types

JuMP macros (for example, `@variable`) accept a `container` keyword argument to force the type of container that is chosen. By default, JuMP supports `container = Array`, `container = DenseAxisArray`, `container = SparseAxisArray` and `container = Auto`. You can extend support to user-defined types by implementing `Containers.container`.

For example, here is a container that reverses the order of the indices:

```

julia> struct Foo end

julia> function Containers.container(f::Function, indices, ::Type{Foo})
           return reverse([f(i...) for i in indices])
       end

julia> model = Model();

julia> @variable(model, x[1:3], container = Foo)
3-element Vector{VariableRef}:
 x[3]
 x[2]
 x[1]

julia> x[1]
x[3]

julia> @variable(model, y[1:3, 1:2], container = Foo)
3x2 Matrix{VariableRef}:
 y[3,2]  y[3,1]
 y[2,2]  y[2,1]
 y[1,2]  y[1,1]

julia> y[1, 1]
y[3,2]

julia> @variable(model, z[i=1:3; isodd(i)], container = Foo)
2-element Vector{VariableRef}:
 z[3]
 z[1]

julia> z[2]
z[1]

```

**Warning**

If you are a general user, you should not need to create a new container type. Instead, consider following [User-defined containers](#) and create a new container using standard Julia syntax. For example:

```
julia> model = Model();

julia> @variable(model, x[1:3])
3-element Vector{VariableRef}:
x[1]
x[2]
x[3]

julia> y = reverse(x)
3-element Vector{VariableRef}:
x[3]
x[2]
x[1]
```

**Performance tips for extensions**

The function-in-set design of MathOptInterface causes type stability issues in Julia if you try to iterate over all of the constraints in a model. The easiest way to fix this is to use a function barrier.

For example, instead of:

```
function all_names_slow(model)
    names = Set{String}()
    for ci in all_constraints(model)
        push!(names, name(ci))
    end
    return names
end
```

use:

```
function _function_barrier(names, model, ::Type{F}, ::Type{S}) where {F,S}
    for ci in all_constraints(model, F, S)
        push!(names, name(ci))
    end
    return
end

function all_names_fast(model)
    names = Set{String}()
    for (F, S) in list_of_constraint_types(model)
        _function_barrier(names, model, F, S)
    end
    return names
end
```

**Note**

It is important to explicitly type the F and S arguments. If you leave them untyped, for example, `function _function_barrier(names, model, F, S)`, Julia will not specialize the function calls and performance will not be improved.

## Chapter 27

# Custom binaries

### 27.1 How to use a custom binary

Many solvers are not written in Julia, but instead in languages like C or C++. JuMP interacts with these solvers through binary dependencies.

For many open-source solvers, we automatically install the appropriate binary when you run `Pkg.add("Solver")`. For example, `Pkg.add("ECOS")` will also install the ECOS binary.

This page explains how this installation works, and how you can use a custom binary.

#### Compat

These instructions require Julia 1.6 or later.

#### Background

Each solver that JuMP supports is structured as a Julia package. For example, the interface for the [ECOS](#) solver is provided by the [ECOS.jl](#) package.

#### Tip

This page uses the example of ECOS.jl because it is simple to compile. Other solvers follow similar conventions. For example, the interface to the Clp solver is provided by Clp.jl.

The ECOS.jl package provides an interface between the C API of ECOS and MathOptInterface. However, it does not handle the installation of the solver binary; that is the job for a JLL package.

A JLL is a Julia package that wraps a pre-compiled binary. Binaries are built using [Yggdrasil](#) (for example, [ECOS](#)) and hosted in the [JuliaBinaryWrappers](#) GitHub repository (for example, [ECOS\\_jll.jl](#)).

JLL packages contain little code. Their only job is to `dlopen` a dynamic library, along with any dependencies.

JLL packages manage their binary dependencies using [Julia's artifact system](#). Each JLL package has an `Artifacts.toml` file which describes where to find each binary artifact for each different platform that it might be installed on. Here is the [Artifacts.toml file for ECOS\\_jll.jl](#).

The binaries installed by the JLL package should be sufficient for most users. In rare cases, however, you may require a custom binary. The two main reasons to use a custom binary are:

- You want a binary with custom compilation settings (for example, debugging)

- You want a binary with a set of dependencies that are not available on Yggdrasil (for example, a commercial solver like Gurobi or CPLEX).

The following sections explain how to replace the binaries provided by a JLL package with the custom ones you have compiled. As a reminder, we use ECOS as an example for simplicity, but the steps are the same for other solvers.

### Explore the JLL you want to override

The first step is to explore the structure and filenames of the JLL package we want to override.

Find the location of the files using `.artifact_dir`:

```
julia> using ECOS_jll

julia> ECOS_jll.artifact_dir
"/Users/oscar/.julia/artifacts/2addb75332eff5a1657b46bb6bf30d2410bc7ecf"
```

#### Tip

This path may be different on other machines.

Here is what it contains:

```
julia> readdir(ECOS_jll.artifact_dir)
4-element Vector{String}:
 "include"
 "lib"
 "logs"
 "share"

julia> readdir(joinpath(ECOS_jll.artifact_dir, "lib"))
1-element Vector{String}:
 "libecos.dylib"
```

Other solvers may have a `bin` directory containing executables. To use a custom binary of ECOS, we need to replace `/lib/libecos.dylib` with our custom binary.

### Compile a custom binary

The next step is to compile a custom binary. Because ECOS is written in C with no dependencies, this is easy to do if you have a C compiler:

```
oscar@Oscars-MBP jll_example % git clone https://github.com/embotech/ecos.git
[... lines omitted ...]
oscar@Oscars-MBP jll_example % cd ecos
oscar@Oscars-MBP ecos % make shared
[... many lines omitted...]
oscar@Oscars-MBP ecos % mkdir lib
oscar@Oscars-MBP ecos % cp libecos.dylib lib
```

**Warning**

Compiling custom solver binaries is an advanced operation. Due to the complexities of compiling various solvers, the JuMP community is unable to help you diagnose and fix compilation issues.

After this compilation step, we now have a folder `/tmp/jll_example/ecos` that contains `lib` and `include` directories with the same files as `ECOS_jll`:

```
julia> readdir(joinpath("ecos", "lib"))
1-element Vector{String}:
 "libecos.dylib"
```

**Overriding a single library**

To override the `libecos` library, we need to know what `ECOS_jll` calls it. (In most cases, it will also be `libecos`, but not always.)

There are two ways you can check.

1. Check the bottom of the JLL's GitHub README. For example, [ECOS\\_jll](#) has a single `LibraryProduct` called `libecos`.
2. Type `ECOS_jll.` and then press the `[TAB]` key twice to auto-complete available options:

```
julia> ECOS_jll.
LIBPATH      PATH_list      best_wrapper      get_libecos_path  libecos_handle
LIBPATH_list __init__       dev_jll           is_available    libecos_path
PATH         artifact_dir   find_artifact_dir libecos
```

Here you can see there is `libecos`, and more usefully for us, `libecos_path`.

Once you know the name of the variable to override (the one that ends in `_path`), use [Preferences.jl](#) to specify a new path:

```
using Preferences
set_preferences!(
    "LocalPreferences.toml",
    "ECOS_jll",
    "libecos_path" => "/tmp/jll_example/ecos/lib/libecos"
)
```

This will create a file in your current directory called `LocalPreferences.toml` with the contents:

```
[ECOS_jll]
libecos_path = "/tmp/jll_example/ecos/lib/libecos"
```

Now if you restart Julia, you will see:

```
julia> using ECOS_jll

julia> ECOS_jll.libecos
"/tmp/jll_example/ecos/lib/libecos"
```

To go back to using the default library, just delete the `LocalPreferences.toml` file.

### Overriding an entire artifact

Sometimes a solver may provide a number of libraries and executables, and specifying the path for each of the becomes tedious. In this case, we can use Julia's `Override.toml` to replace an entire artifact.

Overriding an entire artifact requires you to replicate the structure and contents of the JLL package that we [explored above](#).

In most cases you need only reproduce the `include`, `lib`, and `bin` directories (if they exist). You can safely ignore any logs or share directories. Take careful note of what files each directory contains and what they are called.

For our ECOS example, we already reproduced the structure when we [compiled ECOS](#).

So, now we need to tell Julia to use our custom installation instead of the default. We can do this by making an override file at `~/julia/artifacts/Overrides.toml`.

`Overrides.toml` has the following content:

```
# Override for ECOS_jll
2addb75332eff5a1657b46bb6bf30d2410bc7ecf = "/tmp/jll_example/ecos"
```

where `2addb75332eff5a1657b46bb6bf30d2410bc7ecf` is the folder from the original `ECOS_jll.artifact_dir` and `"/tmp/jll_example/ecos"` is the location of our new installation. Replace these as appropriate for your system.

If you restart Julia after creating the override file, you will see:

```
julia> using ECOS_jll

julia> ECOS_jll.artifact_dir
"/tmp/jll_example/ecos"
```

Now when we use ECOS it will use our custom binary.

### Using Cbc with a custom binary

As a second example, we demonstrate how to use [Cbc.jl](#) with a custom binary.

#### Explore the JLL you want to override

First, let's check where `Cbc_jll` is installed:

```
julia> using Cbc_jll

julia> Cbc_jll.artifact_dir
```

```

"/Users/oscar/.julia/artifacts/e481bc81db5e229ba1f52b2b4bd57484204b1b06"

julia> readdir(Cbc_jll.artifact_dir)
5-element Vector{String}:
 "bin"
 "include"
 "lib"
 "logs"
 "share"

julia> readdir(joinpath(Cbc_jll.artifact_dir, "bin"))
1-element Vector{String}:
 "cbc"

julia> readdir(joinpath(Cbc_jll.artifact_dir, "lib"))
10-element Vector{String}:
 "libCbc.3.10.5.dylib"
 "libCbc.3.dylib"
 "libCbc.dylib"
 "libCbcSolver.3.10.5.dylib"
 "libCbcSolver.3.dylib"
 "libCbcSolver.dylib"
 "libOsiCbc.3.10.5.dylib"
 "libOsiCbc.3.dylib"
 "libOsiCbc.dylib"
 "pkgconfig"

```

### Compile a custom binary

Next, we need to compile Cbc. Cbc can be difficult to compile (it has a lot of dependencies), but for macOS users there is a homebrew recipe:

```

(base) oscar@Oscars-MBP jll_example % brew install cbc
[ ... lines omitted ... ]
(base) oscar@Oscars-MBP jll_example % brew list cbc
/usr/local/Cellar/cbc/2.10.5/bin/cbc
/usr/local/Cellar/cbc/2.10.5/include/cbc/ (76 files)
/usr/local/Cellar/cbc/2.10.5/lib/libCbc.3.10.5.dylib
/usr/local/Cellar/cbc/2.10.5/lib/libCbcSolver.3.10.5.dylib
/usr/local/Cellar/cbc/2.10.5/lib/libOsiCbc.3.10.5.dylib
/usr/local/Cellar/cbc/2.10.5/lib/pkgconfig/ (2 files)
/usr/local/Cellar/cbc/2.10.5/lib/ (6 other files)
/usr/local/Cellar/cbc/2.10.5/share/cbc/ (59 files)
/usr/local/Cellar/cbc/2.10.5/share/coin/ (4 files)

```

### Override single libraries

To use Preferences.jl to override specific libraries we first check the names of each library in Cbc\_jll:

|                 |          |                        |                |
|-----------------|----------|------------------------|----------------|
| julia> Cbc_jll. |          |                        |                |
| LIBPATH         | cbc      | get_libcbc solver_path | libOsiCbc_path |
| LIBPATH_list    | cbc_path | is_available           | libcbc solver  |

|              |                    |                  |                     |
|--------------|--------------------|------------------|---------------------|
| PATH         | dev_jll            | libCbc           | libcbcSolver_handle |
| PATH_list    | find_artifact_dir  | libCbc_handle    | libcbcSolver_path   |
| __init__     | get_cbc_path       | libCbc_path      |                     |
| artifact_dir | get_libCbc_path    | libOsiCbc        |                     |
| best_wrapper | get_libOsiCbc_path | libOsiCbc_handle |                     |

Then we add the following to LocalPreferences.toml:

```
[Cbc_jll]
cbc_path = "/usr/local/Cellar/cbc/2.10.5/bin/cbc"
libCbc_path = "/usr/local/Cellar/cbc/2.10.5/lib/libCbc.3.10.5"
libOsiCbc_path = "/usr/local/Cellar/cbc/2.10.5/lib/libOsiCbc.3.10.5"
libcbcSolver_path = "/usr/local/Cellar/cbc/2.10.5/lib/libCbcSolver.3.10.5"
```

### Info

Note that capitalization matters, so libcbcSolver\_path corresponds to libCbcSolver.3.10.5.

### Override entire artifact

To use the homebrew install as our custom binary we add the following to ~/.julia/artifacts/Overrides.toml:

```
# Override for Cbc_jll
e481bc81db5e229ba1f52b2b4bd57484204b1b06 = "/usr/local/Cellar/cbc/2.10.5"
```

## Chapter 28

# Style Guide

### 28.1 Style guide and design principles

#### Style guide

This section describes the coding style rules that apply to JuMP code and that we recommend for JuMP models and surrounding Julia code. The motivations for a style guide include:

- conveying best practices for writing readable and maintainable code
- reducing the amount of time spent on [bike-shedding](#) by establishing basic naming and formatting conventions
- lowering the barrier for new contributors by codifying the existing practices (for example, you can be more confident your code will pass review if you follow the style guide)

In some cases, the JuMP style guide diverges from the [Julia style guide](#). All such cases will be explicitly noted and justified.

The JuMP style guide adopts many recommendations from the [Google style guides](#).

#### Info

The style guide is always a work in progress, and not all JuMP code follows the rules. When modifying JuMP, please fix the style violations of the surrounding code (that is, leave the code tidier than when you started). If large changes are needed, consider separating them into another PR.

#### JuliaFormatter

JuMP uses [JuliaFormatter.jl](#) as an auto-formatting tool.

We use the options contained in [.JuliaFormatter.toml](#).

To format code, cd to the JuMP directory, then run:

```
] add JuliaFormatter@1  
using JuliaFormatter  
format("docs")  
format("src")  
format("test")
```

**Info**

A continuous integration check verifies that all PRs made to JuMP have passed the formatter.

The following sections outline extra style guide points that are not fixed automatically by JuliaFormatter.

**Abstract types and composition**

Specifying types for method arguments is mostly optional in Julia. The benefit of abstract method arguments is that it enables functions and types from one package to be used with functions and types from another package via multiple dispatch.

However, abstractly typed methods have two main drawbacks:

1. It's possible to find out that you are working with unexpected types deep in the call chain, potentially leading to hard-to-diagnose [MethodErrors](#).
2. Untyped function arguments can lead to correctness problems if the user's choice of input type does not satisfy the assumptions made by the author of the function.

As a motivating example, consider the following function:

```
julia> function my_sum(x)
    y = 0.0
    for i in 1:length(x)
        y += x[i]
    end
    return y
end
my_sum (generic function with 1 method)
```

This function contains a number of implicit assumptions about the type of `x`:

- `x` supports 1-based `getindex` and implements `length`
- The element type of `x` supports addition with `0.0`, and then with the result of `x + 0.0`.

**Info**

As a motivating example for the second point, `VariableRef` plus `Float64` produces an `AffExpr`. Do not assume that `+(:A, ::B)` produces an instance of the type `A` or `B`.

`my_sum` works as expected if the user passes in `Vector{Float64}`:

```
julia> my_sum([1.0, 2.0, 3.0])
6.0
```

but it doesn't respect input types, for example returning a `Float64` if the user passes `Vector{Int}`:

```
julia> my_sum([1, 2, 3])
6.0
```

but it throws a `MethodError` if the user passes String:

```
julia> my_sum("abc")
ERROR: MethodError: no method matching +(::Float64, ::Char)
[...]
```

This particular `MethodError` is hard to debug, particularly for new users, because it mentions `+`, `Float64`, and `Char`, none of which were called or passed by the user.

### Dealing with `MethodErrors`

This section diverges from the [Julia style guide](#), as well as other common guides like [SciML](#). The following suggestions are intended to provide a friendlier experience for novice Julia programmers, at the cost of limiting the power and flexibility of advanced Julia programmers.

Code should follow the `MethodError` principle:

#### The `MethodError` principle

A user should see a `MethodError` only for methods that they called directly.

Bad:

```
_internal_function(x::Integer) = x + 1
# The user sees a MethodError for _internal_function when calling
# public_function("a string"). This is not very helpful.
public_function(x) = _internal_function(x)
```

Good:

```
_internal_function(x::Integer) = x + 1
# The user sees a MethodError for public_function when calling
# public_function("a string"). This is easy to understand.
public_function(x::Integer) = _internal_function(x)
```

If it is hard to provide an error message at the top of the call chain, then the following pattern is also ok:

```
_internal_function(x::Integer) = x + 1
function _internal_function(x)
    error(
        "Internal error. This probably means that you called " *
        "`public_function()`'s with the wrong type.",
    )
end
public_function(x) = _internal_function(x)
```

### Dealing with correctness

Dealing with correctness is harder, because Julia has no way of formally specifying interfaces that abstract types must implement. Instead, here are two options that you can use when writing and interacting with generic code:

#### Option 1: use concrete types and let users extend new methods.

In this option, explicitly restrict input arguments to concrete types that are tested and have been validated for correctness. For example:

```
julia> function my_sum_option_1(x::Vector{Float64})
    y = 0.0
    for i in 1:length(x)
        y += x[i]
    end
    return y
end
my_sum_option_1 (generic function with 1 method)

julia> my_sum_option_1([1.0, 2.0, 3.0])
6.0
```

Using concrete types satisfies the `MethodError` principle:

```
julia> my_sum_option_1("abc")
ERROR: MethodError: no method matching my_sum_option_1(::String)
```

and it allows other types to be supported in future by defining new methods:

```
julia> function my_sum_option_1(x::Array{T,N}) where {T<:Number,N}
    y = zero(T)
    for i in eachindex(x)
        y += x[i]
    end
    return y
end
my_sum_option_1 (generic function with 2 methods)
```

Importantly, these methods do not have to be defined in the original package.

#### Info

Some usage of abstract types is okay. For example, in `my_sum_option_1`, we allowed the element type, `T`, to be a subtype of `Number`. This is fairly safe, but it still has an implicit assumption that `T` supports `zero(T)` and `+(::T, ::T)`.

#### Option 2: program defensively, and validate all assumptions.

An alternative is to program defensively, and to rigorously document and validate all assumptions that the code makes. In particular:

1. All assumptions on abstract types that aren't guaranteed by the definition of the abstract type (for example, optional methods without a fallback) should be documented.

2. If practical, the assumptions should be checked in code, and informative error messages should be provided to the user if the assumptions are not met. In general, these checks may be expensive, so you should prefer to do this once, at the highest level of the call-chain.
3. Tests should cover for a range of corner cases and argument types.

For example:

```
"""
    test_my_sum_defensive_assumptions(x::AbstractArray{T}) where {T}

Test the assumptions made by `my_sum_defensive`.

"""

function test_my_sum_defensive_assumptions(x::AbstractArray{T}) where {T}
    try
        # Some types may not define zero.
        @assert zero(T) isa T
        # Check iteration supported
        @assert iterate(x) isa Union{Nothing, Tuple{T, Int}}
        # Check that + is defined
        @assert +(zero(T), zero(T)) isa Any
    catch err
        error(
            "Unable to call my_sum_defensive(::$(typeof(x))) because " *
            "it failed an internal assumption",
        )
    end
    return
end

"""

my_sum_defensive(x::AbstractArray{T}) where {T}

Return the sum of the elements in the abstract array `x`.

## Assumptions

This function makes the following assumptions:

* That `zero(T)` is defined
* That `x` supports the iteration interface
* That `+(::T, ::T)` is defined
"""

function my_sum_defensive(x::AbstractArray{T}) where {T}
    test_my_sum_defensive_assumptions(x)
    y = zero(T)
    for xi in x
        y += xi
    end
    return y
end

# output

my_sum_defensive
```

This function works on `Vector{Float64}`:

```
julia> my_sum_defensive([1.0, 2.0, 3.0])
6.0
```

as well as `Matrix{Rational{Int}}`:

```
julia> my_sum_defensive([(1//2) + (4//3)*im; (6//5) + (7//11)*im])
17//10 + 65//33*im
```

and it throws an error when the assumptions aren't met:

```
julia> my_sum_defensive(['a', 'b', 'c'])
ERROR: Unable to call my_sum_defensive(::Vector{Char}) because it failed an internal assumption
[...]
```

As an alternative, you may choose not to call `test_my_sum_defensive_assumptions` within `my_sum_defensive`, and instead ask users of `my_sum_defensive` to call it in their tests.

### Juxtaposed multiplication

Only use juxtaposed multiplication when the right-hand side is a symbol.

Good:

```
2x # Acceptable if there are space constraints.
2 * x # This is preferred if space is not an issue.
2 * (x + 1)
```

Bad:

```
2(x + 1)
```

### Empty vectors

For a type `T`, `T[]` and `Vector{T}()` are equivalent ways to create an empty vector with element type `T`. Prefer `T[]` because it is more concise.

### Comments

For non-native speakers and for general clarity, comments in code must be proper English sentences with appropriate punctuation.

Good:

```
# This is a comment demonstrating a good comment.
```

Bad:

```
# a bad comment
```

### JuMP macro syntax

For consistency, always use parentheses.

Good:

```
@variable(model, x >= 0)
```

Bad:

```
@variable model x >= 0
```

For consistency, always use `constant * variable` as opposed to `variable * constant`. This makes it easier to read models in ambiguous cases like `a * x`.

Good:

```
a = 4
@constraint(model, 3 * x <= 1)
@constraint(model, a * x <= 1)
```

Bad:

```
a = 4
@constraint(model, x * 3 <= 1)
@constraint(model, x * a <= 1)
```

In order to reduce boilerplate code, prefer the plural form of macros over lots of repeated calls to singular forms.

Good:

```
@variables(model, begin
    x >= 0
    y >= 1
    z <= 2
end)
```

Bad:

```
@variable(model, x >= 0)
@variable(model, y >= 1)
@variable(model, z <= 2)
```

An exception is made for calls with many keyword arguments, since these need to be enclosed in parentheses in order to parse properly.

Acceptable:

```
@variable(model, x >= 0, start = 0.0, base_name = "my_x")
@variable(model, y >= 1, start = 2.0)
@variable(model, z <= 2, start = -1.0)
```

Also acceptable:

```
@variables(model, begin
    x >= 0, (start = 0.0, base_name = "my_x")
    y >= 1, (start = 2.0)
    z <= 2, (start = -1.0)
end)
```

While we always use `in` for for-loops, it is acceptable to use `=` in the container declarations of JuMP macros.

Okay:

```
@variable(model, x[i=1:3])
```

Also okay:

```
@variable(model, x[i in 1:3])
```

## Naming

```
module SomeModule end
function some_function end
const SOME_CONSTANT = ...
struct SomeStruct
    some_field::SomeType
end
@enum SomeEnum ENUM_VALUE_A ENUM_VALUE_B
some_local_variable = ...
some_file.jl # Except for ModuleName.jl.
```

### Exported and non-exported names

Begin private module level functions and constants with an underscore. All other objects in the scope of a module should be exported. (See JuMP.jl for an example of how to do this.)

Names beginning with an underscore should only be used for distinguishing between exported (public) and non-exported (private) objects. Therefore, never begin the name of a local variable with an underscore.

```
module MyModule

export public_function, PUBLIC_CONSTANT
```

```
function _private_function()
    local_variable = 1
    return
end

function public_function end

const _PRIVATE_CONSTANT = 3.14159
const PUBLIC_CONSTANT = 1.41421

end
```

### Use of underscores within names

The Julia style guide recommends avoiding underscores "when readable," for example, `haskey`, `isequal`, `remotecall`, and `remotecall_fetch`. This convention creates the potential for unnecessary bikeshedding and also forces the user to recall the presence/absence of an underscore, for example, "was that argument named `basename` or `base_name`?". For consistency, *always use underscores* in variable names and function names to separate words.

### Use of !

Julia has a convention of appending `!` to a function name if the function modifies its arguments. We recommend to:

- Omit `!` when the name itself makes it clear that modification is taking place, for example, `add_constraint` and `set_name`. We depart from the Julia style guide because `!` does not provide a reader with any additional information in this case, and adherence to this convention is not uniform even in base Julia itself (consider `Base.println` and `Base.finalize`).
- Use `!` in all other cases. In particular it can be used to distinguish between modifying and non-modifying variants of the same function like `scale` and `scale!`.

Note that `!` is *not* a self-documenting feature because it is still ambiguous which arguments are modified when multiple arguments are present. Be sure to document which arguments are modified in the method's docstring.

See also the Julia style guide recommendations for [ordering of function arguments](#).

### Abbreviations

Abbreviate names to make the code more readable, not to save typing. Don't arbitrarily delete letters from a word to abbreviate it (for example, `indx`). Use abbreviations consistently within a body of code (for example, do not mix `con` and `constr`, `idx` and `indx`).

Common abbreviations:

- `num` for number
- `con` for constraint

### No one-letter variable names

Where possible, avoid one-letter variable names.

Use `model = Model()` instead of `m = Model()`

Exceptions are made for indices in loops.

### `@enum` vs. `Symbol`

The `@enum` macro lets you define types with a finite number of values that are explicitly enumerated (like `enum` in C/C++). `Symbols` are lightweight strings that are used to represent identifiers in Julia (for example, `:x`).

`@enum` provides type safety and can have docstrings attached to explain the possible values. Use `@enums` when applicable, for example, for reporting statuses. Use strings to provide long-form additional information like error messages.

Use of `Symbol` should typically be reserved for identifiers, for example, for lookup in the JuMP model (`model[:my_variable]`).

### `using` vs. `import`

`using ModuleName` brings all symbols exported by the module `ModuleName` into scope, while `import ModuleName` brings only the module itself into scope. (See the Julia [manual](#) for examples and more details.)

For the same reason that `from <module> import *` is not recommended in python ([PEP 8](#)), avoid using `ModuleName` except in throw-away scripts or at the REPL. The `using` statement makes it harder to track where symbols come from and exposes the code to ambiguities when two modules export the same symbol.

Prefer `using ModuleName: x, p` to `import ModuleName.x, ModuleName.p` and `import MyModule: x, p` because the `import` versions allow method extension without qualifying with the module name.

Similarly, `using ModuleName: ModuleName` is an acceptable substitute for `import ModuleName`, because it does not bring all symbols exported by `ModuleName` into scope. However, we prefer `import ModuleName` for consistency.

## Documentation

This section describes the writing style that should be used when writing documentation for JuMP (and supporting packages).

We can recommend the documentation style guides by [Divio](#), [Google](#), and [Write the Docs](#) as general reading for those writing documentation. This guide delegates a thorough handling of the topic to those guides and instead elaborates on the points more specific to Julia and documentation that use [Documenter](#).

- Be concise
- Use lists instead of long sentences
- Use numbered lists when describing a sequence, for example, (1) do X, (2) then Y
- Use bullet points when the items are not ordered
- Example code should be covered by doctests
- When a word is a Julia symbol and not an English word, enclose it with backticks. In addition, if it has a docstring in this doc add a link using `@ref`. If it is a plural, add the "s" after the closing backtick. For example,

```
[`VariableRef`](@ref)s
```

- Use `@meta` blocks for TODOs and other comments that shouldn't be visible to readers. For example,

```
```@meta
# TODO: Mention also X, Y, and Z.
```

```

## Docstrings

- Every exported object needs a docstring
- All examples in docstrings should be `jldoctests`
- Always use complete English sentences with proper punctuation
- Do not terminate lists with punctuation (for example, as in this doc)

Here is an example:

```
"""
signature(args; kwargs...)

Short sentence describing the function.

Optional: add a slightly longer paragraph describing the function.

## Notes

- List any notes that the user should be aware of

## Example

```jldoctest
julia> 1 + 1
2
```
"""

```

## Testing

Use a module to encapsulate tests, and structure all tests as functions. This avoids leaking local variables between tests.

Here is a basic skeleton:

```
module TestPkg

using Test

function runtests()
```

```
for name in names(@__MODULE__; all = true)
    if startswith!("$(name)", "test_")
        @testset "$(name)" begin
            getfield($__MODULE__, name)()
        end
    end
end
return
end

_helper_function() = 2

function test_addition()
    @test 1 + 1 == _helper_function()
    return
end

end # module TestPkg

TestPkg.runtests()
```

Break the tests into multiple files, with one module per file, so that subsets of the codebase can be tested by calling `include` with the relevant file.

# Chapter 29

## Roadmap

### 29.1 Development roadmap

The JuMP developers have compiled this roadmap document to share their plans and goals with the JuMP community. Contributions to roadmap issues are especially invited.

Most of these issues will require changes to both JuMP and MathOptInterface, and are non-trivial in their implementation. They are in no particular order, but represent broad themes that we see as areas in which JuMP could be improved.

- Support nonlinear expressions with vector-valued inputs and outputs. There are a few related components:
  - Representing terms like `log(det(X))` as necessary for Convex.jl
  - Automatic differentiation of terms with vector inputs and outputs
  - User-defined functions with vector-as opposed to scalar-inputs, which is particularly useful for optimal control problems
  - User-defined functions with vector outputs, avoiding the need for [User-defined operators with vector outputs](#)
- Add support for modeling with SI units. The [UnitJuMP.jl](#) extension is a good proof of concept for what this would look like. We want to make units a first-class concept in JuMP. See [#1350](#) for more details.

### Completed

- **Done #3106** Make nonlinear programming a first-class citizen. There have been many issues and discussions about this: currently nonlinear constraints are handled through a `MOI.NLPBlock` and have various limitations and restrictions.
  - <https://github.com/jump-dev/JuMP.jl/issues/1185>
  - <https://github.com/jump-dev/JuMP.jl/issues/1198>
  - <https://github.com/jump-dev/JuMP.jl/issues/2788>
  - <https://github.com/jump-dev/MathOptInterface.jl/issues/846>
  - <https://github.com/jump-dev/MathOptInterface.jl/issues/1397>
- **Done #3385** Add support for coefficient types other than `Float64`: <https://github.com/jump-dev/JuMP.jl/issues/2025> Since the very beginning, JuMP has hard-coded the coefficient type as `Float64`. This has made it impossible to support solvers which can use other types such as `BigFloat` or `Rational{BigInt}`.

- **Done #3385** Add support for constraint programming: <https://github.com/jump-dev/JuMP.jl/issues/2227>  
JuMP has a strong focus on linear, conic and nonlinear optimization problems. We want to add better support for constraint programming.
- **Done #3176** Add support for multiobjective problems: <https://github.com/jump-dev/JuMP.jl/issues/2099>  
JuMP is restricted to problems with scalar-valued objectives. We want to extend this to vector-valued problems.
- **Done #3629** Refactor the internal code of JuMP's macros. The code in `src/macros.jl` is some of the oldest part of JuMP and is difficult to read, modify, and extend. We should overhaul the internals of JuMP's macros--without making user-visible breaking changes--to improve their long-term maintainability.

# Chapter 30

## Checklists

### 30.1 Checklists

The purpose of this page is to collate a series of checklists for commonly performed changes to the source code of JuMP.

In each case, copy the checklist into the description of the pull request.

#### Making a release

In preparation for a release, use the following checklist. These steps can be done in the same commit, or separately. The last commit should have the message "Prep for vX.Y.Z."

```
## Pre-release

- [ ] Check that the pinned packages in `docs/Project.toml` are updated. We pin
      the versions so that changes in the solvers (changes in printing, small
      numeric changes) do not break the printing of the JuMP docs in arbitrary
      commits.
- [ ] Check that the `rev` fields in `docs/packages.toml` are updated. We pin
      the versions of solvers and extensions to ensure that changes to their
      READMEs do not break the JuMP docs in arbitrary commits, and to ensure
      that the versions are compatible with the latest JuMP and
      MathOptInterface releases.
- [ ] Check compat of `DimensionalData` in `Project.toml`
- [ ] Check compat of `MacroTools` in `Project.toml`
- [ ] Update `docs/src/changelog.md`
- [ ] Run https://github.com/jump-dev/JuMP.jl/actions/workflows/extension-tests.yml
      using a `workflow_dispatch` trigger to check for any changes in JuMP that
      broke extensions.
- [ ] Change the version number in `Project.toml`
- [ ] The commit messages in this PR do not contain `[ci skip]`

## The release

- [ ] After merging this pull request, comment `[at]JuliaRegistrar register` in
      the GitHub commit. This should automatically publish a new version to the
      Julia registry, as well as create a tag, and rebuild the documentation
      for this tag.

These steps can take quite a bit of time (1 hour or more), so don't be
```

surprised if the new documentation takes a while to appear. In addition, the links in the README will be broken until JuliaHub fetches the new version on their servers.

```
## Post-release

- [ ] Once the tag is created, update the relevant `release-` branch. The latest release branch at the time of writing is `release-1.0` (we haven't back-ported any patches that needed to create a `release-1.Y` branch). To update the release branch with the v1.10.0 tag, do:
```
git checkout release-1.0
git pull
git merge v1.10.0
git push
```

```

## Adding a new solver to the documentation

Use the following checklist when adding a new solver to the JuMP documentation.

```
## Basic

- [ ] Check that the solver is a registered Julia package
- [ ] Check that the solver supports the long-term support release of Julia
- [ ] Check that the solver has a MathOptInterface wrapper
- [ ] Check that the tests call `MOI.Test.runitests`. Some test excludes are permissible, but the reason for skipping a particular test should be documented.
- [ ] Check that the README and/or documentation provides an example of how to use the solver with JuMP

## Documentation

- [ ] Add a new row to the table in `docs/src/installation.md`

## Optional

- [ ] Add package metadata to `docs/packages.toml`
```

## Adding a new shape

Use the following checklist when adding a new AbstractShape

```
## Basic

- [ ] Add a new subtype of `AbstractShape`
- [ ] Implement `vectorize(data, ::NewShape)::Vector`
- [ ] Implement `reshape_vector(vector, ::NewShape)`
- [ ] Implement `dual_shape`, or verify that the shape is self-dual
- [ ] Add the tests from https://github.com/jump-dev/JuMP.jl/pull/3816
```

## **Part VII**

### **MathOptInterface**

# Chapter 31

## Introduction

### 31.1 Introduction

#### Warning

This documentation in this section is a copy of the official MathOptInterface documentation available at <https://jump.dev/MathOptInterface.jl/v1.35.2>. It is included here to make it easier to link concepts between JuMP and MathOptInterface.

#### What is MathOptInterface?

[MathOptInterface.jl](#) (MOI) is an abstraction layer designed to provide a unified interface to mathematical optimization solvers so that users do not need to understand multiple solver-specific APIs.

#### Tip

This documentation is aimed at developers writing software interfaces to solvers and modeling languages using the MathOptInterface API. If you are a user interested in solving optimization problems, we encourage you instead to use MOI through a higher-level modeling interface like [JuMP](#) or [Convex.jl](#).

#### How the documentation is structured

Having a high-level overview of how this documentation is structured will help you know where to look for certain things.

- The **Tutorials** section contains articles on how to use and implement the MathOptInterface API. Look here if you want to write a model in MOI, or write an interface to a new solver.
- The **Manual** contains short code-snippets that explain how to use the MOI API. Look here for more details on particular areas of MOI.
- The **Background** section contains articles on the theory behind MathOptInterface. Look here if you want to understand *why*, rather than *how*.
- The **API Reference** contains a complete list of functions and types that comprise the MOI API. Look here if you want to know how to use (or implement) a particular function.
- The **Submodules** section contains stand-alone documentation for each of the submodules within MOI. These submodules are not required to interface a solver with MOI, but they make the job much easier.

### Citing MathOptInterface

If you find MathOptInterface useful in your work, we kindly request that you cite the following paper:

```
@article{legat2021mathoptinterface,
    title={{MathOptInterface}: a data structure for mathematical optimization problems},
    author={Legat, Beno{\^{\i}}t and Dowson, Oscar and Garcia, Joaquim Dias and Lubin, Miles},
    journal={INFORMS Journal on Computing},
    year={2021},
    doi={10.1287/ijoc.2021.1067},
    publisher={INFORMS}
}
```

A preprint of this paper is [freely available](#).

## 31.2 Motivation

MathOptInterface (MOI) is a replacement for [MathProgBase](#), the first-generation abstraction layer for mathematical optimization previously used by [JuMP](#) and [Convex.jl](#).

To address a number of limitations of MathProgBase, MOI is designed to:

- Be simple and extensible
  - unifying linear, quadratic, and conic optimization,
  - seamlessly facilitating extensions to essentially arbitrary constraints and functions (for example, indicator constraints, complementarity constraints, and piecewise-linear functions)
- Be fast
  - by allowing access to a solver's in-memory representation of a problem without writing intermediate files (when possible)
  - by using multiple dispatch and avoiding requiring containers of non-concrete types
- Allow a solver to return multiple results (for example, a pool of solutions)
- Allow a solver to return extra arbitrary information via attributes (for example, variable- and constraint-wise membership in an irreducible inconsistent subset for infeasibility analysis)
- Provide a greatly expanded set of status codes explaining what happened during the optimization procedure
- Enable a solver to more precisely specify which problem classes it supports
- Enable both primal and dual warm starts
- Enable adding and removing both variables and constraints by indices that are not required to be consecutive
- Enable any modification that the solver supports to an existing model
- Avoid requiring the solver wrapper to store an additional copy of the problem data

## Chapter 32

# Tutorials

### 32.1 Solving a problem using MathOptInterface

In this tutorial we demonstrate how to use MathOptInterface to solve the binary-constrained knapsack problem:

$$\begin{aligned} & \max c^\top x \\ & \text{s.t. } w^\top x \leq C \\ & \quad x_i \in \{0, 1\}, \quad \forall i = 1, \dots, n \end{aligned}$$

#### Required packages

Load the MathOptInterface module and define the shorthand MOI:

```
import MathOptInterface as MOI
```

As an optimizer, we choose GLPK:

```
using GLPK
optimizer = GLPK.Optimizer()
```

#### Define the data

We first define the constants of the problem:

```
julia> c = [1.0, 2.0, 3.0]
3-element Vector{Float64}:
 1.0
 2.0
 3.0

julia> w = [0.3, 0.5, 1.0]
3-element Vector{Float64}:
 0.3
 0.5
 1.0
```

```
julia> C = 3.2
3.2
```

### Add the variables

```
julia> x = MOI.add_variables(optimizer, length(c));
```

### Set the objective

```
julia> MOI.set(
    optimizer,
    MOI.ObjectiveFunction{MOI.ScalarAffineFunction{Float64}}(),
    MOI.ScalarAffineFunction(MOI.ScalarAffineTerm.(c, x), 0.0),
);
julia> MOI.set(optimizer, MOI.ObjectiveSense(), MOI.MAX_SENSE)
```

#### Tip

`MOI.ScalarAffineTerm.(c, x)` is a shortcut for `[MOI.ScalarAffineTerm(c[i], x[i]) for i = 1:3]`. This is Julia's broadcast syntax in action, and is used quite often throughout MOI.

### Add the constraints

We add the knapsack constraint and integrality constraints:

```
julia> MOI.add_constraint(
    optimizer,
    MOI.ScalarAffineFunction(MOI.ScalarAffineTerm.(w, x), 0.0),
    MOI.LessThan(C),
);
```

Add integrality constraints:

```
julia> for x_i in x
    MOI.add_constraint(optimizer, x_i, MOI.ZeroOne())
end
```

### Optimize the model

```
julia> MOI.optimize!(optimizer)
```

### Understand why the solver stopped

The first thing to check after optimization is why the solver stopped, for example, did it stop because of a time limit or did it stop because it found the optimal solution?

```
julia> MOI.get(optimizer, MOI.TerminationStatus())
OPTIMAL::TerminationStatusCode = 1
```

Looks like we found an optimal solution.

### Understand what solution was returned

```
julia> MOI.get(optimizer, MOI.ResultCount())
1

julia> MOI.get(optimizer, MOI.PrimalStatus())
FEASIBLE_POINT::ResultStatusCode = 1

julia> MOI.get(optimizer, MOI.DualStatus())
NO_SOLUTION::ResultStatusCode = 0
```

### Query the objective

What is its objective value?

```
julia> MOI.get(optimizer, MOI.ObjectiveValue())
6.0
```

### Query the primal solution

And what is the value of the variables x?

```
julia> MOI.get(optimizer, MOI.VariablePrimal(), x)
3-element Vector{Float64}:
 1.0
 1.0
 1.0
```

## 32.2 Implementing a solver interface

This guide outlines the basic steps to implement an interface to MathOptInterface for a new solver.

### Danger

Implementing an interface to MathOptInterface for a new solver is a lot of work. Before starting, we recommend that you join the [Developer chatroom](#) and explain a little bit about the solver you are wrapping. If you have questions that are not answered by this guide, please ask them in the [Developer chatroom](#) so we can improve this guide.

### A note on the API

The API of MathOptInterface is large and varied. In order to support the diversity of solvers and use-cases, we make heavy use of [duck-typing](#). That is, solvers are not expected to implement the full API, nor is there a well-defined minimal subset of what must be implemented. Instead, you should implement the API as necessary to make the solver function as you require.

The main reason for using duck-typing is that solvers work in different ways and target different use-cases.

For example:

- Some solvers support incremental problem construction, support modification after a solve, and have native support for things like variable names.
- Other solvers are "one-shot" solvers that require all of the problem data to construct and solve the problem in a single function call. They do not support modification or things like variable names.
- Other "solvers" are not solvers at all, but things like file readers. These may only support functions like `read_from_file`, and may not even support the ability to add variables or constraints directly.
- Finally, some "solvers" are layers which take a problem as input, transform it according to some rules, and pass the transformed problem to an inner solver.

### Preliminaries

Before starting on your wrapper, you should do some background research and make the solver accessible via Julia.

#### Decide if MathOptInterface is right for you

The first step in writing a wrapper is to decide whether implementing an interface is the right thing to do.

MathOptInterface is an abstraction layer for unifying *constrained* mathematical optimization solvers. If your solver doesn't fit in the category, for example, it implements a derivative-free algorithm for unconstrained objective functions, MathOptInterface may not be the right tool for the job.

#### Tip

If you're not sure whether you should write an interface, ask in the [Developer chatroom](#).

#### Find a similar solver already wrapped

The next step is to find (if possible) a similar solver that is already wrapped. Although not strictly necessary, this will be a good place to look for inspiration when implementing your wrapper.

The [JuMP documentation](#) has a good list of solvers, along with the problem classes they support.

#### Tip

If you're not sure which solver is most similar, ask in the [Developer chatroom](#).

#### Create a low-level interface

Before writing a MathOptInterface wrapper, you first need to be able to call the solver from Julia.

### Wrapping solvers written in Julia

If your solver is written in Julia, there's nothing to do here. Go to the next section.

### Wrapping solvers written in C

Julia is well suited to wrapping solvers written in C.

#### Info

This is *not* true for C++. If you have a solver written in C++, first write a C interface, then wrap the C interface.

Before writing a MathOptInterface wrapper, there are a few extra steps.

#### Create a JLL

If the C code is publicly available under an open source license, create a JLL package via [Yggdrasil](#). The easiest way to do this is to copy an existing solver. Good examples to follow are the [COIN-OR solvers](#).

#### Warning

Building the solver via Yggdrasil is non-trivial. Please ask the [Developer chatroom](#) for help.

If the code is commercial or not publicly available, the user will need to manually install the solver. See [Gurobi.jl](#) or [CPLEX.jl](#) for examples of how to structure this.

#### Use Clang.jl to wrap the C API

The next step is to use [Clang.jl](#) to automatically wrap the C API. The easiest way to do this is to follow an example. Good examples to follow are [Cbc.jl](#) and [HiGHS.jl](#).

Sometimes, you will need to make manual modifications to the resulting files.

### Solvers written in other languages

Ask the [Developer chatroom](#) for advice. You may be able to use one of the [JuliaInterop](#) packages to call out to the solver.

For example, [SeDuMi.jl](#) uses [MATLAB.jl](#) to call the SeDuMi solver written in MATLAB.

### Structuring the package

Structure your wrapper as a Julia package. Consult the [Julia documentation](#) if you haven't done this before.

MOI solver interfaces may be in the same package as the solver itself (either the C wrapper if the solver is accessible through C, or the Julia code if the solver is written in Julia, for example), or in a separate package which depends on the solver package.

#### Note

The JuMP [core contributors](#) request that you do not use "JuMP" in the name of your package without prior consent.

Your package should have the following structure:

```

/.github
  /workflows
    ci.yml
    format_check.yml
    TagBot.yml
/gen
  gen.jl # Code to wrap the C API
/src
  NewSolver.jl
  /gen
    libnewsolver_api.jl
    libnewsolver_common.jl
  /MOI_wrapper
    MOI_wrapper.jl
    other_files.jl
/test
  runtests.jl
  /MOI_wrapper
    MOI_wrapper.jl
.gitignore
.JuliaFormatter.toml
README.md
LICENSE.md
Project.toml

```

- The `/.github` folder contains the scripts for GitHub actions. The easiest way to write these is to copy the ones from an existing solver.
- The `/gen` and `/src/gen` folders are only needed if you are wrapping a [solver written in C](#).
- The `/src/MOI_wrapper` folder contains the Julia code for the MOI wrapper.
- The `/test` folder contains code for testing your package. See [Setup tests](#) for more information.
- The `.JuliaFormatter.toml` and `.github/workflows/format_check.yml` enforce code formatting using [JuliaFormatter.jl](#). Check existing solvers or JuMP.jl for details.

## Documentation

Your package must include documentation explaining how to use the package. The easiest approach is to include documentation in your `README.md`. A more involved option is to use [Documenter.jl](#).

Examples of packages with `README`-based documentation include:

- [Cbc.jl](#)
- [HiGHS.jl](#)
- [SCS.jl](#)

Examples of packages with Documenter-based documentation include:

- [Alpine.jl](#)
- [COSMO.jl](#)
- [Juniper.jl](#)

### Setup tests

The best way to implement an interface to MathOptInterface is via [test-driven development](#).

The [MOI.Test submodule](#) contains a large test suite to help check that you have implemented things correctly.

Follow the guide [How to test a solver](#) to set up the tests for your package.

#### Tip

Run the tests frequently when developing. However, at the start there is going to be a lot of errors. Start by excluding large classes of tests (for example, `exclude = ["test_basic_", "test_model_"]`), implement any missing methods until the tests pass, then remove an exclusion and repeat.

### Initial code

By this point, you should have a package setup with tests, formatting, and access to the underlying solver. Now it's time to start writing the wrapper.

#### The Optimizer object

The first object to create is a subtype of [AbstractOptimizer](#). This type is going to store everything related to the problem.

By convention, these optimizers should not be exported and should be named `PackageName.Optimizer`.

```
import MathOptInterface as MOI

struct Optimizer <: MOI.AbstractOptimizer
    # Fields go here
end
```

### Optimizer objects for C solvers

#### Warning

This section is important if you wrap a solver written in C.

Wrapping a solver written in C will require the use of pointers, and for you to manually free the solver's memory when the Optimizer is garbage collected by Julia.

#### Never pass a pointer directly to a Julia ccall function.

Instead, store the pointer as a field in your Optimizer, and implement `Base.cconvert` and `Base.unsafe_convert`. Then you can pass Optimizer to any `ccall` function that expects the pointer.

In addition, make sure you implement a `finalizer` for each model you create.

If `newsolver_createProblem()` is the low-level function that creates the problem pointer in C, and `newsolver_freeProblem(::Ptr{Cvoid}, ::Model)` is the low-level function that frees memory associated with the pointer, your `Optimizer()` function should look like this:

```

struct Optimizer <: MOI.AbstractOptimizer
ptr::Ptr{Cvoid}

function Optimizer()
    ptr = newsolver_createProblem()
    model = Optimizer(ptr)
    finalizer(model) do m
        newsolver_freeProblem(m)
    return
end
return model
end
end

Base.cconvert(::Type{Ptr{Cvoid}}, model::Optimizer) = model
Base.unsafe_convert(::Type{Ptr{Cvoid}}, model::Optimizer) = model.ptr

```

### Implement methods for Optimizer

All Optimizers must implement the following methods:

- `empty!`
- `is_empty`

Other methods, detailed below, are optional or depend on how you implement the interface.

#### Tip

For this and all future methods, read the docstrings to understand what each method does, what it expects as input, and what it produces as output. If it isn't clear, let us know and we will improve the docstrings. It is also very helpful to look at an existing wrapper for a similar solver.

You should also implement `Base.summary(::IO, ::Optimizer)` to print a nice string when someone shows your model. For example

```

function Base.summary(io::IO, model::Optimizer)
    return print(io, "NewSolver with the pointer $(model.ptr)")
end

```

### Implement attributes

`MathOptInterface` uses attributes to manage different aspects of the problem.

For each attribute

- `get` gets the current value of the attribute
- `set` sets a new value of the attribute. Not all attributes can be set. For example, the user can't modify the `SolverName`.

- `supports` returns a `Bool` indicating whether the solver supports the attribute.

### Info

Use `attribute_value_type` to check the value expected by a given attribute. You should make sure that your `get` function correctly infers to this type (or a subtype of it).

Each column in the table indicates whether you need to implement the particular method for each attribute.

| Attribute                          | <code>get</code> | <code>set</code> | <code>supports</code> |
|------------------------------------|------------------|------------------|-----------------------|
| <code>SolverName</code>            | Yes              | No               | No                    |
| <code>SolverVersion</code>         | Yes              | No               | No                    |
| <code>RawSolver</code>             | Yes              | No               | No                    |
| <code>Name</code>                  | Yes              | Yes              | Yes                   |
| <code>Silent</code>                | Yes              | Yes              | Yes                   |
| <code>TimeLimitSec</code>          | Yes              | Yes              | Yes                   |
| <code>ObjectiveLimit</code>        | Yes              | Yes              | Yes                   |
| <code>SolutionLimit</code>         | Yes              | Yes              | Yes                   |
| <code>NodeLimit</code>             | Yes              | Yes              | Yes                   |
| <code>RawOptimizerAttribute</code> | Yes              | Yes              | Yes                   |
| <code>NumberOfThreads</code>       | Yes              | Yes              | Yes                   |
| <code>AbsoluteGapTolerance</code>  | Yes              | Yes              | Yes                   |
| <code>RelativeGapTolerance</code>  | Yes              | Yes              | Yes                   |

For example:

```
function MOI.get(model::Optimizer, ::MOI.Silent)
    return # true if MOI.Silent is set
end

function MOI.set(model::Optimizer, ::MOI.Silent, v::Bool)
    if v
        # Set a parameter to turn off printing
    else
        # Restore the default printing
    end
    return
end

MOI.supports(::Optimizer, ::MOI.Silent) = true
```

### Define `supports_constraint`

The next step is to define which constraints and objective functions you plan to support.

For each function-set constraint pair, define `supports_constraint`:

```
function MOI.supports_constraint(
    ::Optimizer,
    ::Type{MOI.VariableIndex},
    ::Type{MOI.ZeroOne},
```

```
)  
    return true  
end
```

To make this easier, you may want to use Unions:

```
function MOI.supports_constraint(  
    ::Optimizer,  
    ::Type{MOI.VariableIndex},  
    ::Type{<:Union{MOI.LessThan, MOI.GreaterThan, MOI.EqualTo}},  
)  
    return true  
end
```

### Tip

Only support a constraint if your solver has native support for it.

## The big decision: incremental modification?

Now you need to decide whether to support incremental modification or not.

Incremental modification means that the user can add variables and constraints one-by-one without needing to rebuild the entire problem, and they can modify the problem data after an `optimize!` call. Supporting incremental modification means implementing functions like `add_variable` and `add_constraint`.

The alternative is to accept the problem data in a single `optimize!` or `copy_to` function call. Because these functions see all of the data at once, it can typically call a more efficient function to load data into the underlying solver.

Good examples of solvers supporting incremental modification are MILP solvers like [GLPK.jl](#) and [Gurobi.jl](#). Examples of non-incremental solvers are [AmpINLWriter.jl](#) and [SCS.jl](#)

It is possible for a solver to implement both approaches, but you should probably start with one for simplicity.

### Tip

Only support incremental modification if your solver has native support for it.

In general, supporting incremental modification is more work, and it usually requires some extra book-keeping. However, it provides a more efficient interface to the solver if the problem is going to be resolved multiple times with small modifications. Moreover, once you've implemented incremental modification, it's usually not much extra work to add a `copy_to` interface. The converse is not true.

### Tip

If this is your first time writing an interface, start with the one-shot `optimize!`.

## The non-incremental interface

There are two ways to implement the non-incremental interface. The first uses a two-argument version of `optimize!`, the second implements `copy_to` followed by the one-argument version of `optimize!`.

If your solver does not support modification, and requires all data to solve the problem in a single function call, you should implement the "one-shot" `optimize!`.

- `optimize!(::ModelLike, ::ModelLike)`

If your solver separates data loading and the actual optimization into separate steps, implement the `copy_to` interface.

- `copy_to(::ModelLike, ::ModelLike)`
- `optimize!(::ModelLike)`

### The incremental interface

#### Warning

Writing this interface is a lot of work. The easiest way is to consult the source code of a similar solver.

To implement the incremental interface, implement the following functions:

- `add_variable`
- `add_variables`
- `add_constraint`
- `add_constraints`
- `is_valid`
- `delete`
- `optimize!(::ModelLike)`

#### Info

Solvers do not have to support `AbstractScalarFunction` in `GreaterThan`, `LessThan`, `EqualTo`, or `Interval` with a nonzero constant in the function. Throw `ScalarFunctionConstantNotZero` if the function constant is not zero.

In addition, you should implement the following model attributes:

|  | Attribute                             | get | set | supports |
|--|---------------------------------------|-----|-----|----------|
|  | <code>ListofModelAttributesSet</code> | Yes | No  | No       |
|  | <code>ObjectiveFunctionType</code>    | Yes | No  | No       |
|  | <code>ObjectiveFunction</code>        | Yes | Yes | Yes      |
|  | <code>ObjectiveSense</code>           | Yes | Yes | Yes      |
|  | <code>Name</code>                     | Yes | Yes | Yes      |

Variable-related attributes:

Constraint-related attributes:

|  | Attribute                                    | get | set | supports |
|--|----------------------------------------------|-----|-----|----------|
|  | <code>ListOfVariableAttributesSet</code>     | Yes | No  | No       |
|  | <code>ListOfVariablesWithAttributeSet</code> | Yes | No  | No       |
|  | <code>NumberOfVariables</code>               | Yes | No  | No       |
|  | <code>ListOfVariableIndices</code>           | Yes | No  | No       |

|  | Attribute                                      | get | set | supports |
|--|------------------------------------------------|-----|-----|----------|
|  | <code>ListOfConstraintAttributesSet</code>     | Yes | No  | No       |
|  | <code>ListOfConstraintsWithAttributeSet</code> | Yes | No  | No       |
|  | <code>NumberOfConstraints</code>               | Yes | No  | No       |
|  | <code>ListOfConstraintTypesPresent</code>      | Yes | No  | No       |
|  | <code>ConstraintFunction</code>                | Yes | Yes | No       |
|  | <code>ConstraintSet</code>                     | Yes | Yes | No       |

## Modifications

If your solver supports modifying data in-place, implement `modify` for the following AbstractModifications:

- `ScalarConstantChange`
- `ScalarCoefficientChange`
- `ScalarQuadraticCoefficientChange`
- `VectorConstantChange`
- `MultirowChange`

## Variables constrained on creation

Some solvers require variables be associated with a set *when they are created*. This conflicts with the incremental modification approach, since you cannot first add a free variable and then constrain it to the set.

If this is the case, implement:

- `add_constrained_variable`
- `add_constrained_variables`
- `supports_add_constrained_variables`

By default, MathOptInterface assumes solvers support free variables. If your solver does not support free variables, define:

```
MOI.supports_add_constrained_variables(::Optimizer, ::Type{Reals}) = false
```

### Incremental and copy\_to

If you implement the incremental interface, you have the option of also implementing `copy_to`.

If you don't want to implement `copy_to`, for example, because the solver has no API for building the problem in a single function call, define the following fallback:

```
MOI.supports_incremental_interface(::Optimizer) = true

function MOI.copy_to(dest::Optimizer, src::MOI.ModelLike)
    return MOI.Utilities.default_copy_to(dest, src)
end
```

### Names

Regardless of which interface you implement, you have the option of implementing the `Name` attribute for variables and constraints:

| Attribute                   | get | set | supports |
|-----------------------------|-----|-----|----------|
| <code>VariableName</code>   | Yes | Yes | Yes      |
| <code>ConstraintName</code> | Yes | Yes | Yes      |

If you implement names, you must also implement the following three methods:

```
function MOI.get(model::Optimizer, ::Type{MOI.VariableIndex}, name::String)
    return # The variable named `name`.
end

function MOI.get(model::Optimizer, ::Type{MOI.ConstraintIndex}, name::String)
    return # The constraint any type named `name`.
end

function MOI.get(
    model::Optimizer,
    ::Type{MOI.ConstraintIndex{F,S}},
    name::String,
) where {F,S}
    return # The constraint of type F-in-S named `name`.
end
```

These methods have the following rules:

- If there is no variable or constraint with the name, return nothing
- If there is a single variable or constraint with that name, return the variable or constraint
- If there are multiple variables or constraints with the name, throw an error.

**Warning**

You should *not* implement `ConstraintName` for `VariableIndex` constraints. If you implement `ConstraintName` for other constraints, you can add the following two methods to disable `ConstraintName` for `VariableIndex` constraints.

```
function MOI.supports(
    ::Optimizer,
    ::MOI.ConstraintName,
    ::Type{<:MOI.ConstraintIndex{MOI.VariableIndex,<:MOI.AbstractScalarSet}},
)
    return throw(MOI.VariableIndexConstraintNameError())
end
function MOI.set(
    ::Optimizer,
    ::MOI.ConstraintName,
    ::MOI.ConstraintIndex{MOI.VariableIndex,<:MOI.AbstractScalarSet},
    ::String,
)
    return throw(MOI.VariableIndexConstraintNameError())
end
```

**Solutions**

Implement `optimize!` to solve the model:

- `optimize!`

All Optimizers must implement the following attributes:

- `DualStatus`
- `PrimalStatus`
- `RawStatusString`
- `ResultCount`
- `TerminationStatus`

**Info**

You only need to implement `get` for solution attributes. Don't implement `set` or `supports`.

**Note**

Solver wrappers should document how the low-level statuses map to the MOI statuses. Statuses like `NEARLY_FEASIBLE_POINT` and `INFEASIBLE_POINT`, are designed to be used when the solver explicitly indicates that relaxed tolerances are satisfied or the returned point is infeasible, respectively.

You should also implement the following attributes:

- `ObjectiveValue`
- `SolveTimeSec`
- `VariablePrimal`

**Tip**

Attributes like `VariablePrimal` and `ObjectiveValue` are indexed by the result count. Use `MOI.check_result_index_bounds(model, attr)` to throw an error if the attribute is not available.

If your solver returns dual solutions, implement:

- `ConstraintDual`
- `DualObjectiveValue`

For integer solvers, implement:

- `ObjectiveBound`
- `RelativeGap`

If applicable, implement:

- `SimplexIterations`
- `BarrierIterations`
- `NodeCount`

If your solver uses the Simplex method, implement:

- `ConstraintBasisStatus`

If your solver accepts primal or dual warm-starts, implement:

- `VariablePrimalStart`
- `ConstraintDualStart`

**Other tips**

Here are some other points to be aware of when writing your wrapper.

**Unsupported constraints at runtime**

In some cases, your solver may support a particular type of constraint (for example, quadratic constraints), but only if the data meets some condition (for example, it is convex).

In this case, declare that you support the constraint, and throw `AddConstraintNotAllowed`.

### Dealing with multiple variable bounds

MathOptInterface uses `VariableIndex` constraints to represent variable bounds. Defining multiple variable bounds on a single variable is not allowed.

Throw `LowerBoundAlreadySet` or `UpperBoundAlreadySet` if the user adds a constraint that results in multiple bounds.

Only throw if the constraints conflict. It is okay to add `VariableIndex-in-GreaterThan` and then `VariableIndex-in-LessThan`, but not `VariableIndex-in-Interval` and then `VariableIndex-in-LessThan`,

### Expect duplicate coefficients

Solvers must expect that functions such as `ScalarAffineFunction` and `VectorQuadraticFunction` may contain duplicate coefficients.

For example, `ScalarAffineFunction([ScalarAffineTerm(x, 1), ScalarAffineTerm(x, 1)], 0.0)`.

Use `Utilities.canonical` to return a new function with the duplicate coefficients aggregated together.

### Don't modify user-data

All data passed to the solver must be copied immediately to internal data structures. Solvers may not modify any input vectors and must assume that input vectors will not be modified by users in the future.

This applies, for example, to the `terms` vector in `ScalarAffineFunction`. Vectors returned to the user, for example, via `ObjectiveFunction` or `ConstraintFunction` attributes, must not be modified by the solver afterwards. The in-place version of `get!` can be used by users to avoid extra copies in this case.

### Column Generation

There is no special interface for column generation. If the solver has a special API for setting coefficients in existing constraints when adding a new variable, it is possible to queue modifications and new variables and then call the solver's API once all of the new coefficients are known.

### Solver-specific attributes

You don't need to restrict yourself to the attributes defined in the `MathOptInterface.jl` package.

Solver-specific attributes should be specified by creating an appropriate subtype of `AbstractModelAttribute`, `AbstractOptimizerAttribute`, `AbstractVariableAttribute`, or `AbstractConstraintAttribute`.

For example, `Gurobi.jl` adds attributes for multiobjective optimization by defining:

```
struct NumberOfObjectives <: MOI.AbstractModelAttribute end

function MOI.set(model::Optimizer, ::NumberOfObjectives, n::Integer)
    # Code to set NumberOfObjectives
    return
end

function MOI.get(model::Optimizer, ::NumberOfObjectives)
    n = # Code to get NumberOfObjectives
    return n
end
```

Then, the user can write:

```
model = Gurobi.Optimizer()
MOI.set(model, Gurobi.NumberofObjectives(), 3)
```

### 32.3 Transitioning from MathProgBase

MathOptInterface is a replacement for [MathProgBase.jl](#). However, it is not a direct replacement.

#### Transitioning a solver interface

MathOptInterface is more extensive than MathProgBase which may make its implementation seem daunting at first. There are however numerous utilities in MathOptInterface that the simplify implementation process.

For more information, read [Implementing a solver interface](#).

#### Transitioning the high-level functions

MathOptInterface doesn't provide replacements for the high-level interfaces in MathProgBase. We recommend you use [JuMP](#) as a modeling interface instead.

##### Tip

If you haven't used JuMP before, start with the tutorial [Getting started with JuMP](#)

#### linprog

Here is one way of transitioning from linprog:

```
using JuMP

function linprog(c, A, sense, b, l, u, solver)
    N = length(c)
    model = Model(solver)
    @variable(model, l[i] <= x[i]=N] <= u[i])
    @objective(model, Min, c' * x)
    eq_rows, ge_rows, le_rows = sense .== '=' , sense .== '>' , sense .== '<'
    @constraint(model, A[eq_rows, :] * x == b[eq_rows])
    @constraint(model, A[ge_rows, :] * x .>= b[ge_rows])
    @constraint(model, A[le_rows, :] * x .<= b[le_rows])
    optimize!(model)
    return (
        status = termination_status(model),
        objval = objective_value(model),
        sol = value.(x)
    )
end
```

#### mixintprog

Here is one way of transitioning from mixintprog:

```
using JuMP

function mixintprog(c, A, rowlb, rowub, vartypes, lb, ub, solver)
    N = length(c)
    model = Model(solver)
    @variable(model, lb[i] <= x[i]=1:N] <= ub[i])
    for i in 1:N
        if vartypes[i] == :Bin
            set_binary(x[i])
        elseif vartypes[i] == :Int
            set_integer(x[i])
        end
    end
    @objective(model, Min, c' * x)
    @constraint(model, rowlb .<= A * x .<= rowub)
    optimize!(model)
    return (
        status = termination_status(model),
        objval = objective_value(model),
        sol = value.(x)
    )
end
```

### quadprog

Here is one way of transitioning from quadprog:

```
using JuMP

function quadprog(c, Q, A, rowlb, rowub, lb, ub, solver)
    N = length(c)
    model = Model(solver)
    @variable(model, lb[i] <= x[i]=1:N] <= ub[i])
    @objective(model, Min, c' * x + 0.5 * x' * Q * x)
    @constraint(model, rowlb .<= A * x .<= rowub)
    optimize!(model)
    return (
        status = termination_status(model),
        objval = objective_value(model),
        sol = value.(x)
    )
end
```

## 32.4 Implementing a constraint bridge

This guide outlines the basic steps to create a new bridge from a constraint expressed in the formalism Function-in-Set.

### Preliminaries

First, decide on the set you want to bridge. Then, study its properties: the most important one is whether the set is scalar or vector, which impacts the dimensionality of the functions that can be used with the set.

- A scalar function only has one dimension. MOI defines three types of scalar functions: a variable ([VariableIndex](#)), an affine function ([ScalarAffineFunction](#)), or a quadratic function ([ScalarQuadraticFunction](#)).
- A vector function has several dimensions (at least one). MOI defines three types of vector functions: several variables ([VectorOfVariables](#)), an affine function ([VectorAffineFunction](#)), or a quadratic function ([VectorQuadraticFunction](#)). The main difference with scalar functions is that the order of dimensions can be very important: for instance, in an indicator constraint ([Indicator](#)), the first dimension indicates whether the constraint about the second dimension is active.

To explain how to implement a bridge, we present the example of [Bridges.Constraint.FlipSignBridge](#). This bridge maps  $\leq$  ([LessThan](#)) constraints to  $\geq$  ([GreaterThanOrEqual](#)) constraints. This corresponds to reversing the sign of the inequality. We focus on scalar affine functions (we disregard the cases of a single variable or of quadratic functions). This example is a simplified version of the code included in MOI.

### Four mandatory parts in a constraint bridge

The first part of a constraint bridge is a new concrete subtype of [Bridges.Constraint.AbstractBridge](#). This type must have fields to store all the new variables and constraints that the bridge will add. Typically, these types are parametrized by the type of the coefficients in the model.

Then, three sets of functions must be defined:

1. [Bridges.Constraint.bridge\\_constraint](#): this function implements the bridge and creates the required variables and constraints.
2. [supports\\_constraint](#): these functions must return true when the combination of function and set is supported by the bridge. By default, the base implementation always returns false and the bridge does not have to provide this implementation.
3. [Bridges.added\\_constrained\\_variable\\_types](#) and [Bridges.added\\_constraint\\_types](#): these functions return the types of variables and constraints that this bridge adds. They are used to compute the set of other bridges that are required to use the one you are defining, if need be.

More functions can be implemented, for instance to retrieve properties from the bridge or deleting a bridged constraint.

#### 1. Structure for the bridge

A typical struct behind a bridge depends on the type of the coefficients that are used for the model (typically `Float64`, but coefficients might also be integers or complex numbers).

This structure must hold a reference to all the variables and the constraints that are created as part of the bridge.

The type of this structure is used throughout MOI as an identifier for the bridge. It is passed as argument to most functions related to bridges.

The best practice is to have the name of this type end with `Bridge`.

In our example, the bridge maps any `ScalarAffineFunction{T}-in-LessThan{T}` constraint to a single `ScalarAffineFunction{T}-in-GreaterThan{T}` constraint. The affine function has coefficients of type `T`. The bridge is parametrized with `T`, so that the constraint that the bridge creates also has coefficients of type `T`.

```
struct SignBridge{T<:Number} <: Bridges.Constraint.AbstractBridge
    constraint::ConstraintIndex{ScalarAffineFunction{T}, GreaterThan{T}}
end
```

## 2. Bridge creation

The function `Bridges.Constraint.bridge_constraint` is called whenever the bridge is instantiated for a specific model, with the given function and set. The arguments to `bridge_constraint` are similar to `add_constraint`, with the exception of the first argument: it is the Type of the struct defined in the first step (for our example, `Type{SignBridge{T}}`).

`bridge_constraint` returns an instance of the struct defined in the first step.

In our example, the bridge constraint could be defined as:

```
function Bridges.Constraint.bridge_constraint(
    ::Type{SignBridge{T}}, # Bridge to use.
    model::ModelLike, # Model to which the constraint is being added.
    f::ScalarAffineFunction{T}, # Function to rewrite.
    s::LessThan{T}, # Set to rewrite.
) where {T}
    # Create the variables and constraints required for the bridge.
    con = add_constraint(model, -f, GreaterThan(-s.upper))

    # Return an instance of the bridge type with a reference to all the
    # variables and constraints that were created in this function.
    return SignBridge(con)
end
```

## 3. Supported constraint types

The function `supports_constraint` determines whether the bridge type supports a given combination of function and set.

This function must closely match `bridge_constraint`, because it will not be called if `supports_constraint` returns false.

```
function supports_constraint(
    ::Type{SignBridge{T}}, # Bridge to use.
    ::Type{ScalarAffineFunction{T}}, # Function to rewrite.
    ::Type{LessThan{T}}, # Set to rewrite.
) where {T}
    # Do some computation to ensure that the constraint is supported.
    # Typically, you can directly return true.
    return true
end
```

## 4. Metadata about the bridge

To determine whether a bridge can be used, MOI uses a shortest-path algorithm that uses the variable types and the constraints that the bridge can create. This information is communicated from the bridge to MOI using

the functions `Bridges.added_constrained_variable_types` and `Bridges.added_constraint_types`. Both return lists of tuples: either a list of 1-tuples containing the variable types (typically, `ZeroOne` or `Integer`) or a list of 2-tuples contained the functions and sets (like `ScalarAffineFunction{T}-GreaterThan`).

For our example, the bridge does not create any constrained variables, and only `ScalarAffineFunction{T}-in-GreaterThan{T}` constraints:

```
function Bridges.added_constrained_variable_types(::Type{SignBridge{T}}) where {T}
    # The bridge does not create variables, return an empty list of tuples:
    return Tuple{Type}[]
end

function Bridges.added_constraint_types(::Type{SignBridge{T}}) where {T}
    return Tuple{Type,Type}[
        # One element per F-in-S the bridge creates.
        (ScalarAffineFunction{T}, GreaterThan{T}),
    ]
end
```

A bridge that creates binary variables would rather have this definition of `added_constrained_variable_types`:

```
function Bridges.added_constrained_variable_types(::Type{SomeBridge{T}}) where {T}
    # The bridge only creates binary variables:
    return Tuple{Type}[(ZeroOne,)]
end
```

### Warning

If you declare the creation of constrained variables in `added_constrained_variable_types`, the corresponding constraint type `VariableIndex` must not be indicated in `added_constraint_types`. This would restrict the use of the bridge to solvers that can add such a constraint after the variable is created.

More concretely, if you declare in `added_constrained_variable_types` that your bridge creates binary variables (`ZeroOne`), and if you never add such a constraint afterward (you do not call `add_constraint(model, var, ZeroOne())`), then you must *not* list (`VariableIndex`, `ZeroOne`) in `added_constraint_types`.

Typically, the function `Bridges.Constraint.concrete_bridge_type` does not have to be defined for most bridges.

### Bridge registration

For a bridge to be used by MOI, it must be known by MOI.

#### SingleBridgeOptimizer

The first way to do so is to create a single-bridge optimizer. This type of optimizer wraps another optimizer and adds the possibility to use only one bridge. It is especially useful when unit testing bridges.

It is common practice to use the same name as the type defined for the bridge (SignBridge, in our example) without the suffix Bridge.

```
const Sign{T,OT<: ModelLike} =
    SingleBridgeOptimizer{SignBridge{T}, OT}
```

In the context of unit tests, this bridge is used in conjunction with a `Utilities.MockOptimizer`:

```
mock = Utilities.MockOptimizer(
    Utilities.UniversalFallback(Utilities.Model{Float64}()),
)
bridged_mock = Sign{Float64}(mock)
```

### New bridge for a LazyBridgeOptimizer

Typical user-facing models for MOI are based on `Bridges.LazyBridgeOptimizer`. For instance, this type of model is returned by `Bridges.full_bridge_optimizer`. These models can be added more bridges by using `Bridges.add_bridge`:

```
inner_optimizer = Utilities.Model{Float64}()
optimizer = Bridges.full_bridge_optimizer(inner_optimizer, Float64)
Bridges.add_bridge(optimizer, SignBridge{Float64})
```

## Bridge improvements

### Attribute retrieval

Like models, bridges have attributes that can be retrieved using `get` and `set`. The most important ones are the number of variables and constraints, but also the lists of variables and constraints.

In our example, we only have one constraint and only have to implement the `NumberOfConstraints` and `ListOfConstraintIndices` attributes:

```
function get(
    ::SignBridge{T},
    ::NumberOfConstraints{
        ScalarAffineFunction{T},
        GreaterThan{T},
    },
) where {T}
    return 1
end

function get(
    bridge::SignBridge{T},
    ::ListOfConstraintIndices{
        ScalarAffineFunction{T},
        GreaterThan{T},
    },
) where {T}
    return [bridge.constraint]
end
```

You must implement one such pair of functions for each type of constraint the bridge adds to the model.

**Warning**

Avoid returning a list from the bridge object without copying it. Users must be able to change the contents of the returned list without altering the bridge object.

For variables, the situation is simpler. If your bridge creates new variables, you must implement the `NumberOfVariables` and `ListOfVariableIndices` attributes. However, these attributes do not have parameters, unlike their constraint counterparts. Only two functions suffice:

```
function get(
    ::SignBridge{T},
    ::NumberOfVariables,
) where {T}
    return 0
end

function get(
    ::SignBridge{T},
    ::ListOfVariableIndices,
) where {T}
    return VariableIndex[]
end
```

In order for the user to be able to access the function and set of the original constraint, the bridge needs to implement getters for the `ConstraintFunction` and `ConstraintSet` attributes:

```
function get(
    model::MOI.ModelLike,
    attr::MOI.ConstraintFunction,
    bridge::SignBridge,
)
    return -MOI.get(model, attr, bridge.constraint)
end

function get(
    model::MOI.ModelLike,
    attr::MOI.ConstraintSet,
    bridge::SignBridge,
)
    set = MOI.get(model, attr, bridge.constraint)
    return MOI.LessThan(-set.lower)
end
```

**Warning**

Alternatively, one could store the original function and set in `SignBridge` during `Bridges.Constraint.bridge_constraint` to make these getters simpler and more efficient. On the other hand, this will increase the memory footprint of the bridges as the garbage collector won't be able to delete that object. The convention is to not store the function in the bridge and not care too much about the efficiency of these getters. If the user needs efficient getters for `ConstraintFunction` then they should use a `Utilities.CachingOptimizer`.

### Model modifications

To avoid copying the model when the user request to change a constraint, MOI provides `modify`. Bridges can also implement this API to allow certain changes, such as coefficient changes.

In our case, a modification of a coefficient in the original constraint (for example, replacing the value of the coefficient of a variable in the affine function) must be transmitted to the constraint created by the bridge, but with a sign change.

```
function modify(
    model::ModelLike,
    bridge::SignBridge,
    change::ScalarCoefficientChange,
)
    modify(
        model,
        bridge.constraint,
        ScalarCoefficientChange(change.variable, -change.new_coefficient),
    )
    return
end
```

### Bridge deletion

When a bridge is deleted, the constraints it added must be deleted too.

```
function delete(model::ModelLike, bridge::SignBridge)
    delete(model, bridge.constraint)
    return
end
```

## 32.5 Manipulating expressions

This guide highlights a syntactically appealing way to build expressions at the MOI level, but also to look at their contents. It may be especially useful when writing models or bridge code.

### Creating functions

This section details the ways to create functions with MathOptInterface.

#### Creating scalar affine functions

The simplest scalar function is simply a variable:

```
julia> x = MOI.add_variable(model) # Create the variable x
MOI.VariableIndex(1)
```

This type of function is extremely simple; to express more complex functions, other types must be used. For instance, a `ScalarAffineFunction` is a sum of linear terms (a factor times a variable) and a constant. Such an object can be built using the standard constructor:

```
julia> f = MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(1, x)], 2) # x + 2
(2) + (1) MOI.VariableIndex(1)
```

However, you can also use operators to build the same scalar function:

```
julia> f = x + 2
(2) + (1) MOI.VariableIndex(1)
```

### Creating scalar quadratic functions

Scalar quadratic functions are stored in [ScalarQuadraticFunction](#) objects, in a way that is highly similar to scalar affine functions. You can obtain a quadratic function as a product of affine functions:

```
julia> 1 * x * x
(0) + 1.0 MOI.VariableIndex(1)^2

julia> f * f # (x + 2)^2
(4) + (2) MOI.VariableIndex(1) + (2) MOI.VariableIndex(1) + 1.0 MOI.VariableIndex(1)^2

julia> f^2 # (x + 2)^2 too
(4) + (2) MOI.VariableIndex(1) + (2) MOI.VariableIndex(1) + 1.0 MOI.VariableIndex(1)^2
```

### Creating vector functions

A vector function is a function with several values, irrespective of the number of input variables. Similarly to scalar functions, there are three main types of vector functions: [VectorOfVariables](#), [VectorAffineFunction](#), and [VectorQuadraticFunction](#).

The easiest way to create a vector function is to stack several scalar functions using [Utilities.vectorize](#). It takes a vector as input, and the generated vector function (of the most appropriate type) has each dimension corresponding to a dimension of the vector.

```
julia> g = MOI.Utilities.vectorize([f, 2 * f])
[ (2) + (1) MOI.VariableIndex(1) |
  (4) + (2) MOI.VariableIndex(1) ]
```

#### Warning

[Utilities.vectorize](#) only takes a vector of similar scalar functions: you cannot mix [VariableIndex](#) and [ScalarAffineFunction](#), for instance. In practice, it means that `Utilities.vectorize([x, f])` does not work; you should rather use `Utilities.vectorize([1 * x, f])` instead to only have [ScalarAffineFunction](#) objects.

## Canonicalizing functions

In more advanced use cases, you might need to ensure that a function is "canonical." Functions are stored as an array of terms, but there is no check that these terms are redundant: a `ScalarAffineFunction` object might have two terms with the same variable, like  $x + x + 1$ . These terms could be merged without changing the semantics of the function:  $2x + 1$ .

Working with these objects might be cumbersome. Canonicalization helps maintain redundancy to zero.

`Utilities.is_canonical` checks whether a function is already in its canonical form:

```
julia> MOI.Utilities.is_canonical(f + f) # (x + 2) + (x + 2) is stored as x + x + 4
false
```

`Utilities.canonical` returns the equivalent canonical version of the function:

```
julia> MOI.Utilities.canonical(f + f) # Returns 2x + 4
(4) + (2) MOI.VariableIndex(1)
```

## Exploring functions

At some point, you might need to dig into a function, for instance to map it into solver constructs.

### Vector functions

`Utilities.scalarize` returns a vector of scalar functions from a vector function:

```
julia> MOI.Utilities.scalarize(g) # Returns a vector [f, 2 * f].
2-element Vector{MathOptInterface.ScalarAffineFunction{Int64}}:
 (2) + (1) MOI.VariableIndex(1)
 (4) + (2) MOI.VariableIndex(1)
```

#### Note

`Utilities.eachscalar` returns an iterator on the dimensions, which serves the same purpose as `Utilities.scalarize`.

`output_dimension` returns the number of dimensions of the output of a function:

```
julia> MOI.output_dimension(g)
2
```

## 32.6 Latency

MathOptInterface suffers the "time-to-first-solve" problem of start-up latency.

This hurts both the user- and developer-experience of MathOptInterface. In the first case, because simple models have a multi-second delay before solving, and in the latter, because our tests take so long to run.

This page contains some advice on profiling and fixing latency-related problems in the `MathOptInterface.jl` repository.

## Background

Before reading this part of the documentation, you should familiarize yourself with the reasons for latency in Julia and how to fix them.

- Read the blogposts on julialang.org on [precompilation](#) and [SnoopCompile](#)
- Read the [SnoopCompile](#) documentation.
- Watch Tim Holy's [talk at JuliaCon 2021](#)
- Watch the [package development workshop at JuliaCon 2021](#)

## Causes

There are three main causes of latency in MathOptInterface:

1. A large number of types
2. Lack of method ownership
3. Type-instability in the bridge layer

### A large number of types

Julia is very good at specializing method calls based on the input type. Each specialization has a compilation cost, but the benefit of faster run-time performance.

The best-case scenario is for a method to be called a large number of times with a single set of argument types. The worst-case scenario is for a method to be called a single time for a large set of argument types.

Because of MathOptInterface's *function-in-set* formulation, we fall into the worst-case situation.

This is a fundamental limitation of Julia, so there isn't much we can do about it. However, if we can precompile MathOptInterface, much of the cost can be shifted from start-up latency to the time it takes to precompile a package on installation.

However, there are two things which make MathOptInterface hard to precompile.

### Lack of method ownership

Lack of method ownership happens when a call is made using a mix of structs and methods from different modules. Because of this, no single module "owns" the method that is being dispatched, and so it cannot be precompiled.

#### Tip

This is a slightly simplified explanation. Read the [precompilation tutorial](#) for a more in-depth discussion on back-edges.

Unfortunately, the design of MOI means that this is a frequent occurrence: we have a bunch of types in `MOI.Utilities` that wrap types defined in external packages (for example, the Optimizers), which implement methods of functions defined in MOI (for example, `add_variable`, `add_constraint`).

Here's a simple example of method-ownership in practice:

```

module MyMOI
struct Wrapper{T}
    inner::T
end
optimize!(x::Wrapper) = optimize!(x.inner)
end # MyMOI

module MyOptimizer
using ..MyMOI
struct Optimizer end
MyMOI.optimize!(x::Optimizer) = 1
end # MyOptimizer

using SnoopCompile
model = MyMOI.Wrapper(MyOptimizer.Optimizer())

julia> tinf = @snoopi_deep MyMOI.optimize!(model)
InferenceTimingNode: 0.008256/0.008543 on InferenceFrameInfo for Core.Compiler.Timings.ROOT() with
→ 1 direct children

```

The result is that there was one method that required type inference. If we visualize `tinf`:

```

using ProfileView
ProfileView.view(flamegraph(tinf))

```

we see a flamegraph with a large red-bar indicating that the method `MyMOI.optimize(MyMOI.Wrapper{MyOptimizer.Optimizer})` cannot be precompiled.

To fix this, we need to designate a module to "own" that method (that is, create a back-edge). The easiest way to do this is for `MyOptimizer` to call `MyMOI.optimize(MyMOI.Wrapper{MyOptimizer.Optimizer})` during using `MyOptimizer`. Let's see that in practice:

```

module MyMOI
struct Wrapper{T}
    inner::T
end
optimize(x::Wrapper) = optimize(x.inner)
end # MyMOI

module MyOptimizer
using ..MyMOI
struct Optimizer end
MyMOI.optimize(x::Optimizer) = 1
# The syntax of this let-while loop is very particular:
# * `let ... end` keeps everything local to avoid polluting the MyOptimizer
#   namespace
# * `while true ... break end` runs the code once, and forces Julia to compile
#   the inner loop, rather than interpret it.
let
    while true
        model = MyMOI.Wrapper(Optimizer())
        MyMOI.optimize(model)
        break

```

```

    end
end
end # MyOptimizer

using SnoopCompile
model = MyMOI.Wrapper(MyOptimizer.Optimizer())

julia> tinf = @snoopi_deep MyMOI.optimize(model)
InferenceTimingNode: 0.006822/0.006822 on InferenceFrameInfo for Core.Compiler.Timings.ROOT() with
→ 0 direct children

```

There are now 0 direct children that required type inference because the method was already stored in `MyOptimizer`!

Unfortunately, this trick only works if the call-chain is fully inferrable. If there are breaks (due to type instability), then the benefit of doing this is reduced. And unfortunately for us, the design of `MathOptInterface` has a lot of type instabilities.

### Type instability in the bridge layer

Most of `MathOptInterface` is pretty good at ensuring type-stability. However, a key component is not type stable, and that is the bridging layer.

In particular, the bridging layer defines `Bridges.LazyBridgeOptimizer`, which has fields like:

```

struct LazyBridgeOptimizer
    constraint_bridge_types::Vector{Any}
    constraint_node::Dict{Tuple{Type, Type}, ConstraintNode}
    constraint_types::Vector{Tuple{Type, Type}}
end

```

This is because the `LazyBridgeOptimizer` needs to be able to deal with any *function-in-set* type passed to it, and we also allow users to pass additional bridges that they defined in external packages.

So to recap, `MathOptInterface` suffers package latency because:

1. there are a large number of types and functions
2. and these are split between multiple modules, including external packages
3. and there are type-instabilities like those in the bridging layer.

### Resolutions

There are no magic solutions to reduce latency. [Issue #1313](#) tracks progress on reducing latency in `MathOptInterface`.

A useful script is the following (replace GLPK as needed):

```

import GLPK
import MathOptInterface as MOI

function example_diet(optimizer, bridge)
    category_data = [
        1800.0 2200.0;

```

```

    91.0      Inf;
    0.0     65.0;
    0.0 1779.0
]
cost = [2.49, 2.89, 1.50, 1.89, 2.09, 1.99, 2.49, 0.89, 1.59]
food_data =
    410 24 26 730;
    420 32 10 1190;
    560 20 32 1800;
    380 4 19 270;
    320 12 10 930;
    320 15 12 820;
    320 31 12 1230;
    100 8 2.5 125;
    330 8 10 180
]
bridge_model = if bridge
    MOI.instantiate(optimizer; with_bridge_type=Float64)
else
    MOI.instantiate(optimizer)
end
model = MOI.Utilities.CachingOptimizer(
    MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}()),
    MOI.Utilities.AUTOMATIC,
)
MOI.Utilities.reset_optimizer(model, bridge_model)
MOI.set(model, MOI.Silent(), true)
nutrition = MOI.add_variables(model, size(category_data, 1))
for (i, v) in enumerate(nutrition)
    MOI.add_constraint(model, v, MOI.GreaterThan(category_data[i, 1]))
    MOI.add_constraint(model, v, MOI.LessThan(category_data[i, 2]))
end
buy = MOI.add_variables(model, size(food_data, 1))
MOI.add_constraint.(model, buy, MOI.GreaterThan(0.0))
MOI.set(model, MOI.ObjectiveSense(), MOI.MIN_SENSE)
f = MOI.ScalarAffineFunction(MOI.ScalarAffineTerm.(cost, buy), 0.0)
MOI.set(model, MOI.ObjectiveFunction{typeof(f)}(), f)
for (j, n) in enumerate(nutrition)
    f = MOI.ScalarAffineFunction(
        MOI.ScalarAffineTerm.(food_data[:, j], buy),
        0.0,
    )
    push!(f.terms, MOI.ScalarAffineTerm(-1.0, n))
    MOI.add_constraint(model, f, MOI.EqualTo(0.0))
end
MOI.optimize!(model)
term_status = MOI.get(model, MOI.TerminationStatus())
@assert term_status == MOI.OPTIMAL
MOI.add_constraint(
    model,
    MOI.ScalarAffineFunction(
        MOI.ScalarAffineTerm.(1.0, [buy[end-1], buy[end]]),
        0.0,
    ),
    MOI.LessThan(6.0),
)

```

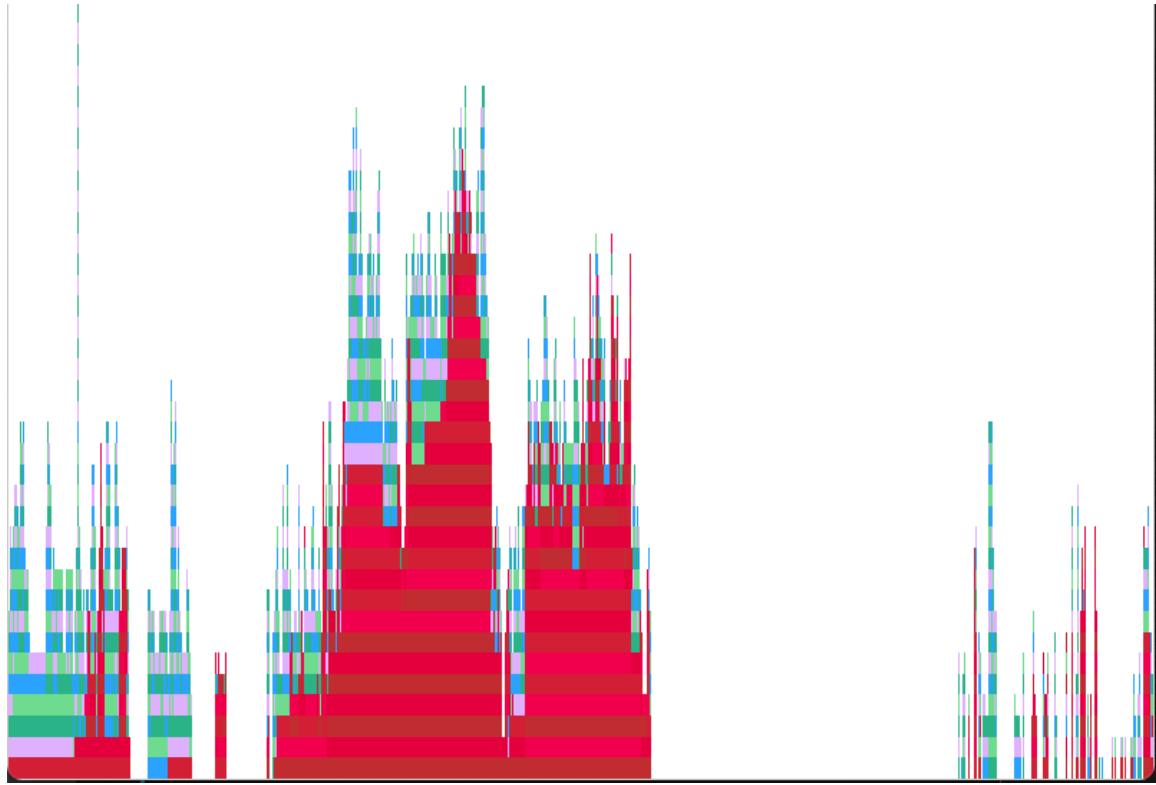


Figure 32.1: flamegraph

```

    )
MOI.optimize!(model)
@assert MOI.get(model, MOI.TerminationStatus()) == MOI.INFEASIBLE
return
end

if length ARGS > 0
    bridge = get ARGS, 2, "" != "--no-bridge"
    println("Running: $(ARGS[1]) $(get ARGS, 2, "")")
    @time example_diet(GLPK.Optimizer, bridge)
    @time example_diet(GLPK.Optimizer, bridge)
    exit(0)
end

```

You can create a flame-graph via

```

using SnoopCompile
tinf = @snoopi_deep example_diet(GLPK.Optimizer, true)
using ProfileView
ProfileView.view(flamegraph(tinf))

```

Here's how things looked in mid-August 2021:

There are a few opportunities for improvement (non-red flames, particularly on the right). But the main problem is a large red (non-precompilable due to method ownership) flame.

# Chapter 33

## Manual

### 33.1 Standard form problem

MathOptInterface represents optimization problems in the standard form:

$$\min_{x \in \mathbb{R}^n} f_0(x) \quad (33.1)$$

$$\text{s.t.} \quad f_i(x) \in \mathcal{S}_i \quad i = 1 \dots m \quad (33.2)$$

where:

- the functions  $f_0, f_1, \dots, f_m$  are specified by `AbstractFunction` objects
- the sets  $\mathcal{S}_1, \dots, \mathcal{S}_m$  are specified by `AbstractSet` objects

#### Tip

For more information on this standard form, read [our paper](#).

MOI defines some commonly used functions and sets, but the interface is extensible to other sets recognized by the solver.

#### Functions

The function types implemented in MathOptInterface.jl are:

Extensions for nonlinear programming are present but not yet well documented.

#### One-dimensional sets

The one-dimensional set types implemented in MathOptInterface.jl are:

#### Vector cones

The vector-valued set types implemented in MathOptInterface.jl are:

| Function                             | Description                                                                                                |
|--------------------------------------|------------------------------------------------------------------------------------------------------------|
| <code>VariableIndex</code>           | $x_j$ , the projection onto a single coordinate defined by a variable index $j$ .                          |
| <code>VectorOfVariables</code>       | The projection onto multiple coordinates (that is, extracting a sub-vector).                               |
| <code>ScalarAffineFunction</code>    | $a^T x + b$ , where $a$ is a vector and $b$ scalar.                                                        |
| <code>ScalarNonlinearFunction</code> | $f(x)$ , where $f$ is a nonlinear function.                                                                |
| <code>VectorAffineFunction</code>    | $Ax + b$ , where $A$ is a matrix and $b$ is a vector.                                                      |
| <code>ScalarQuadraticFunction</code> | $\frac{1}{2}x^T Qx + a^T x + b$ , where $Q$ is a symmetric matrix, $a$ is a vector, and $b$ is a constant. |
| <code>VectorQuadraticFunction</code> | A vector of scalar-valued quadratic functions.                                                             |
| <code>VectorNonlinearFunction</code> | $f(x)$ , where $f$ is a vector-valued nonlinear function.                                                  |

| Set                               | Description                            |
|-----------------------------------|----------------------------------------|
| <code>LessThan(u)</code>          | $(-\infty, u]$                         |
| <code>GreaterThan(l)</code>       | $[l, \infty)$                          |
| <code>EqualTo(v)</code>           | $\{v\}$                                |
| <code>Interval(l, u)</code>       | $[l, u]$                               |
| <code>Integer()</code>            | $\mathbb{Z}$                           |
| <code>ZeroOne()</code>            | $\{0, 1\}$                             |
| <code>Semicontinuous(l, u)</code> | $\{0\} \cup [l, u]$                    |
| <code>Semiinteger(l, u)</code>    | $\{0\} \cup \{l, l+1, \dots, u-1, u\}$ |

| Set                                    | Description                                                                                                                   |
|----------------------------------------|-------------------------------------------------------------------------------------------------------------------------------|
| <code>Reals(d)</code>                  | $\mathbb{R}^d$                                                                                                                |
| <code>Zeros(d)</code>                  | $0^d$                                                                                                                         |
| <code>Nonnegatives(d)</code>           | $\{x \in \mathbb{R}^d : x \geq 0\}$                                                                                           |
| <code>Nonpositives(d)</code>           | $\{x \in \mathbb{R}^d : x \leq 0\}$                                                                                           |
| <code>SecondOrderCone(d)</code>        | $\{(t, x) \in \mathbb{R}^d : t \geq \ x\ _2\}$                                                                                |
| <code>RotatedSecondOrderCone(d)</code> | $\{(t, u, x) \in \mathbb{R}^d : 2tu \geq \ x\ _2^2, t \geq 0, u \geq 0\}$                                                     |
| <code>ExponentialCone()</code>         | $\{(x, y, z) \in \mathbb{R}^3 : y \exp(x/y) \leq z, y > 0\}$                                                                  |
| <code>DualExponentialCone()</code>     | $\{(u, v, w) \in \mathbb{R}^3 : -u \exp(v/u) \leq \exp(1)w, u < 0\}$                                                          |
| <code>GeometricMeanCone(d)</code>      | $\{(t, x) \in \mathbb{R}^{1+n} : x \geq 0, t \leq \sqrt[n]{x_1 x_2 \cdots x_n}\}$ where $n$ is $d-1$                          |
| <code>PowerCone(alpha)</code>          | $\{(x, y, z) \in \mathbb{R}^3 : x^\alpha y^{1-\alpha} \geq  z , x \geq 0, y \geq 0\}$                                         |
| <code>DualPowerCone(alpha)</code>      | $\{(u, v, w) \in \mathbb{R}^3 : (\frac{u}{\alpha})^\alpha \left(\frac{v}{1-\alpha}\right)^{1-\alpha} \geq  w , u, v \geq 0\}$ |
| <code>NormOneCone(d)</code>            | $\{(t, x) \in \mathbb{R}^d : t \geq \sum_i  x_i \}$                                                                           |
| <code>NormInfinityCone(d)</code>       | $\{(t, x) \in \mathbb{R}^d : t \geq \max_i  x_i \}$                                                                           |
| <code>RelativeEntropyCone(d)</code>    | $\{(u, v, w) \in \mathbb{R}^d : u \geq \sum_i w_i \log(\frac{w_i}{v_i}), v_i \geq 0, w_i \geq 0\}$                            |
| <code>HyperRectangle(l, u)</code>      | $\{x \in \bar{\mathbb{R}}^d : x_i \in [l_i, u_i] \forall i = 1, \dots, d\}$                                                   |
| <code>NormCone(p, d)</code>            | $\{(t, x) \in \mathbb{R}^d : t \geq \left(\sum_i  x_i ^p\right)^{\frac{1}{p}}\}$                                              |

## Matrix cones

The matrix-valued set types implemented in `MathOptInterface.jl` are:

Some of these cones can take two forms: `XXXConeTriangle` and `XXXConeSquare`.

In `XXXConeTriangle` sets, the matrix is assumed to be symmetric, and the elements are provided by a vector, in which the entries of the upper-right triangular part of the matrix are given column by column (or equivalently, the entries of the lower-left triangular part are given row by row).

| Set                                            | Description                                                                                                                     |
|------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------|
| <code>RootDetConeTriangle(d)</code>            | $\{(t, X) \in \mathbb{R}^{1+d(1+d)/2} : t \leq \det(X)^{1/d}, X \text{ is the upper triangle of a PSD matrix}\}$                |
| <code>RootDetConeSquare(d)</code>              | $\{(t, X) \in \mathbb{R}^{1+d^2} : t \leq \det(X)^{1/d}, X \text{ is a PSD matrix}\}$                                           |
| <code>PositiveSemidefiniteConeTriangle</code>  | $\{X \in \mathbb{R}^{d(d+1)/2} : X \text{ is the upper triangle of a PSD matrix}\}$                                             |
| <code>PositiveSemidefiniteConeSquare(d)</code> | $\{X \in \mathbb{R}^{d^2} : X \text{ is a PSD matrix}\}$                                                                        |
| <code>LogDetConeTriangle(d)</code>             | $\{(t, u, X) \in \mathbb{R}^{2+d(1+d)/2} : t \leq u \log(\det(X/u)), X \text{ is the upper triangle of a PSD matrix, } u > 0\}$ |
| <code>LogDetConeSquare(d)</code>               | $\{(t, u, X) \in \mathbb{R}^{2+d^2} : t \leq u \log(\det(X/u)), X \text{ is a PSD matrix, } u > 0\}$                            |
| <code>NormSpectralCone(r, c)</code>            | $\{(t, X) \in \mathbb{R}^{1+r \times c} : t \geq \sigma_1(X), X \text{ is a } r \times c \text{ matrix}\}$                      |
| <code>NormNuclearCone(r, c)</code>             | $\{(t, X) \in \mathbb{R}^{1+r \times c} : t \geq \sum_i \sigma_i(X), X \text{ is a } r \times c \text{ matrix}\}$               |
| <code>HermitianPositiveSemidefiniteCone</code> | The cone of Hermitian positive semidefinite matrices, with side_dimension rows and columns.                                     |
| <code>Scaled(S)</code>                         | The set S scaled so that <code>Utilities.set_dot</code> corresponds to <code>LinearAlgebra.dot</code>                           |

In XXXConeSquare sets, the entries of the matrix are given column by column (or equivalently, row by row), and the matrix is constrained to be symmetric. As an example, given a 2-by-2 matrix of variables X and a one-dimensional variable t, we can specify a root-det constraint as  $[t, X_{11}, X_{12}, X_{22}] \in \text{RootDetConeTriangle}$  or  $[t, X_{11}, X_{12}, X_{21}, X_{22}] \in \text{RootDetConeSquare}$ .

We provide both forms to enable flexibility for solvers who may natively support one or the other. Transformations between XXXConeTriangle and XXXConeSquare are handled by bridges, which removes the chance of conversion mistakes by users or solver developers.

### Multi-dimensional sets with combinatorial structure

Other sets are vector-valued, with a particular combinatorial structure. Read their docstrings for more information on how to interpret them.

| Set                            | Description                                         |
|--------------------------------|-----------------------------------------------------|
| <code>SOS1</code>              | A Special Ordered Set (SOS) of Type I               |
| <code>SOS2</code>              | A Special Ordered Set (SOS) of Type II              |
| <code>Indicator</code>         | A set to specify an indicator constraint            |
| <code>Complements</code>       | A set to specify a mixed complementarity constraint |
| <code>AllDifferent</code>      | The all_different global constraint                 |
| <code>BinPacking</code>        | The bin_packing global constraint                   |
| <code>Circuit</code>           | The circuit global constraint                       |
| <code>CountAtLeast</code>      | The at_least global constraint                      |
| <code>CountBelongs</code>      | The nvalue global constraint                        |
| <code>CountDistinct</code>     | The distinct global constraint                      |
| <code>CountGreater Than</code> | The count_gt global constraint                      |
| <code>Cumulative</code>        | The cumulative global constraint                    |
| <code>Path</code>              | The path global constraint                          |
| <code>Table</code>             | The table global constraint                         |

## 33.2 Models

The most significant part of MOI is the definition of the [model API](#) that is used to specify an instance of an optimization problem (for example, by adding variables and constraints). Objects that implement the model API must inherit from the [ModelLike](#) abstract type.

Notably missing from the model API is the method to solve an optimization problem. [ModelLike](#) objects may store an instance (for example, in memory or backed by a file format) without being linked to a particular solver. In addition to the model API, MOI defines [AbstractOptimizer](#) and provides methods to solve the model and interact with solutions. See the [Solutions](#) section for more details.

### Info

Throughout the rest of the manual, `model` is used as a generic `ModelLike`, and `optimizer` is used as a generic `AbstractOptimizer`.

### Tip

MOI does not export functions, but for brevity we often omit qualifying names with the MOI module. Best practice is to have

```
import MathOptInterface as MOI
```

and prefix all MOI methods with `MOI.` in user code. If a name is also available in base Julia, we always explicitly use the module prefix, for example, with `MOI.get`.

## Attributes

Attributes are properties of the model that can be queried and modified. These include constants such as the number of variables in a model ([NumberofVariables](#)), and properties of variables and constraints such as the name of a variable ([VariableName](#)).

There are four types of attributes:

- Model attributes (subtypes of [AbstractModelAttribute](#)) refer to properties of a model.
- Optimizer attributes (subtypes of [AbstractOptimizerAttribute](#)) refer to properties of an optimizer.
- Constraint attributes (subtypes of [AbstractConstraintAttribute](#)) refer to properties of an individual constraint.
- Variable attributes (subtypes of [AbstractVariableAttribute](#)) refer to properties of an individual variable.

Some attributes are values that can be queried by the user but not modified, while other attributes can be modified by the user.

All interactions with attributes occur through the `get` and `set` functions.

Consult the docstrings of each attribute for information on what it represents.

### **ModelLike API**

The following attributes are available:

- [ListOfConstraintAttributesSet](#)
- [ListOfConstraintIndices](#)
- [ListOfConstraintTypesPresent](#)
- [ListOfConstraintsWithAttributeSet](#)
- [ListOfModelAttributesSet](#)
- [ListOfVariableAttributesSet](#)
- [ListOfVariableIndices](#)
- [ListOfVariablesWithAttributeSet](#)
- [NumberOfConstraints](#)
- [NumberOfVariables](#)
- [Name](#)
- [ObjectiveFunction](#)
- [ObjectiveFunctionType](#)
- [ObjectiveSense](#)

### **AbstractOptimizer API**

The following attributes are available:

- [DualStatus](#)
- [PrimalStatus](#)
- [RawStatusString](#)
- [ResultCount](#)
- [TerminationStatus](#)
- [BarrierIterations](#)
- [DualObjectiveValue](#)
- [NodeCount](#)
- [NumberOfThreads](#)
- [ObjectiveBound](#)
- [ObjectiveValue](#)
- [RelativeGap](#)
- [RawOptimizerAttribute](#)

- `RawSolver`
- `Silent`
- `SimplexIterations`
- `SolverName`
- `SolverVersion`
- `SolveTimeSec`
- `TimeLimitSec`
- `ObjectiveLimit`
- `SolutionLimit`
- `NodeLimit`
- `AutomaticDifferentiationBackend`

### 33.3 Variables

#### Add a variable

Use `add_variable` to add a single variable.

```
julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)
```

`add_variable` returns a `VariableIndex` type, which is used to refer to the added variable in other calls.

Check if a `VariableIndex` is valid using `is_valid`.

```
julia> MOI.is_valid(model, x)
true
```

Use `add_variables` to add a number of variables.

```
julia> y = MOI.add_variables(model, 2)
2-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(2)
 MOI.VariableIndex(3)
```

#### Warning

The integer does not necessarily correspond to the column inside an optimizer.

#### Delete a variable

Delete a variable using `delete`.

```
julia> MOI.delete(model, x)
julia> MOI.is_valid(model, x)
false
```

**Warning**

Not all ModelLike models support deleting variables. A `DeleteNotAllowed` error is thrown if this is not supported.

**Variable attributes**

The following attributes are available for variables:

- `VariableName`
- `VariablePrimalStart`
- `VariablePrimal`

Get and set these attributes using `get` and `set`.

```
julia> MOI.set(model, MOI.VariableName(), x, "var_x")
julia> MOI.get(model, MOI.VariableName(), x)
"var_x"
```

**33.4 Constraints****Add a constraint**

Use `add_constraint` to add a single constraint.

```
julia> c = MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.Nonnegatives(2))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
                                MathOptInterface.Nonnegatives}(1)
```

`add_constraint` returns a `ConstraintIndex` type, which is used to refer to the added constraint in other calls.

Check if a `ConstraintIndex` is valid using `is_valid`.

```
julia> MOI.is_valid(model, c)
true
```

Use `add_constraints` to add a number of constraints of the same type.

```
julia> c = MOI.add_constraints(
    model,
    [x[1], x[2]],
    [MOI.GreaterThan(0.0), MOI.GreaterThan(1.0)]
)
2-element Vector{MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.GreaterThan{Float64}}}:  

  MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,  

  ↪ MathOptInterface.GreaterThan{Float64}}(1)  

  MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,  

  ↪ MathOptInterface.GreaterThan{Float64}}(2)
```

This time, a vector of `ConstraintIndex` are returned.

Use `supports_constraint` to check if the model supports adding a constraint type.

```
julia> MOI.supports_constraint(
    model,
    MOI.VariableIndex,
    MOI.GreaterThan{Float64},
)
true
```

## Delete a constraint

Use `delete` to delete a constraint.

```
julia> MOI.delete(model, c)

julia> MOI.is_valid(model, c)
false
```

## Constraint attributes

The following attributes are available for constraints:

- `ConstraintName`
- `ConstraintPrimalStart`
- `ConstraintDualStart`
- `ConstraintPrimal`
- `ConstraintDual`
- `ConstraintBasisStatus`
- `ConstraintFunction`
- `CanonicalConstraintFunction`
- `ConstraintSet`

Get and set these attributes using `get` and `set`.

```
julia> MOI.set(model, MOI.ConstraintName(), c, "con_c")
julia> MOI.get(model, MOI.ConstraintName(), c)
"con_c"
```

### Constraints by function-set pairs

Below is a list of common constraint types and how they are represented as function-set pairs in MOI. In the notation below,  $x$  is a vector of decision variables,  $x_i$  is a scalar decision variable,  $\alpha, \beta$  are scalar constants,  $a, b$  are constant vectors,  $A$  is a constant matrix and  $\mathbb{R}_+$  (resp.  $\mathbb{R}_-$ ) is the set of non-negative (resp. non-positive) real numbers.

#### Linear constraints

| Mathematical Constraint        | MOI Function         | MOI Set      |
|--------------------------------|----------------------|--------------|
| $a^T x \leq \beta$             | ScalarAffineFunction | LessThan     |
| $a^T x \geq \alpha$            | ScalarAffineFunction | GreaterThan  |
| $a^T x = \beta$                | ScalarAffineFunction | EqualTo      |
| $\alpha \leq a^T x \leq \beta$ | ScalarAffineFunction | Interval     |
| $x_i \leq \beta$               | VariableIndex        | LessThan     |
| $x_i \geq \alpha$              | VariableIndex        | GreaterThan  |
| $x_i = \beta$                  | VariableIndex        | EqualTo      |
| $\alpha \leq x_i \leq \beta$   | VariableIndex        | Interval     |
| $Ax + b \in \mathbb{R}_+^n$    | VectorAffineFunction | Nonnegatives |
| $Ax + b \in \mathbb{R}_-^n$    | VectorAffineFunction | Nonpositives |
| $Ax + b = 0$                   | VectorAffineFunction | Zeros        |

By convention, solvers are not expected to support nonzero constant terms in the `ScalarAffineFunctions` the first four rows of the preceding table because they are redundant with the parameters of the sets. For example, encode  $2x + 1 \leq 2$  as  $2x \leq 1$ .

Constraints with `VariableIndex` in `LessThan`, `GreaterThan`, `EqualTo`, or `Interval` sets have a natural interpretation as variable bounds. As such, it is typically not natural to impose multiple lower- or upper-bounds on the same variable, and the solver interfaces will throw respectively `LowerBoundAlreadySet` or `UpperBoundAlreadySet`.

Moreover, adding two `VariableIndex` constraints on the same variable with the same set is impossible because they share the same index as it is the index of the variable, see `ConstraintIndex`.

It is natural, however, to impose upper- and lower-bounds separately as two different constraints on a single variable. The difference between imposing bounds by using a single `Interval` constraint and by using separate `LessThan` and `GreaterThan` constraints is that the latter will allow the solver to return separate dual multipliers for the two bounds, while the former will allow the solver to return only a single dual for the interval constraint.

#### Conic constraints

where  $\mathcal{E}$  is the exponential cone (see `ExponentialCone`),  $\mathcal{S}_+$  is the set of positive semidefinite symmetric matrices,  $A$  is an affine map that outputs symmetric matrices and  $B$  is an affine map that outputs square matrices.

| Mathematical Constraint                                         | MOI Function         | MOI Set                          |
|-----------------------------------------------------------------|----------------------|----------------------------------|
| $\ Ax + b\ _2 \leq c^T x + d$                                   | VectorAffineFunction | SecondOrderCone                  |
| $y \geq \ x\ _2$                                                | VectorOfVariables    | SecondOrderCone                  |
| $2yz \geq \ x\ _2^2, y, z \geq 0$                               | VectorOfVariables    | RotatedSecondOrderCone           |
| $(a_1^T x + b_1, a_2^T x + b_2, a_3^T x + b_3) \in \mathcal{E}$ | VectorAffineFunction | ExponentialCone                  |
| $A(x) \in \mathcal{S}_+$                                        | VectorAffineFunction | PositiveSemidefiniteConeTriangle |
| $B(x) \in \mathcal{S}_+$                                        | VectorAffineFunction | PositiveSemidefiniteConeSquare   |
| $x \in \mathcal{S}_+$                                           | VectorOfVariables    | PositiveSemidefiniteConeTriangle |
| $x \in \mathcal{S}_+$                                           | VectorOfVariables    | PositiveSemidefiniteConeSquare   |

| Mathematical Constraint                | MOI Function            | MOI Set                     |
|----------------------------------------|-------------------------|-----------------------------|
| $\frac{1}{2}x^T Qx + a^T x + b \geq 0$ | ScalarQuadraticFunction | GreaterThan                 |
| $\frac{1}{2}x^T Qx + a^T x + b \leq 0$ | ScalarQuadraticFunction | LessThan                    |
| $\frac{1}{2}x^T Qx + a^T x + b = 0$    | ScalarQuadraticFunction | EqualTo                     |
| Bilinear matrix inequality             | VectorQuadraticFunction | PositiveSemidefiniteCone... |

### Quadratic constraints

**Note**

For more details on the internal format of the quadratic functions see [ScalarQuadraticFunction](#) or [VectorQuadraticFunction](#).

### Discrete and logical constraints

| Mathematical Constraint                                                                  | MOI Function                  | MOI Set        |
|------------------------------------------------------------------------------------------|-------------------------------|----------------|
| $x_i \in \mathbb{Z}$                                                                     | VariableIndex                 | Integer        |
| $x_i \in \{0, 1\}$                                                                       | VariableIndex                 | ZeroOne        |
| $x_i \in \{0\} \cup [l, u]$                                                              | VariableIndex                 | Semicontinuous |
| $x_i \in \{0\} \cup \{l, l+1, \dots, u-1, u\}$                                           | VariableIndex                 | Semiinteger    |
| At most one component of $x$ can be nonzero                                              | VectorOfVariables             | SOS1           |
| At most two components of $x$ can be nonzero, and if so they must be adjacent components | VectorOfVariables             | SOS2           |
| $y = 1 \implies a^T x \in S$                                                             | VectorAffineFunctionIndicator |                |

### JuMP mapping

The following bullet points show examples of how JuMP constraints are translated into MOI function-set pairs:

- `@constraint(m, 2x + y <= 10)` becomes `ScalarAffineFunction-in-LessThan`
- `@constraint(m, 2x + y >= 10)` becomes `ScalarAffineFunction-in-GreaterThan`
- `@constraint(m, 2x + y == 10)` becomes `ScalarAffineFunction-in-EqualTo`
- `@constraint(m, 0 <= 2x + y <= 10)` becomes `ScalarAffineFunction-in-Interval`
- `@constraint(m, 2x + y in ArbitrarySet())` becomes `ScalarAffineFunction-in-ArbitrarySet`.

Variable bounds are handled in a similar fashion:

- `@variable(m, x <= 1)` becomes `VariableIndex-in-LessThan`
- `@variable(m, x >= 1)` becomes `VariableIndex-in-GreaterThan`

One notable difference is that a variable with an upper and lower bound is translated into two constraints, rather than an interval, that is:

- `@variable(m, 0 <= x <= 1)` becomes `VariableIndex-in-LessThan` and `VariableIndex-in-GreaterThan`.

## 33.5 Solutions

### Solving and retrieving the results

Once an optimizer is loaded with the objective function and all of the constraints, we can ask the solver to solve the model by calling `optimize!`.

```
MOI.optimize!(optimizer)
```

### Why did the solver stop?

The optimization procedure may stop for a number of reasons. The `TerminationStatus` attribute of the optimizer returns a `TerminationStatusCode` object which explains why the solver stopped.

The termination statuses distinguish between proofs of optimality, infeasibility, local convergence, limits, and termination because of something unexpected like invalid problem data or failure to converge.

A typical usage of the `TerminationStatus` attribute is as follows:

```
status = MOI.get(optimizer, TerminationStatus())
if status == MOI.OPTIMAL
    # Ok, we solved the problem!
else
    # Handle other cases.
end
```

After checking the `TerminationStatus`, check `ResultCount`. This attribute returns the number of results that the solver has available to return. A *result* is defined as a primal-dual pair, but either the primal or the dual may be missing from the result. While the `OPTIMAL` termination status normally implies that at least one result is available, other statuses do not. For example, in the case of infeasibility, a solver may return no result or a proof of infeasibility. The `ResultCount` attribute distinguishes between these two cases.

### Primal solutions

Use the `PrimalStatus` optimizer attribute to return a `ResultStatusCode` describing the status of the primal solution.

Common returns are described below in the `Common status situations` section.

Query the primal solution using the `VariablePrimal` and `ConstraintPrimal` attributes.

Query the objective function value using the `ObjectiveValue` attribute.

## Dual solutions

### Warning

See [Duality](#) for a discussion of the MOI conventions for primal-dual pairs and certificates.

Use the `DualStatus` optimizer attribute to return a `ResultStatusCode` describing the status of the dual solution.

Query the dual solution using the `ConstraintDual` attribute.

Query the dual objective function value using the `DualObjectiveValue` attribute.

## Common status situations

The sections below describe how to interpret typical or interesting status cases for three common classes of solvers. The example cases are illustrative, not comprehensive. Solver wrappers may provide additional information on how the solver's statuses map to MOI statuses.

### Info

\* in the tables indicate that multiple different values are possible.

## Primal-dual convex solver

Linear programming and conic optimization solvers fall into this category.

| What happened?                          | TerminationStatus | ResultCount | PrimalStatus              | DualStatus                |
|-----------------------------------------|-------------------|-------------|---------------------------|---------------------------|
| Proved optimality                       | OPTIMAL           | 1           | FEASIBLE_POINT            | FEASIBLE_POINT            |
| Proved infeasible                       | INFEASIBLE        | 1           | NO_SOLUTION               | INFEASIBILITY_CERTIFICATE |
| Optimal within relaxed tolerances       | ALMOST_OPTIMAL    | 1           | FEASIBLE_POINT            | FEASIBLE_POINT            |
| Optimal within relaxed tolerances       | ALMOST_OPTIMAL    | 1           | ALMOST_FEASIBLE_POINT     | ALMOST_FEASIBLE_POINT     |
| Detected an unbounded ray of the primal | DUAL_INFEASIBLE   | 1           | INFEASIBILITY_CERTIFICATE | NO_SOLUTION               |
| Stall                                   | SLOW_PROGRESS     | 1           | *                         | *                         |

## Global branch-and-bound solvers

Mixed-integer programming solvers fall into this category.

| What happened?                                   | TerminationStatus       | ResultCount | PrimalStatus     | DualStatus  |
|--------------------------------------------------|-------------------------|-------------|------------------|-------------|
| Proved optimality                                | OPTIMAL                 | 1           | FEASIBLE_POINT   | NO_SOLUTION |
| Presolve detected infeasibility or unboundedness | INFEASIBLE_OR_UNBOUNDED | 0           | NO_SOLUTION      | NO_SOLUTION |
| Proved infeasibility                             | INFEASIBLE              | 0           | NO_SOLUTION      | NO_SOLUTION |
| Timed out (no solution)                          | TIME_LIMIT              | 0           | NO_SOLUTION      | NO_SOLUTION |
| Timed out (with a solution)                      | TIME_LIMIT              | 1           | FEASIBLE_POINT   | NO_SOLUTION |
| CPXMIP_OPTIMAL_INFEAS                            | ALMOST_OPTIMAL          | 1           | INFEASIBLE_POINT | NO_SOLUTION |

**Info**

`CPXMIP_OPTIMAL_INFEAS` is a CPLEX status that indicates that a preprocessed problem was solved to optimality, but the solver was unable to recover a feasible solution to the original problem. Handling this status was one of the motivating drivers behind the design of MOI.

**Local search solvers**

Nonlinear programming solvers fall into this category. It also includes non-global tree search solvers like [Juniper](#).

| What happened?                                            | TerminationStatus                | ResultCount | PrimalStatus     | DualStatus     |
|-----------------------------------------------------------|----------------------------------|-------------|------------------|----------------|
| Converged to a stationary point                           | LOCALLY_SOLVED                   | 1           | FEASIBLE_POINT   | FEASIBLE_POINT |
| Completed a non-global tree search<br>(with a solution)   | LOCALLY_SOLVED                   | 1           | FEASIBLE_POINT   | FEASIBLE_POINT |
| Converged to an infeasible point                          | LOCALLY_INFEASIBLE               | 1           | INFEASIBLE_POINT | *              |
| Completed a non-global tree search<br>(no solution found) | LOCALLY_INFEASIBLE               | 0           | NO_SOLUTION      | NO_SOLUTION    |
| Iteration limit                                           | ITERATION_LIMIT                  | 1           | *                | *              |
| Diverging iterates                                        | NORM_LIMIT or<br>OBJECTIVE_LIMIT | 1           | *                | *              |

**Querying solution attributes**

Some solvers will not implement every solution attribute. Therefore, a call like `MOI.get(model, MOI.SolveTimeSec())` may throw an [UnsupportedAttribute](#) error.

If you need to write code that is agnostic to the solver (for example, you are writing a library that an end-user passes their choice of solver to), you can work-around this problem using a try-catch:

```
function get_solve_time(model)
    try
        return MOI.get(model, MOI.SolveTimeSec())
    catch err
        if err isa MOI.UnsupportedAttribute
            return NaN # Solver doesn't support. Return a placeholder value.
        end
        rethrow(err) # Something else went wrong. Rethrow the error
    end
end
```

If, *after careful profiling*, you find that the try-catch is taking a significant portion of your runtime, you can improve performance by caching the result of the try-catch:

```
mutable struct CachedSolveTime{M}
    model::M
    supports_solve_time::Bool
    CachedSolveTime(model::M) where {M} = new(model, true)
end

function get_solve_time(model::CachedSolveTime)
    if !model.supports_solve_time
```

```

        return NaN
    end
    try
        return MOI.get(model, MOI.SolveTimeSec())
    catch err
        if err isa MOI.UnsupportedAttribute
            model.supports_solve_time = false
            return NaN
        end
        rethrow(err) # Something else went wrong. Rethrow the error
    end
end

```

### 33.6 Problem modification

In addition to adding and deleting constraints and variables, MathOptInterface supports modifying, in-place, coefficients in the constraints and the objective function of a model.

These modifications can be grouped into two categories:

- modifications which replace the set of function of a constraint with a new set or function
- modifications which change, in-place, a component of a function

#### Warning

Some ModelLike objects do not support problem modification.

#### Modify the set of a constraint

Use `set` and `ConstraintSet` to modify the set of a constraint by replacing it with a new instance of the same type.

```

julia> c = MOI.add_constraint(
           model,
           MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(1.0, x)], 0.0),
           MOI.EqualTo(1.0),
       )
MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
                                 MathOptInterface.EqualTo{Float64}}(1)

julia> MOI.set(model, MOI.ConstraintSet(), c, MOI.EqualTo(2.0));

julia> MOI.get(model, MOI.ConstraintSet(), c) == MOI.EqualTo(2.0)
true

```

However, the following will fail as the new set is of a different type to the original set:

```
julia> MOI.set(model, MOI.ConstraintSet(), c, MOI.GreaterThan(2.0))
ERROR: [...]
```

### Special cases: set transforms

If our constraint is an affine inequality, then this corresponds to modifying the right-hand side of a constraint in linear programming.

In some special cases, solvers may support efficiently changing the set of a constraint (for example, from `LessThan` to `GreaterThan`). For these cases, MathOptInterface provides the `transform` method.

The `transform` function returns a new constraint index, and the old constraint index (that is, `c`) is no longer valid.

```
julia> c = MOI.add_constraint(
    model,
    MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(1.0, x)], 0.0),
    MOI.LessThan(1.0),
)
MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
↪ MathOptInterface.LessThan{Float64}}(1)

julia> new_c = MOI.transform(model, c, MOI.GreaterThan(2.0));

julia> MOI.is_valid(model, c)
false

julia> MOI.is_valid(model, new_c)
true
```

#### Note

`transform` cannot be called with a set of the same type. Use `set` instead.

### Modify the function of a constraint

Use `set` and `ConstraintFunction` to modify the function of a constraint by replacing it with a new instance of the same type.

```
julia> c = MOI.add_constraint(
    model,
    MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(1.0, x)], 0.0),
    MOI.EqualTo(1.0),
)
MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
↪ MathOptInterface.EqualTo{Float64}}(1)

julia> new_f = MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(2.0, x)], 1.0);

julia> MOI.set(model, MOI.ConstraintFunction(), c, new_f);
```

```
julia> MOI.get(model, MOI.ConstraintFunction(), c) ≈ new_f
true
```

However, the following will fail as the new function is of a different type to the original function:

```
julia> MOI.set(model, MOI.ConstraintFunction(), c, x)
ERROR: [...]
```

### Modify constant term in a scalar function

Use `modify` and `ScalarConstantChange` to modify the constant term in a `ScalarAffineFunction` or `ScalarQuadraticFunction`.

```
julia> c = MOI.add_constraint(
           model,
           MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(1.0, x)], 0.0),
           MOI.EqualTo(1.0),
       )
MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
                                MathOptInterface.EqualTo{Float64}}(1)

julia> MOI.modify(model, c, MOI.ScalarConstantChange(1.0));

julia> new_f = MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(1.0, x)], 1.0);

julia> MOI.get(model, MOI.ConstraintFunction(), c) ≈ new_f
true
```

`ScalarConstantChange` can also be used to modify the objective function by passing an instance of `ObjectiveFunction`:

```
julia> MOI.set(
           model,
           MOI.ObjectiveFunction{MOI.ScalarAffineFunction{Float64}}(),
           new_f,
       );

julia> MOI.modify(
           model,
           MOI.ObjectiveFunction{MOI.ScalarAffineFunction{Float64}}(),
           MOI.ScalarConstantChange(-1.0)
       );

julia> MOI.get(
           model,
           MOI.ObjectiveFunction{MOI.ScalarAffineFunction{Float64}}(),
       ) ≈ MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(1.0, x)], -1.0)
true
```

### Modify constant terms in a vector function

Use `modify` and `VectorConstantChange` to modify the constant vector in a `VectorAffineFunction` or `VectorQuadraticFunction`.

```
julia> c = MOI.add_constraint(
    model,
    MOI.VectorAffineFunction([
        MOI.VectorAffineTerm(1, MOI.ScalarAffineTerm(1.0, x)),
        MOI.VectorAffineTerm(2, MOI.ScalarAffineTerm(2.0, x)),
    ],
    [0.0, 0.0],
),
MOI.Nonnegatives(2),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorAffineFunction{Float64},
↪ MathOptInterface.Nonnegatives}(1)

julia> MOI.modify(model, c, MOI.VectorConstantChange([3.0, 4.0]));

julia> new_f = MOI.VectorAffineFunction(
    [
        MOI.VectorAffineTerm(1, MOI.ScalarAffineTerm(1.0, x)),
        MOI.VectorAffineTerm(2, MOI.ScalarAffineTerm(2.0, x)),
    ],
    [3.0, 4.0],
);
julia> MOI.get(model, MOI.ConstraintFunction(), c) ≈ new_f
true
```

### Modify affine coefficients in a scalar function

Use `modify` and `ScalarCoefficientChange` to modify the affine coefficient of a `ScalarAffineFunction` or `ScalarQuadraticFunction`.

```
julia> c = MOI.add_constraint(
    model,
    MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(1.0, x)], 0.0),
    MOI.EqualTo(1.0),
)
MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
↪ MathOptInterface.EqualTo{Float64}}(1)

julia> MOI.modify(model, c, MOI.ScalarCoefficientChange(x, 2.0));

julia> new_f = MOI.ScalarAffineFunction([MOI.ScalarAffineTerm(2.0, x)], 0.0);
julia> MOI.get(model, MOI.ConstraintFunction(), c) ≈ new_f
true
```

`ScalarCoefficientChange` can also be used to modify the objective function by passing an instance of `ObjectiveFunction`.

### Modify quadratic coefficients in a scalar function

Use `modify` and `ScalarQuadraticCoefficientChange` to modify the quadratic coefficient of a `ScalarQuadraticFunction`.

```
julia> model = MOI.Utilities.Model{Float64}();
julia> x = MOI.add_variables(model, 2);

julia> c = MOI.add_constraint(
           model,
           1.0 * x[1] * x[1] + 2.0 * x[1] * x[2],
           MOI.EqualTo(1.0),
       )
MathOptInterface.ConstraintIndex{MathOptInterface.ScalarQuadraticFunction{Float64},
→ MathOptInterface.EqualTo{Float64}}(1)

julia> MOI.modify(
           model,
           c,
           MOI.ScalarQuadraticCoefficientChange(x[1], x[1], 3.0),
       );

julia> MOI.modify(
           model,
           c,
           MOI.ScalarQuadraticCoefficientChange(x[1], x[2], 4.0),
       );

julia> new_f = 1.5 * x[1] * x[1] + 4.0 * x[1] * x[2];

julia> MOI.get(model, MOI.ConstraintFunction(), c) ≈ new_f
true
```

`ScalarQuadraticCoefficientChange` can also be used to modify the objective function by passing an instance of `ObjectiveFunction`.

### Modify affine coefficients in a vector function

Use `modify` and `MultirowChange` to modify a vector of affine coefficients in a `VectorAffineFunction` or a `VectorQuadraticFunction`.

```
julia> c = MOI.add_constraint(
           model,
           MOI.VectorAffineFunction([
               MOI.VectorAffineTerm(1, MOI.ScalarAffineTerm(1.0, x)),
               MOI.VectorAffineTerm(2, MOI.ScalarAffineTerm(2.0, x)),
           ],
           [0.0, 0.0],
       ),
       MOI.Nonnegatives(2),
   )
MathOptInterface.ConstraintIndex{MathOptInterface.VectorAffineFunction{Float64},
→ MathOptInterface.Nonnegatives}(1)

julia> MOI.modify(model, c, MOI.MultirowChange(x, [(1, 3.0), (2, 4.0)]));

julia> new_f = MOI.VectorAffineFunction(
           [
```

```
MOI.VectorAffineTerm(1, MOI.ScalarAffineTerm(3.0, x)),
MOI.VectorAffineTerm(2, MOI.ScalarAffineTerm(4.0, x)),
],
[0.0, 0.0],
);
julia> MOI.get(model, MOI.ConstraintFunction(), c) ≈ new_f
true
```

## Chapter 34

### Background

#### 34.1 Duality

Conic duality is the starting point for MOI's duality conventions. When all functions are affine (or coordinate projections), and all constraint sets are closed convex cones, the model may be called a conic optimization problem.

For a minimization problem in geometric conic form, the primal is:

$$\min_{x \in \mathbb{R}^n} \quad a_0^T x + b_0 \quad (34.1)$$

$$\text{s.t.} \quad A_i x + b_i \in \mathcal{C}_i \quad i = 1 \dots m \quad (34.2)$$

and the dual is a maximization problem in standard conic form:

$$\max_{y_1, \dots, y_m} \quad - \sum_{i=1}^m b_i^T y_i + b_0 \quad (34.3)$$

$$\text{s.t.} \quad a_0 - \sum_{i=1}^m A_i^T y_i = 0 \quad (34.4)$$

$$y_i \in \mathcal{C}_i^* \quad i = 1 \dots m \quad (34.5)$$

where each  $\mathcal{C}_i$  is a closed convex cone and  $\mathcal{C}_i^*$  is its dual cone.

For a maximization problem in geometric conic form, the primal is:

$$\max_{x \in \mathbb{R}^n} \quad a_0^T x + b_0 \quad (34.6)$$

$$\text{s.t.} \quad A_i x + b_i \in \mathcal{C}_i \quad i = 1 \dots m \quad (34.7)$$

and the dual is a minimization problem in standard conic form:

$$\min_{y_1, \dots, y_m} \sum_{i=1}^m b_i^T y_i + b_0 \quad (34.8)$$

$$\text{s.t.} \quad a_0 + \sum_{i=1}^m A_i^T y_i = 0 \quad (34.9)$$

$$y_i \in \mathcal{C}_i^* \quad i = 1 \dots m \quad (34.10)$$

A linear inequality constraint  $a^T x + b \geq c$  is equivalent to  $a^T x + b - c \in \mathbb{R}_+$ , and  $a^T x + b \leq c$  is equivalent to  $a^T x + b - c \in \mathbb{R}_-$ . Variable-wise constraints are affine constraints with the appropriate identity mapping in place of  $A_i$ .

For the special case of minimization LPs, the MOI primal form can be stated as:

$$\min_{x \in \mathbb{R}^n} a_0^T x + b_0 \quad (34.11)$$

$$\text{s.t.} \quad A_1 x \geq b_1 \quad (34.12)$$

$$A_2 x \leq b_2 \quad (34.13)$$

$$A_3 x = b_3 \quad (34.14)$$

By applying the stated transformations to conic form, taking the dual, and transforming back into linear inequality form, one obtains the following dual:

$$\max_{y_1, y_2, y_3} b_1^T y_1 + b_2^T y_2 + b_3^T y_3 + b_0 \quad (34.15)$$

$$\text{s.t.} \quad A_1^T y_1 + A_2^T y_2 + A_3^T y_3 = a_0 \quad (34.16)$$

$$y_1 \geq 0 \quad (34.17)$$

$$y_2 \leq 0 \quad (34.18)$$

For maximization LPs, the MOI primal form can be stated as:

$$\max_{x \in \mathbb{R}^n} a_0^T x + b_0 \quad (34.19)$$

$$\text{s.t.} \quad A_1 x \geq b_1 \quad (34.20)$$

$$A_2 x \leq b_2 \quad (34.21)$$

$$A_3 x = b_3 \quad (34.22)$$

and similarly, the dual is:

$$\min_{y_1, y_2, y_3} -b_1^T y_1 - b_2^T y_2 - b_3^T y_3 + b_0 \quad (34.23)$$

$$\text{s.t.} \quad A_1^T y_1 + A_2^T y_2 + A_3^T y_3 = -a_0 \quad (34.24)$$

$$y_1 \geq 0 \quad (34.25)$$

$$y_2 \leq 0 \quad (34.26)$$

**Warning**

For the LP case, the signs of the feasible dual variables depend only on the sense of the corresponding primal inequality and not on the objective sense.

**Duality and scalar product**

The scalar product is different from the canonical one for the sets [PositiveSemidefiniteConeTriangle](#), [LogDetConeTriangle](#), [RootDetConeTriangle](#).

If the set  $C_i$  of the section [Duality](#) is one of these three cones, then the rows of the matrix  $A_i$  corresponding to off-diagonal entries are twice the value of the coefficients field in the [VectorAffineFunction](#) for the corresponding rows. See [PositiveSemidefiniteConeTriangle](#) for details.

**Dual for problems with quadratic functions****Quadratic Programs (QPs)**

For quadratic programs with only affine conic constraints,

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & \frac{1}{2} x^T Q_0 x + a_0^T x + b_0 \\ \text{s.t.} \quad & A_i x + b_i \in C_i \quad i = 1 \dots m. \end{aligned}$$

with cones  $C_i \subseteq \mathbb{R}^{m_i}$  for  $i = 1, \dots, m$ , consider the Lagrangian function

$$L(x, y) = \frac{1}{2} x^T Q_0 x + a_0^T x + b_0 - \sum_{i=1}^m y_i^T (A_i x + b_i).$$

Let  $z(y)$  denote  $\sum_{i=1}^m A_i^T y_i - a_0$ , the Lagrangian can be rewritten as

$$L(x, y) = \frac{1}{2} x^T Q_0 x - z(y)^T x + b_0 - \sum_{i=1}^m y_i^T b_i.$$

The condition  $\nabla_x L(x, y) = 0$  gives

$$0 = \nabla_x L(x, y) = Q_0 x + a_0 - \sum_{i=1}^m y_i^T b_i$$

which gives  $Q_0 x = z(y)$ . This allows to obtain that

$$\min_{x \in \mathbb{R}^n} L(x, y) = -\frac{1}{2} x^T Q_0 x + b_0 - \sum_{i=1}^m y_i^T b_i$$

so the dual problem is

$$\max_{y_i \in \mathcal{C}_i^*} \min_{x \in \mathbb{R}^n} -\frac{1}{2}x^T Q_0 x + b_0 - \sum_{i=1}^m y_i^T b_i.$$

If  $Q_0$  is invertible, we have  $x = Q_0^{-1}z(y)$  hence

$$\min_{x \in \mathbb{R}^n} L(x, y) = -\frac{1}{2}z(y)^T Q_0^{-1}z(y) + b_0 - \sum_{i=1}^m y_i^T b_i$$

so the dual problem is

$$\max_{y_i \in \mathcal{C}_i^*} -\frac{1}{2}z(y)^T Q_0^{-1}z(y) + b_0 - \sum_{i=1}^m y_i^T b_i.$$

### Quadratically Constrained Quadratic Programs (QCQPs)

Given a problem with both quadratic function and quadratic objectives:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & \frac{1}{2}x^T Q_0 x + a_0^T x + b_0 \\ \text{s.t.} \quad & \frac{1}{2}x^T Q_i x + a_i^T x + b_i \in \mathcal{C}_i \quad i = 1 \dots m. \end{aligned}$$

with cones  $\mathcal{C}_i \subseteq \mathbb{R}$  for  $i = 1 \dots m$ , consider the Lagrangian function

$$L(x, y) = \frac{1}{2}x^T Q_0 x + a_0^T x + b_0 - \sum_{i=1}^m y_i \left( \frac{1}{2}x^T Q_i x + a_i^T x + b_i \right)$$

A pair of primal-dual variables  $(x^*, y^*)$  is optimal if

- $x^*$  is a minimizer of

$$\min_{x \in \mathbb{R}^n} L(x, y^*).$$

That is,

$$0 = \nabla_x L(x, y^*) = Q_0 x + a_0 - \sum_{i=1}^m y_i^* (Q_i x + a_i).$$

- and  $y^*$  is a maximizer of

$$\max_{y_i \in \mathcal{C}_i^*} L(x^*, y).$$

That is, for all  $i = 1, \dots, m$ ,  $\frac{1}{2}x^T Q_i x + a_i^T x + b_i$  is either zero or in the [normal cone](#) of  $\mathcal{C}_i^*$  at  $y^*$ . For instance, if  $\mathcal{C}_i$  is  $\{z \in \mathbb{R} : z \leq 0\}$ , this means that if  $\frac{1}{2}x^T Q_i x + a_i^T x + b_i$  is nonzero at  $x^*$  then  $y_i^* = 0$ . This is the classical complementary slackness condition.

If  $\mathcal{C}_i$  is a vector set, the discussion remains valid with  $y_i(\frac{1}{2}x^T Q_i x + a_i^T x + b_i)$  replaced with the scalar product between  $y_i$  and the vector of scalar-valued quadratic functions.

### Dual for square semidefinite matrices

The set [PositiveSemidefiniteConeTriangle](#) is a self-dual. That is, querying [ConstraintDual](#) of a [PositiveSemidefiniteConeTriangle](#) constraint returns a vector that is itself a member of [PositiveSemidefiniteConeTriangle](#).

However, the dual of [PositiveSemidefiniteConeSquare](#) is not so straight forward. This section explains the duality convention we use, and how it is derived.

#### Info

If you have a [PositiveSemidefiniteConeSquare](#) constraint, the result matrix  $A$  from [ConstraintDual](#) is not positive semidefinite. However,  $A + A^\top$  is positive semidefinite.

Let  $\mathcal{S}_+$  be the cone of symmetric semidefinite matrices in the  $\frac{n(n+1)}{2}$  dimensional space of symmetric  $\mathbb{R}^{n \times n}$  matrices. That is,  $\mathcal{S}_+$  is the set [PositiveSemidefiniteConeTriangle](#). It is well known that  $\mathcal{S}_+$  is a self-dual proper cone.

Let  $\mathcal{P}_+$  be the cone of symmetric semidefinite matrices in the  $n^2$  dimensional space of  $\mathbb{R}^{n \times n}$  matrices. That is  $\mathcal{P}_+$  is the set [PositiveSemidefiniteConeSquare](#).

In addition, let  $\mathcal{D}_+$  be the cone of matrices  $A$  such that  $A + A^\top \in \mathcal{P}_+$ .

$\mathcal{P}_+$  is not proper because it is not solid (it is not  $n^2$  dimensional), so it is not necessarily true that  $\mathcal{P}_+^{**} = \mathcal{P}_+$ .

However, this is the case, because we will show that  $\mathcal{P}_+^* = \mathcal{D}_+$  and  $\mathcal{D}_+^* = \mathcal{P}_+$ .

First, let us see why  $\mathcal{P}_+^* = \mathcal{D}_+$ .

If  $B$  is symmetric, then

$$\langle A, B \rangle = \langle A^\top, B^\top \rangle = \langle A^\top, B \rangle$$

so

$$2\langle A, B \rangle = \langle A, B \rangle + \langle A^\top, B \rangle = \langle A + A^\top, B \rangle.$$

Therefore,  $\langle A, B \rangle \geq 0$  for all  $B \in \mathcal{P}_+$  if and only if  $\langle A + A^\top, B \rangle \geq 0$  for all  $B \in \mathcal{P}_+$ . Since  $A + A^\top$  is symmetric, and we know that  $\mathcal{S}_+$  is self-dual, we have shown that  $\mathcal{P}_+^*$  is the set of matrices  $A$  such that  $A + A^\top \in \mathcal{P}_+$ .

Second, let us see why  $\mathcal{D}_+^* = \mathcal{P}_+$ .

Since  $A \in \mathcal{D}_+$  implies that  $A^\top \in \mathcal{D}_+$ ,  $B \in \mathcal{D}_+^*$  means that  $\langle A + A^\top, B \rangle \geq 0$  for all  $A \in \mathcal{D}_+$ , and hence  $B \in \mathcal{P}_+$ .

To see why it should be symmetric, simply notice that if  $B_{i,j} < B_{j,i}$ , then  $\langle A, B \rangle$  can be made arbitrarily small by setting  $A_{i,j} = A_{i,j} + s$  and  $A_{j,i} = A_{j,i} - s$ , with  $s$  arbitrarily large, and  $A$  stays in  $\mathcal{D}_+$  because  $A + A^\top$  does not change.

Typically, the primal/dual pair for semidefinite programs is presented as:

$$\min \langle C, X \rangle \quad (34.27)$$

$$\text{s.t. } \langle A_k, X \rangle = b_k \forall k \quad (34.28)$$

$$X \in \mathcal{S}_+ \quad (34.29)$$

with the dual

$$\max \sum_k b_k y_k \quad (34.30)$$

$$\text{s.t. } C - \sum A_k y_k \in \mathcal{S}_+ \quad (34.31)$$

If we allow  $A_k$  to be non-symmetric, we should instead use:

$$\min \langle C, X \rangle \quad (34.32)$$

$$\text{s.t. } \langle A_k, X \rangle = b_k \forall k \quad (34.33)$$

$$X \in \mathcal{D}_+ \quad (34.34)$$

with the dual

$$\max \sum_k b_k y_k \quad (34.35)$$

$$\text{s.t. } C - \sum A_k y_k \in \mathcal{P}_+ \quad (34.36)$$

This is implemented as:

$$\min \langle C, Z \rangle + \langle C - C^\top, S \rangle \quad (34.37)$$

$$\text{s.t. } \langle A_k, Z \rangle + \langle A_k - A_k^\top, S \rangle = b_k \forall k \quad (34.38)$$

$$Z \in \mathcal{S}_+ \quad (34.39)$$

with the dual

$$\max \sum_k b_k y_k \quad (34.40)$$

$$\text{s.t. } C + C^\top - \sum (A_k + A_k^\top) y_k \in \mathcal{S}_+ \quad (34.41)$$

$$C - C^\top - \sum (A_k - A_k^\top) y_k = 0 \quad (34.42)$$

and we recover  $Z = X + X^\top$ .

## 34.2 Infeasibility certificates

When given a conic problem that is infeasible or unbounded, some solvers can produce a certificate of infeasibility. This page explains what a certificate of infeasibility is, and the related conventions that MathOptInterface adopts.

### Conic duality

MathOptInterface uses conic duality to define infeasibility certificates. A full explanation is given in the section [Duality](#), but here is a brief overview.

#### Minimization problems

For a minimization problem in geometric conic form, the primal is:

$$\min_{x \in \mathbb{R}^n} \quad a_0^\top x + b_0 \quad (34.43)$$

$$\text{s.t.} \quad A_i x + b_i \in \mathcal{C}_i \quad i = 1 \dots m, \quad (34.44)$$

and the dual is a maximization problem in standard conic form:

$$\max_{y_1, \dots, y_m} \quad - \sum_{i=1}^m b_i^\top y_i + b_0 \quad (34.45)$$

$$\text{s.t.} \quad a_0 - \sum_{i=1}^m A_i^\top y_i = 0 \quad (34.46)$$

$$y_i \in \mathcal{C}_i^* \quad i = 1 \dots m, \quad (34.47)$$

where each  $\mathcal{C}_i$  is a closed convex cone and  $\mathcal{C}_i^*$  is its dual cone.

#### Maximization problems

For a maximization problem in geometric conic form, the primal is:

$$\max_{x \in \mathbb{R}^n} \quad a_0^\top x + b_0 \quad (34.48)$$

$$\text{s.t.} \quad A_i x + b_i \in \mathcal{C}_i \quad i = 1 \dots m, \quad (34.49)$$

and the dual is a minimization problem in standard conic form:

$$\min_{y_1, \dots, y_m} \quad \sum_{i=1}^m b_i^\top y_i + b_0 \quad (34.50)$$

$$\text{s.t.} \quad a_0 + \sum_{i=1}^m A_i^\top y_i = 0 \quad (34.51)$$

$$y_i \in \mathcal{C}_i^* \quad i = 1 \dots m. \quad (34.52)$$

### Unbounded problems

A problem is unbounded if and only if:

1. there exists a feasible primal solution
2. the dual is infeasible.

A feasible primal solution—if one exists—can be obtained by setting `ObjectiveSense` to `FEASIBILITY_SENSE` before optimizing. Therefore, most solvers stop after they prove the dual is infeasible via a certificate of dual infeasibility, but *before* they have found a feasible primal solution. This is also the reason that `MathOptInterface` defines the `DUAL_INFEASIBLE` status instead of `UNBOUNDED`.

A certificate of dual infeasibility is an improving ray of the primal problem. That is, there exists some vector  $d$  such that for all  $\eta > 0$ :

$$A_i(x + \eta d) + b_i \in \mathcal{C}_i, \quad i = 1 \dots m,$$

and (for minimization problems):

$$a_0^\top(x + \eta d) + b_0 < a_0^\top x + b_0,$$

for any feasible point  $x$ . The latter simplifies to  $a_0^\top d < 0$ . For maximization problems, the inequality is reversed, so that  $a_0^\top d > 0$ .

If the solver has found a certificate of dual infeasibility:

- `TerminationStatus` must be `DUAL_INFEASIBLE`
- `PrimalStatus` must be `INFEASIBILITY_CERTIFICATE`
- `VariablePrimal` must be the corresponding value of  $d$
- `ConstraintPrimal` must be the corresponding value of  $A_i d$
- `ObjectiveValue` must be the value  $a_0^\top d$ . Note that this is the value of the objective function at  $d$ , ignoring the constant  $b_0$ .

#### Note

The choice of whether to scale the ray  $d$  to have magnitude 1 is left to the solver.

### Infeasible problems

A certificate of primal infeasibility is an improving ray of the dual problem. However, because infeasibility is independent of the objective function, we first homogenize the primal problem by removing its objective.

For a minimization problem, a dual improving ray is some vector  $d$  such that for all  $\eta > 0$ :

$$-\sum_{i=1}^m A_i^\top (y_i + \eta d_i) = 0 \quad (34.53)$$

$$(y_i + \eta d_i) \in \mathcal{C}_i^* \quad i = 1 \dots m, \quad (34.54)$$

and:

$$-\sum_{i=1}^m b_i^\top (y_i + \eta d_i) > -\sum_{i=1}^m b_i^\top y_i,$$

for any feasible dual solution  $y$ . The latter simplifies to  $-\sum_{i=1}^m b_i^\top d_i > 0$ . For a maximization problem, the inequality is  $\sum_{i=1}^m b_i^\top d_i < 0$ . (Note that these are the same inequality, modulo a - sign.)

If the solver has found a certificate of primal infeasibility:

- `TerminationStatus` must be `INFEASIBLE`
- `DualStatus` must be `INFEASIBILITY_CERTIFICATE`
- `ConstraintDual` must be the corresponding value of  $d$
- `DualObjectiveValue` must be the value  $-\sum_{i=1}^m b_i^\top d_i$  for minimization problems and  $\sum_{i=1}^m b_i^\top d_i$  for maximization problems.

#### Note

The choice of whether to scale the ray  $d$  to have magnitude 1 is left to the solver.

#### Infeasibility certificates of variable bounds

Many linear solvers (for example, Gurobi) do not provide explicit access to the primal infeasibility certificate of a variable bound. However, given a set of linear constraints:

$$l_A \leq Ax \leq u_A \quad (34.55)$$

$$l_x \leq x \leq u_x, \quad (34.56)$$

the primal certificate of the variable bounds can be computed using the primal certificate associated with the affine constraints,  $d$ . (Note that  $d$  will have one element for each row of the  $A$  matrix, and that some or all of the elements in the vectors  $l_A$  and  $u_A$  may be  $\pm\infty$ . If both  $l_A$  and  $u_A$  are finite for some row, the corresponding element in  $d$  must be 0.)

Given  $d$ , compute  $\bar{d} = d^\top A$ . If the bound is finite, a certificate for the lower variable bound of  $x_i$  is  $\max\{\bar{d}_i, 0\}$ , and a certificate for the upper variable bound is  $\min\{\bar{d}_i, 0\}$ .

### 34.3 Naming conventions

MOI follows several conventions for naming functions and structures. These should also be followed by packages extending MOI.

## Sets

Sets encode the structure of constraints. Their names should follow the following conventions:

- Abstract types in the set hierarchy should begin with `Abstract` and end in `Set`, for example, `AbstractScalarSet`, `AbstractVectorSet`.
- Vector-valued conic sets should end with `Cone`, for example, `NormInfinityCone`, `SecondOrderCone`.
- Vector-valued Cartesian products should be plural and not end in `Cone`, for example, `Nonnegatives`, not `NonnegativeCone`.
- Matrix-valued conic sets should provide two representations: `ConeSquare` and `ConeTriangle`, for example, `RootDetConeTriangle` and `RootDetConeSquare`. See [Matrix cones](#) for more details.
- Scalar sets should be singular, not plural, for example, `Integer`, not `Integers`.
- As much as possible, the names should follow established conventions in the domain where this set is used: for instance, convex sets should have names close to those of [CVX](#), and constraint-programming sets should follow [MiniZinc](#)'s constraints.

# Chapter 35

## API Reference

### 35.1 Standard form

#### Functions

MathOptInterface.AbstractFunction – Type.

```
AbstractFunction
```

Abstract supertype for function objects.

#### Required methods

All functions must implement:

- `Base.copy`
- `Base.isapprox`
- `constant`

Abstract subtypes of `AbstractFunction` may require additional methods to be implemented.

`source`

MathOptInterface.output\_dimension – Function.

```
output_dimension(f::AbstractFunction)
```

Return 1 if `f` is an `AbstractScalarFunction`, or the number of output components if `f` is an `AbstractVectorFunction`.

`source`

MathOptInterface.constant – Function.

```
constant(f::AbstractFunction[, ::Type{T}]) where {T}
```

Returns the constant term of a scalar-valued function, or the constant vector of a vector-valued function.

If  $f$  is untyped and  $T$  is provided, returns  $\text{zero}(T)$ .

[source](#)

```
constant(set::Union{EqualTo, GreaterThan, LessThan, Parameter})
```

Returns the constant term of the set  $set$ .

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.constant(MOI.GreaterThan(1.0))
1.0

julia> MOI.constant(MOI.LessThan(2.5))
2.5

julia> MOI.constant(MOI.EqualTo(3))
3

julia> MOI.constant(MOI.Parameter(4.5))
4.5
```

[source](#)

## Scalar functions

`MathOptInterface.AbstractScalarFunction` – Type.

```
abstract type AbstractScalarFunction <: AbstractFunction
```

Abstract supertype for scalar-valued `AbstractFunctions`.

[source](#)

`MathOptInterface.VariableIndex` – Type.

```
VariableIndex
```

A type-safe wrapper for `Int64` for use in referencing variables in a model. To allow for deletion, indices need not be consecutive.

[source](#)

`MathOptInterface.ScalarAffineTerm` – Type.

```
ScalarAffineTerm{T}(coefficient::T, variable::VariableIndex) where {T}
```

Represents the scalar-valued term coefficient \* variable.

### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> MOI.ScalarAffineTerm(2.0, x)
MathOptInterface.ScalarAffineTerm{Float64}(2.0, MOI.VariableIndex(1))
```

[source](#)

MathOptInterface.ScalarAffineFunction – Type.

```
ScalarAffineFunction{T}(
    terms::Vector{ScalarAffineTerm{T}},
    constant::T,
) where {T}
```

Represents the scalar-valued affine function  $a^\top x + b$ , where:

- $a^\top x$  is represented by the vector of `ScalarAffineTerms`
- $b$  is a scalar `constant::T`

### Duplicates

Duplicate variable indices in `terms` are accepted, and the corresponding coefficients are summed together.

### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> terms = [MOI.ScalarAffineTerm(2.0, x), MOI.ScalarAffineTerm(3.0, x)]
2-element Vector{MathOptInterface.ScalarAffineTerm{Float64}}:
 MathOptInterface.ScalarAffineTerm{Float64}(2.0, MOI.VariableIndex(1))
 MathOptInterface.ScalarAffineTerm{Float64}(3.0, MOI.VariableIndex(1))

julia> f = MOI.ScalarAffineFunction(terms, 4.0)
4.0 + 2.0 MOI.VariableIndex(1) + 3.0 MOI.VariableIndex(1)
```

[source](#)

MathOptInterface.ScalarQuadraticTerm – Type.

```
ScalarQuadraticTerm{T}(
    coefficient::T,
    variable_1::VariableIndex,
    variable_2::VariableIndex,
) where {T}
```

Represents the scalar-valued term  $cx_i x_j$  where  $c$  is coefficient,  $x_i$  is variable\_1 and  $x_j$  is variable\_2.

### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> MOI.ScalarQuadraticTerm(2.0, x, x)
MathOptInterface.ScalarQuadraticTerm{Float64}(2.0, MOI.VariableIndex(1), MOI.VariableIndex(1))
```

[source](#)

MathOptInterface.ScalarQuadraticFunction – Type.

```
ScalarQuadraticFunction{T}(
    quadratic_terms::Vector{ScalarQuadraticTerm{T}},
    affine_terms::Vector{ScalarAffineTerm{T}},
    constant::T,
) where {T}
```

The scalar-valued quadratic function  $\frac{1}{2}x^\top Qx + a^\top x + b$ , where:

- $Q$  is the symmetric matrix given by the vector of `ScalarQuadraticTerms`
- $a^\top x$  is a sparse vector given by the vector of `ScalarAffineTerms`
- $b$  is the scalar constant`::T`.

### Duplicates

Duplicate indices in `quadratic_terms` or `affine_terms` are accepted, and the corresponding coefficients are summed together.

In `quadratic_terms`, "mirrored" indices,  $(q, r)$  and  $(r, q)$  where  $r$  and  $q$  are `VariableIndexes`, are considered duplicates; only one needs to be specified.

### The 0.5 factor

Coupled with the interpretation of mirrored indices, the 0.5 factor in front of the  $Q$  matrix is a common source of bugs.

As a rule, to represent  $a * x^2 + b * x * y$ :

- The coefficient  $a$  in front of squared variables (diagonal elements in  $Q$ ) must be doubled when creating a `ScalarQuadraticTerm`

- The coefficient  $b$  in front of off-diagonal elements in  $Q$  should be left as  $b$ , because the mirrored index  $b * y * x$  will be implicitly added.

### Example

To represent the function  $f(x, y) = 2 * x^2 + 3 * x * y + 4 * x + 5$ , do:

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1);

julia> y = MOI.VariableIndex(2);

julia> constant = 5.0;

julia> affine_terms = [MOI.ScalarAffineTerm(4.0, x)];

julia> quadratic_terms = [
    MOI.ScalarQuadraticTerm(4.0, x, x), # Note the changed coefficient
    MOI.ScalarQuadraticTerm(3.0, x, y),
]
2-element Vector{MathOptInterface.ScalarQuadraticTerm{Float64}}:
MOI.ScalarQuadraticTerm{Float64}(4.0, MOI.VariableIndex(1), MOI.VariableIndex(1))
MOI.ScalarQuadraticTerm{Float64}(3.0, MOI.VariableIndex(1), MOI.VariableIndex(2))

julia> f = MOI.ScalarQuadraticFunction(quadratic_terms, affine_terms, constant)
5.0 + 4.0 MOI.VariableIndex(1) + 2.0 MOI.VariableIndex(1)^2 + 3.0
→ MOI.VariableIndex(1)*MOI.VariableIndex(2)
```

[source](#)

`MathOptInterface.ScalarNonlinearFunction` – Type.

```
ScalarNonlinearFunction(head::Symbol, args::Vector{Any})
```

The scalar-valued nonlinear function `head(args...)`, represented as a symbolic expression tree, with the call operator `head` and ordered arguments in `args`.

#### head

The `head::Symbol` must be an operator supported by the model.

The default list of supported univariate operators is given by:

- `Nonlinear.DEFAULT_UNIVARIATE_OPERATORS`

and the default list of supported multivariate operators is given by:

- `Nonlinear.DEFAULT_MULTIVARIATE_OPERATORS`

Additional operators can be registered by setting a `UserDefinedFunction` attribute.

See the full list of operators supported by a `ModelLike` by querying `ListOfSupportedNonlinearOperators`.

#### args

The vector args contains the arguments to the nonlinear function. If the operator is univariate, it must contain one element. Otherwise, it may contain multiple elements.

Each element must be one of the following:

- A constant value of type `T<:Real`
- A `VariableIndex`
- A `ScalarAffineFunction`
- A `ScalarQuadraticFunction`
- A `ScalarNonlinearFunction`

### Unsupported operators

If the optimizer does not support head, an `UnsupportedNonlinearOperator` error will be thrown.

There is no guarantee about when this error will be thrown; it may be thrown when the function is first added to the model, or it may be thrown when `optimize!` is called.

### Example

To represent the function  $f(x) = \sin(x)^2$ , do:

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> MOI.ScalarNonlinearFunction(
           :^,
           Any[MOI.ScalarNonlinearFunction(:sin, Any[x]), 2],
       )
^(\sin(MOI.VariableIndex(1)), (2))
```

`source`

## Vector functions

`MathOptInterface.AbstractVectorFunction` – Type.

```
abstract type AbstractVectorFunction <: AbstractFunction
```

Abstract supertype for vector-valued `AbstractFunctions`.

### Required methods

All subtypes of `AbstractVectorFunction` must implement:

- `output_dimension`

`source`

`MathOptInterface.VectorOfVariables` – Type.

```
VectorOfVariables(variables::Vector{VariableIndex}) <: AbstractVectorFunction
```

The vector-valued function  $f(x) = \text{variables}$ , where `variables` is a subset of `VariableIndexes` in the model.

The list of `variables` may contain duplicates.

### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex.(1:2)
2-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(1)
 MOI.VariableIndex(2)

julia> f = MOI.VectorOfVariables([x[1], x[2], x[1]])
 [MOI.VariableIndex(1)]
 [MOI.VariableIndex(2)]
 [MOI.VariableIndex(1)]
 [MOI.VariableIndex(1)]

julia> MOI.output_dimension(f)
3
```

[source](#)

`MathOptInterface.VectorAffineTerm` – Type.

```
VectorAffineTerm{T}(
    output_index::Int64,
    scalar_term::ScalarAffineTerm{T},
) where {T}
```

A `VectorAffineTerm` is a `scalar_term` that appears in the `output_index` row of the vector-valued `VectorAffineFunction` or `VectorQuadraticFunction`.

### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1);

julia> MOI.VectorAffineTerm(Int64(2), MOI.ScalarAffineTerm(3.0, x))
MathOptInterface.VectorAffineTerm{Float64}(2, MathOptInterface.ScalarAffineTerm{Float64}(3.0,
→ MOI.VariableIndex(1)))
```

[source](#)

`MathOptInterface.VectorAffineFunction` – Type.

```
VectorAffineFunction{T}(
    terms::Vector{VectorAffineTerm{T}},
    constants::Vector{T},
) where {T}
```

The vector-valued affine function  $Ax + b$ , where:

- $Ax$  is the sparse matrix given by the vector of `VectorAffineTerms`
- $b$  is the vector constants

### Duplicates

Duplicate indices in the  $A$  are accepted, and the corresponding coefficients are summed together.

### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1);

julia> terms = [
        MOI.VectorAffineTerm(Int64(1), MOI.ScalarAffineTerm(2.0, x)),
        MOI.VectorAffineTerm(Int64(2), MOI.ScalarAffineTerm(3.0, x)),
    ];

julia> f = MOI.VectorAffineFunction(terms, [4.0, 5.0])
[4.0 + 2.0 MOI.VariableIndex(1)]
[5.0 + 3.0 MOI.VariableIndex(1)]
└───────────────────┘

julia> MOI.output_dimension(f)
2
```

[source](#)

`MathOptInterface.VectorQuadraticTerm` – Type.

```
VectorQuadraticTerm{T}(
    output_index::Int64,
    scalar_term::ScalarQuadraticTerm{T},
) where {T}
```

A `VectorQuadraticTerm` is a `ScalarQuadraticTerm` `scalar_term` that appears in the `output_index` row of the vector-valued `VectorQuadraticFunction`.

### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1);
```

```
julia> MOI.VectorQuadraticTerm(Int64(2), MOI.ScalarQuadraticTerm(3.0, x, x))
MathOptInterface.VectorQuadraticTerm{Float64}(2,
    ↳ MathOptInterface.ScalarQuadraticTerm{Float64}(3.0, MOI.VariableIndex(1),
    ↳ MOI.VariableIndex(1)))
```

[source](#)

MathOptInterface.VectorQuadraticFunction – Type.

```
VectorQuadraticFunction{T}(
    quadratic_terms::Vector{VectorQuadraticTerm{T}},
    affine_terms::Vector{VectorAffineTerm{T}},
    constants::Vector{T},
) where {T}
```

The vector-valued quadratic function with  $i$ th component ("output index") defined as  $\frac{1}{2}x^\top Q_i x + a_i^\top x + b_i$ , where:

- $\frac{1}{2}x^\top Q_i x$  is the symmetric matrix given by the `VectorQuadraticTerm` elements in `quadratic_terms` with `output_index == i`
- $a_i^\top x$  is the sparse vector given by the `VectorAffineTerm` elements in `affine_terms` with `output_index == i`
- $b_i$  is a scalar given by `constants[i]`

### Duplicates

Duplicate indices in `quadratic_terms` and `affine_terms` with the same `output_index` are handled in the same manner as duplicates in `ScalarQuadraticFunction`.

### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1);

julia> y = MOI.VariableIndex(2);

julia> constants = [4.0, 5.0];

julia> affine_terms = [
        MOI.VectorAffineTerm(Int64(1), MOI.ScalarAffineTerm(2.0, x)),
        MOI.VectorAffineTerm(Int64(2), MOI.ScalarAffineTerm(3.0, x)),
    ];

julia> quad_terms = [
        MOI.VectorQuadraticTerm(Int64(1), MOI.ScalarQuadraticTerm(2.0, x, x)),
        MOI.VectorQuadraticTerm(Int64(2), MOI.ScalarQuadraticTerm(3.0, x, y)),
    ];

julia> f = MOI.VectorQuadraticFunction(quad_terms, affine_terms, constants)
```

↑

```
|4.0 + 2.0 MOI.VariableIndex(1) + 1.0 MOI.VariableIndex(1)^2
|5.0 + 3.0 MOI.VariableIndex(1) + 3.0 MOI.VariableIndex(1)*MOI.VariableIndex(2)
L
julia> MOI.output_dimension(f)
2
```

[source](#)

MathOptInterface.VectorNonlinearFunction – Type.

```
VectorNonlinearFunction(args::Vector{ScalarNonlinearFunction})
```

The vector-valued nonlinear function composed of a vector of [ScalarNonlinearFunction](#).

#### args

The vector args contains the scalar elements of the nonlinear function. Each element must be a [ScalarNonlinearFunction](#), but if you pass a Vector{Any}, the elements can be automatically converted from one of the following:

- A constant value of type T<:Real
- A [VariableIndex](#)
- A [ScalarAffineFunction](#)
- A [ScalarQuadraticFunction](#)
- A [ScalarNonlinearFunction](#)

#### Example

To represent the function  $f(x) = [\sin(x)^2, x]$ , do:

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> g = MOI.ScalarNonlinearFunction(
           :^,
           Any[MOI.ScalarNonlinearFunction(:sin, Any[x]), 2.0],
           )
^(\sin(MOI.VariableIndex(1)), 2.0)

julia> MOI.VectorNonlinearFunction([g, x])
[^(sin(MOI.VariableIndex(1)), 2.0)
 |+(MOI.VariableIndex(1))]
```

Note the automatic conversion from x to +(x).

[source](#)

## Sets

`MathOptInterface.AbstractSet` – Type.

### AbstractSet

Abstract supertype for set objects used to encode constraints.

#### Required methods

For sets of type `S` with `isbitstype(S) == false`, you must implement:

- `Base.copy(set::S)`
- `Base.:(==)(x::S, y::S)`

Subtypes of `AbstractSet` such as `AbstractScalarSet` and `AbstractVectorSet` may prescribe additional required methods.

#### Optional methods

You may optionally implement:

- `dual_set`
- `dual_set_type`

#### Note for developers

When creating a new set, the set struct must not contain any `VariableIndex` or `ConstraintIndex` objects.

`source`

`MathOptInterface.AbstractScalarSet` – Type.

### AbstractScalarSet

Abstract supertype for subsets of  $\mathbb{R}$ .

`source`

`MathOptInterface.AbstractVectorSet` – Type.

### AbstractVectorSet

Abstract supertype for subsets of  $\mathbb{R}^n$  for some  $n$ .

#### Required methods

All `AbstractVectorSets` of type `S` must implement:

- `dimension`, unless the dimension is stored in the `set.dimension` field
- `Utilities.set_dot`, unless the dot product between two vectors in the set is equivalent to `LinearAlgebra.dot`.

`source`

## Utilities

`MathOptInterface.dimension` – Function.

```
dimension(set::AbstractSet)
```

Return the `output_dimension` that an `AbstractFunction` should have to be used with the set `set`.

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.dimension(MOI.Reals(4))
4

julia> MOI.dimension(MOI.LessThan(3.0))
1

julia> MOI.dimension(MOI.PositiveSemidefiniteConeTriangle(2))
3
```

[source](#)

`MathOptInterface.dual_set` – Function.

```
dual_set(set::AbstractSet)
```

Return the dual set of `set`, that is the dual cone of the set. This follows the definition of duality discussed in [Duality](#).

See [Dual cone](#) for more information.

If the dual cone is not defined it returns an error.

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.dual_set(MOI.Reals(4))
MathOptInterface.Zeros(4)

julia> MOI.dual_set(MOI.SecondOrderCone(5))
MathOptInterface.SecondOrderCone(5)

julia> MOI.dual_set(MOI.ExponentialCone())
MathOptInterface.DualExponentialCone()
```

[source](#)

`MathOptInterface.dual_set_type` – Function.

```
dual_set_type(S::Type{<:AbstractSet})
```

Return the type of dual set of sets of type S, as returned by `dual_set`. If the dual cone is not defined it returns an error.

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.dual_set_type(MOI.Reals)
MathOptInterface.Zeros

julia> MOI.dual_set_type(MOI.SecondOrderCone)
MathOptInterface.SecondOrderCone

julia> MOI.dual_set_type(MOI.ExponentialCone)
MathOptInterface.DualExponentialCone
```

[source](#)

`MathOptInterface.constant` – Method.

```
constant(set::Union{EqualTo, GreaterThan, LessThan, Parameter})
```

Returns the constant term of the set set.

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.constant(MOI.GreaterThan(1.0))
1.0

julia> MOI.constant(MOI.LessThan(2.5))
2.5

julia> MOI.constant(MOI.EqualTo(3))
3

julia> MOI.constant(MOI.Parameter(4.5))
4.5
```

[source](#)

`MathOptInterface.supports_dimension_update` – Function.

```
supports_dimension_update(S::Type{<:MOI.AbstractVectorSet})
```

Return a Bool indicating whether the elimination of any dimension of n-dimensional sets of type S give an n-1-dimensional set S. By default, this function returns false so it should only be implemented for sets that supports dimension update.

For instance, `supports_dimension_update(MOI.Nonnegatives)` is true because the elimination of any dimension of the n-dimensional nonnegative orthant gives the n-1-dimensional nonnegative orthant. However `supports_dimension_update(MOI.ExponentialCone)` is false.

[source](#)

`MathOptInterface.update_dimension` – Function.

```
update_dimension(s::AbstractVectorSet, new_dim::Int)
```

Returns a set with the dimension modified to `new_dim`.

[source](#)

## Scalar sets

List of recognized scalar sets.

`MathOptInterface.GreaterThan` – Type.

```
GreaterThan{T<:Real}(lower::T)
```

The set  $[lower, \infty) \subseteq \mathbb{R}$ .

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.add_constraint(model, x, MOI.GreaterThan(0.0))
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
                                MathOptInterface.GreaterThan{Float64}}(1)
```

[source](#)

`MathOptInterface.LessThan` – Type.

```
LessThan{T<:Real}(upper::T)
```

The set  $(-\infty, upper] \subseteq \mathbb{R}$ .

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.add_constraint(model, x, MOI.LessThan(2.0))
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
→ MathOptInterface.LessThan{Float64}}(1)
```

[source](#)

MathOptInterface.EqualTo – Type.

```
EqualTo{T<:Number}(value::T)
```

The set containing the single point  $\{value\} \subseteq \mathbb{R}$ .

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.add_constraint(model, x, MOI.EqualTo(2.0))
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
→ MathOptInterface.EqualTo{Float64}}(1)
```

[source](#)

MathOptInterface.Interval – Type.

```
Interval{T<:Real}(lower::T, upper::T)
```

The interval  $[lower, upper] \subseteq \mathbb{R} \cup \{-\infty, +\infty\}$ .

If lower or upper is -Inf or Inf, respectively, the set is interpreted as a one-sided interval.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)
```

```
julia> MOI.add_constraint(model, x, MOI.Interval(1.0, 2.0))
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    MathOptInterface.Interval{Float64}}(1)
```

[source](#)

MathOptInterface.Integer – Type.

```
Integer()
```

The set of integers,  $\mathbb{Z}$ .

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.add_constraint(model, x, MOI.Integer())
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.Integer}(1)
```

[source](#)

MathOptInterface.ZeroOne – Type.

```
ZeroOne()
```

The set  $\{0, 1\}$ .

Variables belonging to the ZeroOne set are also known as "binary" variables.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.add_constraint(model, x, MOI.ZeroOne())
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(1)
```

[source](#)

MathOptInterface.Semicontinuous – Type.

```
Semicontinuous{T<:Real}(lower::T, upper::T)
```

The set  $\{0\} \cup [lower, upper]$ .

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.add_constraint(model, x, MOI.Semicontinuous(2.0, 3.0))
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
                                MathOptInterface.Semicontinuous{Float64}}(1)
```

[source](#)

MathOptInterface.Semiinteger - Type.

```
Semiinteger{T<:Real}(lower::T, upper::T)
```

The set  $\{0\} \cup \{lower, lower + 1, \dots, upper - 1, upper\}$ .

Note that if `lower` and `upper` are not equivalent to an integer, then the solver may throw an error, or it may round up `lower` and round down `upper` to the nearest integers.

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.add_constraint(model, x, MOI.Semiinteger(2.0, 3.0))
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
                                MathOptInterface.Semiinteger{Float64}}(1)
```

[source](#)

MathOptInterface.Parameter - Type.

```
Parameter{T<:Number}(value::T)
```

The set containing the single point  $\{value\} \subseteq \mathbb{R}$ .

The Parameter set is conceptually similar to the [EqualTo](#) set, except that a variable constrained to the Parameter set cannot have other constraints added to it, and the Parameter set can never be deleted. Thus, solvers are free to treat the variable as a constant, and they need not add it as a decision variable to the model.

Because of this behavior, you must add parameters using `add_constrained_variable`, and solvers should declare `supports_add_constrained_variable` and not `supports_constraint` for the Parameter set.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> p, ci = MOI.add_constrained_variable(model, MOI.Parameter(2.5))
(MOI.VariableIndex(1), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
→ MathOptInterface.Parameter{Float64}}(1))

julia> MOI.set(model, MOI.ConstraintSet(), ci, MOI.Parameter(3.0))

julia> MOI.get(model, MOI.ConstraintSet(), ci)
MathOptInterface.Parameter{Float64}(3.0)
```

[source](#)

## Vector sets

List of recognized vector sets.

`MathOptInterface.Reals` – Type.

```
Reals(dimension::Int)
```

The set  $\mathbb{R}^{dimension}$  (containing all points) of non-negative dimension `dimension`.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.Reals(3))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables, MathOptInterface.Reals}(1)
```

[source](#)

`MathOptInterface.Zeros` – Type.

```
Zeros(dimension::Int)
```

The set  $\{0\}^{dimension}$  (containing only the origin) of non-negative dimension `dimension`.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.Zeros(3))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables, MathOptInterface.Zeros}(1)
```

[source](#)

`MathOptInterface.Nonnegatives` - Type.

```
Nonnegatives(dimension::Int)
```

The nonnegative orthant  $\{x \in \mathbb{R}^{dimension} : x \geq 0\}$  of non-negative dimension `dimension`.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.Nonnegatives(3))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    → MathOptInterface.Nonnegatives}(1)
```

[source](#)

`MathOptInterface.Nonpositives` - Type.

```
Nonpositives(dimension::Int)
```

The nonpositive orthant  $\{x \in \mathbb{R}^{dimension} : x \leq 0\}$  of non-negative dimension `dimension`.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.Nonpositives(3))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    → MathOptInterface.Nonpositives}(1)
```

[source](#)

MathOptInterface.NormInfinityCone – Type.

```
NormInfinityCone(dimension::Int)
```

The  $\ell_\infty$ -norm cone  $\{(t, x) \in \mathbb{R}^{dimension} : t \geq \|x\|_\infty = \max_i |x_i|\}$  of dimension dimension.

The dimension must be at least 1.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables([t; x]), MOI.NormInfinityCone(4))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    → MathOptInterface.NormInfinityCone}(1)
```

[source](#)

MathOptInterface.NormOneCone – Type.

```
NormOneCone(dimension::Int)
```

The  $\ell_1$ -norm cone  $\{(t, x) \in \mathbb{R}^{dimension} : t \geq \|x\|_1 = \sum_i |x_i|\}$  of dimension dimension.

The dimension must be at least 1.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables([t; x]), MOI.NormOneCone(4))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    → MathOptInterface.NormOneCone}(1)
```

[source](#)

`MathOptInterface.NormCone` – Type.

```
NormCone(p::Float64, dimension::Int)
```

The  $\ell_p$ -norm cone  $\{(t, x) \in \mathbb{R}^{dimension} : t \geq \left( \sum_i |x_i|^p \right)^{\frac{1}{p}}\}$  of dimension `dimension`.

The `dimension` must be at least 1.

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables([t; x]), MOI.NormCone(3, 4))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.NormCone}(1)
```

[source](#)

`MathOptInterface.SecondOrderCone` – Type.

```
SecondOrderCone(dimension::Int)
```

The second-order cone (or Lorenz cone or  $\ell_2$ -norm cone)  $\{(t, x) \in \mathbb{R}^{dimension} : t \geq \|x\|_2\}$  of dimension `dimension`.

The `dimension` must be at least 1.

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables([t; x]), MOI.SecondOrderCone(4))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.SecondOrderCone}(1)
```

[source](#)

`MathOptInterface.RotatedSecondOrderCone` – Type.

```
RotatedSecondOrderCone(dimension::Int)
```

The rotated second-order cone  $\{(t, u, x) \in \mathbb{R}^{dimension} : 2tu \geq \|x\|_2^2, t, u \geq 0\}$  of dimension `dimension`.

The `dimension` must be at least 2.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> u = MOI.add_variable(model)
MOI.VariableIndex(2)

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables([t; u; x]),
    MOI.RotatedSecondOrderCone(5),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    MathOptInterface.RotatedSecondOrderCone}(1)
```

[source](#)

`MathOptInterface.GeometricMeanCone` – Type.

```
GeometricMeanCone(dimension::Int)
```

The geometric mean cone  $\{(t, x) \in \mathbb{R}^{n+1} : x \geq 0, t \leq \sqrt[n]{x_1 x_2 \cdots x_n}\}$ , where `dimension = n + 1 >= 2`.

### Duality note

The dual of the geometric mean cone is  $\{(u, v) \in \mathbb{R}^{n+1} : u \leq 0, v \geq 0, -u \leq \sqrt[n]{\prod_i v_i}\}$ , where `dimension = n + 1 >= 2`.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)
```

```
julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables([t; x]),
    MOI.GeometricMeanCone(4),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.GeometricMeanCone}(1)
```

[source](#)

MathOptInterface.ExponentialCone - Type.

```
ExponentialCone()
```

The 3-dimensional exponential cone  $\{(x, y, z) \in \mathbb{R}^3 : y \exp(x/y) \leq z, y > 0\}$ .

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.ExponentialCone())
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.ExponentialCone}(1)
```

[source](#)

MathOptInterface.DualExponentialCone - Type.

```
DualExponentialCone()
```

The 3-dimensional dual exponential cone  $\{(u, v, w) \in \mathbb{R}^3 : -u \exp(v/u) \leq \exp(1)w, u < 0\}$ .

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.DualExponentialCone())
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.DualExponentialCone}(1)
```

[source](#)

MathOptInterface.PowerCone – Type.

**PowerCone**{T<:Real}(exponent::T)

The 3-dimensional power cone  $\{(x, y, z) \in \mathbb{R}^3 : x^{exponent}y^{1-exponent} \geq |z|, x \geq 0, y \geq 0\}$  with parameter exponent.

**Example**

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.PowerCone(0.5))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
                                MathOptInterface.PowerCone{Float64}}(1)
```

[source](#)

MathOptInterface.DualPowerCone – Type.

**DualPowerCone**{T<:Real}(exponent::T)

The 3-dimensional power cone  $\{(u, v, w) \in \mathbb{R}^3 : (\frac{u}{exponent})^{exponent}(\frac{v}{1-exponent})^{1-exponent} \geq |w|, u \geq 0, v \geq 0\}$  with parameter exponent.

**Example**

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.DualPowerCone(0.5))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
                                MathOptInterface.DualPowerCone{Float64}}(1)
```

[source](#)

MathOptInterface.RelativeEntropyCone – Type.

**RelativeEntropyCone**(dimension::Int)

The relative entropy cone  $\{(u, v, w) \in \mathbb{R}^{1+2n} : u \geq \sum_{i=1}^n w_i \log(\frac{w_i}{v_i}), v_i \geq 0, w_i \geq 0\}$ , where dimension =  $2n + 1 \geq 1$ .

### Duality note

The dual of the relative entropy cone is  $\{(u, v, w) \in \mathbb{R}^{1+2n} : \forall i, w_i \geq u(\log(\frac{u}{v_i}) - 1), v_i \geq 0, u > 0\}$  of dimension dimension =  $2n + 1$ .

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> u = MOI.add_variable(model);

julia> v = MOI.add_variables(model, 3);

julia> w = MOI.add_variables(model, 3);

julia> MOI.add_constraint(
        model,
        MOI.VectorOfVariables([u; v; w]),
        MOI.RelativeEntropyCone(7),
    )
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.RelativeEntropyCone}(1)
```

### source

`MathOptInterface.NormSpectralCone` – Type.

```
NormSpectralCone(row_dim::Int, column_dim::Int)
```

The epigraph of the matrix spectral norm (maximum singular value function)  $\{(t, X) \in \mathbb{R}^{1+row\_dim \times column\_dim} : t \geq \sigma_1(X)\}$ , where  $\sigma_i$  is the  $i$ th singular value of the matrix  $X$  of non-negative row dimension `row_dim` and column dimension `column_dim`.

The matrix `X` is vectorized by stacking the columns, matching the behavior of Julia's `vec` function.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> X = reshape(MOI.add_variables(model, 6), 2, 3)
2×3 Matrix{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(2)  MOI.VariableIndex(4)  MOI.VariableIndex(6)
 MOI.VariableIndex(3)  MOI.VariableIndex(5)  MOI.VariableIndex(7)
```

```
julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables([t; vec(X)]),
    MOI.NormSpectralCone(2, 3),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.NormSpectralCone}(1)
```

[source](#)

MathOptInterface.NormNuclearCone – Type.

```
NormNuclearCone(row_dim::Int, column_dim::Int)
```

The epigraph of the matrix nuclear norm (sum of singular values function)  $\{(t, X) \in \mathbb{R}^{1+row\_dim \times column\_dim} : t \geq \sum_i \sigma_i(X)\}$ , where  $\sigma_i$  is the  $i$ th singular value of the matrix  $X$  of non-negative row dimension `row_dim` and column dimension `column_dim`.

The matrix  $X$  is vectorized by stacking the columns, matching the behavior of Julia's `vec` function.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> X = reshape(MOI.add_variables(model, 6), 2, 3)
2×3 Matrix{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(2) MOI.VariableIndex(4) MOI.VariableIndex(6)
 MOI.VariableIndex(3) MOI.VariableIndex(5) MOI.VariableIndex(7)

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables([t; vec(X)]),
    MOI.NormNuclearCone(2, 3),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.NormNuclearCone}(1)
```

[source](#)

MathOptInterface.SOS1 – Type.

```
SOS1{T<:Real}(weights::Vector{T})
```

The set corresponding to the Special Ordered Set (SOS) constraint of Type I.

Of the variables in the set, at most one can be nonzero.

The weights induce an ordering of the variables such that the  $k$ th element in the set corresponds to the  $k$ th weight in `weights`. Solvers may use these weights to improve the efficiency of the solution process, but the ordering does not change the set of feasible solutions.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables(x),
    MOI.SOS1([1.0, 3.0, 2.5]),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.SOS1{Float64}}(1)
```

[source](#)

`MathOptInterface.SOS2` – Type.

```
SOS2{T<:Real}(weights::Vector{T})
```

The set corresponding to the Special Ordered Set (SOS) constraint of Type II.

The weights induce an ordering of the variables such that the  $k$ th element in the set corresponds to the  $k$ th weight in `weights`. Therefore, the weights must be unique.

Of the variables in the set, at most two can be nonzero, and if two are nonzero, they must be adjacent in the ordering of the set.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3);

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables(x),
    MOI.SOS2([1.0, 3.0, 2.5]),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.SOS2{Float64}}(1)
```

[source](#)

`MathOptInterface.Indicator` – Type.

```
Indicator{A<:ActivationCondition,S<:AbstractScalarSet}(set::S)
```

The set corresponding to an indicator constraint.

When A is ACTIVATE\_ON\_ZERO, this means:  $\{(y, x) \in \{0, 1\} \times \mathbb{R}^n : y = 0 \implies x \in \text{set}\}$

When A is ACTIVATE\_ON\_ONE, this means:  $\{(y, x) \in \{0, 1\} \times \mathbb{R}^n : y = 1 \implies x \in \text{set}\}$

### Notes

Most solvers expect that the first row of the function is interpretable as a variable index  $x_i$  (for example,  $1.0 * x + 0.0$ ). An error will be thrown if this is not the case.

### Example

The constraint  $\{(y, x) \in \{0, 1\} \times \mathbb{R}^2 : y = 1 \implies x_1 + x_2 \leq 9\}$  is defined as

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 2)
2-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(1)
 MOI.VariableIndex(2)

julia> y, _ = MOI.add_constrained_variable(model, MOI.ZeroOne())
(MOI.VariableIndex(3), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
 ↳ MathOptInterface.ZeroOne}(3))

julia> f = MOI.VectorAffineFunction(
    [
        MOI.VectorAffineTerm(1, MOI.ScalarAffineTerm(1.0, y)),
        MOI.VectorAffineTerm(2, MOI.ScalarAffineTerm(1.0, x[1])),
        MOI.VectorAffineTerm(2, MOI.ScalarAffineTerm(1.0, x[2])),
    ],
    [0.0, 0.0],
)

$$\begin{bmatrix} 0.0 + 1.0 \text{MOI.VariableIndex}(3) \\ 0.0 + 1.0 \text{MOI.VariableIndex}(1) + 1.0 \text{MOI.VariableIndex}(2) \end{bmatrix}$$


julia> s = MOI.Indicator{MOI.ACTIVATE_ON_ONE}(MOI.LessThan(9.0))
MathOptInterface.Indicator{MathOptInterface.ACTIVATE_ON_ONE,
 ↳ MathOptInterface.LessThan{Float64}}(MathOptInterface.LessThan{Float64}(9.0))

julia> MOI.add_constraint(model, f, s)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorAffineFunction{Float64},
 ↳ MathOptInterface.Indicator{MathOptInterface.ACTIVATE_ON_ONE,
 ↳ MathOptInterface.LessThan{Float64}}}(1)
```

[source](#)

MathOptInterface.Complements - Type.

```
Complements(dimension::Base.Integer)
```

The set corresponding to a mixed complementarity constraint.

Complementarity constraints should be specified with an `AbstractVectorFunction`-in-`Complements(dimension)` constraint.

The dimension of the vector-valued function  $F$  must be `dimension`. This defines a complementarity constraint between the scalar function  $F[i]$  and the variable in  $F[i + \text{dimension}/2]$ . Thus,  $F[i + \text{dimension}/2]$  must be interpretable as a single variable  $x_i$  (for example,  $1.0 * x + 0.0$ ), and `dimension` must be even.

The mixed complementarity problem consists of finding  $x_i$  in the interval  $[lb, ub]$  (that is, in the set `Interval(lb, ub)`), such that the following holds:

1.  $F_i(x) == 0$  if  $lb_i < x_i < ub_i$
2.  $F_i(x) >= 0$  if  $lb_i == x_i$
3.  $F_i(x) <= 0$  if  $x_i == ub_i$

Classically, the bounding set for  $x_i$  is `Interval(0, Inf)`, which recovers:  $0 \leq F_i(x) \perp x_i \geq 0$ , where the  $\perp$  operator implies  $F_i(x) * x_i = 0$ .

### Example

The problem:

```
x -in- Interval(-1, 1)
[-4 * x - 3, x] -in- Complements(2)
```

defines the mixed complementarity problem where the following holds:

1.  $-4 * x - 3 == 0$  if  $-1 < x < 1$
2.  $-4 * x - 3 \geq 0$  if  $x == -1$
3.  $-4 * x - 3 \leq 0$  if  $x == 1$

There are three solutions:

1.  $x = -3/4$  with  $F(x) = 0$
2.  $x = -1$  with  $F(x) = 1$
3.  $x = 1$  with  $F(x) = -7$

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x, _ = MOI.add_constrained_variable(model, MOI.Interval(-1.0, 1.0));

julia> MOI.add_constraint(
        model,
        MOI.Utilities.vectorize([-4.0 * x - 3.0, x]),
        MOI.Complements(2),
    )
MathOptInterface.ConstraintIndex{MathOptInterface.VectorAffineFunction{Float64},
→ MathOptInterface.Complements}(1)
```

The function F can also be defined in terms of single variables. For example, the problem:

```
[x_3, x_4] -in- Nonnegatives(2)
[x_1, x_2, x_3, x_4] -in- Complements(4)
```

defines the complementarity problem where  $0 \leq x_1 + x_3 \geq 0$  and  $0 \leq x_2 + x_4 \geq 0$ .

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 4);

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x[3:4]), MOI.Nonnegatives(2))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.Nonnegatives}(1)

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables(x),
    MOI.Complements(4),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.Complements}(1)
```

[source](#)

`MathOptInterface.HyperRectangle` – Type.

```
HyperRectangle(lower::Vector{T}, upper::Vector{T}) where {T}
```

The set  $\{x \in \bar{\mathbb{R}}^d : x_i \in [lower_i, upper_i] \forall i = 1, \dots, d\}$ .

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3)
3-element Vector{MathOptInterface.VariableIndex}:
MOI.VariableIndex(1)
MOI.VariableIndex(2)
MOI.VariableIndex(3)

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables(x),
    MOI.HyperRectangle(zeros(3), ones(3)),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.HyperRectangle{Float64}}(1)
```

[source](#)  
**MathOptInterface.Scaled** – Type.

```
struct Scaled{S<:AbstractVectorSet} <: AbstractVectorSet
    set::S
end
```

Given a vector  $a \in \mathbb{R}^d$  and a set representing the set  $\mathcal{S} \in \mathbb{R}^d$  such that `Utilities.set_dot` for  $x \in \mathcal{S}$  and  $y \in \mathcal{S}^*$  is

$$\sum_{i=1}^d a_i x_i y_i$$

the set `Scaled(set)` is defined as

$$\{(\sqrt{a_1}x_1, \sqrt{a_2}x_2, \dots, \sqrt{a_d}x_d) : x \in S\}$$

### Example

This can be used to scale a vector of numbers

```
julia> import MathOptInterface as MOI

julia> set = MOI.PositiveSemidefiniteConeTriangle(2)
MathOptInterface.PositiveSemidefiniteConeTriangle(2)

julia> a = MOI.Utilities.SetDotScalingVector{Float64}(set)
3-element MathOptInterface.Utilities.SetDotScalingVector{Float64,
↪ MathOptInterface.PositiveSemidefiniteConeTriangle}:
1.0
1.4142135623730951
1.0

julia> using LinearAlgebra

julia> MOI.Utilities.operate(*, Float64, Diagonal(a), ones(3))
3-element Vector{Float64}:
1.0
1.4142135623730951
1.0
```

It can be also used to scale a vector of function

```
julia> model = MOI.Utilities.Model{Float64}();
julia> x = MOI.add_variables(model, 3);
```

```

julia> func = MOI.VectorOfVariables(x)
[MOI.VariableIndex(1)]
[MOI.VariableIndex(2)]
[MOI.VariableIndex(3)]

julia> set = MOI.PositiveSemidefiniteConeTriangle(2)
MathOptInterface.PositiveSemidefiniteConeTriangle(2)

julia> MOI.Utilities.operate(*, Float64, Diagonal(a), func)
[0.0 + 1.0 MOI.VariableIndex(1)]
[0.0 + 1.4142135623730951 MOI.VariableIndex(2)]
[0.0 + 1.0 MOI.VariableIndex(3)]

```

[source](#)

## Constraint programming sets

MathOptInterface.AllDifferent - Type.

```
AllDifferent(dimension::Int)
```

The set  $\{x \in \mathbb{Z}^d\}$  such that no two elements in  $x$  take the same value and `dimension = d`.

### Also known as

This constraint is called `all_different` in MiniZinc, and is sometimes also called `distinct`.

### Example

To enforce  $x[1] \neq x[2]$  AND  $x[1] \neq x[3]$  AND  $x[2] \neq x[3]$ :

```

julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = [MOI.add_constrained_variable(model, MOI.Integer())[1] for _ in 1:3]
3-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(1)
 MOI.VariableIndex(2)
 MOI.VariableIndex(3)

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.AllDifferent(3))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
                                MathOptInterface.AllDifferent}(1)

```

[source](#)

MathOptInterface.BinPacking - Type.

```
BinPacking(c::T, w::Vector{T}) where {T}
```

The set  $\{x \in \mathbb{Z}^d\}$  where  $d = \text{length}(w)$ , such that each item  $i$  in  $1:d$  of weight  $w[i]$  is put into bin  $x[i]$ , and the total weight of each bin does not exceed  $c$ .

There are additional assumptions that the capacity,  $c$ , and the weights,  $w$ , must all be non-negative.

The bin numbers depend on the bounds of  $x$ , so they may be something other than the integers  $1:d$ .

#### Also known as

This constraint is called `bin_packing` in MiniZinc.

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> bins = MOI.add_variables(model, 5)
5-element Vector{MathOptInterface.VariableIndex}:
MOI.VariableIndex(1)
MOI.VariableIndex(2)
MOI.VariableIndex(3)
MOI.VariableIndex(4)
MOI.VariableIndex(5)

julia> weights = Float64[1, 1, 2, 2, 3]
5-element Vector{Float64}:
1.0
1.0
2.0
2.0
3.0

julia> MOI.add_constraint.(model, bins, MOI.Integer())
5-element Vector{MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}}:
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.Integer}(1)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.Integer}(2)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.Integer}(3)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.Integer}(4)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.Integer}(5)

julia> MOI.add_constraint.(model, bins, MOI.Interval(4.0, 6.0))
5-element Vector{MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Interval{Float64}}}:
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Interval{Float64}}(1)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Interval{Float64}}(2)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Interval{Float64}}(3)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Interval{Float64}}(4)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Interval{Float64}}(5)
```

```
julia> MOI.add_constraint(model, MOI.VectorOfVariables(bins), MOI.BinPacking(3.0, weights))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
                                MathOptInterface.BinPacking{Float64}}(1)
```

[source](#)

MathOptInterface.Circuit - Type.

```
Circuit(dimension::Int)
```

The set  $\{x \in \{1..d\}^d\}$  that constraints  $x$  to be a circuit, such that  $x_i = j$  means that  $j$  is the successor of  $i$ , and `dimension = d`.

Graphs with multiple independent circuits, such as [2, 1, 3] and [2, 1, 4, 3], are not valid.

#### Also known as

This constraint is called `circuit` in MiniZinc, and it is equivalent to forming a (potentially sub-optimal) tour in the travelling salesperson problem.

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = [MOI.add_constrained_variable(model, MOI.Integer())[1] for _ in 1:3]
3-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(1)
 MOI.VariableIndex(2)
 MOI.VariableIndex(3)

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.Circuit(3))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
                                MathOptInterface.Circuit}(1)
```

[source](#)

MathOptInterface.CountAtLeast - Type.

```
CountAtLeast(n::Int, d::Vector{Int}, set::Set{Int})
```

The set  $\{x \in \mathbb{Z}^{d_1+d_2+\dots+d_N}\}$ , where  $x$  is partitioned into  $N$  subsets  $(\{x_1, \dots, x_{d_1}\}, \{x_{d_1+1}, \dots, x_{d_1+d_2}\}$  and so on), and at least  $n$  elements of each subset take one of the values in `set`.

#### Also known as

This constraint is called `at_least` in MiniZinc.

#### Example

To ensure that 3 appears at least once in each of the subsets {a, b} and {b, c}:

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> a, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(1), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}(1))

julia> b, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(2), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}(2))

julia> c, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(3), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}(3))

julia> x, d, set = [a, b, b, c], [2, 2], [3]
(MathOptInterface.VariableIndex[MOI.VariableIndex(1), MOI.VariableIndex(2),
↪ MOI.VariableIndex(2), MOI.VariableIndex(3)], [2, 2], [3])

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.CountAtLeast(l, d, Set(set)))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
↪ MathOptInterface.CountAtLeast}(1)
```

[source](#)

MathOptInterface.CountBelongs - Type.

```
CountBelongs(dimension::Int, set::Set{Int})
```

The set  $\{(n, x) \in \mathbb{Z}^{1+d}\}$ , such that n elements of the vector x take on of the values in set and dimension = 1 + d.

#### Also known as

This constraint is called among by MiniZinc.

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> n, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(1), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}(1))

julia> x = [MOI.add_constrained_variable(model, MOI.Integer())[1] for _ in 1:3]
3-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(2)
 MOI.VariableIndex(3)
 MOI.VariableIndex(4)

julia> set = Set([3, 4, 5])
```

```
Set{Int64} with 3 elements:
5
4
3

julia> MOI.add_constraint(model, MOI.VectorOfVariables([n; x]), MOI.CountBelongs(4, set))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.CountBelongs}(1)
```

[source](#)

`MathOptInterface.CountDistinct` – Type.

```
CountDistinct(dimension::Int)
```

The set  $\{(n, x) \in \mathbb{Z}^{1+d}\}$ , such that the number of distinct values in  $x$  is  $n$  and `dimension = 1 + d`.

#### Also known as

This constraint is called `nvalues` in MiniZinc.

#### Example

To model:

- if  $n == 1$ , then  $x[1] == x[2] == x[3]$
- if  $n == 2$ , then
  - $x[1] == x[2] != x[3]$  or
  - $x[1] != x[2] == x[3]$  or
  - $x[1] == x[3] != x[2]$
- if  $n == 3$ , then  $x[1] != x[2], x[2] != x[3]$  and  $x[3] != x[1]$

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> n, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(1), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    ↪ MathOptInterface.Integer}(1))

julia> x = [MOI.add_constrained_variable(model, MOI.Integer())[1] for _ in 1:3]
3-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(2)
 MOI.VariableIndex(3)
 MOI.VariableIndex(4)

julia> MOI.add_constraint(model, MOI.VectorOfVariables(vcat(n, x)), MOI.CountDistinct(4))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.CountDistinct}(1)
```

### Relationship to AllDifferent

When the first element is  $d$ , CountDistinct is equivalent to an [AllDifferent](#) constraint.

[source](#)

MathOptInterface.CountGreaterThan - Type.

```
CountGreaterThan(dimension::Int)
```

The set  $\{(c, y, x) \in \mathbb{Z}^{1+1+d}\}$ , such that  $c$  is strictly greater than the number of occurrences of  $y$  in  $x$  and  $\text{dimension} = 1 + 1 + d$ .

### Also known as

This constraint is called `count_gt` in MiniZinc.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> c, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(1), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}(1))

julia> y, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(2), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}(2))

julia> x = [MOI.add_constrained_variable(model, MOI.Integer())[1] for _ in 1:3]
3-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(3)
 MOI.VariableIndex(4)
 MOI.VariableIndex(5)

julia> MOI.add_constraint(model, MOI.VectorOfVariables([c; y; x]), MOI.CountGreater Than(5))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
↪ MathOptInterface.CountGreater Than}(1)
```

[source](#)

MathOptInterface.Cumulative - Type.

```
Cumulative(dimension::Int)
```

The set  $\{(s, d, r, b) \in \mathbb{Z}^{3n+1}\}$ , representing the cumulative global constraint, where  $n == \text{length}(s) == \text{length}(r) == \text{length}(b)$  and  $\text{dimension} = 3n + 1$ .

Cumulative requires that a set of tasks given by start times  $s$ , durations  $d$ , and resource requirements  $r$ , never requires more than the global resource bound  $b$  at any one time.

### Also known as

This constraint is called `cumulative` in MiniZinc.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> s = [MOI.add_constrained_variable(model, MOI.Integer())[1] for _ in 1:3]
3-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(1)
 MOI.VariableIndex(2)
 MOI.VariableIndex(3)

julia> d = [MOI.add_constrained_variable(model, MOI.Integer())[1] for _ in 1:3]
3-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(4)
 MOI.VariableIndex(5)
 MOI.VariableIndex(6)

julia> r = [MOI.add_constrained_variable(model, MOI.Integer())[1] for _ in 1:3]
3-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(7)
 MOI.VariableIndex(8)
 MOI.VariableIndex(9)

julia> b, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(10), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    ↪ MathOptInterface.Integer}(10))

julia> MOI.add_constraint(model, MOI.VectorOfVariables([s; d; r; b]), MOI.Cumulative(10))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
    ↪ MathOptInterface.Cumulative}(1)
```

[source](#)

`MathOptInterface.Path` – Type.

```
Path(from::Vector{Int}, to::Vector{Int})
```

Given a graph comprised of a set of nodes  $1..N$  and a set of arcs  $1..E$  represented by an edge from node `from[i]` to node `to[i]`, `Path` constrains the set  $(s, t, ns, es) \in (1..N) \times (1..E) \times \{0, 1\}^N \times \{0, 1\}^E$ , to form subgraph that is a path from node `s` to node `t`, where node `n` is in the path if `ns[n]` is 1, and edge `e` is in the path if `es[e]` is 1.

The path must be acyclic, and it must traverse all nodes `n` for which `ns[n]` is 1, and all edges `e` for which `es[e]` is 1.

### Also known as

This constraint is called `path` in MiniZinc.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> N, E = 4, 5
(4, 5)

julia> from = [1, 1, 2, 2, 3]
5-element Vector{Int64}:
1
1
2
2
3

julia> to = [2, 3, 3, 4, 4]
5-element Vector{Int64}:
2
3
3
4
4

julia> s, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(1), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}(1))

julia> t, _ = MOI.add_constrained_variable(model, MOI.Integer())
(MOI.VariableIndex(2), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.Integer}(2))

julia> ns = MOI.add_variables(model, N)
4-element Vector{MathOptInterface.VariableIndex}:
MOI.VariableIndex(3)
MOI.VariableIndex(4)
MOI.VariableIndex(5)
MOI.VariableIndex(6)

julia> MOI.add_constraint.(model, ns, MOI.ZeroOne())
4-element Vector{MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
↪ MathOptInterface.ZeroOne}}:
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(3)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(4)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(5)
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(6)

julia> es = MOI.add_variables(model, E)
5-element Vector{MathOptInterface.VariableIndex}:
MOI.VariableIndex(7)
MOI.VariableIndex(8)
MOI.VariableIndex(9)
MOI.VariableIndex(10)
MOI.VariableIndex(11)

julia> MOI.add_constraint.(model, es, MOI.ZeroOne())
```

```

5-element Vector{MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    ↪ MathOptInterface.ZeroOne}}:
    MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(7)
    MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(8)
    MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(9)
    MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(10)
    MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(11)

julia> MOI.add_constraint(model, MOI.VectorOfVariables([s; t; ns; es]), MOI.Path(from, to))
    MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables, MathOptInterface.Path}(1)

```

[source](#)

MathOptInterface.Reified - Type.

```
Reified(set::AbstractSet)
```

The constraint  $[z; f(x)] \in \text{Reified}(S)$  ensures that  $f(x) \in S$  if and only if  $z == 1$ , where  $z \in \{0, 1\}$ .

```

julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}());

julia> z, _ = MOI.add_constrained_variable(model, MOI.ZeroOne())
    (MOI.VariableIndex(1), MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    ↪ MathOptInterface.ZeroOne}(1))

julia> x = MOI.add_variable(model)
    MOI.VariableIndex(2)

julia> MOI.add_constraint(
        model,
        MOI.Utilities.vectorize([z, 2.0 * x]),
        MOI.Reified(MOI.GreaterThan(1.0)),
    )
    MathOptInterface.ConstraintIndex{MathOptInterface.VectorAffineFunction{Float64},
    ↪ MathOptInterface.Reified{MathOptInterface.GreaterThan{Float64}}}(1)

```

[source](#)

MathOptInterface.Table - Type.

```
Table(table::Matrix{T}) where {T}
```

The set  $\{x \in \mathbb{R}^d\}$  where  $d = \text{size}(\text{table}, 2)$ , such that  $x$  belongs to one row of  $\text{table}$ . That is, there exists some  $j$  in  $1:\text{size}(\text{table}, 1)$ , such that  $x[i] = \text{table}[j, i]$  for all  $i=1:\text{size}(\text{table}, 2)$ .

#### Also known as

This constraint is called `table` in MiniZinc.

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 3)
3-element Vector{MathOptInterface.VariableIndex}:
MOI.VariableIndex(1)
MOI.VariableIndex(2)
MOI.VariableIndex(3)

julia> table = Float64[1 1 0; 0 1 1; 1 0 1; 1 1 1]
4×3 Matrix{Float64}:
 1.0  1.0  0.0
 0.0  1.0  1.0
 1.0  0.0  1.0
 1.0  1.0  1.0

julia> MOI.add_constraint(model, MOI.VectorOfVariables(x), MOI.Table(table))
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→  MathOptInterface.Table{Float64}}(1)
```

[source](#)

## Matrix sets

Matrix sets are vectorized to be subtypes of [AbstractVectorSet](#).

For sets of symmetric matrices, storing both the  $(i, j)$  and  $(j, i)$  elements is redundant. Use the [AbstractSymmetricMatrixSet](#) set to represent only the vectorization of the upper triangular part of the matrix.

When the matrix of expressions constrained to be in the set is not symmetric, and hence additional constraints are needed to force the equality of the  $(i, j)$  and  $(j, i)$  elements, use the [AbstractSymmetricMatrixSetSquare](#) set.

The [Bridges.Constraint.SquareBridge](#) can transform a set from the square form to the [triangular\\_form](#) by adding appropriate constraints if the  $(i, j)$  and  $(j, i)$  expressions are different.

`MathOptInterface.AbstractSymmetricMatrixSetTriangle` – Type.

```
abstract type AbstractSymmetricMatrixSetTriangle <: AbstractVectorSet end
```

Abstract supertype for subsets of the (vectorized) cone of symmetric matrices, with `side_dimension` rows and columns. The entries of the upper-right triangular part of the matrix are given column by column (or equivalently, the entries of the lower-left triangular part are given row by row). A vectorized cone of `dimension n` corresponds to a square matrix with side dimension  $\sqrt{1/4 + 2n} - 1/2$ . (Because a  $d \times d$  matrix has  $d(d+1)/2$  elements in the upper or lower triangle.)

### Example

The matrix

$$\begin{bmatrix} 1 & 2 & 4 \\ 2 & 3 & 5 \\ 4 & 5 & 6 \end{bmatrix}$$

has `side_dimension` 3 and vectorization (1, 2, 3, 4, 5, 6).

### Note

Two packed storage formats exist for symmetric matrices, the respective orders of the entries are:

- upper triangular column by column (or lower triangular row by row);
- lower triangular column by column (or upper triangular row by row).

The advantage of the first format is the mapping between the (i, j) matrix indices and the k index of the vectorized form. It is simpler and does not depend on the side dimension of the matrix. Indeed,

- the entry of matrix indices (i, j) has vectorized index  $k = \text{div}((j - 1) * j, 2) + i$  if  $i \leq j$  and  $k = \text{div}((i - 1) * i, 2) + j$  if  $j \leq i$ ;
- and the entry with vectorized index k has matrix indices  $i = \text{div}(1 + \text{isqrt}(8k - 7), 2)$  and  $j = k - \text{div}((i - 1) * i, 2)$  or  $j = \text{div}(1 + \text{isqrt}(8k - 7), 2)$  and  $i = k - \text{div}((j - 1) * j, 2)$ .

### Duality note

The scalar product for the symmetric matrix in its vectorized form is the sum of the pairwise product of the diagonal entries plus twice the sum of the pairwise product of the upper diagonal entries; see [p. 634, 1]. This has important consequence for duality.

Consider for example the following problem (`PositiveSemidefiniteConeTriangle` is a subtype of `AbstractSymmetricMatrix`)

$$\begin{array}{ll} \max_{x \in \mathbb{R}} & x \\ \text{s.t.} & (1, -x, 1) \in \text{PositiveSemidefiniteConeTriangle}(2). \end{array}$$

The dual is the following problem

$$\begin{array}{ll} \min_{x \in \mathbb{R}^3} & y_1 + y_3 \\ \text{s.t.} & 2y_2 = 1 \\ & y \in \text{PositiveSemidefiniteConeTriangle}(2). \end{array}$$

Why do we use  $2y_2$  in the dual constraint instead of  $y_2$ ? The reason is that  $2y_2$  is the scalar product between  $y$  and the symmetric matrix whose vectorized form is  $(0, 1, 0)$ . Indeed, with our modified scalar products we have

$$\langle (0, 1, 0), (y_1, y_2, y_3) \rangle = \text{trace} \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} y_1 & y_2 \\ y_2 & y_3 \end{pmatrix} = 2y_2.$$

### References

[1] Boyd, S. and Vandenberghe, L.. *Convex optimization*. Cambridge university press, 2004.

[source](#)

`MathOptInterface.AbstractSymmetricMatrixSetSquare` – Type.

```
abstract type AbstractSymmetricMatrixSetSquare <: AbstractVectorSet end
```

Abstract supertype for subsets of the (vectorized) cone of symmetric matrices, with `side_dimension` rows and columns. The entries of the matrix are given column by column (or equivalently, row by row). The matrix is both constrained to be symmetric and to have its `triangular_form` belong to the corresponding set. That is, if the functions in entries  $(i, j)$  and  $(j, i)$  are different, then a constraint will be added to make sure that the entries are equal.

### Example

`PositiveSemidefiniteConeSquare` is a subtype of `AbstractSymmetricMatrixSetSquare` and constraining the matrix

$$\begin{bmatrix} 1 & -y \\ -z & 0 \end{bmatrix}$$

to be symmetric positive semidefinite can be achieved by constraining the vector  $(1, -z, -y, 0)$  (or  $(1, -y, -z, 0)$ ) to belong to the `PositiveSemidefiniteConeSquare(2)`. It both constrains  $y = z$  and  $(1, -y, 0)$  (or  $(1, -z, 0)$ ) to be in `PositiveSemidefiniteConeTriangle(2)`, since `triangular_form(PositiveSemidefiniteConeSquare)` is `PositiveSemidefiniteConeTriangle`.

`source`

`MathOptInterface.side_dimension` – Function.

```
side_dimension(
    set::Union{
        AbstractSymmetricMatrixSetTriangle,
        AbstractSymmetricMatrixSetSquare,
        HermitianPositiveSemidefiniteConeTriangle,
    },
)
```

Side dimension of the matrices in set.

### Convention

By convention, the side dimension should be stored in the `side_dimension` field. If this is not the case for a subtype of `AbstractSymmetricMatrixSetTriangle`, or `AbstractSymmetricMatrixSetSquare` you must implement this method.

`source`

`MathOptInterface.triangular_form` – Function.

```
triangular_form(S)::Type{<:AbstractSymmetricMatrixSetSquare})
triangular_form(set::AbstractSymmetricMatrixSetSquare)
```

Return the `AbstractSymmetricMatrixSetTriangle` corresponding to the vectorization of the upper triangular part of matrices in the `AbstractSymmetricMatrixSetSquare` set.

`source`

List of recognized matrix sets.

`MathOptInterface.PositiveSemidefiniteConeTriangle` – Type.

```
PositiveSemidefiniteConeTriangle(side_dimension::Int) <: AbstractSymmetricMatrixSetTriangle
```

The (vectorized) cone of symmetric positive semidefinite matrices, with non-negative `side_dimension` rows and columns.

See [AbstractSymmetricMatrixSetTriangle](#) for more details on the vectorized form.

`source`

`MathOptInterface.PositiveSemidefiniteConeSquare` – Type.

```
PositiveSemidefiniteConeSquare(side_dimension::Int) <: AbstractSymmetricMatrixSetSquare
```

The cone of symmetric positive semidefinite matrices, with non-negative side length `side_dimension`.

See [AbstractSymmetricMatrixSetSquare](#) for more details on the vectorized form.

The entries of the matrix are given column by column (or equivalently, row by row).

The matrix is both constrained to be symmetric and to be positive semidefinite. That is, if the functions in entries  $(i, j)$  and  $(j, i)$  are different, then a constraint will be added to make sure that the entries are equal.

### Example

Constraining the matrix

$$\begin{bmatrix} 1 & -y \\ -z & 0 \end{bmatrix}$$

to be symmetric positive semidefinite can be achieved by constraining the vector  $(1, -z, -y, 0)$  (or  $(1, -y, -z, 0)$ ) to belong to the `PositiveSemidefiniteConeSquare(2)`.

It both constrains  $y = z$  and  $(1, -y, 0)$  (or  $(1, -z, 0)$ ) to be in `PositiveSemidefiniteConeTriangle(2)`.

`source`

`MathOptInterface.HermitianPositiveSemidefiniteConeTriangle` – Type.

```
HermitianPositiveSemidefiniteConeTriangle(side_dimension::Int) <: AbstractVectorSet
```

The (vectorized) cone of Hermitian positive semidefinite matrices, with non-negative `side_dimension` rows and columns.

Because the matrix is Hermitian, the diagonal elements are real, and the complex-valued lower triangular entries are obtained as the conjugate of corresponding upper triangular entries.

### Vectorization format

The vectorized form starts with real part of the entries of the upper triangular part of the matrix, given column by column as explained in [AbstractSymmetricMatrixSetSquare](#).

It is then followed by the imaginary part of the off-diagonal entries of the upper triangular part, also given column by column.

For example, the matrix

$$\begin{bmatrix} 1 & 2 + 7im & 4 + 8im \\ 2 - 7im & 3 & 5 + 9im \\ 4 - 8im & 5 - 9im & 6 \end{bmatrix}$$

has `side_dimension` 3 and is represented as the vector [1, 2, 3, 4, 5, 6, 7, 8, 9].

`source`

`MathOptInterface.LogDetConeTriangle` – Type.

```
LogDetConeTriangle(side_dimension::Int)
```

The log-determinant cone  $\{(t, u, X) \in \mathbb{R}^{2+d(d+1)/2} : t \leq u \log(\det(X/u)), u > 0\}$ , where the matrix  $X$  is represented in the same symmetric packed format as in the `PositiveSemidefiniteConeTriangle`.

The non-negative argument `side_dimension` is the side dimension of the matrix  $X$ , that is, its number of rows or columns.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> X = MOI.add_variables(model, 3);

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables([t; X]),
    MOI.LogDetConeTriangle(2),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.LogDetConeTriangle}(1)
```

`source`

`MathOptInterface.LogDetConeSquare` – Type.

```
LogDetConeSquare(side_dimension::Int)
```

The log-determinant cone  $\{(t, u, X) \in \mathbb{R}^{2+d^2} : t \leq u \log(\det(X/u)), X \text{ symmetric}, u > 0\}$ , where the matrix  $X$  is represented in the same format as in the [PositiveSemidefiniteConeSquare](#).

Similarly to [PositiveSemidefiniteConeSquare](#), constraints are added to ensure that  $X$  is symmetric.

The non-negative argument `side_dimension` is the side dimension of the matrix  $X$ , that is, its number of rows or columns.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> X = reshape(MOI.add_variables(model, 4), 2, 2)
2×2 Matrix{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(2)  MOI.VariableIndex(4)
 MOI.VariableIndex(3)  MOI.VariableIndex(5)

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables([t; vec(X)]),
    MOI.LogDetConeSquare(2),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.LogDetConeSquare}(1)
```

[source](#)

`MathOptInterface.RootDetConeTriangle` – Type.

```
RootDetConeTriangle(side_dimension::Int)
```

The root-determinant cone  $\{(t, X) \in \mathbb{R}^{1+d(d+1)/2} : t \leq \det(X)^{1/d}\}$ , where the matrix  $X$  is represented in the same symmetric packed format as in the [PositiveSemidefiniteConeTriangle](#).

The non-negative argument `side_dimension` is the side dimension of the matrix  $X$ , that is, its number of rows or columns.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> X = MOI.add_variables(model, 3);

julia> MOI.add_constraint(
```

```

        model,
        MOI.VectorOfVariables([t; X]),
        MOI.RootDetConeTriangle(2),
    )
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.RootDetConeTriangle}(1)

```

**source**

MathOptInterface.RootDetConeSquare - Type.

```
RootDetConeSquare(side_dimension::Int)
```

The root-determinant cone  $\{(t, X) \in \mathbb{R}^{1+d^2} : t \leq \det(X)^{1/d}, X \text{ symmetric}\}$ , where the matrix  $X$  is represented in the same format as [PositiveSemidefiniteConeSquare](#).

Similarly to [PositiveSemidefiniteConeSquare](#), constraints are added to ensure that  $X$  is symmetric.

The non-negative argument `side_dimension` is the side dimension of the matrix  $X$ , that is, its number of rows or columns.

### Example

```

julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> t = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> X = reshape(MOI.add_variables(model, 4), 2, 2)
2×2 Matrix{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(2)  MOI.VariableIndex(4)
 MOI.VariableIndex(3)  MOI.VariableIndex(5)

julia> MOI.add_constraint(
    model,
    MOI.VectorOfVariables([t; vec(X)]),
    MOI.RootDetConeSquare(2),
)
MathOptInterface.ConstraintIndex{MathOptInterface.VectorOfVariables,
→ MathOptInterface.RootDetConeSquare}(1)

```

**source**

## 35.2 Models

### Attribute interface

MathOptInterface.is\_set\_by\_optimize - Function.

```
is_set_by_optimize(::AnyAttribute)
```

Return a Bool indicating whether the value of the attribute is set during an `optimize!` call, that is, the attribute is used to query the result of the optimization.

If an attribute can be set by the user, define `is_copyable` instead.

An attribute cannot be both `is_copyable` and `is_set_by_optimize`.

#### Default fallback

This function returns false by default so it should be implemented for attributes that are set by `optimize!`.

#### Undefined behavior

Querying the value of the attribute that `is_set_by_optimize` before a call to `optimize!` is undefined and depends on solver-specific behavior.

`source`

`MathOptInterface.is_copyable` - Function.

```
is_copyable(::AnyAttribute)
```

Return a Bool indicating whether the value of the attribute may be copied during `copy_to` using `set`.

If an attribute `is_copyable`, then it cannot be modified by the optimizer, and `get` must always return the value that was `set` by the user.

If an attribute is the result of an optimization, define `is_set_by_optimize` instead.

An attribute cannot be both `is_set_by_optimize` and `is_copyable`.

#### Default fallback

By default `is_copyable(attr)` returns `!is_set_by_optimize(attr)`, which is most probably true.

If an attribute should not be copied, define `is_copyable(::MyAttribute) = false`.

`source`

`MathOptInterface.get` - Function.

```
MOI.get(b::AbstractBridge, ::MOI.NumberOfVariables)::Int64
```

Return the number of variables created by the bridge `b` in the model.

See also `MOI.NumberOfConstraints`.

#### Implementation notes

- There is a default fallback, so you need only implement this if the bridge adds new variables.

`source`

```
MOI.get(b::AbstractBridge, ::MOI.ListOfVariableIndices)
```

Return the list of variables created by the bridge b.

See also [MOI.ListOfVariableIndices](#).

#### Implementation notes

- There is a default fallback, so you need only implement this if the bridge adds new variables.

[source](#)

```
MOI.get(b::AbstractBridge, ::MOI.NumberOfConstraints{F,S})::Int64 where {F,S}
```

Return the number of constraints of the type F-in-S created by the bridge b.

See also [MOI.NumberOfConstraints](#).

#### Implementation notes

- There is a default fallback, so you need only implement this for the constraint types returned by [added\\_constraint\\_types](#).

[source](#)

```
MOI.get(b::AbstractBridge, ::MOI.ListOfConstraintIndices{F,S}) where {F,S}
```

Return a Vector{ConstraintIndex{F,S}} with indices of all constraints of type F-in-S created by the bridge b.

See also [MOI.ListOfConstraintIndices](#).

#### Implementation notes

- There is a default fallback, so you need only implement this for the constraint types returned by [added\\_constraint\\_types](#).

[source](#)

```
function MOI.get(
    model::MOI.ModelLike,
    attr::MOI.AbstractConstraintAttribute,
    bridge::AbstractBridge,
)
```

Return the value of the attribute attr of the model model for the constraint bridged by bridge.

[source](#)

```
get(optimizer::AbstractOptimizer, attr::AbstractOptimizerAttribute)
```

Return an attribute attr of the optimizer optimizer.

```
get(model::ModelLike, attr::AbstractModelAttribute)
```

Return an attribute `attr` of the model `model`.

```
get(model::ModelLike, attr::AbstractVariableAttribute, v::VariableIndex)
```

If the attribute `attr` is set for the variable `v` in the model `model`, return its value, return nothing otherwise. If the attribute `attr` is not supported by `model` then an error should be thrown instead of returning nothing.

```
get(model::ModelLike, attr::AbstractVariableAttribute, v::Vector{VariableIndex})
```

Return a vector of attributes corresponding to each variable in the collection `v` in the model `model`.

```
get(model::ModelLike, attr::AbstractConstraintAttribute, c::ConstraintIndex)
```

If the attribute `attr` is set for the constraint `c` in the model `model`, return its value, return nothing otherwise. If the attribute `attr` is not supported by `model` then an error should be thrown instead of returning nothing.

```
get(
    model::ModelLike,
    attr::AbstractConstraintAttribute,
    c::Vector{ConstraintIndex{F,S}},
) where {F,S}
```

Return a vector of attributes corresponding to each constraint in the collection `c` in the model `model`.

```
get(model::ModelLike, ::Type{VariableIndex}, name::String)
```

If a variable with name `name` exists in the model `model`, return the corresponding index, otherwise return nothing. Errors if two variables have the same name.

```
get(
    model::ModelLike,
    ::Type{ConstraintIndex{F,S}},
    name::String,
) where {F,S}
```

If an F-in-S constraint with name `name` exists in the model `model`, return the corresponding index, otherwise return nothing. Errors if two constraints have the same name.

```
get(model::ModelLike, ::Type{ConstraintIndex}, name::String)
```

If *any* constraint with name `name` exists in the model `model`, return the corresponding index, otherwise return nothing. This version is available for convenience but may incur a performance penalty because it is not type stable. Errors if two constraints have the same name.

[source](#)

```
get(model::GenericModel, attr::MathOptInterface.AbstractOptimizerAttribute)
```

Return the value of the attribute attr from the model's MOI backend.

[source](#)

```
get(model::GenericModel, attr::MathOptInterface.AbstractModelAttribute)
```

Return the value of the attribute attr from the model's MOI backend.

[source](#)

MathOptInterface.get! – Function.

```
get!(output, model::ModelLike, args...)
```

An in-place version of [get](#).

The signature matches that of [get](#) except that the result is placed in the vector output.

[source](#)

MathOptInterface.set – Function.

```
function MOI.set(
    model::MOI.ModelLike,
    attr::MOI.AbstractConstraintAttribute,
    bridge::AbstractBridge,
    value,
)
```

Set the value of the attribute attr of the model model for the constraint bridged by bridge.

[source](#)

```
set(optimizer::AbstractOptimizer, attr::AbstractOptimizerAttribute, value)
```

Assign value to the attribute attr of the optimizer optimizer.

```
set(model::ModelLike, attr::AbstractModelAttribute, value)
```

Assign value to the attribute attr of the model model.

```
set(model::ModelLike, attr::AbstractVariableAttribute, v::VariableIndex, value)
```

Assign value to the attribute attr of variable v in model model.

```
set(
    model::ModelLike,
    attr::AbstractVariableAttribute,
    v::Vector{VariableIndex},
    vector_of_values,
)
```

Assign a value respectively to the attribute attr of each variable in the collection v in model model.

```
set(
    model::ModelLike,
    attr::AbstractConstraintAttribute,
    c::ConstraintIndex,
    value,
)
```

Assign a value to the attribute attr of constraint c in model model.

```
set(
    model::ModelLike,
    attr::AbstractConstraintAttribute,
    c::Vector{ConstraintIndex{F,S}},
    vector_of_values,
) where {F,S}
```

Assign a value respectively to the attribute attr of each constraint in the collection c in model model.

An [UnsupportedAttribute](#) error is thrown if model does not support the attribute attr (see [supports](#)) and a [SetAttributeNotAllowed](#) error is thrown if it supports the attribute attr but it cannot be set.

```
set(
    model::ModelLike,
    ::ConstraintSet,
    c::ConstraintIndex{F,S},
    set::S,
) where {F,S}
```

Change the set of constraint c to the new set set which should be of the same type as the original set.

```
set(
    model::ModelLike,
    ::ConstraintFunction,
    c::ConstraintIndex{F,S},
    func::F,
) where {F,S}
```

Replace the function in constraint c with func. F must match the original function type used to define the constraint.

**Note**

Setting the constraint function is not allowed if `F` is `VariableIndex`; a `SettingVariableIndexNotAllowed` error is thrown instead. This is because, it would require changing the index `c` since the index of `VariableIndex` constraints must be the same as the index of the variable.

`source`

```
MOI.set(
    model::Optimizer,
    attr::ConstraintAttribute,
    ci::MOI.ConstraintIndex{MOI.ScalarAffineFunction{Float64}, <:Any},
    value
)
```

Set a constraint attribute.

`source`

```
MOI.set(
    model::Optimizer,
    attr::VariableAttribute,
    vi::MOI.VariableIndex,
    value
)
```

Set a variable attribute.

`source`

```
MOI.set(model::Optimizer, attr::ModelAttribute, value)
```

Set a model attribute.

`source`

`MathOptInterface.supports` – Function.

```
MOI.supports(
    model::MOI.ModelLike,
    attr::MOI.AbstractConstraintAttribute,
    BT::Type{<:AbstractBridge},
)
```

Return a `Bool` indicating whether `BT` supports setting `attr` to `model`.

`source`

```
supports(model::ModelLike, sub::AbstractSubmittable)::Bool
```

Return a Bool indicating whether model supports the submittable sub.

```
supports(model::ModelLike, attr::AbstractOptimizerAttribute)::Bool
```

Return a Bool indicating whether model supports the optimizer attribute attr. That is, it returns false if `copy_to(model, src)` shows a warning in case attr is in the `ListOfOptimizerAttributesSet` of src; see `copy_to` for more details on how unsupported optimizer attributes are handled in copy.

```
supports(model::ModelLike, attr::AbstractModelAttribute)::Bool
```

Return a Bool indicating whether model supports the model attribute attr. That is, it returns false if `copy_to(model, src)` cannot be performed in case attr is in the `ListOfModelAttributeSet` of src.

```
supports(
    model::ModelLike,
    attr::AbstractVariableAttribute,
    ::Type{VariableIndex},
))::Bool
```

Return a Bool indicating whether model supports the variable attribute attr. That is, it returns false if `copy_to(model, src)` cannot be performed in case attr is in the `ListOfVariableAttributesSet` of src.

```
supports(
    model::ModelLike,
    attr::AbstractConstraintAttribute,
    ::Type{ConstraintIndex{F,S}},
))::Bool where {F,S}
```

Return a Bool indicating whether model supports the constraint attribute attr applied to an F-in-S constraint. That is, it returns false if `copy_to(model, src)` cannot be performed in case attr is in the `ListOfConstraintAttributesSet` of src.

For all five methods, if the attribute is only not supported in specific circumstances, it should still return true.

Note that `supports` is only defined for attributes for which `is_copyable` returns true as other attributes do not appear in the list of attributes set obtained by `ListOfXXXAttributesSet`.

#### source

`MathOptInterface.attribute_value_type` - Function.

```
attribute_value_type(attr::AnyAttribute)
```

Given an attribute attr, return the type of value expected by `get`, or returned by `set`.

#### Notes

- Only implement this if it make sense to do so. If un-implemented, the default is Any.

[source](#)

## Model interface

MathOptInterface.ModelLike – Type.

ModelLike

Abstract supertype for objects that implement the "Model" interface for defining an optimization problem.

[source](#)

MathOptInterface.is\_empty – Function.

is\_empty(model::ModelLike)

Returns false if the model has any model attribute set or has any variables or constraints.

Note that an empty model can have optimizer attributes set.

[source](#)

MathOptInterface.empty! – Function.

empty!(model::ModelLike)

Empty the model, that is, remove all variables, constraints and model attributes but not optimizer attributes.

[source](#)

MathOptInterface.write\_to\_file – Function.

write\_to\_file(model::ModelLike, filename::String)

Write the current model to the file at filename.

Supported file types depend on the model type.

[source](#)

MathOptInterface.read\_from\_file – Function.

read\_from\_file(model::ModelLike, filename::String)

Read the file filename into the model model. If model is non-empty, this may throw an error.

Supported file types depend on the model type.

#### Note

Once the contents of the file are loaded into the model, users can query the variables via `get(model, ListOfVariableIndices())`. However, some filetypes, such as LP files, do not maintain an explicit ordering of the variables. Therefore, the returned list may be in an arbitrary order.

To avoid depending on the order of the indices, look up each variable index by name using `get(model, VariableIndex, "name")`.

[source](#)

`MathOptInterface.supports_incremental_interface` – Function.

```
supports_incremental_interface(model::ModelLike)
```

Return a Bool indicating whether model supports building incrementally via `add_variable` and `add_constraint`.

The main purpose of this function is to determine whether a model can be loaded into model incrementally or whether it should be cached and copied at once instead.

[source](#)

`MathOptInterface.copy_to` – Function.

```
copy_to(dest::ModelLike, src::ModelLike)::IndexMap
```

Copy the model from src into dest.

The target dest is emptied, and all previous indices to variables and constraints in dest are invalidated.

Returns an `IndexMap` object that translates variable and constraint indices from the src model to the corresponding indices in the dest model.

#### Notes

- If a constraint that in src is not supported by dest, then an `UnsupportedConstraint` error is thrown.
- If an `AbstractModelAttribute`, `AbstractVariableAttribute`, or `AbstractConstraintAttribute` is set in src but not supported by dest, then an `UnsupportedAttribute` error is thrown.

`AbstractOptimizerAttributes` are not copied to the dest model.

#### IndexMap

Implementations of `copy_to` must return an `IndexMap`. For technical reasons, this type is defined in the Utilities submodule as `MOI.Utilities.IndexMap`. However, since it is an integral part of the MOI API, we provide `MOI.IndexMap` as an alias.

#### Example

```
# Given empty `ModelLike` objects `src` and `dest`.

x = add_variable(src)

is_valid(src, x)    # true
is_valid(dest, x)  # false ('dest' has no variables)

index_map = copy_to(dest, src)
is_valid(dest, x) # false (unless index_map[x] == x)
is_valid(dest, index_map[x]) # true
```

`source`

`MathOptInterface.IndexMap` – Type.

```
IndexMap()
```

The dictionary-like object returned by `copy_to`.

### IndexMap

Implementations of `copy_to` must return an `IndexMap`. For technical reasons, the `IndexMap` type is defined in the Utilities submodule as `MOI.Utilities.IndexMap`. However, since it is an integral part of the MOI API, we provide this `MOI.IndexMap` as an alias.

`source`

### Model attributes

`MathOptInterface.AbstractModelAttribute` – Type.

```
AbstractModelAttribute
```

Abstract supertype for attribute objects that can be used to set or get attributes (properties) of the model.

`source`

`MathOptInterface.Name` – Type.

```
Name()
```

A model attribute for the string identifying the model. It has a default value of "" if not set'.

`source`

`MathOptInterface.ObjectiveFunction` – Type.

```
ObjectiveFunction{F<:AbstractScalarFunction}()
```

A model attribute for the objective function which has a type `F<:AbstractScalarFunction`.

`F` should be guaranteed to be equivalent but not necessarily identical to the function type provided by the user.

Throws an `InexactError` if the objective function cannot be converted to `F`, for example, the objective function is quadratic and `F` is `ScalarAffineFunction{Float64}` or it has non-integer coefficient and `F` is `ScalarAffineFunction{Int}`.

[source](#)

`MathOptInterface.ObjectiveFunctionType` – Type.

```
ObjectiveFunctionType()
```

A model attribute for the type `F` of the objective function set using the `ObjectiveFunction{F}` attribute.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.set(model, MOI.ObjectiveFunction{MOI.VariableIndex}(), x)

julia> MOI.get(model, MOI.ObjectiveFunctionType())
MathOptInterface.VariableIndex
```

[source](#)

`MathOptInterface.ObjectiveSense` – Type.

```
ObjectiveSense()
```

A model attribute for the objective sense of the objective function, which must be an `OptimizationSense`: `MIN_SENSE`, `MAX_SENSE`, or `FEASIBILITY_SENSE`. The default is `FEASIBILITY_SENSE`.

### Interaction with `ObjectiveFunction`

Setting the sense to `FEASIBILITY_SENSE` unsets the `ObjectiveFunction` attribute. That is, if you first set `ObjectiveFunction` and then set `ObjectiveSense` to be `FEASIBILITY_SENSE`, no objective function will be passed to the solver.

In addition, some reformulations of `ObjectiveFunction` via bridges rely on the value of `ObjectiveSense`. Therefore, you should set `ObjectiveSense` before setting `ObjectiveFunction`.

[source](#)

`MathOptInterface.OptimizationSense` – Type.

**OptimizationSense**

An enum for the value of the `ObjectiveSense` attribute.

**Values**

Possible values are:

- `MIN_SENSE`: the goal is to minimize the objective function
- `MAX_SENSE`: the goal is to maximize the objective function
- `FEASIBILITY_SENSE`: the model does not have an objective function

`source`

`MathOptInterface.MIN_SENSE` – Constant.

**MIN\_SENSE::OptimizationSense**

An instance of the `OptimizationSense` enum.

`MIN_SENSE`: the goal is to minimize the objective function

`source`

`MathOptInterface.MAX_SENSE` – Constant.

**MAX\_SENSE::OptimizationSense**

An instance of the `OptimizationSense` enum.

`MAX_SENSE`: the goal is to maximize the objective function

`source`

`MathOptInterface.FEASIBILITY_SENSE` – Constant.

**FEASIBILITY\_SENSE::OptimizationSense**

An instance of the `OptimizationSense` enum.

`FEASIBILITY_SENSE`: the model does not have an objective function

`source`

`MathOptInterface.NumberOfVariables` – Type.

**NumberOfVariables()**

A model attribute for the number of variables in the model.

`source`

MathOptInterface.ListOfVariableIndices – Type.

```
ListOfVariableIndices()
```

A model attribute for the Vector{VariableIndex} of all variable indices present in the model (that is, of length equal to the value of [NumberOfVariables](#) in the order in which they were added).

[source](#)

MathOptInterface.ListOfConstraintTypesPresent – Type.

```
ListOfConstraintTypesPresent()
```

A model attribute for the list of tuples of the form (F,S), where F is a function type and S is a set type indicating that the attribute [NumberOfConstraints{F,S}](#) has a value greater than zero.

[source](#)

MathOptInterface.NumberOfConstraints – Type.

```
NumberOfConstraints{F,S}()
```

A model attribute for the number of constraints of the type F-in-S present in the model.

[source](#)

MathOptInterface.ListOfConstraintIndices – Type.

```
ListOfConstraintIndices{F,S}()
```

A model attribute for the Vector{ConstraintIndex{F,S}} of all constraint indices of type F-in-S in the model (that is, of length equal to the value of [NumberOfConstraints{F,S}](#)) in the order in which they were added.

[source](#)

MathOptInterface.ListOfOptimizerAttributesSet – Type.

```
ListOfOptimizerAttributesSet()
```

An optimizer attribute for the Vector{AbstractOptimizerAttribute} of all optimizer attributes that were set.

[source](#)

MathOptInterface.ListOfModelAttributesSet – Type.

```
List0fModelAttributesSet()
```

A model attribute for the Vector{AbstractModelAttribute} of all model attributes attr such that:

1. `is_copyable(attr)` returns true, and
2. the attribute was set to the model

`source`

`MathOptInterface.List0fVariableAttributesSet` – Type.

```
List0fVariableAttributesSet()
```

A model attribute for the Vector{AbstractVariableAttribute} of all variable attributes attr such that  
1) `is_copyable(attr)` returns true and 2) the attribute was set to variables.

`source`

`MathOptInterface.List0fVariablesWithAttributeSet` – Type.

```
List0fVariablesWithAttributeSet(attr::AbstractVariableAttribute)
```

A model attribute for the Vector{VariableIndex} of all variables with the attribute attr set.

The returned list may not be minimal, so some elements may have their default value set.

**Note**

This is an optional attribute to implement. The default fallback is to get `List0fVariableIndices`.

`source`

`MathOptInterface.List0fConstraintAttributesSet` – Type.

```
List0fConstraintAttributesSet{F, S}()
```

A model attribute for the Vector{AbstractConstraintAttribute} of all constraint attributes attr such that:

1. `is_copyable(attr)` returns true and
2. the attribute was set to F-in-S constraints.

**Note**

The attributes `ConstraintFunction` and `ConstraintSet` should not be included in the list even if they have been set with `set`.

`source`

`MathOptInterface.List0fConstraintsWithAttributeSet` – Type.

```
ListofConstraintsWithAttributeSet{F,S}(attr:AbstractConstraintAttribute)
```

A model attribute for the `Vector{ConstraintIndex{F,S}}` of all constraints with the attribute `attr` set.

The returned list may not be minimal, so some elements may have their default value set.

#### Note

This is an optional attribute to implement. The default fallback is to get [List<sup>of</sup>ConstraintIndices](#).

`source`

`MathOptInterface.UserDefinedFunction` - Type.

```
UserDefinedFunction(name::Symbol, arity::Int) <: AbstractModelAttribute
```

Set this attribute to register a user-defined function by the name of `name` with `arity` arguments.

Once registered, `name` will appear in [List<sup>of</sup>SupportedNonlinearOperators](#).

You cannot register multiple `UserDefinedFunctions` with the same name but different `arity`.

#### Value type

The value to be set is a tuple containing one, two, or three functions to evaluate the function, the first-order derivative, and the second-order derivative respectively. Both derivatives are optional, but if you pass the second-order derivative you must also pass the first-order derivative.

For univariate functions with `arity == 1`, the functions in the tuple must have the form:

- `f(x)::T`: returns the value of the function at `x`
- `∇f(x)::T`: returns the first-order derivative of `f` with respect to `x`
- `∇²f(x)::T`: returns the second-order derivative of `f` with respect to `x`.

For multivariate functions with `arity > 1`, the functions in the tuple must have the form:

- `f(x::T...)::T`: returns the value of the function at `x`
- `∇f(g::AbstractVector{T}, x::T...)::Nothing`: fills the components of `g`, with `g[i]` being the first-order partial derivative of `f` with respect to `x[i]`
- `∇²f(H::AbstractMatrix{T}, x::T...)::Nothing`: fills the non-zero components of `H`, with `H[i, j]` being the second-order partial derivative of `f` with respect to `x[i]` and then `x[j]`. `H` is initialized to the zero matrix, so you do not need to set any zero elements.

#### Example

```
julia> import MathOptInterface as MOI

julia> f(x, y) = x^2 + y^2
f (generic function with 1 method)

julia> function ∇f(g, x, y)
    g .= 2 * x, 2 * y
```

```

        return
    end
∇f (generic function with 1 method)

julia> function ∇²f(H, x...)
    H[1, 1] = H[2, 2] = 2.0
    return
end
∇²f (generic function with 1 method)

julia> model = MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}());

julia> MOI.set(model, MOI.UserDefinedFunction(:f, 2), (f,))
julia> MOI.set(model, MOI.UserDefinedFunction(:g, 2), (f, ∇f))
julia> MOI.set(model, MOI.UserDefinedFunction(:h, 2), (f, ∇f, ∇²f))

julia> x = MOI.add_variables(model, 2)
2-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(1)
 MOI.VariableIndex(2)

julia> MOI.set(model, MOI.ObjectiveSense(), MOI.MIN_SENSE)

julia> obj_f = MOI.ScalarNonlinearFunction(:f, Any[x[1], x[2]])
f(MOI.VariableIndex(1), MOI.VariableIndex(2))

julia> MOI.set(model, MOI.ObjectiveFunction{typeof(obj_f)}(), obj_f)

julia> print(model)
Minimize ScalarNonlinearFunction:
f(v[1], v[2])

Subject to:
```

**source**

MathOptInterface.ListOfSupportedNonlinearOperators - Type.

```
ListOfSupportedNonlinearOperators() <: AbstractModelAttribute
```

When queried with `get`, return a `Vector{Symbol}` listing the operators supported by the model.

**source**

## Optimizer interface

MathOptInterface.AbstractOptimizer - Type.

```
AbstractOptimizer <: ModelLike
```

Abstract supertype for objects representing an instance of an optimization problem tied to a particular solver. This is typically a solver's in-memory representation. In addition to `ModelLike`, `AbstractOptimizer` objects let you solve the model and query the solution.

`source`

`MathOptInterface.OptimizerWithAttributes` – Type.

```
struct OptimizerWithAttributes
    optimizer_constructor
    params::Vector{Pair{AbstractOptimizerAttribute,<:Any}}
end
```

Object grouping an optimizer constructor and a list of optimizer attributes. Instances are created with `instantiate`.

`source`

`MathOptInterface.optimize!` – Function.

```
optimize!(optimizer::AbstractOptimizer)
```

Optimize the problem contained in `optimizer`.

Before calling `optimize!`, the problem should first be constructed using the incremental interface (see `supports_incremental_interface`) or `copy_to`.

`source`

`MathOptInterface.optimize!` – Method.

```
optimize!(dest::AbstractOptimizer, src::ModelLike)::Tuple{IndexMap,Bool}
```

A "one-shot" call that copies the problem from `src` into `dest` and then uses `dest` to optimize the problem.

Returns a tuple of an `IndexMap` and a `Bool` copied.

- The `IndexMap` object translates variable and constraint indices from the `src` model to the corresponding indices in the `dest` optimizer. See `copy_to` for details.
- If `copied == true`, `src` was copied to `dest` and then cached, allowing incremental modification if supported by the solver.
- If `copied == false`, a cache of the model was *not* kept in `dest`. Therefore, only the solution information (attributes for which `is_set_by_optimize` is true) is available to query.

**Note**

The main purpose of `optimize!` method with two arguments is for use in `Utilities.CachingOptimizer`.

**Relationship to the single-argument `optimize!`**

The default fallback of `optimize!(dest::AbstractOptimizer, src::ModelLike)` is

```
function optimize!(dest::AbstractOptimizer, src::ModelLike)
    index_map = copy_to(dest, src)
    optimize!(dest)
    return index_map, true
end
```

Therefore, subtypes of `AbstractOptimizer` should either implement this two-argument method, or implement both `copy_to(::Optimizer, ::ModelLike)` and `optimize!(::Optimizer)`.

`source`

`MathOptInterface.instantiate` - Function.

```
instantiate(
    optimizer_constructor,
    with_cache_type::Union{Nothing,Type} = nothing,
    with_bridge_type::Union{Nothing,Type} = nothing,
)
```

Create an instance of an optimizer by either:

- calling `optimizer_constructor.optimizer_constructor()` and setting the parameters in `optimizer_constructor.p` if `optimizer_constructor` is a `OptimizerWithAttributes`
- calling `optimizer_constructor()` if `optimizer_constructor` is callable.

**withcachetype**

If `with_cache_type` is not `nothing`, then the optimizer is wrapped in a `Utilities.CachingOptimizer` to store a cache of the model. This is most useful if the optimizer you are constructing does not support the incremental interface (see `supports_incremental_interface`).

**withbridgetype**

If `with_bridge_type` is not `nothing`, the optimizer is wrapped in a `Bridges.full_bridge_optimizer`, enabling all the bridges defined in the `MOI.Bridges` submodule with coefficient type `with_bridge_type`.

In addition, if the optimizer created by `optimizer_constructor` does not support the incremental interface (see `supports_incremental_interface`), then, irrespective of `with_cache_type`, the optimizer is wrapped in a `Utilities.CachingOptimizer` to store a cache of the bridged model.

If `with_cache_type` and `with_bridge_type` are both `nothing`, then they must be the same type.

`source`

`MathOptInterface.default_cache` - Function.

```
default_cache(optimizer::ModelLike, ::Type{T}) where {T}
```

Return a new instance of the default model type to be used as cache for optimizer in a `Utilities.CachingOptimizer` for holding constraints of coefficient type T. By default, this returns `Utilities.UniversalFallback(Utilities.Model{T}())`. If copying from a instance of a given model type is faster for optimizer then a new method returning an instance of this model type should be defined.

[source](#)

## Optimizer attributes

`MathOptInterface.AbstractOptimizerAttribute` – Type.

```
AbstractOptimizerAttribute
```

Abstract supertype for attribute objects that can be used to set or get attributes (properties) of the optimizer.

### Notes

The difference between `AbstractOptimizerAttribute` and `AbstractModelAttribute` lies in the behavior of `is_empty`, `empty!` and `copy_to`. Typically optimizer attributes affect only how the model is solved.

[source](#)

`MathOptInterface.SolverName` – Type.

```
SolverName()
```

An optimizer attribute for the string identifying the solver/optimizer.

[source](#)

`MathOptInterface.SolverVersion` – Type.

```
SolverVersion()
```

An optimizer attribute for the string identifying the version of the solver.

### Note

For solvers supporting [semantic versioning](#), the `SolverVersion` should be a string of the form "`vMAJOR.MINOR.PATCH`", so that it can be converted to a Julia `VersionNumber` (for example, `VersionNumber("v1.2.3")`).

We do not require Semantic Versioning because some solvers use alternate versioning systems. For example, CPLEX uses Calendar Versioning, so `SolverVersion` will return a string like "202001".

[source](#)

MathOptInterface.Silent - Type.

```
Silent()
```

An optimizer attribute for silencing the output of an optimizer. When set to true, it takes precedence over any other attribute controlling verbosity and requires the solver to produce no output. The default value is false which has no effect. In this case the verbosity is controlled by other attributes.

**Note**

Every optimizer should have verbosity on by default. For instance, if a solver has a solver-specific log level attribute, the MOI implementation should set it to 1 by default. If the user sets Silent to true, then the log level should be set to 0, even if the user specifically sets a value of log level. If the value of Silent is false then the log level set to the solver is the value given by the user for this solver-specific parameter or 1 if none is given.

[source](#)

MathOptInterface.TimeLimitSec - Type.

```
TimeLimitSec()
```

An optimizer attribute for setting a time limit (in seconds) for an optimization. When set to nothing, it deactivates the solver time limit. The default value is nothing.

[source](#)

MathOptInterface.ObjectiveLimit - Type.

```
ObjectiveLimit()
```

An optimizer attribute for setting a limit on the objective value.

The provided limit must be a Union{Real, Nothing}.

When set to nothing, the limit reverts to the solver's default.

The default value is nothing.

The solver may stop when the [ObjectiveValue](#) is better (lower for minimization, higher for maximization) than the ObjectiveLimit. If stopped, the [TerminationStatus](#) should be OBJECTIVE\_LIMIT.

[source](#)

MathOptInterface.SolutionLimit - Type.

```
SolutionLimit()
```

An optimizer attribute for setting a limit on the number of available feasible solutions.

**Default values**

The provided limit must be a Union{Nothing, Int}.

When set to nothing, the limit reverts to the solver's default.

The default value is nothing.

#### Termination criteria

The solver may stop when the `ResultCount` is larger than or equal to the `SolutionLimit`. If stopped because of this attribute, the `TerminationStatus` must be `SOLUTION_LIMIT`.

#### Solution quality

The quality of the available solutions is solver-dependent. The set of resulting solutions is not guaranteed to contain an optimal solution.

`source`

`MathOptInterface.NodeLimit` – Type.

```
NodeLimit()
```

An optimizer attribute for setting a limit on the number of branch-and-bound nodes explored by a mixed-integer program (MIP) solver.

#### Default values

The provided limit must be a Union{Nothing, Int}.

When set to nothing, the limit reverts to the solver's default.

The default value is nothing.

#### Termination criteria

The solver may stop when the `NodeCount` is larger than or equal to the `NodeLimit`. If stopped because of this attribute, the `TerminationStatus` must be `NODE_LIMIT`.

`source`

`MathOptInterface.RawOptimizerAttribute` – Type.

```
RawOptimizerAttribute(name: :String)
```

An optimizer attribute for the solver-specific parameter identified by name.

`source`

`MathOptInterface.NumberOfThreads` – Type.

```
NumberOfThreads()
```

An optimizer attribute for setting the number of threads used for an optimization. When set to nothing uses solver default. Values are positive integers. The default value is nothing.

`source`

`MathOptInterface.RawSolver` – Type.

```
RawSolver()
```

A model attribute for the object that may be used to access a solver-specific API for this optimizer.

[source](#)

`MathOptInterface.AbsoluteGapTolerance` – Type.

```
AbsoluteGapTolerance()
```

An optimizer attribute for setting the absolute gap tolerance for an optimization. This is an *optimizer* attribute, and should be set before calling `optimize!`. When set to nothing (if supported), uses solver default.

To set a *relative* gap tolerance, see [RelativeGapTolerance](#).

#### Warning

The mathematical definition of "absolute gap", and its treatment during the optimization, are solver-dependent. However, assuming no other limit nor issue is encountered during the optimization, most solvers that implement this attribute will stop once  $|f - b| g_{abs}$ , where  $b$  is the best bound,  $f$  is the best feasible objective value, and  $g_{abs}$  is the absolute gap.

[source](#)

`MathOptInterface.RelativeGapTolerance` – Type.

```
RelativeGapTolerance()
```

An optimizer attribute for setting the relative gap tolerance for an optimization. This is an *optimizer* attribute, and should be set before calling `optimize!`. When set to nothing (if supported), uses solver default.

If you are looking for the relative gap of the current best solution, see [RelativeGap](#). If no limit nor issue is encountered during the optimization, the value of `RelativeGap` should be at most as large as `RelativeGapTolerance`.

```
# Before optimizing: set relative gap tolerance
# set 0.1% relative gap tolerance
MOI.set(model, MOI.RelativeGapTolerance(), 1e-3)
MOI.optimize!(model)

# After optimizing (assuming all went well)
# The relative gap tolerance has not changed...
MOI.get(model, MOI.RelativeGapTolerance()) # returns 1e-3
# ... and the relative gap of the obtained solution is smaller or equal to the
# tolerance
MOI.get(model, MOI.RelativeGap()) # should return something <= 1e-3
```

**Warning**

The mathematical definition of "relative gap", and its allowed range, are solver-dependent. Typically, solvers expect a value between 0.0 and 1.0.

[source](#)

`MathOptInterface.AutomaticDifferentiationBackend` – Type.

`AutomaticDifferentiationBackend() <: AbstractOptimizerAttribute`

An [AbstractOptimizerAttribute](#) for setting the automatic differentiation backend used by the solver.

The value must be a subtype of [Nonlinear.AbstractAutomaticDifferentiation](#).

[source](#)

List of attributes useful for optimizers

`MathOptInterface.TerminationStatus` – Type.

`TerminationStatus()`

A model attribute for the `TerminationStatusCode` explaining why the optimizer stopped.

[source](#)

`MathOptInterface.TerminationStatusCode` – Type.

`TerminationStatusCode`

An Enum of possible values for the `TerminationStatus` attribute. This attribute is meant to explain the reason why the optimizer stopped executing in the most recent call to [optimize!](#).

**Values**

Possible values are:

- [OPTIMIZE\\_NOT\\_CALLED](#): The algorithm has not started.
- [OPTIMAL](#): The algorithm found a globally optimal solution.
- [INFEASIBLE](#): The algorithm concluded that no feasible solution exists.
- [DUAL\\_INFEASIBLE](#): The algorithm concluded that no dual bound exists for the problem. If, additionally, a feasible (primal) solution is known to exist, this status typically implies that the problem is unbounded, with some technical exceptions.
- [LOCALLY\\_SOLVED](#): The algorithm converged to a stationary point, local optimal solution, could not find directions for improvement, or otherwise completed its search without global guarantees.
- [LOCALLY\\_INFEASIBLE](#): The algorithm converged to an infeasible point or otherwise completed its search without finding a feasible solution, without guarantees that no feasible solution exists.

- [INFEASIBLE\\_OR\\_UNBOUNDED](#): The algorithm stopped because it decided that the problem is infeasible or unbounded; this occasionally happens during MIP presolve.
- [ALMOST\\_OPTIMAL](#): The algorithm found a globally optimal solution to relaxed tolerances.
- [ALMOST\\_INFEASIBLE](#): The algorithm concluded that no feasible solution exists within relaxed tolerances.
- [ALMOST\\_DUAL\\_INFEASIBLE](#): The algorithm concluded that no dual bound exists for the problem within relaxed tolerances.
- [ALMOST\\_LOCALLY\\_SOLVED](#): The algorithm converged to a stationary point, local optimal solution, or could not find directions for improvement within relaxed tolerances.
- [ITERATION\\_LIMIT](#): An iterative algorithm stopped after conducting the maximum number of iterations.
- [TIME\\_LIMIT](#): The algorithm stopped after a user-specified computation time.
- [NODE\\_LIMIT](#): A branch-and-bound algorithm stopped because it explored a maximum number of nodes in the branch-and-bound tree.
- [SOLUTION\\_LIMIT](#): The algorithm stopped because it found the required number of solutions. This is often used in MIPs to get the solver to return the first feasible solution it encounters.
- [MEMORY\\_LIMIT](#): The algorithm stopped because it ran out of memory.
- [OBJECTIVE\\_LIMIT](#): The algorithm stopped because it found a solution better than a minimum limit set by the user.
- [NORM\\_LIMIT](#): The algorithm stopped because the norm of an iterate became too large.
- [OTHER\\_LIMIT](#): The algorithm stopped due to a limit not covered by one of the \_LIMIT\_ statuses above.
- [SLOW\\_PROGRESS](#): The algorithm stopped because it was unable to continue making progress towards the solution.
- [NUMERICAL\\_ERROR](#): The algorithm stopped because it encountered unrecoverable numerical error.
- [INVALID\\_MODEL](#): The algorithm stopped because the model is invalid.
- [INVALID\\_OPTION](#): The algorithm stopped because it was provided an invalid option.
- [INTERRUPTED](#): The algorithm stopped because of an interrupt signal.
- [OTHER\\_ERROR](#): The algorithm stopped because of an error not covered by one of the statuses defined above.

[source](#)

MathOptInterface.OPTIMIZE\_NOT\_CALLED – Constant.

OPTIMIZE\_NOT\_CALLED::[TerminationStatusCode](#)

An instance of the [TerminationStatusCode](#) enum.

OPTIMIZE\_NOT\_CALLED: The algorithm has not started.

[source](#)

MathOptInterface.OPTIMAL – Constant.

**OPTIMAL::TerminationStatusCode**

An instance of the [TerminationStatusCode](#) enum.

OPTIMAL: The algorithm found a globally optimal solution.

[source](#)

`MathOptInterface.INFEASIBLE` – Constant.

**INFEASIBLE::TerminationStatusCode**

An instance of the [TerminationStatusCode](#) enum.

INFEASIBLE: The algorithm concluded that no feasible solution exists.

[source](#)

`MathOptInterface.DUAL_INFEASIBLE` – Constant.

**DUAL\_INFEASIBLE::TerminationStatusCode**

An instance of the [TerminationStatusCode](#) enum.

DUAL\_INFEASIBLE: The algorithm concluded that no dual bound exists for the problem. If, additionally, a feasible (primal) solution is known to exist, this status typically implies that the problem is unbounded, with some technical exceptions.

[source](#)

`MathOptInterface.LOCALLY_SOLVED` – Constant.

**LOCALLY\_SOLVED::TerminationStatusCode**

An instance of the [TerminationStatusCode](#) enum.

LOCALLY\_SOLVED: The algorithm converged to a stationary point, local optimal solution, could not find directions for improvement, or otherwise completed its search without global guarantees.

[source](#)

`MathOptInterface.LOCALLY_INFEASIBLE` – Constant.

**LOCALLY\_INFEASIBLE::TerminationStatusCode**

An instance of the [TerminationStatusCode](#) enum.

LOCALLY\_INFEASIBLE: The algorithm converged to an infeasible point or otherwise completed its search without finding a feasible solution, without guarantees that no feasible solution exists.

[source](#)

MathOptInterface.INFEASIBLE\_OR\_UNBOUNDED – Constant.

```
INFEASIBLE_OR_UNBOUNDED::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

INFEASIBLE\_OR\_UNBOUNDED: The algorithm stopped because it decided that the problem is infeasible or unbounded; this occasionally happens during MIP presolve.

[source](#)

MathOptInterface.ALMOST\_OPTIMAL – Constant.

```
ALMOST_OPTIMAL::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

ALMOST\_OPTIMAL: The algorithm found a globally optimal solution to relaxed tolerances.

[source](#)

MathOptInterface.ALMOST\_INFEASIBLE – Constant.

```
ALMOST_INFEASIBLE::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

ALMOST\_INFEASIBLE: The algorithm concluded that no feasible solution exists within relaxed tolerances.

[source](#)

MathOptInterface.ALMOST\_DUAL\_INFEASIBLE – Constant.

```
ALMOST_DUAL_INFEASIBLE::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

ALMOST\_DUAL\_INFEASIBLE: The algorithm concluded that no dual bound exists for the problem within relaxed tolerances.

[source](#)

MathOptInterface.ALMOST\_LOCALLY\_SOLVED – Constant.

```
ALMOST_LOCALLY_SOLVED::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

ALMOST\_LOCALLY\_SOLVED: The algorithm converged to a stationary point, local optimal solution, or could not find directions for improvement within relaxed tolerances.

[source](#)

MathOptInterface.ITERATION\_LIMIT – Constant.

```
ITERATION_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

ITERATION\_LIMIT: An iterative algorithm stopped after conducting the maximum number of iterations.

[source](#)

MathOptInterface.TIME\_LIMIT – Constant.

```
TIME_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

TIME\_LIMIT: The algorithm stopped after a user-specified computation time.

[source](#)

MathOptInterface.NODE\_LIMIT – Constant.

```
NODE_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

NODE\_LIMIT: A branch-and-bound algorithm stopped because it explored a maximum number of nodes in the branch-and-bound tree.

[source](#)

MathOptInterface.SOLUTION\_LIMIT – Constant.

```
SOLUTION_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

SOLUTION\_LIMIT: The algorithm stopped because it found the required number of solutions. This is often used in MIPs to get the solver to return the first feasible solution it encounters.

[source](#)

MathOptInterface.MEMORY\_LIMIT – Constant.

```
MEMORY_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

MEMORY\_LIMIT: The algorithm stopped because it ran out of memory.

[source](#)

MathOptInterface.OBJECTIVE\_LIMIT – Constant.

```
OBJECTIVE_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

OBJECTIVE\_LIMIT: The algorithm stopped because it found a solution better than a minimum limit set by the user.

[source](#)

MathOptInterface.NORM\_LIMIT – Constant.

```
NORM_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

NORM\_LIMIT: The algorithm stopped because the norm of an iterate became too large.

[source](#)

MathOptInterface.OTHER\_LIMIT – Constant.

```
OTHER_LIMIT::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

OTHER\_LIMIT: The algorithm stopped due to a limit not covered by one of the \_LIMIT\_ statuses above.

[source](#)

MathOptInterface.SLOW\_PROGRESS – Constant.

```
SLOW_PROGRESS::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

SLOW\_PROGRESS: The algorithm stopped because it was unable to continue making progress towards the solution.

[source](#)

MathOptInterface.NUMERICAL\_ERROR – Constant.

```
NUMERICAL_ERROR::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

NUMERICAL\_ERROR: The algorithm stopped because it encountered unrecoverable numerical error.

[source](#)

MathOptInterface.INVALID\_MODEL – Constant.

```
INVALID_MODEL::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

INVALID\_MODEL: The algorithm stopped because the model is invalid.

[source](#)

MathOptInterface.INVALID\_OPTION – Constant.

```
INVALID_OPTION::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

INVALID\_OPTION: The algorithm stopped because it was provided an invalid option.

[source](#)

MathOptInterface.INTERRUPTED – Constant.

```
INTERRUPTED::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

INTERRUPTED: The algorithm stopped because of an interrupt signal.

[source](#)

MathOptInterface.OTHER\_ERROR – Constant.

```
OTHER_ERROR::TerminationStatusCode
```

An instance of the [TerminationStatusCode](#) enum.

OTHER\_ERROR: The algorithm stopped because of an error not covered by one of the statuses defined above.

[source](#)

MathOptInterface.PrimalStatus – Type.

```
PrimalStatus(result_index:Int = 1)
```

A model attribute for the [ResultStatusCode](#) of the primal result `result_index`. If `result_index` is omitted, it defaults to 1.

See [ResultCount](#) for information on how the results are ordered.

If `result_index` is larger than the value of [ResultCount](#) then `NO_SOLUTION` is returned.

[source](#)

MathOptInterface.DualStatus – Type.

```
DualStatus(result_index::Int = 1)
```

A model attribute for the ResultStatusCode of the dual result result\_index. If result\_index is omitted, it defaults to 1.

See [ResultCount](#) for information on how the results are ordered.

If result\_index is larger than the value of [ResultCount](#) then NO\_SOLUTION is returned.

[source](#)

MathOptInterface.RawStatusString – Type.

```
RawStatusString()
```

A model attribute for a solver specific string explaining why the optimizer stopped.

[source](#)

MathOptInterface.ResultCount – Type.

```
ResultCount()
```

A model attribute for the number of results available.

### Order of solutions

A number of attributes contain an index, result\_index, which is used to refer to one of the available results. Thus, result\_index must be an integer between 1 and the number of available results.

As a general rule, the first result (result\_index=1) is the most important result (for example, an optimal solution or an infeasibility certificate). Other results will typically be alternate solutions that the solver found during the search for the first result.

If a (local) optimal solution is available, that is, [TerminationStatus](#) is OPTIMAL or LOCALLY\_SOLVED, the first result must correspond to the (locally) optimal solution. Other results may be alternative optimal solutions, or they may be other suboptimal solutions; use [ObjectiveValue](#) to distinguish between them.

If a primal or dual infeasibility certificate is available, that is, [TerminationStatus](#) is INFEASIBLE or DUAL\_INFEASIBLE and the corresponding [PrimalStatus](#) or [DualStatus](#) is INFEASIBILITY\_CERTIFICATE, then the first result must be a certificate. Other results may be alternate certificates, or infeasible points.

[source](#)

MathOptInterface.ObjectiveValue – Type.

```
ObjectiveValue(result_index::Int = 1)
```

A model attribute for the objective value of the primal solution result\_index.

If the solver does not have a primal value for the objective because the `result_index` is beyond the available solutions (whose number is indicated by the `ResultCount` attribute), getting this attribute must throw a `ResultIndexBoundsError`. Otherwise, if the result is unavailable for another reason (for instance, only a dual solution is available), the result is undefined. Users should first check `PrimalStatus` before accessing the `ObjectiveValue` attribute.

See `ResultCount` for information on how the results are ordered.

[source](#)

`MathOptInterface.DualObjectiveValue` – Type.

```
DualObjectiveValue(result_index::Int = 1)
```

A model attribute for the value of the objective function of the dual problem for the `result_index`th dual result.

If the solver does not have a dual value for the objective because the `result_index` is beyond the available solutions (whose number is indicated by the `ResultCount` attribute), getting this attribute must throw a `ResultIndexBoundsError`. Otherwise, if the result is unavailable for another reason (for instance, only a primal solution is available), the result is undefined. Users should first check `DualStatus` before accessing the `DualObjectiveValue` attribute.

See `ResultCount` for information on how the results are ordered.

[source](#)

`MathOptInterface.ObjectiveBound` – Type.

```
ObjectiveBound()
```

A model attribute for the best known bound on the optimal objective value.

[source](#)

`MathOptInterface.RelativeGap` – Type.

```
RelativeGap()
```

A model attribute for the final relative optimality gap.

### Warning

The definition of this gap is solver-dependent. However, most solvers implementing this attribute define the relative gap as some variation of  $\frac{|b-f|}{|f|}$ , where  $b$  is the best bound and  $f$  is the best feasible objective value.

[source](#)

`MathOptInterface.SolveTimeSec` – Type.

```
SolveTimeSec()
```

A model attribute for the total elapsed solution time (in seconds) as reported by the optimizer.

[source](#)

`MathOptInterface.SimplexIterations` – Type.

```
SimplexIterations()
```

A model attribute for the cumulative number of simplex iterations during the optimization process.

For a mixed-integer program (MIP), the return value is the total simplex iterations for all nodes.

[source](#)

`MathOptInterface.BarrierIterations` – Type.

```
BarrierIterations()
```

A model attribute for the cumulative number of barrier iterations while solving a problem.

[source](#)

`MathOptInterface.NodeCount` – Type.

```
NodeCount()
```

A model attribute for the total number of branch-and-bound nodes explored while solving a mixed-integer program (MIP).

[source](#)

### **ResultStatusCode**

`MathOptInterface.ResultStatusCode` – Type.

```
ResultStatusCode
```

An Enum of possible values for the `PrimalStatus` and `DualStatus` attributes.

The values indicate how to interpret the result vector.

#### **Values**

Possible values are:

- `NO_SOLUTION`: the result vector is empty.
- `FEASIBLE_POINT`: the result vector is a feasible point.

- [NEARLY\\_FEASIBLE\\_POINT](#): the result vector is feasible if some constraint tolerances are relaxed.
- [INFEASIBLE\\_POINT](#): the result vector is an infeasible point.
- [INFEASIBILITY\\_CERTIFICATE](#): the result vector is an infeasibility certificate. If the PrimalStatus is INFEASIBILITY\_CERTIFICATE, then the primal result vector is a certificate of dual infeasibility. If the DualStatus is INFEASIBILITY\_CERTIFICATE, then the dual result vector is a proof of primal infeasibility.
- [NEARLY\\_INFEASIBILITY\\_CERTIFICATE](#): the result satisfies a relaxed criterion for a certificate of infeasibility.
- [REDUCTION\\_CERTIFICATE](#): the result vector is an ill-posed certificate; see [this article](#) for details. If the PrimalStatus is REDUCTION\_CERTIFICATE, then the primal result vector is a proof that the dual problem is ill-posed. If the DualStatus is REDUCTION\_CERTIFICATE, then the dual result vector is a proof that the primal is ill-posed.
- [NEARLY\\_REDUCTION\\_CERTIFICATE](#): the result satisfies a relaxed criterion for an ill-posed certificate.
- [UNKNOWN\\_RESULT\\_STATUS](#): the result vector contains a solution with an unknown interpretation.
- [OTHER\\_RESULT\\_STATUS](#): the result vector contains a solution with an interpretation not covered by one of the statuses defined above

[source](#)

MathOptInterface.NO\_SOLUTION – Constant.

**NO\_SOLUTION**:[ResultStatusCode](#)An instance of the [ResultStatusCode](#) enum.

NO\_SOLUTION: the result vector is empty.

[source](#)

MathOptInterface.FEASIBLE\_POINT – Constant.

**FEASIBLE\_POINT**:[ResultStatusCode](#)An instance of the [ResultStatusCode](#) enum.

FEASIBLE\_POINT: the result vector is a feasible point.

[source](#)

MathOptInterface.NEARLY\_FEASIBLE\_POINT – Constant.

**NEARLY\_FEASIBLE\_POINT**:[ResultStatusCode](#)An instance of the [ResultStatusCode](#) enum.

NEARLY\_FEASIBLE\_POINT: the result vector is feasible if some constraint tolerances are relaxed.

[source](#)

MathOptInterface.INFEASIBLE\_POINT – Constant.

**INFEASIBLE\_POINT::ResultStatusCode**

An instance of the [ResultStatusCode](#) enum.

INFEASIBLE\_POINT: the result vector is an infeasible point.

[source](#)

MathOptInterface.INFEASIBILITY\_CERTIFICATE – Constant.

**INFEASIBILITY\_CERTIFICATE::ResultStatusCode**

An instance of the [ResultStatusCode](#) enum.

INFEASIBILITY\_CERTIFICATE: the result vector is an infeasibility certificate. If the PrimalStatus is INFEASIBILITY\_CERTIFICATE, then the primal result vector is a certificate of dual infeasibility. If the DualStatus is INFEASIBILITY\_CERTIFICATE, then the dual result vector is a proof of primal infeasibility.

[source](#)

MathOptInterface.NEARLY\_INFEASIBILITY\_CERTIFICATE – Constant.

**NEARLY\_INFEASIBILITY\_CERTIFICATE::ResultStatusCode**

An instance of the [ResultStatusCode](#) enum.

NEARLY\_INFEASIBILITY\_CERTIFICATE: the result satisfies a relaxed criterion for a certificate of infeasibility.

[source](#)

MathOptInterface.REDUCTION\_CERTIFICATE – Constant.

**REDUCTION\_CERTIFICATE::ResultStatusCode**

An instance of the [ResultStatusCode](#) enum.

REDUCTION\_CERTIFICATE: the result vector is an ill-posed certificate; see [this article](#) for details. If the PrimalStatus is REDUCTION\_CERTIFICATE, then the primal result vector is a proof that the dual problem is ill-posed. If the DualStatus is REDUCTION\_CERTIFICATE, then the dual result vector is a proof that the primal is ill-posed.

[source](#)

MathOptInterface.NEARLY\_REDUCTION\_CERTIFICATE – Constant.

**NEARLY\_REDUCTION\_CERTIFICATE::ResultStatusCode**

An instance of the [ResultStatusCode](#) enum.

NEARLY\_REDUCTION\_CERTIFICATE: the result satisfies a relaxed criterion for an ill-posed certificate.

[source](#)

MathOptInterface.UNKNOWN\_RESULT\_STATUS – Constant.

```
UNKNOWN_RESULT_STATUS::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

UNKNOWN\_RESULT\_STATUS: the result vector contains a solution with an unknown interpretation.

[source](#)

MathOptInterface.OTHER\_RESULT\_STATUS – Constant.

```
OTHER_RESULT_STATUS::ResultStatusCode
```

An instance of the [ResultStatusCode](#) enum.

OTHER\_RESULT\_STATUS: the result vector contains a solution with an interpretation not covered by one of the statuses defined above

[source](#)

### Conflict Status

MathOptInterface.compute\_conflict! – Function.

```
compute_conflict!(optimizer::AbstractOptimizer)
```

Computes a minimal subset of constraints such that the model with the other constraint removed is still infeasible.

Some solvers call a set of conflicting constraints an Irreducible Inconsistent Subsystem (IIS).

See also [ConflictStatus](#) and [ConstraintConflictStatus](#).

#### Note

If the model is modified after a call to `compute_conflict!`, the implementor is not obliged to purge the conflict. Any calls to the above attributes may return values for the original conflict without a warning. Similarly, when modifying the model, the conflict can be discarded.

[source](#)

MathOptInterface.ConflictStatus – Type.

```
ConflictStatus()
```

A model attribute for the [ConflictStatusCode](#) explaining why the conflict refiner stopped when computing the conflict.

[source](#)

MathOptInterface.ConstraintConflictStatus – Type.

```
ConstraintConflictStatus()
```

A constraint attribute indicating whether the constraint participates in the conflict. Its type is [ConflictParticipationStatus](#).  
[source](#)

MathOptInterface.ConflictStatusCode – Type.

```
ConflictStatusCode
```

An Enum of possible values for the ConflictStatus attribute. This attribute is meant to explain the reason why the conflict finder stopped executing in the most recent call to [compute\\_conflict!](#).

Possible values are:

- COMPUTE\_CONFLICT\_NOT\_CALLED: the function [compute\\_conflict!](#) has not yet been called
- NO\_CONFLICT\_EXISTS: there is no conflict because the problem is feasible
- NO\_CONFLICT\_FOUND: the solver could not find a conflict
- CONFLICT\_FOUND: at least one conflict could be found

```
source
```

MathOptInterface.ConflictParticipationStatusCode – Type.

```
ConflictParticipationStatusCode
```

An Enum of possible values for the [ConstraintConflictStatus](#) attribute. This attribute is meant to indicate whether a given constraint participates or not in the last computed conflict.

### Values

Possible values are:

- [NOT\\_IN\\_CONFLICT](#): the constraint does not participate in the conflict
- [IN\\_CONFLICT](#): the constraint participates in the conflict
- [MAYBE\\_IN\\_CONFLICT](#): the constraint may participate in the conflict, the solver was not able to prove that the constraint can be excluded from the conflict

```
source
```

MathOptInterface.NOT\_IN\_CONFLICT – Constant.

```
NOT_IN_CONFLICT::ConflictParticipationStatusCode
```

An instance of the [ConflictParticipationStatusCode](#) enum.

[NOT\\_IN\\_CONFLICT](#): the constraint does not participate in the conflict

```
source
```

MathOptInterface.IN\_CONFLICT – Constant.

```
IN_CONFLICT::ConflictParticipationStatusCode
```

An instance of the `ConflictParticipationStatusCode` enum.

`IN_CONFLICT`: the constraint participates in the conflict

`source`

MathOptInterface.MAYBE\_IN\_CONFLICT – Constant.

```
MAYBE_IN_CONFLICT::ConflictParticipationStatusCode
```

An instance of the `ConflictParticipationStatusCode` enum.

`MAYBE_IN_CONFLICT`: the constraint may participate in the conflict, the solver was not able to prove that the constraint can be excluded from the conflict

`source`

### 35.3 Variables

#### Functions

MathOptInterface.add\_variable – Function.

```
add_variable(model::ModelLike)::VariableIndex
```

Add a scalar variable to the model, returning a variable index.

A `AddVariableNotAllowed` error is thrown if adding variables cannot be done in the current state of the model `model`.

#### Example

```
julia> import MathOptInterface as MOI  
  
julia> model = MOI.Utilities.Model{Float64}();  
  
julia> x = MOI.add_variable(model)  
MOI.VariableIndex(1)
```

`source`

MathOptInterface.add\_variables – Function.

```
add_variables(model::ModelLike, n::Int)::Vector{VariableIndex}
```

Add n scalar variables to the model, returning a vector of variable indices.

An `AddVariableNotAllowed` error is thrown if adding variables cannot be done in the current state of the model model.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> MOI.add_variables(model, 2)
2-element Vector{MathOptInterface.VariableIndex}:
 MOI.VariableIndex(1)
 MOI.VariableIndex(2)
```

`source`

`MathOptInterface.add_constrained_variable` – Function.

```
add_constrained_variable(
    model::ModelLike,
    set)::AbstractScalarSet
) :: Tuple{MOI.VariableIndex,
          MOI.ConstraintIndex{MOI.VariableIndex, typeof(set)}}
```

Add to model a scalar variable constrained to belong to set, returning the index of the variable created and the index of the constraint constraining the variable to belong to set.

By default, this function falls back to creating a free variable with `add_variable` and then constraining it to belong to set with `add_constraint`.

`source`

```
add_constrained_variable(
    model::ModelLike,
    set):: Tuple{<: GreaterThan, <: LessThan},
)
```

A special-case method to add a scalar variable with a lower and upper bound.

This method should be implemented by optimizers which have native support for adding a variable with bounds and which cannot performantly modify the variable bounds after creation.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> set = (MOI.GreaterThan(1.0), MOI.LessThan(2.0));

julia> x, (c_l, c_u) = MOI.add_constrained_variable(model, set);
```

```

julia> c_l
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    ↪ MathOptInterface.GreaterThan{Float64}}(1)

julia> c_u
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    ↪ MathOptInterface.LessThan{Float64}}(1)

julia> print(model)
Feasibility

Subject to:

VariableIndex-in-GreaterThan{Float64}
v[1] >= 1.0

VariableIndex-in-LessThan{Float64}
v[1] <= 2.0

```

**source**

`MathOptInterface.add_constrained_variables` – Function.

```

add_constrained_variables(
    model::ModelLike,
    sets::AbstractVector{<:AbstractScalarSet}
) :: Tuple{
    Vector{MOI.VariableIndex},
    Vector{MOI.ConstraintIndex{MOI.VariableIndex, eltype(sets)}},
}

```

Add to model scalar variables constrained to belong to sets, returning the indices of the variables created and the indices of the constraints constraining the variables to belong to each set in sets. That is, if it returns variables and constraints, `constraints[i]` is the index of the constraint constraining `variable[i]` to belong to `sets[i]`.

By default, this function falls back to calling `add_constrained_variable` on each set.

**source**

```

add_constrained_variables(
    model::ModelLike,
    set::AbstractVectorSet,
) :: Tuple{
    Vector{MOI.VariableIndex},
    MOI.ConstraintIndex{MOI.VectorOfVariables, typeof(set)},
}

```

Add to model a vector of variables constrained to belong to set, returning the indices of the variables created and the index of the constraint constraining the vector of variables to belong to set.

By default, this function falls back to creating free variables with `add_variables` and then constraining it to belong to set with `add_constraint`.

`source`

`MathOptInterface.supports_add_constrained_variable` - Function.

```
supports_add_constrained_variable(
    model::ModelLike,
    S::Type{<:AbstractScalarSet}
)::Bool
```

Return a `Bool` indicating whether `model` supports constraining a variable to belong to a set of type `S` either on creation of the variable with `add_constrained_variable` or after the variable is created with `add_constraint`.

By default, this function falls back to `supports_add_constrained_variables(model, Reals) && supports_constraint(model, MOI.VariableIndex, S)` which is the correct definition for most models.

### Example

Suppose that a solver supports only two kind of variables: binary variables and continuous variables with a lower bound. If the solver decides not to support `VariableIndex-in-Binary` and `VariableIndex-in-GreaterThan` constraints, it only has to implement `add_constrained_variable` for these two sets which prevents the user to add both a binary constraint and a lower bound on the same variable. Moreover, if the user adds a `VariableIndex-in-GreaterThan` constraint, implementing this interface (that is, `supports_add_constrained_variables`) enables the constraint to be transparently bridged into a supported constraint.

`source`

`MathOptInterface.supports_add_constrained_variables` - Function.

```
supports_add_constrained_variables(
    model::ModelLike,
    S::Type{<:AbstractVectorSet}
)::Bool
```

Return a `Bool` indicating whether `model` supports constraining a vector of variables to belong to a set of type `S` either on creation of the vector of variables with `add_constrained_variables` or after the variable is created with `add_constraint`.

By default, if `S` is `Reals` then this function returns `true` and otherwise, it falls back to `supports_add_constrained_variables(model, MOI.VectorOfVariables, S)` which is the correct definition for most models.

### Example

In the standard conic form (see [Duality](#)), the variables are grouped into several cones and the constraints are affine equality constraints. If `Reals` is not one of the cones supported by the solvers then it needs to implement `supports_add_constrained_variables(::Optimizer, ::Type{Reals}) = false` as free variables are not supported. The solvers should then implement `supports_add_constrained_variables(::Optimizer, ::Type{<:SupportedCones}) = true` where `SupportedCones` is the union of all cone types that are supported; it does not have to implement the method `supports_constraint(::Type{VectorOfVariables},`

Type{<:SupportedCones}) as it should return false and it's the default. This prevents the user to constrain the same variable in two different cones. When a VectorOfVariables-in-S is added, the variables of the vector have already been created so they already belong to given cones. If bridges are enabled, the constraint will therefore be bridged by adding slack variables in S and equality constraints ensuring that the slack variables are equal to the corresponding variables of the given constraint function.

Note that there may also be sets for which !supports\_add\_constrained\_variables(model, S) and supports\_constraint(model, MOI.VectorOfVariables, S). For instance, suppose a solver supports positive semidefinite variable constraints and two types of variables: binary variables and nonnegative variables. Then the solver should support adding VectorOfVariables-in-PositiveSemidefiniteConeTriangle constraints, but it should not support creating variables constrained to belong to the PositiveSemidefiniteConeTriangle because the variables in PositiveSemidefiniteConeTriangle should first be created as either binary or non-negative.

[source](#)

MathOptInterface.is\_valid - Method.

```
is_valid(model::ModelLike, index::Index)::Bool
```

Return a Bool indicating whether this index refers to a valid object in the model model.

[source](#)

MathOptInterface.delete - Method.

```
delete(model::ModelLike, index::Index)
```

Delete the referenced object from the model. Throw [DeleteNotAllowed](#) if index cannot be deleted.

The following modifications also take effect if Index is [VariableIndex](#):

- If index used in the objective function, it is removed from the function, that is, it is substituted for zero.
- For each func-in-set constraint of the model:
  - If func isa VariableIndex and func == index then the constraint is deleted.
  - If func isa VectorOfVariables and index in func.variables then
    - \* if length(func.variables) == 1 is one, the constraint is deleted;
    - \* if length(func.variables) > 1 and supports\_dimension\_update(set) then then the variable is removed from func and set is replaced by update\_dimension(set, MOI.dimension(set) - 1).
    - \* Otherwise, a [DeleteNotAllowed](#) error is thrown.
  - Otherwise, the variable is removed from func, that is, it is substituted for zero.

[source](#)

MathOptInterface.delete - Method.

```
delete(model::ModelLike, indices::Vector{R<:Index}) where {R}
```

Delete the referenced objects in the vector `indices` from the model. It may be assumed that `R` is a concrete type. The default fallback sequentially deletes the individual items in `indices`, although specialized implementations may be more efficient.

[source](#)

## Attributes

`MathOptInterface.AbstractVariableAttribute` - Type.

```
AbstractVariableAttribute
```

Abstract supertype for attribute objects that can be used to set or get attributes (properties) of variables in the model.

[source](#)

`MathOptInterface.VariableName` - Type.

```
VariableName()
```

A variable attribute for a string identifying the variable. It is *valid* for two variables to have the same name; however, variables with duplicate names cannot be looked up using `get`. It has a default value of "" if not set'.

[source](#)

`MathOptInterface.VariablePrimalStart` - Type.

```
VariablePrimalStart()
```

A variable attribute for the initial assignment to some primal variable's value that the optimizer may use to warm-start the solve. May be a number or nothing (unset).

[source](#)

`MathOptInterface.VariablePrimal` - Type.

```
VariablePrimal(result_index::Int = 1)
```

A variable attribute for the assignment to some primal variable's value in result `result_index`. If `result_index` is omitted, it is 1 by default.

If the solver does not have a primal value for the variable because the `result_index` is beyond the available solutions (whose number is indicated by the `ResultCount` attribute), getting this attribute must throw a

[ResultIndexBoundsError](#). Otherwise, if the result is unavailable for another reason (for instance, only a dual solution is available), the result is undefined. Users should first check [PrimalStatus](#) before accessing the [VariablePrimal](#) attribute.

See [ResultCount](#) for information on how the results are ordered.

[source](#)

`MathOptInterface.VariableBasisStatus` – Type.

```
VariableBasisStatus(result_index::Int = 1)
```

A variable attribute for the [BasisStatusCode](#) of a variable in result `result_index`, with respect to an available optimal solution basis.

If the solver does not have a basis status for the variable because the `result_index` is beyond the available solutions (whose number is indicated by the [ResultCount](#) attribute), getting this attribute must throw a [ResultIndexBoundsError](#). Otherwise, if the result is unavailable for another reason (for instance, only a dual solution is available), the result is undefined. Users should first check [PrimalStatus](#) before accessing the [VariableBasisStatus](#) attribute.

See [ResultCount](#) for information on how the results are ordered.

[source](#)

## 35.4 Constraints

### Types

`MathOptInterface.ConstraintIndex` – Type.

```
ConstraintIndex{F,S}
```

A type-safe wrapper for `Int64` for use in referencing F-in-S constraints in a model.

The parameter `F` is the type of the function in the constraint, and the parameter `S` is the type of set in the constraint.

To allow for deletion, indices need not be consecutive.

Indices within a constraint type (that is, F-in-S) must be unique, but non-unique indices across different constraint types are allowed.

If `F` is [VariableIndex](#) then the index is equal to the index of the variable. That is for an `index::ConstraintIndex{VariableIndex}` we always have

```
index.value == MOI.get(model, MOI.ConstraintFunction(), index).value
```

[source](#)

## Functions

`MathOptInterface.is_valid` – Method.

```
is_valid(model::ModelLike, index::Index)::Bool
```

Return a `Bool` indicating whether this index refers to a valid object in the model `model`.

`source`

`MathOptInterface.add_constraint` – Function.

```
MOI.add_constraint(map::Map, vi::MOI.VariableIndex, set::MOI.AbstractScalarSet)
```

Record that a constraint `vi`-in-`set` is added and throws if a lower or upper bound is set by this constraint and such bound has already been set for `vi`.

`source`

```
add_constraint(model::ModelLike, func::F, set::S)::ConstraintIndex{F,S} where {F,S}
```

Add the constraint  $f(x) \in S$  where  $f$  is defined by `func`, and  $S$  is defined by `set`.

```
add_constraint(model::ModelLike, v::VariableIndex, set::S)::ConstraintIndex{VariableIndex,S}
  ↳ where {S}
add_constraint(model::ModelLike, vec::Vector{VariableIndex},
  ↳ set::S)::ConstraintIndex{VectorOfVariables,S} where {S}
```

Add the constraint  $v \in S$  where  $v$  is the variable (or vector of variables) referenced by `v` and  $S$  is defined by `set`.

- An `UnsupportedConstraint` error is thrown if `model` does not support F-in-S constraints,
- a `AddConstraintNotAllowed` error is thrown if it supports F-in-S constraints but it cannot add the constraint in its current state and
- a `ScalarFunctionConstantNotZero` error may be thrown if `func` is an `AbstractScalarFunction` with nonzero constant and `set` is `EqualTo`, `GreaterThan`, `LessThan` or `Interval`.
- a `LowerBoundAlreadySet` error is thrown if `F` is a `VariableIndex` and a constraint was already added to this variable that sets a lower bound.
- a `UpperBoundAlreadySet` error is thrown if `F` is a `VariableIndex` and a constraint was already added to this variable that sets an upper bound.

`source`

`MathOptInterface.add_constraints` – Function.

```
add_constraints(model::ModelLike, funcs::Vector{F},
  ↳ sets::Vector{S})::Vector{ConstraintIndex{F,S}} where {F,S}
```

Add the set of constraints specified by each function-set pair in `funcs` and `sets`. `F` and `S` should be concrete types. This call is equivalent to `add_constraint.(model, funcs, sets)` but may be more efficient.

`source`

`MathOptInterface.transform` – Function.

```
transform(
    model::ModelLike,
    c::ConstraintIndex{F,S1},
    newset::S2,
) :: ConstraintIndex{F,S2}
```

Replace the set in constraint `c` with `newset`.

The constraint index `c` will no longer be valid, and the function returns a new constraint index with the correct type.

Solvers may only support a subset of constraint transforms that they perform efficiently (for example, changing from a `LessThan` to `GreaterThan` set). In addition, set modification (where `S1 = S2`) should be performed via the `modify` function.

Typically, the user should delete the constraint and add a new one.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model);

julia> c = MOI.add_constraint(model, 1.0 * x, MOI.LessThan(2.0));

julia> print(model)
Feasibility

Subject to:

ScalarAffineFunction{Float64}-in-LessThan{Float64}
0.0 + 1.0 v[1] <= 2.0

julia> c2 = MOI.transform(model, c, MOI.GreaterThan(0.0))
MathOptInterface.ConstraintIndex{MathOptInterface.ScalarAffineFunction{Float64},
→ MathOptInterface.GreaterThan{Float64}}(1)

julia> print(model)
Feasibility

Subject to:

ScalarAffineFunction{Float64}-in-GreaterThan{Float64}
0.0 + 1.0 v[1] >= 0.0

julia> MOI.is_valid(model, c)
false
```

**source**

MathOptInterface.supports\_constraint – Function.

```
MOI.supports_constraint(
    BT::Type{<:AbstractBridge},
    F::Type{<:MOI.AbstractFunction},
    S::Type{<:MOI.AbstractSet},
) ::Bool
```

Return a Bool indicating whether the bridges of type BT support bridging F-in-S constraints.

#### Implementation notes

- This method depends only on the type of the inputs, not the runtime values.
- There is a default fallback, so you need only implement this method for constraint types that the bridge implements.

**source**

```
supports_constraint(
    model::ModelLike,
    ::Type{F},
    ::Type{S},
) ::Bool where {F<:AbstractFunction,S<:AbstractSet}
```

Return a Bool indicating whether model supports F-in-S constraints, that is, `copy_to(model, src)` does not throw `UnsupportedConstraint` when `src` contains F-in-S constraints. If F-in-S constraints are only not supported in specific circumstances, for example, F-in-S constraints cannot be combined with another type of constraint, it should still return true.

**source**

#### Attributes

MathOptInterface.AbstractConstraintAttribute – Type.

```
AbstractConstraintAttribute
```

Abstract supertype for attribute objects that can be used to set or get attributes (properties) of constraints in the model.

**source**

MathOptInterface.ConstraintName – Type.

```
ConstraintName()
```

A constraint attribute for a string identifying the constraint.

It is *valid* for constraints variables to have the same name; however, constraints with duplicate names cannot be looked up using [get](#), regardless of whether they have the same F-in-S type.

ConstraintName has a default value of "" if not set.

### Notes

You should *not* implement ConstraintName for VariableIndex constraints.

[source](#)

MathOptInterface.ConstraintPrimalStart - Type.

```
ConstraintPrimalStart()
```

A constraint attribute for the initial assignment to some constraint's [ConstraintPrimal](#) that the optimizer may use to warm-start the solve.

May be nothing (unset), a number for [AbstractScalarFunction](#), or a vector for [AbstractVectorFunction](#).

[source](#)

MathOptInterface.ConstraintDualStart - Type.

```
ConstraintDualStart()
```

A constraint attribute for the initial assignment to some constraint's [ConstraintDual](#) that the optimizer may use to warm-start the solve.

May be nothing (unset), a number for [AbstractScalarFunction](#), or a vector for [AbstractVectorFunction](#).

[source](#)

MathOptInterface.ConstraintPrimal - Type.

```
ConstraintPrimal(result_index::Int = 1)
```

A constraint attribute for the assignment to some constraint's primal value in result `result_index`.

If the constraint is  $f(x) \in S$ , then in most cases the `ConstraintPrimal` is the value of  $f$ , evaluated at the corresponding [VariablePrimal](#) solution.

However, some conic solvers reformulate  $b - Ax \in S$  to  $s = b - Ax$ ,  $s \in S$ . These solvers may return the value of  $s$  for `ConstraintPrimal`, rather than  $b - Ax$ . (Although these are constrained by an equality constraint, due to numerical tolerances they may not be identical.)

If the solver does not have a primal value for the constraint because the `result_index` is beyond the available solutions (whose number is indicated by the [ResultCount](#) attribute), getting this attribute must throw a [ResultIndexBoundsError](#). Otherwise, if the result is unavailable for another reason (for instance, only a dual solution is available), the result is undefined. Users should first check [PrimalStatus](#) before accessing the `ConstraintPrimal` attribute.

If `result_index` is omitted, it is 1 by default. See [ResultCount](#) for information on how the results are ordered.

[source](#)

MathOptInterface.ConstraintDual – Type.

```
ConstraintDual(result_index::Int = 1)
```

A constraint attribute for the assignment to some constraint's dual value in result `result_index`. If `result_index` is omitted, it is 1 by default.

If the solver does not have a dual value for the variable because the `result_index` is beyond the available solutions (whose number is indicated by the `ResultCount` attribute), getting this attribute must throw a `ResultIndexBoundsError`. Otherwise, if the result is unavailable for another reason (for instance, only a primal solution is available), the result is undefined. Users should first check `DualStatus` before accessing the `ConstraintDual` attribute.

See `ResultCount` for information on how the results are ordered.

`source`

MathOptInterface.ConstraintBasisStatus – Type.

```
ConstraintBasisStatus(result_index::Int = 1)
```

A constraint attribute for the `BasisStatusCode` of some constraint in result `result_index`, with respect to an available optimal solution basis. If `result_index` is omitted, it is 1 by default.

If the solver does not have a basis status for the constraint because the `result_index` is beyond the available solutions (whose number is indicated by the `ResultCount` attribute), getting this attribute must throw a `ResultIndexBoundsError`. Otherwise, if the result is unavailable for another reason (for instance, only a dual solution is available), the result is undefined. Users should first check `PrimalStatus` before accessing the `ConstraintBasisStatus` attribute.

See `ResultCount` for information on how the results are ordered.

### Notes

For the basis status of a variable, query `VariableBasisStatus`.

`ConstraintBasisStatus` does not apply to `VariableIndex` constraints. You can infer the basis status of a `VariableIndex` constraint by looking at the result of `VariableBasisStatus`.

`source`

MathOptInterface.ConstraintFunction – Type.

```
ConstraintFunction()
```

A constraint attribute for the `AbstractFunction` object used to define the constraint.

It is guaranteed to be equivalent but not necessarily identical to the function provided by the user.

`source`

MathOptInterface.CanonicalConstraintFunction – Type.

**CanonicalConstraintFunction()**

A constraint attribute for a canonical representation of the [AbstractFunction](#) object used to define the constraint.

Getting this attribute is guaranteed to return a function that is equivalent but not necessarily identical to the function provided by the user.

By default, `MOI.get(model, MOI.CanonicalConstraintFunction(), ci)` falls back to `MOI.Utilities.canonical(MOI.get(MOI.ConstraintFunction(), ci))`. However, if `model` knows that the constraint function is canonical then it can implement a specialized method that directly return the function without calling [Utilities.canonical](#). Therefore, the value returned **cannot** be assumed to be a copy of the function stored in `model`. Moreover, [Utilities.Model](#) checks with [Utilities.is\\_canonical](#) whether the function stored internally is already canonical and if it's the case, then it returns the function stored internally instead of a copy.

[source](#)

`MathOptInterface.ConstraintSet` – Type.

**ConstraintSet()**

A constraint attribute for the [AbstractSet](#) object used to define the constraint.

[source](#)

`MathOptInterface.BasisStatusCode` – Type.

**BasisStatusCode**

An Enum of possible values for the [ConstraintBasisStatus](#) and [VariableBasisStatus](#) attributes, explaining the status of a given element with respect to an optimal solution basis.

**Notes**

- `NONBASIC_AT_LOWER` and `NONBASIC_AT_UPPER` should be used only for constraints with the `Interval` set. In this case, they are necessary to distinguish which side of the constraint is active. One-sided constraints (for example, `LessThan` and `GreaterThan`) should use `NONBASIC` instead of the `NONBASIC_AT_*` values. This restriction does not apply to [VariableBasisStatus](#), which should return `NONBASIC_AT_*` regardless of whether the alternative bound exists.
- In linear programs, `SUPER_BASIC` occurs when a variable with no bounds is not in the basis.

**Values**

Possible values are:

- [BASIC](#): element is in the basis
- [NONBASIC](#): element is not in the basis
- [NONBASIC\\_AT\\_LOWER](#): element is not in the basis and is at its lower bound
- [NONBASIC\\_AT\\_UPPER](#): element is not in the basis and is at its upper bound

- [SUPER\\_BASIC](#): element is not in the basis but is also not at one of its bounds

[source](#)

MathOptInterface.BASIC – Constant.

BASIC::[BasisStatusCode](#)

An instance of the [BasisStatusCode](#) enum.

BASIC: element is in the basis

[source](#)

MathOptInterface.NONBASIC – Constant.

NONBASIC::[BasisStatusCode](#)

An instance of the [BasisStatusCode](#) enum.

NONBASIC: element is not in the basis

[source](#)

MathOptInterface.NONBASIC\_AT\_LOWER – Constant.

NONBASIC\_AT\_LOWER::[BasisStatusCode](#)

An instance of the [BasisStatusCode](#) enum.

NONBASIC\_AT\_LOWER: element is not in the basis and is at its lower bound

[source](#)

MathOptInterface.NONBASIC\_AT\_UPPER – Constant.

NONBASIC\_AT\_UPPER::[BasisStatusCode](#)

An instance of the [BasisStatusCode](#) enum.

NONBASIC\_AT\_UPPER: element is not in the basis and is at its upper bound

[source](#)

MathOptInterface.SUPER\_BASIC – Constant.

SUPER\_BASIC::[BasisStatusCode](#)

An instance of the [BasisStatusCode](#) enum.

SUPER\_BASIC: element is not in the basis but is also not at one of its bounds

[source](#)

## 35.5 Modifications

`MathOptInterface.modify` – Function.

```
modify(
    model::ModelLike,
    ci::ConstraintIndex,
    change::AbstractFunctionModification,
)
```

Apply the modification specified by `change` to the function of constraint `ci`.

An `ModifyConstraintNotAllowed` error is thrown if modifying constraints is not supported by the model model.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model);

julia> ci = MOI.add_constraint(model, 1.0 * x, MOI.EqualTo(1.0));

julia> MOI.modify(model, ci, MOI.ScalarConstantChange(10.0))

julia> print(model)
Feasibility

Subject to:

ScalarAffineFunction{Float64}-in-EqualTo{Float64}
  10.0 + 1.0 v[1] == 1.0
```

`source`

```
modify(
    model::ModelLike,
    cis::AbstractVector{<: ConstraintIndex},
    changes::AbstractVector{<: AbstractFunctionModification},
)
```

Apply multiple modifications specified by `changes` to the functions of constraints `cis`.

An `ModifyConstraintNotAllowed` error is thrown if modifying constraints is not supported by `model`.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();
```

```
julia> x = MOI.add_variables(model, 2);

julia> ci = MOI.add_constraint.(model, 1.0 .* x, MOI.EqualTo(1.0));

julia> MOI.modify(model, ci, MOI.ScalarCoefficientChange.(x, [2.0, 0.5]));

julia> print(model)
Feasibility

Subject to:

ScalarAffineFunction{Float64}-in-EqualTo{Float64}
  0.0 + 2.0 v[1] == 1.0
  0.0 + 0.5 v[2] == 1.0
```

**source**

```
modify(model::ModelLike, ::ObjectiveFunction, change::AbstractFunctionModification)
```

Apply the modification specified by `change` to the objective function of `model`. To change the function completely, call `set` instead.

An `ModifyObjectiveNotAllowed` error is thrown if modifying objectives is not supported by the model `model`.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model);

julia> MOI.set(model, MOI.ObjectiveSense(), MOI.MIN_SENSE)

julia> f = 1.0 * x;

julia> attr = MOI.ObjectiveFunction{typeof(f)}()
MathOptInterface.ObjectiveFunction{MathOptInterface.ScalarAffineFunction{Float64}}()

julia> MOI.set(model, attr, f)

julia> MOI.modify(model, attr, MOI.ScalarConstantChange(10.0))

julia> print(model)
Minimize ScalarAffineFunction{Float64}:
  10.0 + 1.0 v[1]

Subject to:
```

**source**

```
modify(
    model::ModelLike,
    attr::ObjectiveFunction,
    changes::AbstractVector{<:AbstractFunctionModification},
)
```

Apply multiple modifications specified by changes to the functions or constraints cis.

A `ModifyObjectiveNotAllowed` error is thrown if modifying objective coefficients is not supported by model.

### Example

#### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variables(model, 2);

julia> MOI.set(model, MOI.ObjectiveSense(), MOI.MIN_SENSE)

julia> f = 1.0 * x[1] + 1.0 * x[2];

julia> attr = MOI.ObjectiveFunction{typeof(f)}()
MathOptInterface.ObjectiveFunction{MathOptInterface.ScalarAffineFunction{Float64}}()

julia> MOI.set(model, attr, f)

julia> MOI.modify(model, attr, MOI.ScalarCoefficientChange.(x, [2.0, 0.5]))

julia> print(model)
Minimize ScalarAffineFunction{Float64}:
  0.0 + 2.0 v[1] + 0.5 v[2]

Subject to:
```

#### source

`MathOptInterface.AbstractFunctionModification` – Type.

`AbstractFunctionModification`

An abstract supertype for structs which specify partial modifications to functions, to be used for making small modifications instead of replacing the functions entirely.

#### source

`MathOptInterface.ScalarConstantChange` – Type.

```
ScalarConstantChange{T}(new_constant::T)
```

A struct used to request a change in the constant term of a scalar-valued function.

Applicable to [ScalarAffineFunction](#) and [ScalarQuadraticFunction](#).

`source`

`MathOptInterface.VectorConstantChange` – Type.

```
VectorConstantChange{T}(new_constant::Vector{T})
```

A struct used to request a change in the constant vector of a vector-valued function.

Applicable to [VectorAffineFunction](#) and [VectorQuadraticFunction](#).

`source`

`MathOptInterface.ScalarCoefficientChange` – Type.

```
ScalarCoefficientChange{T}(variable::VariableIndex, new_coefficient::T)
```

A struct used to request a change in the linear coefficient of a single variable in a scalar-valued function.

Applicable to [ScalarAffineFunction](#) and [ScalarQuadraticFunction](#).

`source`

`MathOptInterface.ScalarQuadraticCoefficientChange` – Type.

```
ScalarQuadraticCoefficientChange{T}()
  variable_1::VariableIndex,
  variable_2::VariableIndex,
  new_coefficient::T,
)
```

A struct used to request a change in the quadratic coefficient of a [ScalarQuadraticFunction](#).

### Scaling factors

A [ScalarQuadraticFunction](#) has an implicit 0.5 scaling factor in front of the Q matrix. This modification applies to terms in the Q matrix.

If `variable_1 == variable_2`, this modification sets the corresponding diagonal element of the Q matrix to `new_coefficient`.

If `variable_1 != variable_2`, this modification is equivalent to setting both the corresponding upper- and lower-triangular elements of the Q matrix to `new_coefficient`.

As a consequence:

- to modify the term  $x^2$  to become  $2x^2$ , `new_coefficient` must be 4

- to modify the term  $xy$  to become  $2xy$ , new\_coefficient must be 2

[source](#)

MathOptInterface.MultirowChange – Type.

```
MultirowChange{T}(
    variable::VariableIndex,
    new_coefficients::Vector{Tuple{Int64,T}},
) where {T}
```

A struct used to request a change in the linear coefficients of a single variable in a vector-valued function.

New coefficients are specified by (output\_index, coefficient) tuples.

Applicable to [VectorAffineFunction](#) and [VectorQuadraticFunction](#).

[source](#)

## 35.6 Nonlinear programming

### Types

MathOptInterface.AbstractNLPEvaluator – Type.

```
AbstractNLPEvaluator
```

Abstract supertype for the callback object that is used to query function values, derivatives, and expression graphs.

It is used in [NLPBlockData](#).

### Example

This example uses the [Test.HS071](#) evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> supertype(typeof(evaluator))
MathOptInterface.AbstractNLPEvaluator
```

[source](#)

MathOptInterface.NLPBoundsPair – Type.

```
NLPBoundsPair(lower::Float64, upper::Float64)
```

A struct holding a pair of lower and upper bounds.

`-Inf` and `Inf` can be used to indicate no lower or upper bound, respectively.

### Example

```
julia> import MathOptInterface as MOI

julia> bounds = MOI.NLPBoundsPair.([25.0, 40.0], [Inf, 40.0])
2-element Vector{MathOptInterface.NLPBoundsPair}:
 MathOptInterface.NLPBoundsPair(25.0, Inf)
 MathOptInterface.NLPBoundsPair(40.0, 40.0)
```

[source](#)

`MathOptInterface.NLPBlockData` – Type.

```
struct NLPBlockData
    constraint_bounds::Vector{NLPBoundsPair}
    evaluator::AbstractNLPEvaluator
    has_objective::Bool
end
```

A struct encoding a set of nonlinear constraints of the form  $lb \leq g(x) \leq ub$  and, if `has_objective == true`, a nonlinear objective function  $f(x)$ .

Nonlinear objectives *override* any objective set by using the `ObjectiveFunction` attribute.

The evaluator is a callback object that is used to query function values, derivatives, and expression graphs. If `has_objective == false`, then it is an error to query properties of the objective function, and in Hessian-of-the-Lagrangian queries, `o` must be set to zero.

### Note

Throughout the evaluator, all variables are ordered according to `ListOfVariableIndices`. Hence, MOI copies of nonlinear problems must not re-order variables.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}());

julia> block = MOI.NLPBlockData(
    MOI.NLPBoundsPair.([25.0, 40.0], [Inf, 40.0]),
    MOI.Test.HS071(true),
    true,
);

julia> MOI.set(model, MOI.NLPBlock(), block)
```

[source](#)

## Attributes

MathOptInterface.NLPBlock – Type.

```
NLPBlock()
```

An [AbstractModelAttribute](#) that stores an [NLPBlockData](#), representing a set of nonlinear constraints, and optionally a nonlinear objective.

### Example

This example uses the [Test.HS071](#) evaluator.

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}());

julia> block = MOI.NLPBlockData(
           MOI.NLPBoundsPair.([25.0, 40.0], [Inf, 40.0]),
           MOI.Test.HS071(true),
           true,
       );

julia> MOI.set(model, MOI.NLPBlock(), block)
```

[source](#)

MathOptInterface.NLPBlockDual – Type.

```
NLPBlockDual(result_index::Int = 1)
```

An [AbstractModelAttribute](#) for the Lagrange multipliers on the constraints from the [NLPBlock](#) in `result_index`.

If `result_index` is omitted, it is 1 by default.

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.NLPBlockDual()
MathOptInterface.NLPBlockDual(1)

julia> MOI.NLPBlockDual(2)
MathOptInterface.NLPBlockDual(2)
```

[source](#)

MathOptInterface.NLPBlockDualStart – Type.

```
NLPBlockDualStart()
```

An [AbstractModelAttribute](#) for the initial assignment of the Lagrange multipliers on the constraints from the [NLPBlock](#) that the solver may use to warm-start the solve.

### Example

This example uses the [Test.HS071](#) evaluator.

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}());

julia> block = MOI.NLPBlockData(
        MOI.NLPBoundsPair.([25.0, 40.0], [Inf, 40.0]),
        MOI.Test.HS071(true),
        true,
    );

julia> MOI.set(model, MOI.NLPBlock(), block)

julia> MOI.set(model, MOI.NLPBlockDualStart(), [1.0, 2.0])
```

[source](#)

### Functions

`MathOptInterface.initialize` – Function.

```
initialize(
    d::AbstractNLPEvaluator,
    requested_features::Vector{Symbol},
)::Nothing
```

Initialize `d` with the set of features in `requested_features`. Check [features\\_available](#) before calling `initialize` to see what features are supported by `d`.

#### Warning

This method must be called before any other methods.

### Features

The following features are defined:

- `:Grad`: enables `eval_objective_gradient`
- `:Jac`: enables `eval_constraint_jacobian` and `eval_constraint_gradient`
- `:JacVec`: enables `eval_constraint_jacobian_product` and `eval_constraint_jacobian_transpose_product`
- `:Hess`: enables `eval_hessian_lagrangian`

- `:HessVec`: enables `eval_hessian_lagrangian_product`
- `:ExprGraph`: enables `objective_expr` and `constraint_expr`.

In all cases, including when `requested_features` is empty, `eval_objective` and `eval_constraint` are supported.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, [:Grad, :Jac])
```

`source`

`MathOptInterface.features_available` – Function.

```
features_available(d::AbstractNLPEvaluator)::Vector{Symbol}
```

Returns the subset of features available for this problem instance.

See `initialize` for the list of defined features.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true, true);

julia> MOI.features_available(evaluator)
6-element Vector{Symbol}:
:Grad
:Jac
:JacVec
:ExprGraph
:Hess
:HessVec
```

`source`

`MathOptInterface.eval_objective` – Function.

```
eval_objective(d::AbstractNLPEvaluator, x::AbstractVector{T})::T where {T}
```

Evaluate the objective  $f(x)$ , returning a scalar value.

### Initialize

Before calling this function, you must call `initialize`, but you do not need to pass a value.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[])

julia> MOI.eval_objective(evaluator, [1.0, 2.0, 3.0, 4.0])
27.0
```

[source](#)

`MathOptInterface.eval_constraint` – Function.

```
eval_constraint(
    d::AbstractNLPEvaluator,
    g::AbstractVector{T},
    x::AbstractVector{T},
) where {T}
```

Given a set of vector-valued constraints  $l \leq g(x) \leq u$ , evaluate the constraint function  $g(x)$ , storing the result in the vector `g`.

### Initialize

Before calling this function, you must call `initialize`, but you do not need to pass a value.

### Implementation notes

When implementing this method, you must not assume that `g` is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[])

julia> g = fill(NaN, 2);

julia> MOI.eval_constraint(evaluator, g, [1.0, 2.0, 3.0, 4.0])

julia> g
2-element Vector{Float64}:
 24.0
 30.0
```

[source](#)  
**MathOptInterface.eval\_objective\_gradient** – Function.

```
eval_objective_gradient(
    d::AbstractNLPEvaluator,
    grad::AbstractVector{T},
    x::AbstractVector{T},
) where {T}
```

Evaluate the gradient of the objective function  $grad = \nabla f(x)$  as a dense vector, storing the result in the vector `grad`.

### Initialize

Before calling this function, you must call `initialize` with `:Grad`.

### Implementation notes

When implementing this method, you must not assume that `grad` is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Grad])

julia> grad = fill(NaN, 4);

julia> MOI.eval_objective_gradient(evaluator, grad, [1.0, 2.0, 3.0, 4.0])

julia> grad
4-element Vector{Float64}:
 28.0
  4.0
  5.0
  6.0
```

[source](#)  
**MathOptInterface.jacobian\_structure** – Function.

```
jacobian_structure(d::AbstractNLPEvaluator)::Vector{Tuple{Int64, Int64}}
```

Returns a vector of tuples, `(row, column)`, where each indicates the position of a structurally nonzero element in the Jacobian matrix:  $J_g(x) = \begin{bmatrix} \nabla g_1(x) \\ \nabla g_2(x) \\ \vdots \\ \nabla g_m(x) \end{bmatrix}$ , where  $g_i$  is the  $i$ th component of the nonlinear constraints  $g(x)$ .

The indices are not required to be sorted and can contain duplicates, in which case the solver should combine the corresponding elements by adding them together.

The sparsity structure is assumed to be independent of the point  $x$ .

### Initialize

Before calling this function, you must call `initialize` with `:Jac`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Jac])

julia> MOI.jacobian_structure(evaluator)
8-element Vector{Tuple{Int64, Int64}}:
 (1, 1)
 (1, 2)
 (1, 3)
 (1, 4)
 (2, 1)
 (2, 2)
 (2, 3)
 (2, 4)
```

[source](#)

`MathOptInterface.eval_constraint_gradient` – Function.

```
eval_constraint_gradient(
    d::AbstractNLPEvaluator,
    ∇g::AbstractVector{T},
    x::AbstractVector{T},
    i::Int,
) where {T}
```

Evaluate the gradient of constraint  $i$ ,  $\nabla g_i(x)$ , and store the non-zero values in  $\nabla g$ , corresponding to the structure returned by `constraint_gradient_structure`.

### Implementation notes

When implementing this method, you must not assume that  $\nabla g$  is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

### Initialize

Before calling this function, you must call `initialize` with `:Jac`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Jac])

julia> indices = MOI.constraint_gradient_structure(evaluator, 1);

julia> ∇g = zeros(length(indices));

julia> MOI.eval_constraint_gradient(evaluator, ∇g, [1.0, 2.0, 3.0, 4.0], 1)

julia> ∇g
4-element Vector{Float64}:
 24.0
 12.0
  8.0
  6.0
```

**source**

MathOptInterface.constraint\_gradient\_structure - Function.

```
constraint_gradient_structure(d::AbstractNLPEvaluator, i::Int)::Vector{Int64}
```

Returns a vector of indices, where each element indicates the position of a structurally nonzero element in the gradient of constraint  $\nabla g_i(x)$ .

The indices are not required to be sorted and can contain duplicates, in which case the solver should combine the corresponding elements by adding them together.

The sparsity structure is assumed to be independent of the point  $x$ .

### Initialize

Before calling this function, you must call `initialize` with `:Jac`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Jac])

julia> indices = MOI.constraint_gradient_structure(evaluator, 1)
4-element Vector{Int64}:
 1
 2
 3
 4
```

**source**

`MathOptInterface.eval_constraint_jacobian` - Function.

```
eval_constraint_jacobian(
    d::AbstractNLPEvaluator,
    J::AbstractVector{T},
    x::AbstractVector{T},
) :: Nothing where {T}
```

Evaluates the sparse Jacobian matrix  $J_g(x) = \begin{bmatrix} \nabla g_1(x) \\ \nabla g_2(x) \\ \vdots \\ \nabla g_m(x) \end{bmatrix}$ .

The result is stored in the vector `J` in the same order as the indices returned by `jacobian_structure`.

### Implementation notes

When implementing this method, you must not assume that `J` is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

### Initialize

Before calling this function, you must call `initialize` with `:Hess`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Jac])

julia> J_indices = MOI.jacobian_structure(evaluator);

julia> J = zeros(length(J_indices));

julia> MOI.eval_constraint_jacobian(evaluator, J, [1.0, 2.0, 3.0, 4.0])

julia> J
8-element Vector{Float64}:
 24.0
 12.0
  8.0
  6.0
  2.0
  4.0
  6.0
  8.0
```

[source](#)

`MathOptInterface.eval_constraint_jacobian_product` - Function.

```
eval_constraint_jacobian_product(
    d::AbstractNLPEvaluator,
    y::AbstractVector{T},
    x::AbstractVector{T},
    w::AbstractVector{T},
)>::Nothing where {T}
```

Computes the Jacobian-vector product  $y = J_g(x)w$ , storing the result in the vector  $y$ .

The vectors have dimensions such that `length(w) == length(x)`, and `length(y)` is the number of nonlinear constraints.

#### Implementation notes

When implementing this method, you must not assume that  $y$  is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

#### Initialize

Before calling this function, you must call `initialize` with `:JacVec`.

#### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Jac, :JacVec])

julia> y = zeros(2);

julia> x = [1.0, 2.0, 3.0, 4.0];

julia> w = [1.5, 2.5, 3.5, 4.5];

julia> MOI.eval_constraint_jacobian_product(evaluator, y, x, w)

julia> y
2-element Vector{Float64}:
 121.0
 70.0
```

[source](#)

`MathOptInterface.eval_constraint_jacobian_transpose_product` – Function.

```
eval_constraint_jacobian_transpose_product(
    d::AbstractNLPEvaluator,
    y::AbstractVector{T},
    x::AbstractVector{T},
    w::AbstractVector{T},
)>::Nothing where {T}
```

Computes the Jacobian-transpose-vector product  $y = J_g(x)^T w$ , storing the result in the vector  $y$ .

The vectors have dimensions such that `length(y) == length(x)`, and `length(w)` is the number of nonlinear constraints.

### Implementation notes

When implementing this method, you must not assume that  $y$  is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

### Initialize

Before calling this function, you must call `initialize` with `:JacVec`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Jac, :JacVec])

julia> y = zeros(4);

julia> x = [1.0, 2.0, 3.0, 4.0];

julia> w = [1.5, 2.5];

julia> MOI.eval_constraint_jacobian_transpose_product(evaluator, y, x, w)

julia> y
4-element Vector{Float64}:
 41.0
 28.0
 27.0
 29.0
```

[source](#)

`MathOptInterface.hessian_lagrangian_structure` – Function.

```
hessian_lagrangian_structure(
    d::AbstractNLPEvaluator,
) :: Vector{Tuple{Int64, Int64}}
```

Returns a vector of tuples,  $(\text{row}, \text{column})$ , where each indicates the position of a structurally nonzero element in the Hessian-of-the-Lagrangian matrix:  $\nabla^2 f(x) + \sum_{i=1}^m \nabla^2 g_i(x)$ .

The indices are not required to be sorted and can contain duplicates, in which case the solver should combine the corresponding elements by adding them together.

Any mix of lower and upper-triangular indices is valid. Elements  $(i, j)$  and  $(j, i)$ , if both present, should be treated as duplicates.

The sparsity structure is assumed to be independent of the point  $x$ .

**Initialize**

Before calling this function, you must call `initialize` with `:Hess`.

**Example**

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Hess])

julia> MOI.hessian_lagrangian_structure(evaluator)
10-element Vector{Tuple{Int64, Int64}}:
 (1, 1)
 (2, 1)
 (2, 2)
 (3, 1)
 (3, 2)
 (3, 3)
 (4, 1)
 (4, 2)
 (4, 3)
 (4, 4)
```

[source](#)

`MathOptInterface.hessian_objective_structure` – Function.

```
hessian_objective_structure(
    d::AbstractNLPEvaluator,
)::Vector{Tuple{Int64,Int64}}
```

Returns a vector of tuples, `(row, column)`, where each indicates the position of a structurally nonzero element in the Hessian matrix:  $\nabla^2 f(x)$ .

The indices are not required to be sorted and can contain duplicates, in which case the solver should combine the corresponding elements by adding them together.

Any mix of lower and upper-triangular indices is valid. Elements `(i, j)` and `(j, i)`, if both present, should be treated as duplicates.

The sparsity structure is assumed to be independent of the point  $x$ .

**Initialize**

Before calling this function, you must call `initialize` with `:Hess`.

**Example**

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI
```

```
julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Hess])

julia> MOI.hessian_objective_structure(evaluator)
6-element Vector{Tuple{Int64, Int64}}:
 (1, 1)
 (2, 1)
 (3, 1)
 (4, 1)
 (4, 2)
 (4, 3)
```

[source](#)

`MathOptInterface.hessian_constraint_structure` – Function.

```
hessian_constraint_structure(
    d::AbstractNLPEvaluator,
    i::Int64,
) ::Vector{Tuple{Int64, Int64}}
```

Returns a vector of tuples,  $(\text{row}, \text{column})$ , where each indicates the position of a structurally nonzero element in the Hessian matrix:  $\nabla^2 g_i(x)$ .

The indices are not required to be sorted and can contain duplicates, in which case the solver should combine the corresponding elements by adding them together.

Any mix of lower and upper-triangular indices is valid. Elements  $(i, j)$  and  $(j, i)$ , if both present, should be treated as duplicates.

The sparsity structure is assumed to be independent of the point  $x$ .

### Initialize

Before calling this function, you must call `initialize` with `:Hess`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Hess])

julia> MOI.hessian_constraint_structure(evaluator, 1)
6-element Vector{Tuple{Int64, Int64}}:
 (2, 1)
 (3, 1)
 (3, 2)
 (4, 1)
 (4, 2)
 (4, 3)
```

```
julia> MOI.hessian_constraint_structure(evaluator, 2)
4-element Vector{Tuple{Int64, Int64}}:
 (1, 1)
 (2, 2)
 (3, 3)
 (4, 4)
```

[source](#)  
`MathOptInterface.eval_hessian_objective` – Function.

```
eval_hessian_objective(
    d::AbstractNLPEvaluator,
    H::AbstractVector{T},
    x::AbstractVector{T},
) where {T}
```

This function computes the sparse Hessian matrix:  $\nabla^2 f(x)$ , storing the result in the vector `H` in the same order as the indices returned by `hessian_objective_structure`.

#### Implementation notes

When implementing this method, you must not assume that `H` is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

#### Initialize

Before calling this function, you must call `initialize` with `:Hess`.

#### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true, true);

julia> MOI.initialize(evaluator, Symbol[:Hess])

julia> indices = MOI.hessian_objective_structure(evaluator);

julia> H = zeros(length(indices));

julia> x = [1.0, 2.0, 3.0, 4.0];

julia> MOI.eval_hessian_objective(evaluator, H, x)

julia> H
6-element Vector{Float64}:
 8.0
 4.0
 4.0
 7.0
 1.0
 1.0
```

[source](#)

MathOptInterface.eval\_hessian\_constraint – Function.

```
eval_hessian_constraint(
    d::AbstractNLPEvaluator,
    H::AbstractVector{T},
    x::AbstractVector{T},
    i::Int64,
) :: Nothing where {T}
```

This function computes the sparse Hessian matrix:  $\nabla^2 g_i(x)$ , storing the result in the vector H in the same order as the indices returned by [hessian\\_constraint\\_structure](#).

### Implementation notes

When implementing this method, you must not assume that H is Vector{Float64}, but you may assume that it supports setindex! and length. For example, it may be the view of a vector.

### Initialize

Before calling this function, you must call [initialize](#) with :Hess.

### Example

This example uses the [Test.HS071](#) evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true, true);

julia> MOI.initialize(evaluator, Symbol[:Hess])

julia> indices = MOI.hessian_constraint_structure(evaluator, 1);

julia> H = zeros(length(indices));

julia> x = [1.0, 2.0, 3.0, 4.0];

julia> MOI.eval_hessian_constraint(evaluator, H, x, 1)

julia> H
6-element Vector{Float64}:
 12.0
  8.0
  4.0
  6.0
  3.0
  2.0
```

[source](#)

MathOptInterface.eval\_hessian\_lagrangian – Function.

```
eval_hessian_lagrangian(
    d::AbstractNLPEvaluator,
    H::AbstractVector{T},
    x::AbstractVector{T},
    σ::T,
    μ::AbstractVector{T},
) where {T}
```

Given scalar weight  $\sigma$  and vector of constraint weights  $\mu$ , this function computes the sparse Hessian-of-the-Lagrangian matrix:  $\sigma \nabla^2 f(x) + \sum_{i=1}^m \mu_i \nabla^2 g_i(x)$ , storing the result in the vector  $H$  in the same order as the indices returned by [hessian\\_lagrangian\\_structure](#).

### Implementation notes

When implementing this method, you must not assume that  $H$  is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

### Initialize

Before calling this function, you must call `initialize` with `:Hess`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, Symbol[:Hess])

julia> indices = MOI.hessian_lagrangian_structure(evaluator);

julia> H = zeros(length(indices));

julia> x = [1.0, 2.0, 3.0, 4.0];

julia> σ = 1.0;

julia> μ = [1.0, 1.0];

julia> MOI.eval_hessian_lagrangian(evaluator, H, x, σ, μ)

julia> H
10-element Vector{Float64}:
 10.0
 16.0
  2.0
 12.0
  4.0
  2.0
 13.0
  4.0
  3.0
  2.0
```

[source](#)  
**MathOptInterface.eval\_hessian\_lagrangian\_product** – Function.

```
eval_hessian_lagrangian_product(
    d::AbstractNLPEvaluator,
    h::AbstractVector{T},
    x::AbstractVector{T},
    v::AbstractVector{T},
    σ::T,
    μ::AbstractVector{T},
) where {T}
```

Given scalar weight  $\sigma$  and vector of constraint weights  $\mu$ , computes the Hessian-of-the-Lagrangian-vector product  $h = (\sigma \nabla^2 f(x) + \sum_{i=1}^m \mu_i \nabla^2 g_i(x)) v$ , storing the result in the vector  $h$ .

The vectors have dimensions such that `length(h) == length(x) == length(v)`.

### Implementation notes

When implementing this method, you must not assume that `h` is `Vector{Float64}`, but you may assume that it supports `setindex!` and `length`. For example, it may be the view of a vector.

### Initialize

Before calling this function, you must call `initialize` with `:HessVec`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true, true);

julia> MOI.initialize(evaluator, Symbol[:HessVec])

julia> H = fill(NaN, 4);

julia> x = [1.0, 2.0, 3.0, 4.0];

julia> v = [1.5, 2.5, 3.5, 4.5];

julia> σ = 1.0;

julia> μ = [1.0, 1.0];

julia> MOI.eval_hessian_lagrangian_product(evaluator, H, x, v, σ, μ)

julia> H
4-element Vector{Float64}:
 155.5
  61.0
  48.5
  49.0
```

[source](#)

`MathOptInterface.objective_expr` – Function.

```
objective_expr(d::AbstractNLPEvaluator)::Expr
```

Returns a Julia `Expr` object representing the expression graph of the objective function.

### Format

The expression has a number of limitations, compared with arbitrary Julia expressions:

- All sums and products are flattened out as simple `Expr(:+, ...)` and `Expr(:*, ...)` objects.
- All decision variables must be of the form `Expr(:ref, :x, MOI.VariableIndex(i))`, where  $i$  is the  $i$ th variable in `ListofVariableIndices`.
- There are currently no restrictions on recognized functions; typically these will be built-in Julia functions like `^`, `exp`, `log`, `cos`, `tan`, `sqrt`, etc., but modeling interfaces may choose to extend these basic functions, or error if they encounter unsupported functions.

### Initialize

Before calling this function, you must call `initialize` with `:ExprGraph`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI
julia> evaluator = MOI.Test.HS071(true);
julia> MOI.initialize(evaluator, [:ExprGraph])
julia> MOI.objective_expr(evaluator)
:(x[MOI.VariableIndex(1)] * x[MOI.VariableIndex(4)] * (x[MOI.VariableIndex(1)] +
    ↳ x[MOI.VariableIndex(2)] + x[MOI.VariableIndex(3)]) + x[MOI.VariableIndex(3)])
```

[source](#)

`MathOptInterface.constraint_expr` – Function.

```
constraint_expr(d::AbstractNLPEvaluator, i::Integer)::Expr
```

Returns a Julia `Expr` object representing the expression graph for the  $i$ th nonlinear constraint.

### Format

The format is the same as `objective_expr`, with an additional comparison operator indicating the sense of and bounds on the constraint.

For single-sided comparisons, the body of the constraint must be on the left-hand side, and the right-hand side must be a constant.

For double-sided comparisons (that is,  $l \leq g(x) \leq u$ ), the body of the constraint must be in the middle, and the left- and right-hand sides must be constants.

The bounds on the constraints must match the `NLPBoundsPair`s passed to `NLPBlockData`.

### Initialize

Before calling this function, you must call `initialize` with `:ExprGraph`.

### Example

This example uses the `Test.HS071` evaluator.

```
julia> import MathOptInterface as MOI

julia> evaluator = MOI.Test.HS071(true);

julia> MOI.initialize(evaluator, [:ExprGraph])

julia> MOI.constraint_expr(evaluator, 1)
:(x[MOI.VariableIndex(1)] * x[MOI.VariableIndex(2)] * x[MOI.VariableIndex(3)] *
    ↳ x[MOI.VariableIndex(4)] >= 25.0)

julia> MOI.constraint_expr(evaluator, 2)
:(x[MOI.VariableIndex(1)] ^ 2 + x[MOI.VariableIndex(2)] ^ 2 + x[MOI.VariableIndex(3)] ^ 2 +
    ↳ x[MOI.VariableIndex(4)] ^ 2 == 40.0)
```

[source](#)

## 35.7 Callbacks

`MathOptInterface.AbstractCallback` – Type.

```
abstract type AbstractCallback <: AbstractModelAttribute end
```

Abstract type for a model attribute representing a callback function. The value set to subtypes of `AbstractCallback` is a function that may be called during `optimize!`. As `optimize!` is in progress, the result attributes (that is, the attributes `attr` such that `is_set_by_optimize(attr)`) may not be accessible from the callback, hence trying to get result attributes might throw a `OptimizeInProgress` error.

At most one callback of each type can be registered. If an optimizer already has a function for a callback type, and the user registers a new function, then the old one is replaced.

The value of the attribute should be a function taking only one argument, commonly called `callback_data`, that can be used for instance in `LazyConstraintCallback`, `HeuristicCallback` and `UserCutCallback`.

[source](#)

`MathOptInterface.AbstractSubmittable` – Type.

```
AbstractSubmittable
```

Abstract supertype for objects that can be submitted to the model.

[source](#)

`MathOptInterface.submit` – Function.

```
submit(
    optimizer::AbstractOptimizer,
    sub::AbstractSubmittable,
    values...,
)::Nothing
```

Submit values to the submittable sub of the optimizer optimizer.

An [UnsupportedSubmittable](#) error is thrown if model does not support the attribute attr (see [supports](#)) and a [SubmitNotAllowed](#) error is thrown if it supports the submittable sub but it cannot be submitted.

[source](#)

## Attributes

`MathOptInterface.CallbackNodeStatus` – Type.

```
CallbackNodeStatus(callback_data)
```

An optimizer attribute describing the (in)feasibility of the primal solution available from [CallbackVariablePrimal](#) during a callback identified by `callback_data`.

Returns a [CallbackNodeStatusCode](#) Enum.

[source](#)

`MathOptInterface.CallbackVariablePrimal` – Type.

```
CallbackVariablePrimal(callback_data)
```

A variable attribute for the assignment to some primal variable's value during the callback identified by `callback_data`.

[source](#)

`MathOptInterface.CallbackNodeStatusCode` – Type.

```
CallbackNodeStatusCode
```

An Enum of possible return values from calling `get` with [CallbackNodeStatus](#).

## Values

Possible values are:

- [CALLBACK\\_NODE\\_STATUS\\_INTEGER](#): the primal solution available from [CallbackVariablePrimal](#) is integer feasible.
- [CALLBACK\\_NODE\\_STATUS\\_FRACTIONAL](#): the primal solution available from [CallbackVariablePrimal](#) is integer infeasible.

- [CALLBACK\\_NODE\\_STATUS\\_UNKNOWN](#): the primal solution available from [CallbackVariablePrimal](#) might be integer feasible or infeasible.

[source](#)

`MathOptInterface.CALLBACK_NODE_STATUS_INTEGER` – Constant.

```
CALLBACK_NODE_STATUS_INTEGER::CallbackNodeStatusCode
```

An instance of the [CallbackNodeStatusCode](#) enum.

`CALLBACK_NODE_STATUS_INTEGER`: the primal solution available from [CallbackVariablePrimal](#) is integer feasible.

[source](#)

`MathOptInterface.CALLBACK_NODE_STATUS_FRACTIONAL` – Constant.

```
CALLBACK_NODE_STATUS_FRACTIONAL::CallbackNodeStatusCode
```

An instance of the [CallbackNodeStatusCode](#) enum.

`CALLBACK_NODE_STATUS_FRACTIONAL`: the primal solution available from [CallbackVariablePrimal](#) is integer infeasible.

[source](#)

`MathOptInterface.CALLBACK_NODE_STATUS_UNKNOWN` – Constant.

```
CALLBACK_NODE_STATUS_UNKNOWN::CallbackNodeStatusCode
```

An instance of the [CallbackNodeStatusCode](#) enum.

`CALLBACK_NODE_STATUS_UNKNOWN`: the primal solution available from [CallbackVariablePrimal](#) might be integer feasible or infeasible.

[source](#)

## Lazy constraints

`MathOptInterface.LazyConstraintCallback` – Type.

```
LazyConstraintCallback() <: AbstractCallback
```

The callback can be used to reduce the feasible set given the current primal solution by submitting a [LazyConstraint](#). For instance, it may be called at an incumbent of a mixed-integer problem. Note that there is no guarantee that the callback is called at every feasible primal solution.

The current primal solution is accessed through [CallbackVariablePrimal](#). Trying to access other result attributes will throw [OptimizeInProgress](#) as discussed in [AbstractCallback](#).

### Example

```

x = MOI.add_variables(optimizer, 8)
MOI.set(optimizer, MOI.LazyConstraintCallback(), callback_data -> begin
    sol = MOI.get(optimizer, MOI.CallbackVariablePrimal(callback_data), x)
    if # should add a lazy constraint
        func = # computes function
        set = # computes set
        MOI.submit(optimizer, MOI.LazyConstraint(callback_data), func, set)
    end
end)

```

**source**

MathOptInterface.LazyConstraint - Type.

```
LazyConstraint(callback_data)
```

Lazy constraint `func`-in-`set` submitted as `func`, `set`. The optimal solution returned by `VariablePrimal` will satisfy all lazy constraints that have been submitted.

This can be submitted only from the `LazyConstraintCallback`. The field `callback_data` is a solver-specific callback type that is passed as the argument to the feasible solution callback.

### Example

Suppose `x` and `y` are `VariableIndex`s of `optimizer`. To add a `LazyConstraint` for  $2x + 3y \leq 1$ , write

```

func = 2.0x + 3.0y
set = MOI.LessThan(1.0)
MOI.submit(optimizer, MOI.LazyConstraint(callback_data), func, set)

```

inside a `LazyConstraintCallback` of data `callback_data`.

**source**

### User cuts

MathOptInterface.UserCutCallback - Type.

```
UserCutCallback() <: AbstractCallback
```

The callback can be used to submit `UserCut` given the current primal solution. For instance, it may be called at fractional (that is, non-integer) nodes in the branch and bound tree of a mixed-integer problem. Note that there is not guarantee that the callback is called *everytime* the solver has an infeasible solution.

The infeasible solution is accessed through `CallbackVariablePrimal`. Trying to access other result attributes will throw `OptimizeInProgress` as discussed in `AbstractCallback`.

### Example

```

x = MOI.add_variables(optimizer, 8)
MOI.set(optimizer, MOI.UserCutCallback(), callback_data -> begin
    sol = MOI.get(optimizer, MOI.CallbackVariablePrimal(callback_data), x)
    if # can find a user cut
        func = # computes function
        set = # computes set
        MOI.submit(optimizer, MOI.UserCut(callback_data), func, set)
    end
end

```

**source**

MathOptInterface.UserCut – Type.

```
UserCut(callback_data)
```

Constraint func-to-set suggested to help the solver detect the solution given by [CallbackVariablePrimal](#) as infeasible. The cut is submitted as func, set. Typically [CallbackVariablePrimal](#) will violate integrality constraints, and a cut would be of the form [ScalarAffineFunction-in-LessThan](#) or [ScalarAffineFunction-in-GreaterThan](#). Note that, as opposed to [LazyConstraint](#), the provided constraint cannot modify the feasible set, the constraint should be redundant, for example, it may be a consequence of affine and integrality constraints.

This can be submitted only from the [UserCutCallback](#). The field `callback_data` is a solver-specific callback type that is passed as the argument to the infeasible solution callback.

Note that the solver may silently ignore the provided constraint.

**source**

## Heuristic solutions

MathOptInterface.HeuristicCallback – Type.

```
HeuristicCallback() <: AbstractCallback
```

The callback can be used to submit [HeuristicSolution](#) given the current primal solution. For example, it may be called at fractional (that is, non-integer) nodes in the branch and bound tree of a mixed-integer problem. Note that there is no guarantee that the callback is called every time the solver has an infeasible solution.

The current primal solution is accessed through [CallbackVariablePrimal](#). Trying to access other result attributes will throw [OptimizeInProgress](#) as discussed in [AbstractCallback](#).

### Example

```

x = MOI.add_variables(optimizer, 8)
MOI.set(optimizer, MOI.HeuristicCallback(), callback_data -> begin
    sol = MOI.get(optimizer, MOI.CallbackVariablePrimal(callback_data), x)
    if # can find a heuristic solution
        values = # computes heuristic solution

```

```

        MOI.submit(optimizer, MOI.HeuristicSolution(callback_data), x,
                  values)
    end
end

```

[source](#)

MathOptInterface.HeuristicSolution – Type.

```
HeuristicSolution(callback_data)
```

Heuristically obtained feasible solution. The solution is submitted as `variables`, `values` where `values[i]` gives the value of `variables[i]`, similarly to `set`. The `submit` call returns a `HeuristicSolutionStatus` indicating whether the provided solution was accepted or rejected.

This can be submitted only from the `HeuristicCallback`. The field `callback_data` is a solver-specific callback type that is passed as the argument to the heuristic callback.

Some solvers require a complete solution, others only partial solutions.

[source](#)

MathOptInterface.HeuristicSolutionStatus – Type.

```
HeuristicSolutionStatus
```

An Enum of possible return values for `submit` with `HeuristicSolution`. This informs whether the heuristic solution was accepted or rejected.

### Values

Possible values are:

- `HEURISTIC SOLUTION ACCEPTED`: The heuristic solution was accepted
- `HEURISTIC SOLUTION REJECTED`: The heuristic solution was rejected
- `HEURISTIC SOLUTION UNKNOWN`: No information available on the acceptance

[source](#)

MathOptInterface.HEURISTIC SOLUTION ACCEPTED – Constant.

```
HEURISTIC SOLUTION ACCEPTED::HeuristicSolutionStatus
```

An instance of the `HeuristicSolutionStatus` enum.

`HEURISTIC SOLUTION ACCEPTED`: The heuristic solution was accepted

[source](#)

MathOptInterface.HEURISTIC SOLUTION REJECTED – Constant.

```
HEURISTIC_SOLUTION_REJECTED::HeuristicSolutionStatus
```

An instance of the [HeuristicSolutionStatus](#) enum.

**HEURISTIC\_SOLUTION\_REJECTED:** The heuristic solution was rejected

[source](#)

`MathOptInterface.HEURISTIC_SOLUTION_UNKNOWN` – Constant.

```
HEURISTIC_SOLUTION_UNKNOWN::HeuristicSolutionStatus
```

An instance of the [HeuristicSolutionStatus](#) enum.

**HEURISTIC\_SOLUTION\_UNKNOWN:** No information available on the acceptance

[source](#)

## 35.8 Errors

When an MOI call fails on a model, precise errors should be thrown when possible instead of simply calling `error` with a message. The docstrings for the respective methods describe the errors that the implementation should throw in certain situations. This error-reporting system allows code to distinguish between internal errors (that should be shown to the user) and unsupported operations which may have automatic workarounds.

When an invalid index is used in an MOI call, an [InvalidIndex](#) is thrown:

`MathOptInterface.InvalidIndex` – Type.

```
struct InvalidIndex{IndexType<:Index} <: Exception
    index::IndexType
end
```

An error indicating that the index `index` is invalid.

[source](#)

When an invalid result index is used to retrieve an attribute, a [ResultIndexBoundsError](#) is thrown:

`MathOptInterface.ResultIndexBoundsError` – Type.

```
struct ResultIndexBoundsError{AttrType} <: Exception
    attr::AttrType
    result_count::Int
end
```

An error indicating that the requested attribute `attr` could not be retrieved, because the solver returned too few results compared to what was requested. For instance, the user tries to retrieve `VariablePrimal(2)` when only one solution is available, or when the model is infeasible and has no solution.

See also: [check\\_result\\_index\\_bounds](#).

[source](#)

`MathOptInterface.check_result_index_bounds` – Function.

```
check_result_index_bounds(model::ModelLike, attr)
```

This function checks whether enough results are available in the `model` for the requested `attr`, using its `result_index` field. If the model does not have sufficient results to answer the query, it throws a `ResultIndexBoundsError`.

`source`

As discussed in [JuMP mapping](#), for scalar constraint with a nonzero function constant, a `ScalarFunctionConstantNotZero` exception may be thrown:

`MathOptInterface.ScalarFunctionConstantNotZero` – Type.

```
struct ScalarFunctionConstantNotZero{T, F, S} <: Exception
    constant::T
end
```

An error indicating that the constant part of the function in the constraint `F-in-S` is nonzero.

`source`

Some `VariableIndex` constraints cannot be combined on the same variable:

`MathOptInterface.LowerBoundAlreadySet` – Type.

```
LowerBoundAlreadySet{S1, S2}
```

Error thrown when setting a `VariableIndex-in-S2` when a `VariableIndex-in-S1` has already been added and the sets `S1, S2` both set a lower bound, that is, they are `EqualTo`, `GreaterThan`, `Interval`, `Semicontinuous` or `Semienteger`.

`source`

`MathOptInterface.UpperBoundAlreadySet` – Type.

```
UpperBoundAlreadySet{S1, S2}
```

Error thrown when setting a `VariableIndex-in-S2` when a `VariableIndex-in-S1` has already been added and the sets `S1, S2` both set an upper bound, that is, they are `EqualTo`, `LessThan`, `Interval`, `Semicontinuous` or `Semienteger`.

`source`

As discussed in [AbstractCallback](#), trying to `get` attributes inside a callback may throw:

`MathOptInterface.OptimizeInProgress` – Type.

```
struct OptimizeInProgress{AttrType<:AnyAttribute} <: Exception
    attr::AttrType
end
```

Error thrown from optimizer when `MOI.get(optimizer, attr)` is called inside an `AbstractCallback` while it is only defined once `optimize!` has completed. This can only happen when `is_set_by_optimize(attr)` is true.

`source`

Trying to submit the wrong type of `AbstractSubmittable` inside an `AbstractCallback` (for example, a `UserCut` inside a `LazyConstraintCallback`) will throw:

`MathOptInterface.InvalidCallbackUsage` – Type.

```
struct InvalidCallbackUsage{C, S} <: Exception
    callback::C
    submittable::S
end
```

An error indicating that submittable cannot be submitted inside callback.

For example, `UserCut` cannot be submitted inside `LazyConstraintCallback`.

`source`

The rest of the errors defined in MOI fall in two categories represented by the following two abstract types:

`MathOptInterface.UnsupportedError` – Type.

```
UnsupportedError <: Exception
```

Abstract type for error thrown when an element is not supported by the model.

`source`

`MathOptInterface.NotAllowedError` – Type.

```
NotAllowedError <: Exception
```

Abstract type for error thrown when an operation is supported but cannot be applied in the current state of the model.

`source`

The different `UnsupportedError` and `NotAllowedError` are the following errors:

`MathOptInterface.UnsupportedAttribute` – Type.

```
struct UnsupportedAttribute{AttrType} <: UnsupportedError
    attr::AttrType
    message::String
end
```

An error indicating that the attribute `attr` is not supported by the model, that is, that `supports` returns `false`.

`source`

`MathOptInterface.SetAttributeNotAllowed` - Type.

```
struct SetAttributeNotAllowed{AttrType} <: NotAllowedError
    attr::AttrType
    message::String
end
```

An error indicating that the attribute `attr` is supported (see `supports`) but cannot be set for some reason (see the error string).

`source`

`MathOptInterface.AddVariableNotAllowed` - Type.

```
struct AddVariableNotAllowed <: NotAllowedError
    message::String # Human-friendly explanation why the attribute cannot be set
end
```

An error indicating that variables cannot be added to the model.

`source`

`MathOptInterface.UnsupportedConstraint` - Type.

```
struct UnsupportedConstraint{F<:AbstractFunction,S<:AbstractSet} <: UnsupportedError
    message::String
end
```

An error indicating that constraints of type `F-in-S` are not supported by the model, that is, that `supports_constraint` returns `false`.

```
julia> import MathOptInterface as MOI

julia> showerror(stdout, MOI.UnsupportedConstraint{MOI.VariableIndex,MOI.ZeroOne}())
UnsupportedConstraint: `MathOptInterface.VariableIndex`-in-`MathOptInterface.ZeroOne`
→ constraints are not supported by the
solver you have chosen, and we could not reformulate your model into a
form that is supported.
```

To fix this error you must choose a different solver.

[source](#)

MathOptInterface.AddConstraintNotAllowed – Type.

```
struct AddConstraintNotAllowed{F<:AbstractFunction, S<:AbstractSet} <: NotAllowedError
    message::String # Human-friendly explanation why the attribute cannot be set
end
```

An error indicating that constraints of type F-in-S are supported (see [supports\\_constraint](#)) but cannot be added.

[source](#)

MathOptInterface.ModifyConstraintNotAllowed – Type.

```
struct ModifyConstraintNotAllowed{F<:AbstractFunction, S<:AbstractSet,
                                C<:AbstractFunctionModification} <: NotAllowedError
    constraint_index::ConstraintIndex{F, S}
    change::C
    message::String
end
```

An error indicating that the constraint modification change cannot be applied to the constraint of index ci.

[source](#)

MathOptInterface.ModifyObjectiveNotAllowed – Type.

```
struct ModifyObjectiveNotAllowed{C<:AbstractFunctionModification} <: NotAllowedError
    change::C
    message::String
end
```

An error indicating that the objective modification change cannot be applied to the objective.

[source](#)

MathOptInterface.DeleteNotAllowed – Type.

```
struct DeleteNotAllowed{IndexType <: Index} <: NotAllowedError
    index::IndexType
    message::String
end
```

An error indicating that the index index cannot be deleted.

[source](#)

MathOptInterface.UnsupportedSubmittable – Type.

```
struct UnsupportedSubmittable{SubmitType} <: UnsupportedError
    sub::SubmitType
    message::String
end
```

An error indicating that the submittable sub is not supported by the model, that is, that [supports](#) returns `false`.

[source](#)

`MathOptInterface.SubmitNotAllowed` - Type.

```
struct SubmitNotAllowed{SubmitType<:AbstractSubmittable} <: NotAllowedError
    sub::SubmitType
    message::String
end
```

An error indicating that the submittable sub is supported (see [supports](#)) but cannot be added for some reason (see the error string).

[source](#)

`MathOptInterface.UnsupportedNonlinearOperator` - Type.

```
UnsupportedNonlinearOperator(head)::Symbol[, message::String]) <: UnsupportedError
```

An error thrown by optimizers if they do not support the operator head in a `ScalarNonlinearFunction`.

### Example

```
julia> import MathOptInterface as MOI

julia> throw(MOI.UnsupportedNonlinearOperator(:black_box))
ERROR: MathOptInterface.UnsupportedNonlinearOperator: The nonlinear operator `:black_box` is not
↪ supported by the model.
Stacktrace:
[...]
```

[source](#)

Note that setting the `ConstraintFunction` of a `VariableIndex` constraint is not allowed:

`MathOptInterface.SettingVariableIndexNotAllowed` - Type.

```
SettingVariableIndexNotAllowed()
```

Error type that should be thrown when the user calls `set` to change the `ConstraintFunction` of a `VariableIndex` constraint.

[source](#)

# Chapter 36

## Submodules

### 36.1 Benchmarks

#### Overview

##### The Benchmarks submodule

To aid the development of efficient solver wrappers, MathOptInterface provides benchmarking capability. Benchmarking a wrapper follows a two-step process.

First, prior to making changes, create a baseline for the benchmark results on a given benchmark suite as follows:

```
using SolverPackage # Replace with your choice of solver.
import MathOptInterface as MOI

suite = MOI.Benchmarks.suite() do
    SolverPackage.Optimizer()
end

MOI.Benchmarks.create_baseline(
    suite, "current"; directory = "/tmp", verbose = true
)
```

Use the `exclude` argument to `Benchmarks.suite` to exclude benchmarks that the solver doesn't support.

Second, after making changes to the package, re-run the benchmark suite and compare to the prior saved results:

```
using SolverPackage
import MathOptInterface as MOI

suite = MOI.Benchmarks.suite() do
    SolverPackage.Optimizer()
end

MOI.Benchmarks.compare_against_baseline(
    suite, "current"; directory = "/tmp", verbose = true
)
```

This comparison will create a report detailing improvements and regressions.

## API Reference

### Benchmarks

Functions to help benchmark the performance of solver wrappers. See [The Benchmarks submodule](#) for more details.

`MathOptInterface.Benchmarks.suite` – Function.

```
suite(
    new_model::Function;
    exclude::Vector{Regex} = Regex[]
)
```

Create a suite of benchmarks. `new_model` should be a function that takes no arguments, and returns a new instance of the optimizer you wish to benchmark.

Use `exclude` to exclude a subset of benchmarks.

### Example

```
julia> MOI.Benchmarks.suite() do
           return GLPK.Optimizer()
       end

julia> MOI.Benchmarks.suite(; exclude = [r"delete"]) do
           return Gurobi.Optimizer()
       end
```

`source`

`MathOptInterface.Benchmarks.create_baseline` – Function.

```
create_baseline(suite, name::String; directory::String = ""; kwargs...)
```

Run all benchmarks in `suite` and save to files called `name` in `directory`.

Extra `kwargs` are based to `BenchmarkTools.run`.

### Example

```
julia> import MathOptInterface as MOI

julia> import GLPK

julia> my_suite = MOI.Benchmarks.suite(() -> GLPK.Optimizer());

julia> MOI.Benchmarks.create_baseline(
           my_suite,
           "glpk_master";
           directory = "/tmp",
           verbose = true,
       )
```

[source](#)  
**MathOptInterface.Benchmarks.compare\_against\_baseline** - Function.

```
compare_against_baseline(
    suite, name::String; directory::String = "",
    report_filename::String = "report.txt"
)
```

Run all benchmarks in `suite` and compare against files called `name` in `directory` that were created by a call to `create_baseline`.

A report summarizing the comparison is written to `report_filename` in `directory`.

Extra kwargs are based to `BenchmarkTools.run`.

### Example

```
julia> import MathOptInterface as MOI

julia> import GLPK

julia> my_suite = MOI.Benchmarks.suite(() -> GLPK.Optimizer());

julia> MOI.Benchmarks.compare_against_baseline(
    my_suite,
    "glpk_master";
    directory = "/tmp",
    verbose = true,
)
```

[source](#)

## 36.2 Bridges

### Overview

#### The Bridges submodule

The Bridges module simplifies the process of converting models between equivalent formulations.

#### Tip

Read our paper for more details on how bridges are implemented.

#### Why bridges?

A constraint can often be written in a number of equivalent formulations. For example, the constraint  $l \leq a^\top x \leq u$  ([ScalarAffineFunction-in-Interval](#)) could be re-formulated as two constraints:  $a^\top x \geq l$  ([ScalarAffineFunction-in-GreaterThan](#)) and  $a^\top x \leq u$  ([ScalarAffineFunction-in-LessThan](#)). An alternative re-formulation is to add a dummy variable  $y$  with the constraints  $l \leq y \leq u$  ([VariableIndex-in-Interval](#)) and  $a^\top x - y = 0$  ([ScalarAffineFunction-in-EqualTo](#)).

To avoid each solver having to code these transformations manually, MathOptInterface provides *bridges*.

A bridge is a small transformation from one constraint type to another (potentially collection of) constraint type.

Because these bridges are included in MathOptInterface, they can be re-used by any optimizer. Some bridges also implement constraint modifications and constraint primal and dual translations.

Several bridges can be used in combination to transform a single constraint into a form that the solver may understand. Choosing the bridges to use takes the form of finding a shortest path in the hyper-graph of bridges. The methodology is detailed in [the MOI paper](#).

### The three types of bridges

There are three types of bridges in MathOptInterface:

1. Constraint bridges
2. Variable bridges
3. Objective bridges

#### Constraint bridges

Constraint bridges convert constraints formulated by the user into an equivalent form supported by the solver. Constraint bridges are subtypes of [Bridges.Constraint.AbstractBridge](#).

The equivalent formulation may add constraints (and possibly also variables) in the underlying model.

In particular, constraint bridges can focus on rewriting the function of a constraint, and do not change the set. Function bridges are subtypes of [Bridges.Constraint.AbstractFunctionConversionBridge](#).

Read the [list of implemented constraint bridges](#) for more details on the types of transformations that are available. Function bridges are [Bridges.Constraint.ScalarFunctionizeBridge](#) and [Bridges.Constraint.VectorFunctionizeBridge](#).

#### Variable bridges

Variable bridges convert variables added by the user, either free with [add\\_variable/add\\_variables](#), or constrained with [add\\_constrained\\_variable/add\\_constrained\\_variables](#), into an equivalent form supported by the solver. Variable bridges are subtypes of [Bridges.Variable.AbstractBridge](#).

The equivalent formulation may add constraints (and possibly also variables) in the underlying model.

Read the [list of implemented variable bridges](#) for more details on the types of transformations that are available.

#### Objective bridges

Objective bridges convert the [ObjectiveFunction](#) set by the user into an equivalent form supported by the solver. Objective bridges are subtypes of [Bridges.Objective.AbstractBridge](#).

The equivalent formulation may add constraints (and possibly also variables) in the underlying model.

Read the [list of implemented objective bridges](#) for more details on the types of transformations that are available.

**Bridges.full\_bridge\_optimizer****Tip**

Unless you have an advanced use-case, this is probably the only function you need to care about.

To enable the full power of MathOptInterface's bridges, wrap an optimizer in a `Bridges.full_bridge_optimizer`.

```
julia> inner_optimizer = MOI.Utilities.Model{Float64}()
MOIU.Model{Float64}
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberofVariables: 0
└ NumberofConstraints: 0

julia> optimizer = MOI.Bridges.full_bridge_optimizer(inner_optimizer, Float64)
MOIB.LazyBridgeOptimizer{MOIU.Model{Float64}}
├ Variable bridges: none
├ Constraint bridges: none
├ Objective bridges: none
└ model: MOIU.Model{Float64}
    ├ ObjectiveSense: FEASIBILITY_SENSE
    ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
    ├ NumberofVariables: 0
    └ NumberofConstraints: 0
```

Now, use `optimizer` as normal, and bridging will happen lazily behind the scenes. By lazily, we mean that bridging will happen if and only if the constraint is not supported by the `inner_optimizer`.

**Info**

Most bridges are added by default in `Bridges.full_bridge_optimizer`. However, for technical reasons, some bridges are not added by default. Three examples include `Bridges.Constraint.SOCToPSDBridge`, `Bridges.Constraint.SOCToNonConvexQuadBridge` and `Bridges.Constraint.RSOCToNonConvexQuadBridge`. See the docs of those bridges for more information.

**Add a single bridge**

If you don't want to use `Bridges.full_bridge_optimizer`, you can wrap an optimizer in a single bridge.

However, this will force the constraint to be bridged, even if the `inner_optimizer` supports it.

```
julia> inner_optimizer = MOI.Utilities.Model{Float64}();

julia> optimizer = MOI.Bridges.Constraint.SplitInterval{Float64}(inner_optimizer);

julia> x = MOI.add_variable(optimizer)
MOI.VariableIndex(1)

julia> MOI.add_constraint(optimizer, x, MOI.Interval(0.0, 1.0))
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
→   MathOptInterface.Interval{Float64}}(1)
```

```
julia> MOI.get(optimizer, MOI.ListOfConstraintTypesPresent())
1-element Vector{Tuple{Type, Type}}:
 (MathOptInterface.VariableIndex, MathOptInterface.Interval{Float64})

julia> MOI.get(inner_optimizer, MOI.ListOfConstraintTypesPresent())
2-element Vector{Tuple{Type, Type}}:
 (MathOptInterface.VariableIndex, MathOptInterface.GreaterThan{Float64})
 (MathOptInterface.VariableIndex, MathOptInterface.LessThan{Float64})
```

### Bridges.LazyBridgeOptimizer

If you don't want to use `Bridges.full_bridge_optimizer`, but you need more than a single bridge (or you want the bridging to happen lazily), you can manually construct a `Bridges.LazyBridgeOptimizer`.

First, wrap an inner optimizer:

```
julia> inner_optimizer = MOI.Utilities.Model{Float64}()
MOIU.Model{Float64}
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberofConstraints: 0

julia> optimizer = MOI.Bridges.LazyBridgeOptimizer(inner_optimizer)
MOIB.LazyBridgeOptimizer{MOIU.Model{Float64}}
├ Variable bridges: none
├ Constraint bridges: none
├ Objective bridges: none
└ model: MOIU.Model{Float64}
    ├ ObjectiveSense: FEASIBILITY_SENSE
    ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
    ├ NumberofVariables: 0
    └ NumberofConstraints: 0
```

Then use `Bridges.add_bridge` to add individual bridges:

```
julia> MOI.Bridges.add_bridge(optimizer, MOI.Bridges.Constraint.SplitIntervalBridge{Float64})
julia> MOI.Bridges.add_bridge(optimizer, MOI.Bridges.Objective.FunctionizeBridge{Float64})
```

Now the constraints will be bridged only if needed:

```
julia> x = MOI.add_variable(optimizer)
MOI.VariableIndex(1)

julia> MOI.add_constraint(optimizer, x, MOI.Interval(0.0, 1.0))
MathOptInterface.ConstraintIndex[MathOptInterface.VariableIndex,
    ↳ MathOptInterface.Interval{Float64}](1)

julia> MOI.get(optimizer, MOI.ListOfConstraintTypesPresent())
1-element Vector{Tuple{Type, Type}}:
```

```
(MathOptInterface.VariableIndex, MathOptInterface.Interval{Float64})  
  
julia> MOI.get(inner_optimizer, MOI.ListOfConstraintTypesPresent())  
1-element Vector{Tuple{Type, Type}}:  
 (MathOptInterface.VariableIndex, MathOptInterface.Interval{Float64})
```

## Implementation

### Implementing a bridge

The easiest way to implement a bridge is to follow an existing example. There are three locations of bridges in the source code:

- Constraint bridges are stored in `src/Bridges/Constraint/bridges`
- Objective bridges are stored in `src/Bridges/Objective/bridges`
- Variable bridges are stored in `src/Bridges/Variable/bridges`

The [Implementing a constraint bridge](#) tutorial has a more detailed guide on what is required to implement a bridge.

When opening a pull request that adds a new bridge, use the checklist [Adding a new bridge](#).

If you need help or advice, please contact the [Developer Chatroom](#).

### SetMap bridges

For constraint and variable bridges, a common reformulation is that  $f(x) \in F$  is reformulated to  $g(x) \in G$ . In this case, no additional variables and constraints are added, and the bridge needs only a way to map between the functions  $f$  and  $g$  and the sets  $F$  and  $G$ .

To implementation a bridge of this form, subtype the abstract type `Bridges.Constraint.SetMapBridge` or `Bridges.Variable.SetMapBridge` and implement the API described in the docstring of each type.

### `final_touch`

Some bridges require information from other parts of the model. One set of examples are the various combinatorial ToMILP bridges, such as `Bridges.Constraint.SOS1ToMILPBridge`, which require knowledge of the variable bounds.

Bridges requiring information from other parts of the model should implement `Bridges.final_touch` and `Bridges.needs_final_touch`.

During the bridge's construction, store the function and set and make no changes to the underlying model. Then, in `Bridges.final_touch`, query the additional information and add the reformulated problem to the model.

When implementing, you must consider that:

- `Bridges.final_touch` may be called multiple times, so that your reformulation should be applied only if necessary. Sometimes the additional data will be the same, and sometimes it may be different.
- We do not currently support `final_touch` bridges that introduce constraints which also require a `final_touch` bridge. Therefore, you should implement `final_touch` only if necessary, and we recommend that you contact the [Developer Chatroom](#) for advice before doing so.

## Testing

Use the `Bridges.runtests` function to test a bridge. It takes three arguments: the type of the bridge, the input model as a string, and the output model as a string.

Here is an example:

```
julia> MOI.Bridges.runtests(
    MOI.Bridges.Constraint.GreaterToLessBridge,
    """
    variables: x
    x >= 1.0
    """,
    """
    variables: x
    -1.0 * x <= -1.0
    """,
)
```

There are a number of other useful keyword arguments.

- `eltype` can be used to specify the element type of the model (and bridge). It defaults to `Float64`.
- `variable_start` and `constraint_start` are used as the values to set the `VariablePrimalStart` and `ConstraintPrimalStart` attributes to. They default to 1.2. If you use a different `eltype`, you must set appropriate starting values of the same type. The default 1.2 was chosen to minimize the risk that the starting point is undefined, which could happen for common situations like `0.0` and `1.0`. The tests associated with the starting values do not necessarily check for correctness, only that they can be set and get to produce the same result.
- `print_inner_model` can be used to print the reformulated output model from the bridge. This is especially helpful during debugging to see what the bridge is doing, and to spot mistakes. It defaults to `false`.

Here is an example:

```
julia> MOI.Bridges.runtests(
    MOI.Bridges.Constraint.GreaterToLessBridge,
    """
    variables: x
    x >= 1
    """,
    """
    variables: x
    ::Int: -1 * x <= -1
    """;
    eltype = Int,
    print_inner_model = true,
    variable_start = 2,
    constraint_start = 2,
)
Feasibility

Subject to:
```

```
ScalarAffineFunction{Int64}-in-LessThan{Int64}
(0) - (1) x <= (-1)
```

## List of bridges

### List of bridges

This section describes the `Bridges.AbstractBridges` that are implemented in `MathOptInterface`.

### Constraint bridges

These bridges are subtypes of `Bridges.Constraint.AbstractBridge`.

`MathOptInterface.Bridges.Constraint.AbstractFunctionConversionBridge` – Type.

```
abstract type AbstractFunctionConversionBridge{F,S} <: AbstractBridge end
```

Abstract type to support writing bridges in which the function changes but the set does not.

By convention, the transformed function is stored in the `.constraint` field.

[source](#)

`MathOptInterface.Bridges.Constraint.AbstractToIntervalBridge` – Type.

```
AbstractToIntervalBridge{T<:AbstractFloat,S,F}
```

An abstract type that simplifies the creation of other bridges.

#### Warning

T must be a `AbstractFloat` type because otherwise `typemin` and `typemax` would either be not implemented (for example, `BigInt`), or would not give infinite value (for example, `Int`). For this reason, this bridge is only added to `MOI.Bridges.full_bridge_optimizer` when T is a subtype of `AbstractFloat`.

[source](#)

`MathOptInterface.Bridges.Constraint.AllDifferentToCountDistinctBridge` – Type.

```
AllDifferentToCountDistinctBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

`AllDifferentToCountDistinctBridge` implements the following reformulations:

- $x \in \text{AllDifferent}(d)$  to  $(n, x) \in \text{CountDistinct}(1 + d)$  and  $n = d$
- $f(x) \in \text{AllDifferent}(d)$  to  $(d, f(x)) \in \text{CountDistinct}(1 + d)$

**Source node**

`AllDifferentToCountDistinctBridge` supports:

- `F` in `MOI.AllDifferent`

where `F` is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

**Target nodes**

`AllDifferentToCountDistinctBridge` creates:

- `F` in `MOI.CountDistinct`
- `MOI.VariableIndex` in `MOI.EqualTo{T}`

`source`

`MathOptInterface.Bridges.Constraint.BinPackingToMILPBridge` - Type.

`BinPackingToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge`

`BinPackingToMILPBridge` implements the following reformulation:

- $x \in BinPacking(c, w)$  into a mixed-integer linear program.

**Reformulation**

The reformulation is non-trivial, and it depends on the finite domain of each variable  $x_i$ , which we as define  $S_i = \{l_i, \dots, u_i\}$ .

First, we introduce new binary variables  $z_{ij}$ , which are 1 if variable  $x_i$  takes the value  $j$  in the optimal solution and 0 otherwise:

$$\begin{aligned} z_{ij} &\in \{0, 1\} \quad \forall i \in 1 \dots d, j \in S_i \\ x_i - \sum_{j \in S_i} j \cdot z_{ij} &= 0 \quad \forall i \in 1 \dots d \\ \sum_{j \in S_i} z_{ij} &= 1 \quad \forall i \in 1 \dots d \end{aligned}$$

Then, we add the capacity constraint for all possible bins  $j$ :

$$\sum_i w_i z_{ij} \leq c \quad \forall j \in \bigcup_{i=1, \dots, d} S_i$$

**Source node**

`BinPackingToMILPBridge` supports:

- `F` in `MOI.BinPacking{T}`

**Target nodes**

`BinPackingToMILPBridge` creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.LessThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.CircuitToMILPBridge` - Type.

```
CircuitToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

`CircuitToMILPBridge` implements the following reformulation:

- $x \in \text{Circuit}(d)$  to the Miller-Tucker-Zemlin formulation of the Traveling Salesperson Problem.

**Source node**

`CircuitToMILPBridge` supports:

- `F` in `MOI.Circuit`

where `F` is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

**Target nodes**

`CircuitToMILPBridge` creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.VariableIndex` in `MOI.Integer`
- `MOI.VariableIndex` in `MOI.Interval{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.LessThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.ComplexNormInfinityToSecondOrderConeBridge` - Type.

```
ComplexNormInfinityToSecondOrderConeBridge{T} <: Bridges.Constraint.AbstractBridge
```

`ComplexNormInfinityToSecondOrderConeBridge` implements the following reformulation:

- $(t, x) \in \text{NormInfinity}(1 + d)$  into  $(t, \text{real}(x_i), \text{imag}(x_i)) \in \text{SecondOrderCone}()$  for all  $i$ .

**Source node**

`ComplexNormInfinityToSecondOrderConeBridge` supports:

- `MOI.VectorAffineFunction{Complex{T}}` in `MOI.NormInfinityCone`

### Target nodes

`ComplexNormInfinityToSecondOrderConeBridge` creates:

- `MOI.VectorAffineFunction{T}` in `MOI.SecondOrderCone`

`source`

`MathOptInterface.Bridges.Constraint.CountAtLeastToCountBelongsBridge` – Type.

```
CountAtLeastToCountBelongsBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

`CountAtLeastToCountBelongsBridge` implements the following reformulation:

- $x \in \text{CountAtLeast}(n, d, \mathcal{S})$  to  $(n_i, x_{d_i}) \in \text{CountBelongs}(1 + d, \mathcal{S})$  and  $n_i \geq n$  for all  $i$ .

### Source node

`CountAtLeastToCountBelongsBridge` supports:

- `F` in `MOI.CountAtLeast`

where `F` is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

### Target nodes

`CountAtLeastToCountBelongsBridge` creates:

- `F` in `MOI.CountBelongs`
- `MOI.VariableIndex` in `MOI.GreaterThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.CountBelongsToMILPBridge` – Type.

```
CountBelongsToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

`CountBelongsToMILPBridge` implements the following reformulation:

- $(n, x) \in \text{CountBelongs}(1 + d, \mathcal{S})$  into a mixed-integer linear program.

### Reformulation

The reformulation is non-trivial, and it depends on the finite domain of each variable  $x_i$ , which we define  $S_i = \{l_i, \dots, u_i\}$ .

First, we introduce new binary variables  $z_{ij}$ , which are 1 if variable  $x_i$  takes the value  $j$  in the optimal solution and 0 otherwise:

$$\begin{aligned} z_{ij} &\in \{0, 1\} \quad \forall i \in 1 \dots d, j \in S_i \\ x_i - \sum_{j \in S_i} j \cdot z_{ij} &= 0 \quad \forall i \in 1 \dots d \\ \sum_{j \in S_i} z_{ij} &= 1 \quad \forall i \in 1 \dots d \end{aligned}$$

Finally,  $n$  is constrained to be the number of  $z_{ij}$  elements that are in  $S$ :

$$n - \sum_{i \in 1 \dots d, j \in S} z_{ij} = 0$$

### Source node

`CountBelongsToMILPBridge` supports:

- $F$  in `MOI.CountBelongs`

where  $F$  is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

### Target nodes

`CountBelongsToMILPBridge` creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`

`source`

`MathOptInterface.Bridges.Constraint.CountDistinctToMILPBridge` – Type.

```
CountDistinctToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

`CountDistinctToMILPBridge` implements the following reformulation:

- $(n, x) \in \text{CountDistinct}(1 + d)$  into a mixed-integer linear program.

### Reformulation

The reformulation is non-trivial, and it depends on the finite domain of each variable  $x_i$ , which we define  $S_i = \{l_i, \dots, u_i\}$ .

First, we introduce new binary variables  $z_{ij}$ , which are 1 if variable  $x_i$  takes the value  $j$  in the optimal solution and 0 otherwise:

$$\begin{aligned} z_{ij} &\in \{0, 1\} \quad \forall i \in 1 \dots d, j \in S_i \\ x_i - \sum_{j \in S_i} j \cdot z_{ij} &= 0 \quad \forall i \in 1 \dots d \\ \sum_{j \in S_i} z_{ij} &= 1 \quad \forall i \in 1 \dots d \end{aligned}$$

Then, we introduce new binary variables  $y_j$ , which are 1 if a variable takes the value  $j$  in the optimal solution and 0 otherwise.

$$\begin{aligned} y_j &\in \{0, 1\} \quad \forall j \in \bigcup_{i=1, \dots, d} S_i \\ y_j &\leq \sum_{i \in 1 \dots d : j \in S_i} z_{ij} \leq M y_j \quad \forall j \in \bigcup_{i=1, \dots, d} S_i \end{aligned}$$

Finally,  $n$  is constrained to be the number of  $y_j$  elements that are non-zero:

$$n - \sum_{j \in \bigcup_{i=1, \dots, d} S_i} y_j = 0$$

### Formulation (special case)

In the special case that the constraint is `[2, x, y]` in `CountDistinct(3)`, then the constraint is equivalent to `[x, y]` in `AllDifferent(2)`, which is equivalent to `x != y`.

$$(x - y \leq -1) \vee (y - x \leq -1)$$

which is equivalent to (for suitable  $M$ ):

$$\begin{aligned} z &\in \{0, 1\} \\ x - y - Mz &\leq -1 \\ y - x - M(1 - z) &\leq -1 \end{aligned}$$

### Source node

`CountDistinctToMILPBridge` supports:

- `F` in `MOI.CountDistinct`

where `F` is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

### Target nodes

`CountDistinctToMILPBridge` creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.LessThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.CountGreaterThanOrEqualToMILPBridge - Type`.

`CountGreaterThanOrEqualToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge`

`CountGreaterThanOrEqualToMILPBridge` implements the following reformulation:

- $(c, y, x) \in CountGreaterThan()$  into a mixed-integer linear program.

### Source node

CountGreaterThanToMILPBridge supports:

- F in `MOI.CountGreaterThan`

### Target nodes

CountGreaterThanToMILPBridge creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.GreaterThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.ExponentialConeToScalarNonlinearFunctionBridge` – Type.

```
ExponentialConeToScalarNonlinearFunctionBridge{T,F} <:
    Bridges.Constraint.AbstractBridge
```

ExponentialConeToScalarNonlinearFunctionBridge implements the following reformulation:

- $(x, y, z) \in ExponentialCone() \text{ to } y \cdot \exp(x/y) - z \leq 0, y \geq 0.$

### Source node

ExponentialConeToScalarNonlinearFunctionBridge supports:

- F in `MOI.ExponentialCone`

### Target nodes

ExponentialConeToScalarNonlinearFunctionBridge creates:

- `MOI.ScalarNonlinearFunction` in `MOI.LessThan{T}`
- `MOI.ScalarAffineFunction` in `MOI.GreaterThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.FlipSignBridge` – Type.

```
FlipSignBridge{T,S1,S2,F,G}
```

An abstract type that simplifies the creation of other bridges.

`source`

`MathOptInterface.Bridges.Constraint.FunctionConversionBridge` – Type.

```
FunctionConversionBridge{T,F,G,S} <: AbstractFunctionConversionBridge{G,S}
```

FunctionConversionBridge implements the following reformulations:

- $g(x) \in S$  into  $f(x) \in S$

for these pairs of functions:

- [MOI.ScalarAffineFunction](#) to [\[MOI.ScalarQuadraticFunction'\]\(@ref\)](#)
- [MOI.ScalarQuadraticFunction](#) to [MOI.ScalarNonlinearFunction](#)
- [MOI.VectorAffineFunction](#) to [MOI.VectorQuadraticFunction](#)

See also [SetConversionBridge](#).

### Source node

FunctionConversionBridge supports:

- $G$  in  $S$

### Target nodes

FunctionConversionBridge creates:

- $F$  in  $S$

`source`

`MathOptInterface.Bridges.Constraint.GeoMeanBridge - Type.`

```
GeoMeanBridge{T,F,G,H} <: Bridges.Constraint.AbstractBridge
```

GeoMeanBridge implements a reformulation from [MOI.GeometricMeanCone](#) into [MOI.RotatedSecondOrderCone](#).

The reformulation is best described in an example.

Consider the cone of dimension 4:

$$t \leq \sqrt[3]{x_1 x_2 x_3}$$

This can be rewritten as  $\exists y \geq 0$  such that:

$$\begin{aligned} t &\leq y, \\ y^4 &\leq x_1 x_2 x_3 y. \end{aligned}$$

Note that we need to create  $y$  and not use  $t^4$  directly because  $t$  is not allowed to be negative.

This is equivalent to:

$$\begin{aligned} t &\leq \frac{y_1}{\sqrt{4}}, \\ y_1^2 &\leq 2y_2y_3, \\ y_2^2 &\leq 2x_1x_2, \\ y_3^2 &\leq 2x_3(y_1/\sqrt{4}) \\ y &\geq 0. \end{aligned}$$

More generally, you can show how the geometric mean code is recursively expanded into a set of new variables  $y$  in `MOI.Nonnegatives`, a set of `MOI.RotatedSecondOrderCone` constraints, and a `MOI.LessThan` constraint between  $t$  and  $y_1$ .

### Source node

`GeoMeanBridge` supports:

- $H$  in `MOI.GeometricMeanCone`

### Target nodes

`GeoMeanBridge` creates:

- $F$  in `MOI.LessThan{T}`
- $G$  in `MOI.RotatedSecondOrderCone`
- $G$  in `MOI.Nonnegatives`

`source`

`MathOptInterface.Bridges.Constraint.GeoMeanToPowerBridge` - Type.

`GeoMeanToPowerBridge{T,F} <: Bridges.Constraint.AbstractBridge`

`GeoMeanToPowerBridge` implements the following reformulation:

- $(y, x\dots) \in GeometricMeanCone(1+d)$  into  $(x_1, t, y) \in PowerCone(1/d)$  and  $(t, x_2, \dots, x_d)$  in `GeometricMeanCone` which is then recursively expanded into more `PowerCone` constraints.

### Source node

`GeoMeanToPowerBridge` supports:

- $F$  in `MOI.GeometricMeanCone`

### Target nodes

`GeoMeanToPowerBridge` creates:

- $F$  in `MOI.PowerCone{T}`
- `MOI.VectorOfVariables` in `MOI.Nonnegatives`

`source`

`MathOptInterface.Bridges.Constraint.GeoMeantoRelEntrBridge` - Type.

```
GeoMeantoRelEntrBridge{T,F,G,H} <: Bridges.Constraint.AbstractBridge
```

`GeoMeantoRelEntrBridge` implements the following reformulation:

- $(u, w) \in \text{GeometricMeanCone}$  into  $(0, w, (u + y)\mathbf{1}) \in \text{RelativeEntropyCone}$  and  $y \geq 0$

### Source node

`GeoMeantoRelEntrBridge` supports:

- H in `MOI.GeometricMeanCone`

### Target nodes

`GeoMeantoRelEntrBridge` creates:

- G in `MOI.RelativeEntropyCone`
- F in `MOI.Nonnegatives`

### Derivation

The derivation of the bridge is as follows:

$$\begin{aligned}
(u, w) \in \text{GeometricMeanCone} &\iff u \leq \left( \prod_{i=1}^n w_i \right)^{1/n} \\
&\iff 0 \leq u + y \leq \left( \prod_{i=1}^n w_i \right)^{1/n}, y \geq 0 \\
&\iff 1 \leq \frac{\left( \prod_{i=1}^n w_i \right)^{1/n}}{u + y}, y \geq 0 \\
&\iff 1 \leq \left( \prod_{i=1}^n \frac{w_i}{u + y} \right)^{1/n}, y \geq 0 \\
&\iff 0 \leq \sum_{i=1}^n \log \left( \frac{w_i}{u + y} \right), y \geq 0 \\
&\iff 0 \geq \sum_{i=1}^n \log \left( \frac{u + y}{w_i} \right), y \geq 0 \\
&\iff 0 \geq \sum_{i=1}^n (u + y) \log \left( \frac{u + y}{w_i} \right), y \geq 0 \\
&\iff (0, w, (u + y)\mathbf{1}) \in \text{RelativeEntropyCone}, y \geq 0
\end{aligned}$$

This derivation assumes that  $u + y > 0$ , which is enforced by the relative entropy cone.

`source`

`MathOptInterface.Bridges.Constraint.GreaterToIntervalBridge` - Type.

```
GreaterToIntervalBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

GreaterToIntervalBridge implements the following reformulations:

- $f(x) \geq l$  into  $f(x) \in [l, \infty)$

#### Source node

GreaterToIntervalBridge supports:

- F in [MOI.GreaterThan{T}](#)

#### Target nodes

GreaterToIntervalBridge creates:

- F in [MOI.Interval{T}](#)

`source`

`MathOptInterface.Bridges.Constraint.GreaterToLessBridge - Type.`

```
GreaterToLessBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

GreaterToLessBridge implements the following reformulation:

- $f(x) \geq l$  into  $-f(x) \leq -l$

#### Source node

GreaterToLessBridge supports:

- G in [MOI.GreaterThan{T}](#)

#### Target nodes

GreaterToLessBridge creates:

- F in [MOI.LessThan{T}](#)

`source`

`MathOptInterface.Bridges.Constraint.HermitianToSymmetricPSDBridge - Type.`

```
HermitianToSymmetricPSDBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

HermitianToSymmetricPSDBridge implements the following reformulation:

- Hermitian positive semidefinite  $n \times n$  complex matrix to a symmetric positive semidefinite  $2n \times 2n$  real matrix.

See also [MOI.Bridges.Variable.HermitianToSymmetricPSDBridge](#).

### Source node

`HermitianToSymmetricPSDBridge` supports:

- `G` in [MOI.HermitianPositiveSemidefiniteConeTriangle](#)

### Target node

`HermitianToSymmetricPSDBridge` creates:

- `F` in [MOI.PositiveSemidefiniteConeTriangle](#)

### Reformulation

The reformulation is best described by example.

The Hermitian matrix:

$$\begin{bmatrix} x_{11} & x_{12} + y_{12}im & x_{13} + y_{13}im \\ x_{12} - y_{12}im & x_{22} & x_{23} + y_{23}im \\ x_{13} - y_{13}im & x_{23} - y_{23}im & x_{33} \end{bmatrix}$$

is positive semidefinite if and only if the symmetric matrix:

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} & 0 & y_{12} & y_{13} \\ x_{22} & x_{23} & -y_{12} & 0 & y_{23} & \\ x_{33} & -y_{13} & -y_{23} & 0 & & \\ x_{11} & x_{12} & x_{13} & & & \\ x_{22} & x_{23} & & & & \\ x_{33} & & & & & \end{bmatrix}$$

is positive semidefinite.

The bridge achieves this reformulation by constraining the above matrix to belong to the `MOI.PositiveSemidefiniteConeTri`

`source`

`MathOptInterface.Bridges.Constraint.IndicatorActiveOnFalseBridge` – Type.

```
IndicatorActiveOnFalseBridge{T,F,S} <: Bridges.Constraint.AbstractBridge
```

`IndicatorActiveOnFalseBridge` implements the following reformulation:

- $\neg z \implies f(x) \in S$  into  $y \implies f(x) \in S, z + y = 1$ , and  $y \in \{0, 1\}$

### Source node

`IndicatorActiveOnFalseBridge` supports:

- `MOI.VectorAffineFunction{T}` in `MOI.Indicator{MOI.ACTIVATE_ON_ZERO,S}`

**Target nodes**

IndicatorActiveOnFalseBridge creates:

- MOI.VectorAffineFunction{T} in MOI.Indicator{MOI.ACTIVATE\_ON\_ONE,S}
- MOI.ScalarAffineFunction{T} in MOI.EqualTo
- MOI.VariableIndex in MOI.ZeroOne

`source`

MathOptInterface.Bridges.Constraint.IndicatorGreaterToLessThanBridge - Type.

`IndicatorGreaterToLessThanBridge{T,A} <: Bridges.Constraint.AbstractBridge`

IndicatorGreaterToLessThanBridge implements the following reformulation:

- $z \implies f(x) \geq l$  into  $z \implies -f(x) \leq -l$

**Source node**

IndicatorGreaterToLessThanBridge supports:

- MOI.VectorAffineFunction{T} in MOI.Indicator{A,MOI.GreaterThan{T}}

**Target nodes**

IndicatorGreaterToLessThanBridge creates:

- MOI.VectorAffineFunction{T} in MOI.Indicator{A,MOI.LessThan{T}}

`source`

MathOptInterface.Bridges.Constraint.IndicatorLessToGreaterThanBridge - Type.

`IndicatorLessToGreaterThanBridge{T,A} <: Bridges.Constraint.AbstractBridge`

IndicatorLessToGreaterThanBridge implements the following reformulations:

- $z \implies f(x) \leq u$  into  $z \implies -f(x) \geq -u$

**Source node**

IndicatorLessToGreaterThanBridge supports:

- MOI.VectorAffineFunction{T} in MOI.Indicator{A,MOI.LessThan{T}}

**Target nodes**

IndicatorLessToGreaterThanBridge creates:

- MOI.VectorAffineFunction{T} in MOI.Indicator{A,MOI.GreaterThan{T}}

```
source
MathOptInterface.Bridges.Constraint.IndicatorSOS1Bridge - Type.
```

```
IndicatorSOS1Bridge{T,S} <: Bridges.Constraint.AbstractBridge
```

IndicatorSOS1Bridge implements the following reformulation:

- $z \implies f(x) \in S$  into  $f(x) + y \in S, SOS1(y, z)$

#### Warning

This bridge assumes that the solver supports `MOI.SOS1{T}` constraints in which one of the variables ( $y$ ) is continuous.

#### Source node

IndicatorSOS1Bridge supports:

- `MOI.VectorAffineFunction{T}` in `MOI.Indicator{MOI.ACTIVATE_ON_ONE,S}`

#### Target nodes

IndicatorSOS1Bridge creates:

- `MOI.ScalarAffineFunction{T}` in  $S$
- `MOI.VectorOfVariables` in `MOI.SOS1{T}`

source

```
MathOptInterface.Bridges.Constraint.IndicatorSetMapBridge - Type.
```

```
IndicatorSetMapBridge{T,A,S1,S2} <: Bridges.Constraint.AbstractBridge
```

IndicatorSetMapBridge implements the following reformulations:

- $z \implies f(x) \geq l$  into  $z \implies -f(x) \leq -l$
- $z \implies f(x) \leq u$  into  $z \implies -f(x) \geq -u$

#### Source node

IndicatorSetMapBridge supports:

- `MOI.VectorAffineFunction{T}` in `MOI.Indicator{A,S1}`

#### Target nodes

IndicatorSetMapBridge creates:

- `MOI.VectorAffineFunction{T}` in `MOI.Indicator{A,S2}`

```
source
MathOptInterface.Bridges.Constraint.IndicatorToMILPBridge - Type.
```

```
IndicatorToMILPBridge{T,F,A,S} <: Bridges.Constraint.AbstractBridge
```

IndicatorToMILPBridge implements the following reformulation:

- $x \in \text{Indicator}(s)$  into a mixed-integer linear program.

#### Source node

IndicatorToMILPBridge supports:

- F in MOI.Indicator{A,S}

where F is MOI.VectorOfVariables or MOI.VectorAffineFunction{T}.

#### Target nodes

IndicatorToMILPBridge creates:

- MOI.VariableIndex in MOI.ZeroOne
- MOI.ScalarAffineFunction{T} in S

```
source
MathOptInterface.Bridges.Constraint.InequalityToComplementsBridge - Type.
```

```
InequalityToComplementsBridge{T,F,S,G} <: Bridges.Constraint.AbstractBridge
```

InequalityToComplementsBridge implements the following reformulations:

- $f(x) \geq b$  into  $\exists y \text{ such that } f(x) - b \perp y \geq 0$
- $f(x) \leq b$  into  $f(x) - b \perp y \leq 0$
- $f(x) = b$  into  $f(x) - b \perp y$

#### Source node

InequalityToComplementsBridge supports:

- F in MOI.GreaterThan{T}
- F in MOI.LessThan{T}
- F in MOI.EqualTo

#### Target nodes

InequalityToComplementsBridge creates:

- MOI.VariableIndex in MOI.LessThan{T}

- `MOI.VariableIndex` in `MOI.GreaterThan{T}`
- `G` in `MOI.Complements`

`source`

`MathOptInterface.Bridges.Constraint.IntegerToZeroOneBridge` – Type.

`IntegerToZeroOneBridge{T} <: Bridges.Constraint.AbstractBridge`

`IntegerToZeroOneBridge` implements the following reformulation:

- $x \in \mathbb{Z}$  into  $y_i \in \{0, 1\}$ ,  $x == lb + \sum 2^{i-1}y_i$ .

#### Source node

`IntegerToZeroOneBridge` supports:

- `VariableIndex` in `MOI.Integer`

#### Target nodes

`IntegerToZeroOneBridge` creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`

#### Developer note

This bridge is implemented as a constraint bridge instead of a variable bridge because we don't want to substitute the linear combination of  $y$  for every instance of  $x$ . Doing so would be expensive and greatly reduce the sparsity of the constraints.

`source`

`MathOptInterface.Bridges.Constraint.LessToGreaterBridge` – Type.

`LessToGreaterBridge{T,F,G} <: Bridges.Constraint.AbstractBridge`

`LessToGreaterBridge` implements the following reformulation:

- $f(x) \leq u$  into  $-f(x) \geq -u$

#### Source node

`LessToGreaterBridge` supports:

- `G` in `MOI.LessThan{T}`

#### Target nodes

`LessToGreaterBridge` creates:

- $F$  in `MOI.GreaterThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.LessToIntervalBridge` – Type.

`LessToIntervalBridge{T,F} <: Bridges.Constraint.AbstractBridge`

`LessToIntervalBridge` implements the following reformulations:

- $f(x) \leq u$  into  $f(x) \in (-\infty, u]$

#### Source node

`LessToIntervalBridge` supports:

- $F$  in `MOI.LessThan{T}`

#### Target nodes

`LessToIntervalBridge` creates:

- $F$  in `MOI.Interval{T}`

`source`

`MathOptInterface.Bridges.Constraint.LogDetBridge` – Type.

`LogDetBridge{T,F,G,H,I} <: Bridges.Constraint.AbstractBridge`

The `MOI.LogDetConeTriangle` is representable by `MOI.PositiveSemidefiniteConeTriangle` and `MOI.ExponentialCone` constraints.

Indeed,  $\log \det(X) = \sum_{i=1}^n \log(\delta_i)$  where  $\delta_i$  are the eigenvalues of  $X$ .

Adapting the method from [1, p. 149], we see that  $t \leq u \log(\det(X/u))$  for  $u > 0$  if and only if there exists a lower triangular matrix such that

$$\begin{aligned} \begin{pmatrix} X & \\ \top & \text{Diag}() \end{pmatrix} &\succeq 0 \\ t - \sum_{i=1}^n u \log\left(\frac{i}{u}\right) &\leq 0 \end{aligned}$$

Which we reformulate further into

$$\begin{aligned} \begin{pmatrix} X & \\ \top & \text{Diag}() \end{pmatrix} &\succeq 0 \\ (l_i, u, i) &\in \text{ExponentialCone} \quad \forall i \\ t - \sum_{i=1}^n l_i &\leq 0 \end{aligned}$$

**Source node**

LogDetBridge supports:

- I in MOI.LogDetConeTriangle

**Target nodes**

LogDetBridge creates:

- F in MOI.PositiveSemidefiniteConeTriangle
- G in MOI.ExponentialCone
- H in MOI.LessThan{T}

[1] Ben-Tal, Aharon, and Arkadi Nemirovski. *Lectures on modern convex optimization: analysis, algorithms, and engineering applications*. Society for Industrial and Applied Mathematics, 2001.

`source`

MathOptInterface.Bridges.Constraint.MultiSetMapBridge - Type.

```
abstract type MultiSetMapBridge{T,S1,G} <: AbstractBridge end
```

Same as SetMapBridge but the output constraint type does not only depend on the input constraint type.

When subtyping MultiSetMapBridge, added\_constraint\_types and supports should additionally be implemented by the bridge.

For example, if a bridge BridgeType may create either a constraint of type F2-in-S2 or F3-in-S3, these methods should be implemented as follows:

```
function MOI.Bridges.added_constraint_types(
    ::Type{<:BridgeType{T,F2,F3}},
) where {T,F2,F3}
    return Tuple{Type,Type}[(F2, S2), (F3, S3)]
end

function MOI.supports(
    model::MOI.ModelLike,
    attr::Union{MOI.ConstraintPrimalStart,MOI.ConstraintDualStart},
    ::Type{<:BridgeType{T,F2,F3}},
) where {T,F2,F3}
    return MOI.supports(model, attr, MOI.ConstraintIndex{F2,S2}) ||
           MOI.supports(model, attr, MOI.ConstraintIndex{F3,S3})
end
```

`source`

MathOptInterface.Bridges.Constraint.NonnegToNonposBridge - Type.

```
NonnegToNonposBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

NonnegToNonposBridge implements the following reformulation:

- $f(x) \in \mathbb{R}_+$  into  $-f(x) \in \mathbb{R}_-$

### Source node

`NonnegToNonposBridge` supports:

- $G$  in `MOI.Nonnegatives`

### Target nodes

`NonnegToNonposBridge` creates:

- $F$  in `MOI.Nonpositives`

`source`

`MathOptInterface.Bridges.Constraint.NonposToNonnegBridge` - Type.

```
NonposToNonnegBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

`NonposToNonnegBridge` implements the following reformulation:

- $f(x) \in \mathbb{R}_-$  into  $-f(x) \in \mathbb{R}_+$

### Source node

`NonposToNonnegBridge` supports:

- $G$  in `MOI.Nonpositives`

### Target nodes

`NonposToNonnegBridge` creates:

- $F$  in `MOI.Nonnegatives`

`source`

`MathOptInterface.Bridges.Constraint.NormInfinityBridge` - Type.

```
NormInfinityBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

`NormInfinityBridge` implements the following reformulation:

- $|x|_\infty \leq t$  into  $[t - x_i, t + x_i] \in \mathbb{R}_+$ .

### Source node

`NormInfinityBridge` supports:

- $G$  in `MOI.NormInfinityCone{T}`

**Target nodes**

`NormInfinityBridge` creates:

- F in `MOI.Nonnegatives`

`source`

`MathOptInterface.Bridges.Constraint.NormInfinityConeToNormConeBridge` – Type.

```
NormInfinityConeToNormConeBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

`NormInfinityConeToNormConeBridge` implements the following reformulations:

- $(t, x) \in NormInfinityCone(d)$  into  $(t, x) \in NormCone(Inf, d)$

**Source node**

`NormInfinityConeToNormConeBridge` supports:

- F in `MOI.NormInfinityCone`

**Target nodes**

`NormInfinityConeToNormConeBridge` creates:

- F in `MOI.NormCone`

`source`

`MathOptInterface.Bridges.Constraint.NormNuclearBridge` – Type.

```
NormNuclearBridge{T,F,G,H} <: Bridges.Constraint.AbstractBridge
```

`NormNuclearBridge` implements the following reformulation:

- $t \geq \sum_i \sigma_i(X)$  into  $\begin{bmatrix} U & X^\top \\ X & V \end{bmatrix} \succeq 0$  and  $2t \geq \text{tr}(U) + \text{tr}(V)$ .

**Source node**

`NormNuclearBridge` supports:

- H in `MOI.NormNuclearCone`

**Target nodes**

`NormNuclearBridge` creates:

- F in `MOI.GreaterThan{T}`
- G in `MOI.PositiveSemidefiniteConeTriangle`

```
source
MathOptInterface.Bridges.Constraint.NormOneBridge - Type.
```

```
NormOneBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

NormOneBridge implements the following reformulation:

- $\sum |x_i| \leq t$  into  $[t - \sum y_i, y_i - x_i, y_i + x_i] \in \mathbb{R}_+$ .

#### **Source node**

NormOneBridge supports:

- F in MOI.Nonnegatives

#### **Target nodes**

NormOneBridge creates:

- F in MOI.Nonnegatives

```
source
MathOptInterface.Bridges.Constraint.NormOneConeToNormConeBridge - Type.
```

```
NormOneConeToNormConeBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

NormOneConeToNormConeBridge implements the following reformulations:

- $(t, x) \in NormOneCone(d)$  into  $(t, x) \in NormCone(1, d)$

#### **Source node**

NormOneConeToNormConeBridge supports:

- F in MOI.NormOneCone

#### **Target nodes**

NormOneConeToNormConeBridge creates:

- F in MOI.NormCone

```
source
MathOptInterface.Bridges.Constraint.NormSpectralBridge - Type.
```

```
NormSpectralBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

NormSpectralBridge implements the following reformulation:

- $t \geq \sigma_1(X)$  into  $\begin{bmatrix} t\mathbf{I} & X^\top \\ X & t\mathbf{I} \end{bmatrix} \succeq 0$

### Source node

`NormSpectralBridge` supports:

- `G` in `MOI.NormSpectralCone`

### Target nodes

`NormSpectralBridge` creates:

- `F` in `MOI.PositiveSemidefiniteConeTriangle`

`source`

`MathOptInterface.Bridges.Constraint.NormToPowerBridge` – Type.

`NormToPowerBridge{T,F} <: Bridges.Constraint.AbstractBridge`

`NormToPowerBridge` implements the following reformulation:

- $(t, x) \in NormCone(p, 1 + d)$  into  $(r_i, t, x_i) \in PowerCone(1/p)$  for all  $i$ , and  $\sum_i r_i == t$ .

For details, see Alizadeh, F., and Goldfarb, D. (2001). "Second-order cone programming." Mathematical Programming, Series B, 95:3-51.

### Source node

`NormToPowerBridge` supports:

- `F` in `MOI.NormCone`

### Target nodes

`NormToPowerBridge` creates:

- `F` in `MOI.PowerCone{T}`
- `MOI.ScalarAffineFunction` in `MOI.EqualTo`

`source`

`MathOptInterface.Bridges.Constraint.NumberConversionBridge` – Type.

`NumberConversionBridge{T,F1,S1,F2,S2} <: Bridges.Constraint.AbstractBridge`

`NumberConversionBridge` implements the following reformulation:

- $f1(x) \in S1$  to  $f2(x) \in S2$

where  $f$  and  $S$  are the same functional form, but differ in their coefficient type.

### Source node

NumberConversionBridge supports:

- $F_1$  in  $S_1$

### Target node

NumberConversionBridge creates:

- $F_2$  in  $S_2$

`source`

`MathOptInterface.Bridges.Constraint.QuadtoSOCBridge - Type.`

`QuadtoSOCBridge{T} <: Bridges.Constraint.AbstractBridge`

QuadtoSOCBridge converts quadratic inequalities

$$\frac{1}{2}x^T Qx + a^T x \leq ub$$

into `MOI.RotatedSecondOrderCone` constraints, but it only applies when  $Q$  is positive definite.

This is because, if  $Q$  is positive definite, there exists  $U$  such that  $Q = U^T U$ , and so the inequality can then be rewritten as;

$$\|Ux\|_2^2 \leq 2(-a^T x + ub)$$

Therefore, QuadtoSOCBridge implements the following reformulations:

- $\frac{1}{2}x^T Qx + a^T x \leq ub$  into  $(1, -a^T x + ub, Ux) \in RotatedSecondOrderCone$  where  $Q = U^T U$
- $\frac{1}{2}x^T Qx + a^T x \geq lb$  into  $(1, a^T x - lb, Ux) \in RotatedSecondOrderCone$  where  $-Q = U^T U$

### Source node

QuadtoSOCBridge supports:

- `MOI.ScalarAffineFunction{T}` in `MOI.LessThan{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.GreaterThan{T}`

### Target nodes

RelativeEntropyBridge creates:

- `MOI.VectorAffineFunction{T}` in `MOI.RotatedSecondOrderCone`

### Errors

This bridge errors if Q is not positive definite.

`source`

`MathOptInterface.Bridges.Constraint.RSOCtoNonConvexQuadBridge - Type`.

```
RSOCtoNonConvexQuadBridge{T} <: Bridges.Constraint.AbstractBridge
```

`RSOCtoNonConvexQuadBridge` implements the following reformulations:

- $\|x\|_2^2 \leq 2tu$  into  $\sum x^2 - 2tu \leq 0$ ,  $1t + 0 \geq 0$ , and  $1u + 0 \geq 0$ .

The `MOI.ScalarAffineFunctions`  $1t + 0$  and  $1u + 0$  are used in case the variables have other bound constraints.

### Warning

This transformation starts from a convex constraint and creates a non-convex constraint. Unless the solver has explicit support for detecting rotated second-order cones in quadratic form, this may (wrongly) be interpreted by the solver as being non-convex. Therefore, this bridge is not added automatically by `MOI.Bridges.full_bridge_optimizer`. Care is recommended when adding this bridge to a optimizer.

### Source node

`RSOCtoNonConvexQuadBridge` supports:

- `MOI.VectorOfVariables` in `MOI.RotatedSecondOrderCone`

### Target nodes

`RSOCtoNonConvexQuadBridge` creates:

- `MOI.ScalarQuadraticFunction{T}` in `MOI.LessThan{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.GreaterThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.RSOCtoPSDBridge - Type`.

```
RSOCtoPSDBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

`RSOCtoPSDBridge` implements the following reformulation:

- $\|x\|_2^2 \leq 2t \cdot u$  into  $\begin{bmatrix} t & x^\top \\ x & 2tu\mathbf{I} \end{bmatrix} \succeq 0$

### Source node

`RSOCtoPSDBridge` supports:

- G in `MOI.RotatedSecondOrderCone`

#### Target nodes

`RSOCToPSDBridge` creates:

- F in `MOI.PositiveSemidefiniteConeTriangle`

`source`

`MathOptInterface.Bridges.Constraint.RSOCToSOCBridge` – Type.

```
RSOCToSOCBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

`RSOCToSOCBridge` implements the following reformulation:

- $\|x\|_2^2 \leq 2tu$  into  $\left\|\frac{t-u}{\sqrt{2}}, x\right\|_2 \leq \frac{t+u}{\sqrt{2}}$

#### Source node

`RSOCToSOCBridge` supports:

- G in `MOI.RotatedSecondOrderCone`

#### Target node

`RSOCToSOCBridge` creates:

- F in `MOI.SecondOrderCone`

`source`

`MathOptInterface.Bridges.Constraint.ReifiedAllDifferentToCountDistinctBridge` – Type.

```
ReifiedAllDifferentToCountDistinctBridge{T,F} <:
Bridges.Constraint.AbstractBridge
```

`ReifiedAllDifferentToCountDistinctBridge` implements the following reformulations:

- $r \iff x \in \text{AllDifferent}(d)$  to  $r \iff (n, x) \in \text{CountDistinct}(1 + d)$  and  $n = d$
- $r \iff f(x) \in \text{AllDifferent}(d)$  to  $r \iff (d, f(x)) \in \text{CountDistinct}(1 + d)$

#### Source node

`ReifiedAllDifferentToCountDistinctBridge` supports:

- F in `MOI.Reified{MOI.AllDifferent}`

where F is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

#### Target nodes

`ReifiedAllDifferentToCountDistinctBridge` creates:

- `F` in `MOI.Reified{MOI.CountDistinct}`
- `MOI.VariableIndex` in `MOI.EqualTo{T}`

`source`

`MathOptInterface.Bridges.Constraint.ReifiedCountDistinctToMILPBridge - Type.`

`ReifiedCountDistinctToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge`

`ReifiedCountDistinctToMILPBridge` implements the following reformulation:

- $r \iff (n, x) \in \text{CountDistinct}(1 + d)$  into a mixed-integer linear program.

### Reformulation

The reformulation is non-trivial, and it depends on the finite domain of each variable  $x_i$ , which we as define  $S_i = \{l_i, \dots, u_i\}$ .

First, we introduce new binary variables  $z_{ij}$ , which are 1 if variable  $x_i$  takes the value  $j$  in the optimal solution and 0 otherwise:

$$\begin{aligned} z_{ij} &\in \{0, 1\} \quad \forall i \in 1 \dots d, j \in S_i \\ x_i - \sum_{j \in S_i} j \cdot z_{ij} &= 0 \quad \forall i \in 1 \dots d \\ \sum_{j \in S_i} z_{ij} &= 1 \quad \forall i \in 1 \dots d \end{aligned}$$

Then, we introduce new binary variables  $y_j$ , which are 1 if a variable takes the value  $j$  in the optimal solution and 0 otherwise.

$$\begin{aligned} y_j &\in \{0, 1\} \quad \forall j \in \bigcup_{i=1, \dots, d} S_i \\ y_j &\leq \sum_{i \in 1 \dots d : j \in S_i} z_{ij} \leq M y_j \quad \forall j \in \bigcup_{i=1, \dots, d} S_i \end{aligned}$$

Finally,  $n$  is constrained to be the number of  $y_j$  elements that are non-zero, with some slack:

$$n - \sum_{j \in \bigcup_{i=1, \dots, d} S_i} y_j = \delta^+ - \delta^-$$

And then the slack is constrained to respect the reif variable  $r$ :

$$\begin{aligned} d_1 &\leq \delta^+ \leq M d_1 \\ d_2 &\leq \delta^- \leq M d_s \\ d_1 + d_2 + r &= 1 \\ d_1, d_2 &\in \{0, 1\} \end{aligned}$$

### Source node

`ReifiedCountDistinctToMILPBridge` supports:

- F in `MOI.Reified{MOI.CountDistinct}`

where F is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

### Target nodes

`ReifiedCountDistinctToMILPBridge` creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.LessThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.RelativeEntropyBridge` – Type.

```
RelativeEntropyBridge{T,F,G,H} <: Bridges.Constraint.AbstractBridge
```

`RelativeEntropyBridge` implements the following reformulation that converts a `MOI.RelativeEntropyCone` into an `MOI.ExponentialCone`:

- $u \geq \sum_{i=1}^n w_i \log\left(\frac{w_i}{v_i}\right)$  into  $y_i \geq 0$ ,  $u \geq \sum_{i=1}^n y_i$ , and  $(-y_i, w_i, v_i) \in \text{ExponentialCone}$ .

### Source node

`RelativeEntropyBridge` supports:

- H in `MOI.RelativeEntropyCone`

### Target nodes

`RelativeEntropyBridge` creates:

- F in `MOI.GreaterThan{T}`
- G in `MOI.ExponentialCone`

`source`

`MathOptInterface.Bridges.Constraint.RootDetBridge` – Type.

```
RootDetBridge{T,F,G,H} <: Bridges.Constraint.AbstractBridge
```

The `MOI.RootDetConeTriangle` is representable by `MOI.PositiveSemidefiniteConeTriangle` and `MOI.GeometricMeanCone` constraints, see [1, p. 149].

Indeed,  $t \leq \det(X)^{1/n}$  if and only if there exists a lower triangular matrix such that:

$$\begin{pmatrix} X & \\ \top & \text{Diag}() \end{pmatrix} \succeq 0$$

$$(t, \text{Diag}()) \in \text{GeometricMeanCone}$$

### Source node

`RootDetBridge` supports:

- I in `MOI.RootDetConeTriangle`

#### Target nodes

`RootDetBridge` creates:

- F in `MOI.PositiveSemidefiniteConeTriangle`
- G in `MOI.GeometricMeanCone`

[1] Ben-Tal, Aharon, and Arkadi Nemirovski. *Lectures on modern convex optimization: analysis, algorithms, and engineering applications*. Society for Industrial and Applied Mathematics, 2001.

`source`

`MathOptInterface.Bridges.Constraint.SOCtoNonConvexQuadBridge` – Type.

```
SOCtoNonConvexQuadBridge{T} <: Bridges.Constraint.AbstractBridge
```

`SOCtoNonConvexQuadBridge` implements the following reformulations:

- $\|x\|_2 \leq t$  into  $\sum x^2 - t^2 \leq 0$  and  $1t + 0 \geq 0$

The `MOI.ScalarAffineFunction`  $1t + 0$  is used in case the variable has other bound constraints.

#### Warning

This transformation starts from a convex constraint and creates a non-convex constraint. Unless the solver has explicit support for detecting second-order cones in quadratic form, this may (wrongly) be interpreted by the solver as being non-convex. Therefore, this bridge is not added automatically by `MOI.Bridges.full_bridge_optimizer`. Care is recommended when adding this bridge to a optimizer.

#### Source node

`SOCtoNonConvexQuadBridge` supports:

- `MOI.VectorOfVariables` in `MOI.SecondOrderCone`

#### Target nodes

`SOCtoNonConvexQuadBridge` creates:

- `MOI.ScalarQuadraticFunction{T}` in `MOI.LessThan{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.GreaterThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.SOCtoPSDBridge` – Type.

```
SOCtoPSDBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

`SOCtoPSDBridge` implements the following reformulation:

- $\|x\|_2 \leq t$  into  $\begin{bmatrix} t & x^\top \\ x & t\mathbf{I} \end{bmatrix} \succeq 0$

### Warning

This bridge is not added by default by `MOI.Bridges.full_bridge_optimizer` because bridging second order cone constraints to semidefinite constraints can be achieved by the `SOCtoRSOCBridge` followed by the `RSOCtoPSDBridge`, while creating a smaller semidefinite constraint.

### Source node

`SOCtoPSDBridge` supports:

- G in `MOI.SecondOrderCone`

### Target nodes

`SOCtoPSDBridge` creates:

- F in `MOI.PositiveSemidefiniteConeTriangle`

`source`

`MathOptInterface.Bridges.Constraint.SOCtoRSOCBridge` - Type.

```
SOCtoRSOCBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

`SOCtoRSOCBridge` implements the following reformulation:

- $\|x\|_2 \leq t$  into  $(t + x_1)(t - x_1) \geq \|(x_2 \dots, x_N)\|_2^2$

### Assumptions

- `SOCtoRSOCBridge` assumes that the length of x is at least one.

### Source node

`SOCtoRSOCBridge` supports:

- G in `MOI.SecondOrderCone`

### Target node

`SOCtoRSOCBridge` creates:

- F in `MOI.RotatedSecondOrderCone`

`source`

`MathOptInterface.Bridges.Constraint.SOS1ToMILPBridge` - Type.

```
SOS1ToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

`SOS1ToMILPBridge` implements the following reformulation:

- $x \in \text{SOS1}(d)$  into a mixed-integer linear program.

#### Source node

`SOS1ToMILPBridge` supports:

- $F$  in `MOI.SOS1`

where  $F$  is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

#### Target nodes

`SOS1ToMILPBridge` creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.LessThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.SOS2ToMILPBridge - Type.`

```
SOS2ToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge
```

`SOS2ToMILPBridge` implements the following reformulation:

- $x \in \text{SOS2}(d)$  into a mixed-integer linear program.

#### Source node

`SOS2ToMILPBridge` supports:

- $F$  in `MOI.SOS2`

where  $F$  is `MOI.VectorOfVariables` or `MOI.VectorAffineFunction{T}`.

#### Target nodes

`SOS2ToMILPBridge` creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.LessThan{T}`

`source`

`MathOptInterface.Bridges.Constraint.ScalarFunctionizeBridge - Type.`

```
ScalarFunctionizeBridge{T,S} =
    FunctionConversionBridge{T,MOI.ScalarAffineFunction{T},MOI.VariableIndex,S}
```

ScalarFunctionizeBridge implements the following reformulations:

- $x \in S$  into  $1x + 0 \in S$

#### Source node

ScalarFunctionizeBridge supports:

- `MOI.VariableIndex` in  $S$

#### Target nodes

ScalarFunctionizeBridge creates:

- `MOI.ScalarAffineFunction{T}` in  $S$

`source`

`MathOptInterface.Bridges.Constraint.ScalarSlackBridge` – Type.

```
ScalarSlackBridge{T,F,S} <: Bridges.Constraint.AbstractBridge
```

ScalarSlackBridge implements the following reformulation:

- $f(x) \in S$  into  $f(x) - y == 0$  and  $y \in S$

#### Source node

ScalarSlackBridge supports:

- $G$  in  $S$ , where  $G$  is not `MOI.VariableIndex` and  $S$  is not `MOI.EqualTo`

#### Target nodes

ScalarSlackBridge creates:

- $F$  in `MOI.EqualTo{T}`
- `MOI.VariableIndex` in  $S$

`source`

`MathOptInterface.Bridges.Constraint.ScalarizeBridge` – Type.

```
ScalarizeBridge{T,F,S}
```

ScalarizeBridge implements the following reformulations:

- $f(x) - a \in \mathbb{R}_+$  into  $f_i(x) \geq a_i$  for all  $i$
- $f(x) - a \in \mathbb{R}_-$  into  $f_i(x) \leq a_i$  for all  $i$
- $f(x) - a \in \{0\}$  into  $f_i(x) == a_i$  for all  $i$

### Source node

ScalarizeBridge supports:

- G in `MOI.Nonnegatives{T}`
- G in `MOI.Nonpositives{T}`
- G in `MOI.Zeros{T}`

### Target nodes

ScalarizeBridge creates:

- F in S, where S is one of `MOI.GreaterThan{T}`, `MOI.LessThan{T}`, and `MOI.EqualTo{T}`, depending on the type of the input set.

`source`

`MathOptInterface.Bridges.Constraint.SecondOrderConeToNormConeBridge` – Type.

`SecondOrderConeToNormConeBridge{T,F} <: Bridges.Constraint.AbstractBridge`

`SecondOrderConeToNormConeBridge` implements the following reformulations:

- $(t, x)$  in `SecondOrderCone(d)` into  $(t, x)$  in `NormCone(2, d)`

### Source node

`SecondOrderConeToNormConeBridge` supports:

- F in `MOI.SecondOrderCone`

### Target nodes

`SecondOrderConeToNormConeBridge` creates:

- F in `MOI.NormCone`

`source`

`MathOptInterface.Bridges.Constraint.SemiToBinaryBridge` – Type.

`SemiToBinaryBridge{T,S} <: Bridges.Constraint.AbstractBridge`

`SemiToBinaryBridge` implements the following reformulations:

- $x \in \{0\} \cup [l, u]$  into

$$\begin{aligned}x &\leq zu \\x &\geq zl \\z &\in \{0, 1\}\end{aligned}$$

- $x \in \{0\} \cup \{l, \dots, u\}$  into

$$\begin{aligned}x &\leq zu \\x &\geq zl \\z &\in \{0, 1\} \\x &\in \mathbb{Z}\end{aligned}$$

### Source node

SemiToBinaryBridge supports:

- `MOI.VariableIndex` in `MOI.Semicontinuous{T}`
- `MOI.VariableIndex` in `MOI.Semiinteger{T}`

### Target nodes

SemiToBinaryBridge creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.LessThan{T}`
- `MOI.ScalarAffineFunction{T}` in `MOI.GreaterThan{T}`
- `MOI.VariableIndex{T}` in `MOI.Integer` (if S is `MOI.Semiinteger{T}`)

`source`

`MathOptInterface.Bridges.Constraint.SetConversionBridge - Type.`

```
SetConversionBridge{T,S2,S1,F} <:
MOI.Bridges.Constraint.SetMapBridge{T,S2,S1,F,F}
```

`SetConversionBridge` implements the following reformulations:

- $f(x) \in S1$  into  $f(x) \in S2$

In order to add this bridge, you need to create a bridge specific for a given type T and set S2:

```
MOI.Bridges.add_bridge(model, MOI.Bridges.Constraint.SetConversionBridge{T,S2})
```

In order to define a bridge with S2 specified but T unspecified, for example for `JuMP.add_bridge`, you can use

```
const MyBridge{T,S1,F} = MOI.Bridges.Constraint.SetConversionBridge{T,S2,S1,F}
```

See also [FunctionConversionBridge](#).

#### Source node

SetConversionBridge supports:

- F in S1

#### Target nodes

SetConversionBridge creates:

- F in S2

`source`

`MathOptInterface.Bridges.Constraint.SetDotInverseScalingBridge` - Type.

```
SetDotInverseScalingBridge{T,S,F,G} <: Bridges.Constraint.AbstractBridge
```

SetDotInverseScalingBridge implements the reformulation from constraints in the `MOI.Scaled{S}` to constraints in the S.

#### Source node

SetDotInverseScalingBridge supports:

- G in [MOI.Scaled{S}](#)

#### Target node

SetDotInverseScalingBridge creates:

- F in S

`source`

`MathOptInterface.Bridges.Constraint.SetDotScalingBridge` - Type.

```
SetDotScalingBridge{T,S,F,G} <: Bridges.Constraint.AbstractBridge
```

SetDotScalingBridge implements the reformulation from constraints in S to constraints in [MOI.Scaled{S}](#).

#### Source node

SetDotScalingBridge supports:

- G in S

**Target node**

`SetDotScalingBridge` creates:

- `F` in `MOI.Scaled{S}`

`source`

`MathOptInterface.Bridges.Constraint.SetMapBridge` – Type.

```
abstract type SetMapBridge{T,S2,S1,F,G} <: MultiSetMapBridge{T,S1,G} end
```

Consider two type of sets,  $S_1$  and  $S_2$ , and a linear mapping  $A$  such that the image of a set of type  $S_1$  under  $A$  is a set of type  $S_2$ .

A `SetMapBridge{T,S2,S1,F,G}` is a bridge that maps  $G$ -in- $S_1$  constraints into  $F$ -in- $S_2$  by mapping the function through  $A$ .

The linear map  $A$  is described by:

- `MOI.Bridges.map_set`
- `MOI.Bridges.map_function`.

Implementing a method for these two functions is sufficient to bridge constraints. However, in order for the getters and setters of attributes such as dual solutions and starting values to work as well, a method for the following functions must be implemented:

- `MOI.Bridges.inverse_map_set`
- `MOI.Bridges.inverse_map_function`
- `MOI.Bridges.adjoint_map_function`
- `MOI.Bridges.inverse_adjoint_map_function`

See the docstrings of each function to see which feature would be missing if it was not implemented for a given bridge.

`source`

`MathOptInterface.Bridges.Constraint.SplitComplexEqualToBridge` – Type.

```
SplitComplexEqualToBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

`SplitComplexEqualToBridge` implements the following reformulation:

- $f(x) + g(x) * im = a + b * im$  into  $f(x) = a$  and  $g(x) = b$

**Source node**

`SplitComplexEqualToBridge` supports:

- `G` in `MOI.EqualTo{Complex{T}}`

where  $G$  is a function with Complex coefficients.

#### Target nodes

`SplitComplexEqualToBridge` creates:

- $F$  in `MOI.EqualTo{T}`

where  $F$  is the type of the real/imaginary part of  $G$ .

`source`

`MathOptInterface.Bridges.Constraint.SplitComplexZerosBridge` – Type.

```
SplitComplexZerosBridge{T,F,G} <: Bridges.Constraint.AbstractBridge
```

`SplitComplexZerosBridge` implements the following reformulation:

- $f(x) \in \{0\}^n$  into  $\text{Re}(f(x)) \in \{0\}^n$  and  $\text{Im}(f(x)) \in \{0\}^n$

#### Source node

`SplitComplexZerosBridge` supports:

- $G$  in `MOI.Zeros`

where  $G$  is a function with Complex coefficients.

#### Target nodes

`SplitComplexZerosBridge` creates:

- $F$  in `MOI.Zeros`

where  $F$  is the type of the real/imaginary part of  $G$ .

`source`

`MathOptInterface.Bridges.Constraint.SplitHyperRectangleBridge` – Type.

```
SplitHyperRectangleBridge{T,G,F} <: Bridges.Constraint.AbstractBridge
```

`SplitHyperRectangleBridge` implements the following reformulation:

- $f(x) \in \text{HyperRectangle}(l, u)$  to  $[f(x) - l; u - f(x)] \in \mathbb{R}_+$ .

#### Source node

`SplitHyperRectangleBridge` supports:

- $F$  in `MOI.HyperRectangle`

#### Target nodes

`SplitHyperRectangleBridge` creates:

- G in `MOI.Nonnegatives`

`source`

`MathOptInterface.Bridges.Constraint.SplitIntervalBridge` – Type.

`SplitIntervalBridge{T,F,S,LS,US} <: Bridges.Constraint.AbstractBridge`

`SplitIntervalBridge` implements the following reformulations:

- $l \leq f(x) \leq u$  into  $f(x) \geq l$  and  $f(x) \leq u$
- $f(x) = b$  into  $f(x) \geq b$  and  $f(x) \leq b$
- $f(x) \in \{0\}$  into  $f(x) \in \mathbb{R}_+$  and  $f(x) \in \mathbb{R}_-$

#### Source node

`SplitIntervalBridge` supports:

- F in `MOI.Interval{T}`
- F in `MOI.EqualTo{T}`
- F in `MOI.Zeros`

#### Target nodes

`SplitIntervalBridge` creates:

- F in `MOI.LessThan{T}`
- F in `MOI.GreaterThan{T}`

or

- F in `MOI.Nonnegatives`
- F in `MOI.Nonpositives`

#### Note

If `T <: AbstractFloat` and S is `MOI.Interval{T}` then no lower (resp. upper) bound constraint is created if the lower (resp. upper) bound is `typemin(T)` (resp. `typemax(T)`). Similarly, when `MOI.ConstraintSet` is set, a lower or upper bound constraint may be deleted or created accordingly.

`source`

`MathOptInterface.Bridges.Constraint.SquareBridge` – Type.

`SquareBridge{T,F,G,TT,ST} <: Bridges.Constraint.AbstractBridge`

`SquareBridge` implements the following reformulations:

- $(t, u, X) \in LogDetConeSquare$  into  $(t, u, Y)$  in  $LogDetConeTriangle$
- $(t, X) \in RootDetConeSquare$  into  $(t, Y)$  in  $RootDetConeTriangle$
- $X \in AbstractSymmetricMatrixSetSquare$  into  $Y$  in  $AbstractSymmetricMatrixSetTriangle$

where  $Y$  is the upper triangular component of  $X$ .

In addition, constraints are added as necessary to constrain the matrix  $X$  to be symmetric. For example, the constraint for the matrix:

$$\begin{pmatrix} 1 & 1+x & 2-3x \\ 1+x & 2+x & 3-x \\ 2-3x & 2+x & 2x \end{pmatrix}$$

can be broken down to the constraint of the symmetric matrix

$$\begin{pmatrix} 1 & 1+x & 2-3x \\ \cdot & 2+x & 3-x \\ \cdot & \cdot & 2x \end{pmatrix}$$

and the equality constraint between the off-diagonal entries  $(2, 3)$  and  $(3, 2)$   $3-x == 2+x$ . Note that no symmetrization constraint needs to be added between the off-diagonal entries  $(1, 2)$  and  $(2, 1)$  or between  $(1, 3)$  and  $(3, 1)$  because the expressions are the same.

### Source node

SquareBridge supports:

- F in ST

### Target nodes

SquareBridge creates:

- G in TT

`source`

`MathOptInterface.Bridges.Constraint.TableToMILPBridge` - Type.

`TableToMILPBridge{T,F} <: Bridges.Constraint.AbstractBridge`

`TableToMILPBridge` implements the following reformulation:

- $x \in Table(t)$  into

$$\begin{aligned} z_j &\in \{0, 1\} \quad \forall i, j \\ \sum_{j=1}^n z_j &= 1 \\ \sum_{j=1}^n t_{ij} z_j &= x_i \quad \forall i \end{aligned}$$

**Source node**

TableToMILPBridge supports:

- F in `MOI.Table{T}`

**Target nodes**

TableToMILPBridge creates:

- `MOI.VariableIndex` in `MOI.ZeroOne`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`

`source`

`MathOptInterface.Bridges.Constraint.ToScalarNonlinearBridge - Type.`

```
ToScalarNonlinearBridge{T,G,S} <: AbstractFunctionConversionBridge{G,S}
```

ToScalarNonlinearBridge implements the following reformulation:

- $g(x) \in S$  into  $f(x) \in S$

where g is an abstract scalar function and f is a `MOI.ScalarNonlinearFunction`.

**Source node**

ToScalarNonlinearBridge supports:

- `G<:AbstractScalarFunction in S`

**Target nodes**

ToScalarNonlinearBridge creates:

- `MOI.ScalarNonlinearFunction` in S

`source`

`MathOptInterface.Bridges.Constraint.ToScalarQuadraticBridge - Type.`

```
ToScalarQuadraticBridge{T,G,S} <: AbstractFunctionConversionBridge{G,S}
```

ToScalarQuadraticBridge implements the following reformulation:

- $g(x) \in S$  into  $f(x) \in S$

where g is an abstract scalar function and f is a `MOI.ScalarQuadraticFunction`.

**Source node**

ToScalarQuadraticBridge supports:

- $G <: \text{AbstractScalarFunction}$  in  $S$

### Target nodes

`ToScalarQuadraticBridge` creates:

- `MOI.ScalarQuadraticFunction` in  $S$

`source`

`MathOptInterface.Bridges.Constraint.ToVectorQuadraticBridge` – Type.

```
ToVectorQuadraticBridge{T, G, S} <: AbstractFunctionConversionBridge{G, S}
```

`ToVectorQuadraticBridge` implements the following reformulation:

- $g(x) \in S$  into  $f(x) \in S$

where  $g$  is an abstract vector function and  $f$  is a `MOI.VectorQuadraticFunction`.

### Source node

`ToVectorQuadraticBridge` supports:

- $G <: \text{AbstractVectorFunction}$  in  $S$

### Target nodes

`ToVectorQuadraticBridge` creates:

- `MOI.VectorQuadraticFunction` in  $S$

`source`

`MathOptInterface.Bridges.Constraint.VectorFunctionizeBridge` – Type.

```
VectorFunctionizeBridge{T, S} = FunctionConversionBridge{T, MOI.VectorAffineFunction{T}, S}
```

`VectorFunctionizeBridge` implements the following reformulations:

- $x \in S$  into  $Ix + 0 \in S$

### Source node

`VectorFunctionizeBridge` supports:

- `MOI.VectorOfVariables` in  $S$

### Target nodes

`VectorFunctionizeBridge` creates:

- `MOI.VectorAffineFunction{T}` in S

`source`

`MathOptInterface.Bridges.Constraint.VectorSlackBridge` – Type.

```
VectorSlackBridge{T,F,S} <: Bridges.Constraint.AbstractBridge
```

`VectorSlackBridge` implements the following reformulation:

- $f(x) \in S$  into  $f(x) - y \in \{0\}$  and  $y \in S$

#### Source node

`VectorSlackBridge` supports:

- G in S, where G is not `MOI.VectorOfVariables` and S is not `MOI.Zeros`

#### Target nodes

`VectorSlackBridge` creates:

- F in `MOI.Zeros`
- `MOI.VectorOfVariables` in S

`source`

`MathOptInterface.Bridges.Constraint.VectorizeBridge` – Type.

```
VectorizeBridge{T,F,S,G} <: Bridges.Constraint.AbstractBridge
```

`VectorizeBridge` implements the following reformulations:

- $g(x) \geq a$  into  $[g(x) - a] \in \mathbb{R}_+$
- $g(x) \leq a$  into  $[g(x) - a] \in \mathbb{R}_-$
- $g(x) == a$  into  $[g(x) - a] \in \{0\}$

where T is the coefficient type of  $g(x) - a$ .

#### Source node

`VectorizeBridge` supports:

- G in `MOI.GreaterThan{T}`
- G in `MOI.LessThan{T}`
- G in `MOI.EqualTo{T}`

#### Target nodes

`VectorizeBridge` creates:

- $F$  in  $S$ , where  $S$  is one of `MOI.Nonnegatives`, `MOI.Nonpositives`, `MOI.Zeros` depending on the type of the input set.

`source`

`MathOptInterface.Bridges.Constraint.ZeroOneBridge - Type.`

```
ZeroOneBridge{T} <: Bridges.Constraint.AbstractBridge
```

`ZeroOneBridge` implements the following reformulation:

- $x \in \{0, 1\}$  into  $x \in \mathbb{Z}$ ,  $1x \in [0, 1]$ .

#### Note

`ZeroOneBridge` adds a linear constraint instead of adding variable bounds to avoid conflicting with bounds set by the user.

#### Source node

`ZeroOneBridge` supports:

- `MOI.VariableIndex` in `MOI.ZeroOne`

#### Target nodes

`ZeroOneBridge` creates:

- `MOI.VariableIndex` in `MOI.Integer`
- `MOI.ScalarAffineFunction{T}` in `MOI.Interval{T}`

`source`

#### Objective bridges

These bridges are subtypes of `Bridges.Objective.AbstractBridge`.

`MathOptInterface.Bridges.Objective.FunctionConversionBridge - Type.`

```
FunctionConversionBridge{T,F,G} <: AbstractBridge
```

`FunctionConversionBridge` implements the following reformulations:

- $\min\{g(x)\}$  into  $\min\{f(x)\}$
- $\max\{g(x)\}$  into  $\max\{f(x)\}$

for these pairs of functions:

- `MOI.ScalarAffineFunction` to `[MOI.ScalarQuadraticFunction'](@ref)`

- `MOI.ScalarQuadraticFunction` to `MOI.ScalarNonlinearFunction`
- `MOI.VectorAffineFunction` to `MOI.VectorQuadraticFunction`

### Source node

`FunctionConversionBridge` supports:

- `MOI.ObjectiveFunction{G}`

### Target nodes

`FunctionConversionBridge` creates:

- One objective node: `MOI.ObjectiveFunction{F}`

`source`

`MathOptInterface.Bridges.Objective.FunctionizeBridge` – Type.

```
FunctionizeBridge{T,G} <: FunctionConversionBridge{T,MOI.ScalarAffineFunction{T},G}
```

`FunctionizeBridge` implements the following reformulations:

- $\min\{x\}$  into  $\min\{1x + 0\}$
- $\max\{x\}$  into  $\max\{1x + 0\}$

where `T` is the coefficient type of 1 and 0.

### Source node

`FunctionizeBridge` supports:

- `MOI.ObjectiveFunction{G}`

### Target nodes

`FunctionizeBridge` creates:

- One objective node: `MOI.ObjectiveFunction{MOI.ScalarAffineFunction{T}}`

`source`

`MathOptInterface.Bridges.Objective.QuadratizeBridge` – Type.

```
QuadratizeBridge{T,G} <: FunctionConversionBridge{T,MOI.ScalarQuadraticFunction{T},G}
```

`QuadratizeBridge` implements the following reformulations:

- $\min\{a^\top x + b\}$  into  $\min\{x^\top \mathbf{0}x + a^\top x + b\}$
- $\max\{a^\top x + b\}$  into  $\max\{x^\top \mathbf{0}x + a^\top x + b\}$

where  $T$  is the coefficient type of  $0$ .

#### Source node

`QuadratizeBridge` supports:

- `MOI.ObjectiveFunction{G}`

#### Target nodes

`QuadratizeBridge` creates:

- One objective node: `MOI.ObjectiveFunction{MOI.ScalarQuadraticFunction{T}}`

`source`

`MathOptInterface.Bridges.Objective.SlackBridge` - Type.

`SlackBridge{T,F,G}`

`SlackBridge` implements the following reformulations:

- $\min\{f(x)\}$  into  $\min\{y \mid f(x) - y \leq 0\}$
- $\max\{f(x)\}$  into  $\max\{y \mid f(x) - y \geq 0\}$

where  $F$  is the type of  $f(x) - y$ ,  $G$  is the type of  $f(x)$ , and  $T$  is the coefficient type of  $f(x)$ .

#### Source node

`SlackBridge` supports:

- `MOI.ObjectiveFunction{G}`

#### Target nodes

`SlackBridge` creates:

- One variable node: `MOI.VariableIndex` in `MOI.Reals`
- One objective node: `MOI.ObjectiveFunction{MOI.VariableIndex}`
- One constraint node, that depends on the `MOI.ObjectiveSense`:
  - $F$ -in-`MOI.LessThan` if `MIN_SENSE`
  - $F$ -in-`MOI.GreaterThan` if `MAX_SENSE`

#### Warning

When using this bridge, changing the optimization sense is not supported. Set the sense to `MOI.FEASIBILITY_SENSE` first to delete the bridge, then set `MOI.ObjectiveSense` and re-add the objective.

`source`

`MathOptInterface.Bridges.Objective.VectorFunctionizeBridge` - Type.

```
VectorFunctionizeBridge{T,G} <: FunctionConversionBridge{T,MOI.VectorAffineFunction{T},G}
```

`VectorFunctionizeBridge` implements the following reformulations:

- $\min\{x\}$  into  $\min\{1x + 0\}$
- $\max\{x\}$  into  $\max\{1x + 0\}$

where `T` is the coefficient type of 1 and 0.

#### Source node

`VectorFunctionizeBridge` supports:

- `MOI.ObjectiveFunction{G}`

#### Target nodes

`VectorFunctionizeBridge` creates:

- One objective node: `MOI.ObjectiveFunction{MOI.VectorAffineFunction{T}}`

`source`

`MathOptInterface.Bridges.Objective.VectorSlackBridge` - Type.

```
VectorSlackBridge{T,F,G}
```

`VectorSlackBridge` implements the following reformulations:

- $\min\{f(x)\}$  into  $\min\{y \mid y - f(x) \in \mathbb{R}_+\}$
- $\max\{f(x)\}$  into  $\max\{y \mid f(x) - y \in \mathbb{R}_+\}$

where `F` is the type of  $f(x)$  -  $y$ , `G` is the type of  $f(x)$ , and `T` is the coefficient type of  $f(x)$ .

#### Source node

`VectorSlackBridge` supports:

- `MOI.ObjectiveFunction{G}`

#### Target nodes

`VectorSlackBridge` creates:

- One variable node: `MOI.VectorOfVariables` in `MOI.Reals`
- One objective node: `MOI.ObjectiveFunction{MOI.VectorOfVariables}`
- One constraint node: `F`-in-`MOI.Nonnegatives`

#### Warning

When using this bridge, changing the optimization sense is not supported. Set the sense to `MOI.FEASIBILITY_SENSE` first to delete the bridge, then set `MOI.ObjectiveSense` and re-add the objective.

`source`

### Variable bridges

These bridges are subtypes of `Bridges.Variable.AbstractBridge`.

`MathOptInterface.Bridges.Variable.FlipSignBridge` – Type.

```
abstract type FlipSignBridge{T,S1,S2} <: SetMapBridge{T,S2,S1} end
```

An abstract type that simplifies the creation of other bridges.

`source`

`MathOptInterface.Bridges.Variable.FreeBridge` – Type.

```
FreeBridge{T} <: Bridges.Variable.AbstractBridge
```

`FreeBridge` implements the following reformulation:

- $x \in \mathbb{R}$  into  $y, z \geq 0$  with the substitution rule  $x = y - z$ ,

where `T` is the coefficient type of  $y - z$ .

#### Source node

`FreeBridge` supports:

- `MOI.VectorOfVariables` in `MOI.Reals`

#### Target nodes

`FreeBridge` creates:

- One variable node: `MOI.VectorOfVariables` in `MOI.Nonnegatives`

`source`

`MathOptInterface.Bridges.Variable.HermitianToSymmetricPSDBridge` – Type.

```
HermitianToSymmetricPSDBridge{T} <: Bridges.Variable.AbstractBridge
```

`HermitianToSymmetricPSDBridge` implements the following reformulation:

- Hermitian positive semidefinite  $n \times n$  complex matrix to a symmetric positive semidefinite  $2n \times 2n$  real matrix satisfying equality constraints described below.

#### Source node

`HermitianToSymmetricPSDBridge` supports:

- `MOI.VectorOfVariables` in `MOI.HermitianPositiveSemidefiniteConeTriangle`

**Target node**

`HermitianToSymmetricPSDBridge` creates:

- `MOI.VectorOfVariables` in `MOI.PositiveSemidefiniteConeTriangle`
- `MOI.ScalarAffineFunction{T}` in `MOI.EqualTo{T}`

**Reformulation**

The reformulation is best described by example.

The Hermitian matrix:

$$\begin{bmatrix} x_{11} & x_{12} + y_{12}im & x_{13} + y_{13}im \\ x_{12} - y_{12}im & x_{22} & x_{23} + y_{23}im \\ x_{13} - y_{13}im & x_{23} - y_{23}im & x_{33} \end{bmatrix}$$

is positive semidefinite if and only if the symmetric matrix:

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} & 0 & y_{12} & y_{13} \\ x_{22} & x_{23} & -y_{12} & 0 & y_{23} & \\ x_{33} & -y_{13} & -y_{23} & 0 & & \\ x_{11} & x_{12} & x_{13} & & & \\ x_{22} & x_{23} & x_{23} & & & \\ x_{33} & & & & & \end{bmatrix}$$

is positive semidefinite.

The bridge achieves this reformulation by adding a new set of variables in `MOI.PositiveSemidefiniteConeTriangle(6)`, and then adding three groups of equality constraints to:

- constrain the two x blocks to be equal
- force the diagonal of the y blocks to be 0
- force the lower triangular of the y block to be the negative of the upper triangle.

`source`

`MathOptInterface.Bridges.Variable.NonposToNonnegBridge` – Type.

`NonposToNonnegBridge{T} <: Bridges.Variable.AbstractBridge`

`NonposToNonnegBridge` implements the following reformulation:

- $x \in \mathbb{R}_-$  into  $y \in \mathbb{R}_+$  with the substitution rule  $x = -y$ ,

where T is the coefficient type of -y.

**Source node**

`NonposToNonnegBridge` supports:

- `MOI.VectorOfVariables` in `MOI.Nonpositives`

### Target nodes

`NonposToNonnegBridge` creates:

- One variable node: `MOI.VectorOfVariables` in `MOI.Nonnegatives`,

`source`

`MathOptInterface.Bridges.Variable.ParameterEqualToBridge` - Type.

```
ParameterEqualToBridge{T} <: Bridges.Variable.AbstractBridge
```

`ParameterEqualToBridge` implements the following reformulation:

- $x \in \text{Parameter}(v)$  into  $x == v$

### Source node

`ParameterEqualToBridge` supports:

- `MOI.VariableIndex` in `MOI.Parameter`

### Target nodes

`ParameterEqualToBridge` creates:

- One variable node: `MOI.VariableIndex` in `MOI.EqualTo{T}`

`source`

`MathOptInterface.Bridges.Variable.RSOCtoPSDBridge` - Type.

```
RSOCtoPSDBridge{T} <: Bridges.Variable.AbstractBridge
```

`RSOCtoPSDBridge` implements the following reformulation:

- $\|x\|_2^2 \leq 2tu$  where  $t, u \geq 0$  into  $Y \succeq 0$ , with the substitution rule:  $Y = \begin{bmatrix} t & x^\top \\ x & 2uI \end{bmatrix}$ .

Additional bounds are added to ensure the off-diagonals of the  $2uI$  submatrix are 0, and linear constraints are added to ensure the diagonal of  $2uI$  takes the same values.

As a special case, if  $|x| = 0$ , then `RSOCtoPSDBridge` reformulates into  $(t, u) \in \mathbb{R}_+$ .

### Source node

`RSOCtoPSDBridge` supports:

- `MOI.VectorOfVariables` in `MOI.RotatedSecondOrderCone`

**Target nodes**

`RSOCToPSDBridge` creates:

- One variable node that depends on the input dimension:
  - `MOI.VectorOfVariables` in `MOI.Nonnegatives` if dimension is 1 or 2
  - `MOI.VectorOfVariables` in `MOI.PositiveSemidefiniteConeTriangle` otherwise
- The constraint node `MOI.VariableIndex` in `MOI.EqualTo`
- The constant node `MOI.ScalarAffineFunction` in `MOI.EqualTo`

`source`

`MathOptInterface.Bridges.Variable.RSOCToSOCBridge` - Type.

```
RSOCToSOCBridge{T} <: Bridges.Variable.AbstractBridge
```

`RSOCToSOCBridge` implements the following reformulation:

- $\|x\|_2^2 \leq 2tu$  into  $\|v\|_2 \leq w$ , with the substitution rules  $t = \frac{w}{\sqrt{2}} + \frac{v_1}{\sqrt{2}}$ ,  $u = \frac{w}{\sqrt{2}} - \frac{v_1}{\sqrt{2}}$ , and  $x = (v_2, \dots, v_N)$ .

**Source node**

`RSOCToSOCBridge` supports:

- `MOI.VectorOfVariables` in `MOI.RotatedSecondOrderCone`

**Target node**

`RSOCToSOCBridge` creates:

- `MOI.VectorOfVariables` in `MOI.SecondOrderCone`

`source`

`MathOptInterface.Bridges.Variable.SOCToRSOCBridge` - Type.

```
SOCtoRSOCBridge{T} <: Bridges.Variable.AbstractBridge
```

`SOCtoRSOCBridge` implements the following reformulation:

- $\|x\|_2 \leq t$  into  $2uv \geq \|w\|_2^2$ , with the substitution rules  $t = \frac{u}{\sqrt{2}} + \frac{v}{\sqrt{2}}$ ,  $x = (\frac{u}{\sqrt{2}} - \frac{v}{\sqrt{2}}, w)$ .

**Assumptions**

- `SOCtoRSOCBridge` assumes that  $|x| \geq 1$ .

**Source node**

SOCtoRSOCBridge supports:

- `MOI.VectorOfVariables` in `MOI.SecondOrderCone`

**Target node**

SOCtoRSOCBridge creates:

- `MOI.VectorOfVariables` in `MOI.RotatedSecondOrderCone`

`source`

`MathOptInterface.Bridges.Variable.SetMapBridge` – Type.

```
abstract type SetMapBridge{T,S1,S2} <: AbstractBridge end
```

Consider two type of sets,  $S_1$  and  $S_2$ , and a linear mapping  $A$  such that the image of a set of type  $S_1$  under  $A$  is a set of type  $S_2$ .

A `SetMapBridge{T,S1,S2}` is a bridge that substitutes constrained variables in  $S_2$  into the image through  $A$  of constrained variables in  $S_1$ .

The linear map  $A$  is described by:

- `MOI.Bridges.map_set`
- `MOI.Bridges.map_function`

Implementing a method for these two functions is sufficient to bridge constrained variables. However, in order for the getters and setters of attributes such as dual solutions and starting values to work as well, a method for the following functions must be implemented:

- `MOI.Bridges.inverse_map_set`
- `MOI.Bridges.inverse_map_function`
- `MOI.Bridges.adjoint_map_function`
- `MOI.Bridges.inverse_adjoint_map_function`.

See the docstrings of each function to see which feature would be missing if it was not implemented for a given bridge.

`source`

`MathOptInterface.Bridges.Variable.VectorizeBridge` – Type.

```
VectorizeBridge{T,S} <: Bridges.Variable.AbstractBridge
```

`VectorizeBridge` implements the following reformulations:

- $x \geq a$  into  $[y] \in \mathbb{R}_+$  with the substitution rule  $x = a + y$

- $x \leq a$  into  $[y] \in \mathbb{R}_-$  with the substitution rule  $x = a + y$
- $x == a$  into  $[y] \in \{0\}$  with the substitution rule  $x = a + y$

where T is the coefficient type of a + y.

#### Source node

VectorizeBridge supports:

- MOI.VariableIndex in MOI.GreaterThan{T}
- MOI.VariableIndex in MOI.LessThan{T}
- MOI.VariableIndex in MOI.EqualTo{T}

#### Target nodes

VectorizeBridge creates:

- One variable node: MOI.VectorOfVariables in S, where S is one of MOI.Nonnegatives, MOI.Nonpositives, MOI.Zeros depending on the type of S.

source

MathOptInterface.Bridges.Variable.ZerosBridge - Type.

ZerosBridge{T} <: Bridges.Variable.AbstractBridge

ZerosBridge implements the following reformulation:

- $x \in \{0\}$  into the substitution rule  $x = 0$ ,

where T is the coefficient type of 0.

#### Source node

ZerosBridge supports:

- MOI.VectorOfVariables in MOI.Zeros

#### Target nodes

ZerosBridge does not create target nodes. It replaces all instances of x with 0 via substitution. This means that no variables are created in the underlying model.

#### Caveats

The bridged variables are similar to parameters with zero values. Parameters with non-zero values can be created with constrained variables in MOI.EqualTo by combining a VectorizeBridge and this bridge.

However, functions modified by ZerosBridge cannot be unbridged. That is, for a given function, we cannot determine if the bridged variables were used.

A related implication is that this bridge does not support MOI.ConstraintDual. However, if a MOI.Utilities.CachingOptimizer is used, the dual can be determined by the bridged optimizer using MOI.Utilities.get\_fallback because the caching optimizer records the unbridged function.

source

## API Reference

### Bridges

#### AbstractBridge API

`MathOptInterface.Bridges.AbstractBridge` – Type.

```
abstract type AbstractBridge end
```

An abstract type representing a bridged constraint or variable in a `MOI.Bridges.AbstractBridgeOptimizer`.

All bridges must implement:

- `added_constrained_variable_types`
- `added_constraint_types`
- `MOI.get(::AbstractBridge, ::MOI.NumberOfVariables)`
- `MOI.get(::AbstractBridge, ::MOI.ListOfVariableIndices)`
- `MOI.get(::AbstractBridge, ::MOI.NumberOfConstraints)`
- `MOI.get(::AbstractBridge, ::MOI.ListOfConstraintIndices)`

Subtypes of `AbstractBridge` may have additional requirements. Consult their docstrings for details.

In addition, all subtypes may optionally implement the following constraint attributes with the bridge in place of the constraint index:

- `MOI.ConstraintDual`
- `MOI.ConstraintPrimal`

`source`

`MathOptInterface.Bridges.added_constrained_variable_types` – Function.

```
added_constrained_variable_types(
    BT::Type{<:AbstractBridge},
) ::Vector{Tuple{Type}}
```

Return a list of the types of constrained variables that bridges of concrete type BT add.

#### Implementation notes

- This method depends only on the type of the bridge, not the runtime value. If the bridge *may* add a constrained variable, the type *must* be included in the return vector.
- If the bridge adds a free variable via `MOI.add_variable` or `MOI.add_variables`, the return vector *must* include `(MOI.Reals,)`.

#### Example

```
julia> MOI.Bridges.added_constrained_variable_types(
    MOI.Bridges.Variable.NonposToNonnegBridge{Float64},
)
1-element Vector{Tuple{Type}}:
 (MathOptInterface.Nonnegatives,)
```

**source**

MathOptInterface.Bridges.added\_constraint\_types - Function.

```
added_constraint_types(
    BT::Type{<:AbstractBridge},
)::Vector{Tuple{Type,Type}}
```

Return a list of the types of constraints that bridges of concrete type BT add.

#### Implementation notes

- This method depends only on the type of the bridge, not the runtime value. If the bridge *may* add a constraint, the type *must* be included in the return vector.

#### Example

```
julia> MOI.Bridges.added_constraint_types(
    MOI.Bridges.Constraint.ZeroOneBridge{Float64},
)
2-element Vector{Tuple{Type, Type}}:
 (MathOptInterface.ScalarAffineFunction{Float64}, MathOptInterface.Interval{Float64})
 (MathOptInterface.VariableIndex, MathOptInterface.Integer)
```

**source**

MathOptInterface.get - Method.

```
MOI.get(b::AbstractBridge, ::MOI.NumberOfVariables)::Int64
```

Return the number of variables created by the bridge b in the model.

See also [MOI.NumberOfConstraints](#).

#### Implementation notes

- There is a default fallback, so you need only implement this if the bridge adds new variables.

**source**

MathOptInterface.get - Method.

```
MOI.get(b::AbstractBridge, ::MOI.ListOfVariableIndices)
```

Return the list of variables created by the bridge b.

See also [MOI.ListOfVariableIndices](#).

#### **Implementation notes**

- There is a default fallback, so you need only implement this if the bridge adds new variables.

[source](#)

MathOptInterface.get – Method.

```
MOI.get(b::AbstractBridge, ::MOI.NumberOfConstraints{F,S})::Int64 where {F,S}
```

Return the number of constraints of the type F-in-S created by the bridge b.

See also [MOI.NumberOfConstraints](#).

#### **Implementation notes**

- There is a default fallback, so you need only implement this for the constraint types returned by [added\\_constraint\\_types](#).

[source](#)

MathOptInterface.get – Method.

```
MOI.get(b::AbstractBridge, ::MOI.ListOfConstraintIndices{F,S}) where {F,S}
```

Return a Vector{ConstraintIndex{F,S}} with indices of all constraints of type F-in-S created by the bridge b.

See also [MOI.ListOfConstraintIndices](#).

#### **Implementation notes**

- There is a default fallback, so you need only implement this for the constraint types returned by [added\\_constraint\\_types](#).

[source](#)

MathOptInterface.Bridges.needs\_final\_touch – Function.

```
needs_final_touch(bridge::AbstractBridge)::Bool
```

Return whether [final\\_touch](#) is implemented by bridge.

[source](#)

MathOptInterface.Bridges.final\_touch – Function.

```
final_touch(bridge::AbstractBridge, model::MOI.ModelLike)::Nothing
```

A function that is called immediately prior to `MOI.optimize!` to allow bridges to modify their reformulations with respect to other variables and constraints in `model`.

For example, if the correctness of bridge depends on the bounds of a variable or the fact that variables are integer, then the bridge can implement `final_touch` to check assumptions immediately before a call to `MOI.optimize!`.

If you implement this method, you must also implement `needs_final_touch`.

`source`

`MathOptInterface.Bridges.bridging_cost` - Function.

```
bridging_cost(b::AbstractBridgeOptimizer, S::Type{<:MOI.AbstractSet})
```

Return the cost of bridging variables constrained in `S` on creation, `is_bridged(b, S)` is assumed to be true.

```
bridging_cost(
    b::AbstractBridgeOptimizer,
    F::Type{<:MOI.AbstractFunction},
    S::Type{<:MOI.AbstractSet},
)
```

Return the cost of bridging `F`-in-`S` constraints.

`is_bridged(b, S)` is assumed to be true.

`source`

`MathOptInterface.Bridges.runtests` - Function.

```
runtests(
    Bridge::Type{<:AbstractBridge},
    input_fn::Function,
    output_fn::Function;
    variable_start = 1.2,
    constraint_start = 1.2,
    eltype = Float64,
    cannot_unbridge::Bool = false,
)
```

Run a series of tests that check the correctness of Bridge.

`input_fn` and `output_fn` are functions such that `input_fn(model)` and `output_fn(model)` load the corresponding model into `model`.

Set `cannot_unbridge` to `true` if the bridge is a variable bridge for which `Variable.unbridged_map` returns nothing so that the tests allow errors that can be raised due to this.

### Example

```
julia> MOI.Bridges.runtests(
    MOI.Bridges.Constraint.ZeroOneBridge,
    model -> MOI.add_constrained_variable(model, MOI.ZeroOne()),
    model -> begin
        x, _ = MOI.add_constrained_variable(model, MOI.Integer())
        MOI.add_constraint(model, 1.0 * x, MOI.Interval(0.0, 1.0))
    end,
)
```

source

```
runtests(
    Bridge::Type{<:AbstractBridge},
    input::String,
    output::String;
    variable_start = 1.2,
    constraint_start = 1.2,
    eltype = Float64,
)
```

Run a series of tests that check the correctness of Bridge.

input and output are models in the style of `MOI.Utilities.loadfromstring!`.

### Example

```
julia> MOI.Bridges.runtests(
    MOI.Bridges.Constraint.ZeroOneBridge,
    """
    variables: x
    x in ZeroOne()
    """,
    """
    variables: x
    x in Integer()
    1.0 * x in Interval(0.0, 1.0)
    """
)
```

source

### Constraint bridge API

`MathOptInterface.Bridges.Constraint.AbstractBridge` – Type.

```
abstract type AbstractBridge <: MOI.Bridges.AbstractType
```

Subtype of `MOI.Bridges.AbstractBridge` for constraint bridges.

In addition to the required implementation described in `MOI.Bridges.AbstractBridge`, subtypes of `AbstractBridge` must additionally implement:

```

    • MOI.supports_constraint(::Type{<:AbstractBridge}, ::Type{<:MOI.AbstractFunction}, ::Type{<:MOI.Abst
    • concrete_bridge_type
    • bridge_constraint

source

```

MathOptInterface.Bridges.Constraint.SingleBridgeOptimizer - Type.

```
SingleBridgeOptimizer{BT<:AbstractBridge}(model::MOI.ModelLike)
```

Return AbstractBridgeOptimizer that always bridges any objective function supported by the bridge BT.

This is in contrast with the `MOI.Bridges.LazyBridgeOptimizer`, which only bridges the objective function if it is supported by the bridge BT and unsupported by model.

### Example

```
julia> struct MyNewBridge{T} <: MOI.Bridges.Constraint.AbstractBridge end

julia> bridge = MOI.Bridges.Constraint.SingleBridgeOptimizer{MyNewBridge{Float64}}(
        MOI.Utilities.Model{Float64}(),
    )
MOIB.Constraint.SingleBridgeOptimizer{MyNewBridge{Float64}, MOIU.Model{Float64}}
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberofVariables: 0
└ NumberofConstraints: 0
```

### Implementation notes

All bridges should simplify the creation of SingleBridgeOptimizers by defining a constant that wraps the bridge in a SingleBridgeOptimizer.

```
julia> const MyNewBridgeModel{T,OT<:MOI.ModelLike} =
        MOI.Bridges.Constraint.SingleBridgeOptimizer{MyNewBridge{T},OT};
```

This enables users to create bridged models as follows:

```
julia> MyNewBridgeModel{Float64}(MOI.Utilities.Model{Float64}());
```

source

MathOptInterface.supports\_constraint - Method.

```
MOI.supports_constraint(
    BT::Type{<:AbstractBridge},
    F::Type{<:MOI.AbstractFunction},
    S::Type{<:MOI.AbstractSet},
) :: Bool
```

Return a Bool indicating whether the bridges of type BT support bridging F-in-S constraints.

#### Implementation notes

- This method depends only on the type of the inputs, not the runtime values.
- There is a default fallback, so you need only implement this method for constraint types that the bridge implements.

[source](#)

MathOptInterface.Bridges.Constraint.concrete\_bridge\_type - Function.

```
concrete_bridge_type(
    BT::Type{<:AbstractBridge},
    F::Type{<:MOI.AbstractFunction},
    S::Type{<:MOI.AbstractSet}
) :: Type
```

Return the concrete type of the bridge supporting F-in-S constraints.

This function can only be called if MOI.supports\_constraint(BT, F, S) is true.

#### Example

The `SplitIntervalBridge` bridges a `MOI.VariableIndex`-in-`MOI.Interval` constraint into a `MOI.VariableIndex`-in-`MOI.GreaterThan` and a `MOI.VariableIndex`-in-`MOI.LessThan` constraint.

```
julia> MOI.Bridges.Constraint.concrete_bridge_type(
    MOI.Bridges.Constraint.SplitIntervalBridge{Float64},
    MOI.VariableIndex,
    MOI.Interval{Float64},
)
MathOptInterface.Bridges.Constraint.SplitIntervalBridge{Float64, MathOptInterface.VariableIndex,
→ MOI.Interval{Float64}, MathOptInterface.GreaterThan{Float64},
→ MathOptInterface.LessThan{Float64}}
```

[source](#)

MathOptInterface.Bridges.Constraint.bridge\_constraint - Function.

```
bridge_constraint(
    BT::Type{<:AbstractBridge},
    model::MOI.ModelLike,
    func::AbstractFunction,
    set::MOI.AbstractSet,
) :: BT
```

Bridge the constraint func-in-set using bridge BT to model and returns a bridge object of type BT.

#### Implementation notes

- The bridge type BT should be a concrete type, that is, all the type parameters of the bridge must be set.

`source``MathOptInterface.Bridges.Constraint.add_all_bridges - Function.`

```
add_all_bridges(model, ::Type{T}) where {T}
```

Add all bridges defined in the `Bridges.Constraint` submodule to `model`.

The coefficient type used is `T`.

`source``MathOptInterface.Bridges.Constraint.conversion_cost - Function.`

```
conversion_cost(
    F::Type{<:MOI.AbstractFunction},
    G::Type{<:MOI.AbstractFunction},
) ::Float64
```

Return a `Float64` returning the cost of converting any function of type `G` to a function of type `F` with `convert`.

This cost is used to compute `MOI.Bridges.bridging_cost`.

The default cost is `Inf`, which means that `MOI.Bridges.Constraint.FunctionConversionBridge` should not attempt the conversion.

`source`

### Objective bridge API

`MathOptInterface.Bridges.Objective.AbstractBridge - Type.`

```
abstract type AbstractBridge <: MOI.Bridges.AbstractBridge end
```

Subtype of `MOI.Bridges.AbstractBridge` for objective bridges.

In addition to the required implementation described in `MOI.Bridges.AbstractBridge`, subtypes of `AbstractBridge` must additionally implement:

- `supports_objective_function`
- `concrete_bridge_type`
- `bridge_objective`
- `MOI.Bridges.set_objective_function_type`

`source``MathOptInterface.Bridges.Objective.SingleBridgeOptimizer - Type.`

```
SingleBridgeOptimizer{BT<:AbstractBridge}(model::MOI.ModelLike)
```

Return AbstractBridgeOptimizer that always bridges any objective function supported by the bridge BT.

This is in contrast with the `MOI.Bridges.LazyBridgeOptimizer`, which only bridges the objective function if it is supported by the bridge BT and unsupported by model.

### Example

```
julia> struct MyNewBridge{T} <: MOI.Bridges.Objective.AbstractBridge end

julia> bridge = MOI.Bridges.Objective.SingleBridgeOptimizer{MyNewBridge{Float64}}(
    MOI.Utilities.Model{Float64}(),
);
```

### Implementation notes

All bridges should simplify the creation of SingleBridgeOptimizers by defining a constant that wraps the bridge in a SingleBridgeOptimizer.

```
julia> const MyNewBridgeModel{T,OT<:MOI.ModelLike} =
    MOI.Bridges.Objective.SingleBridgeOptimizer{MyNewBridge{T},OT};
```

This enables users to create bridged models as follows:

```
julia> MyNewBridgeModel{Float64}(MOI.Utilities.Model{Float64}());
```

source

```
MathOptInterface.Bridges.Objective.supports_objective_function - Function.

    supports_objective_function(
        BT::Type{<:MOI.Bridges.Objective.AbstractBridge},
        F::Type{<:MOI.AbstractFunction},
    )::Bool
```

Return a Bool indicating whether the bridges of type BT support bridging objective functions of type F.

### Implementation notes

- This method depends only on the type of the inputs, not the runtime values.
- There is a default fallback, so you need only implement this method for objective functions that the bridge implements.

source

```
MathOptInterface.Bridges.set_objective_function_type - Function.
```

```
set_objective_function_type(
    BT::Type{<:Objective.AbstractBridge},
) :: Type{<:MOI.AbstractFunction}
```

Return the type of objective function that bridges of concrete type BT set.

#### Implementation notes

- This method depends only on the type of the bridge, not the runtime value.

#### Example

```
julia> MOI.Bridges.set_objective_function_type(
    MOI.Bridges.Objective.FunctionizeBridge{Float64},
)
MathOptInterface.ScalarAffineFunction{Float64}
```

`source`

`MathOptInterface.Bridges.Objective.concrete_bridge_type` - Function.

```
concrete_bridge_type(
    BT::Type{<:MOI.Bridges.Objective.AbstractBridge},
    F::Type{<:MOI.AbstractFunction},
) :: Type
```

Return the concrete type of the bridge supporting objective functions of type F.

This function can only be called if `MOI.supports_objective_function(BT, F)` is true.

`source`

`MathOptInterface.Bridges.Objective.bridge_objective` - Function.

```
bridge_objective(
    BT::Type{<:MOI.Bridges.Objective.AbstractBridge},
    model::MOI.ModelLike,
    func::MOI.AbstractFunction,
) :: BT
```

Bridge the objective function `func` using bridge `BT` to `model` and returns a bridge object of type `BT`.

#### Implementation notes

- The bridge type `BT` must be a concrete type, that is, all the type parameters of the bridge must be set.

`source`

`MathOptInterface.Bridges.Objective.add_all_bridges` - Function.

```
add_all_bridges(model, ::Type{T}) where {T}
```

Add all bridges defined in the Bridges.Objective submodule to model.

The coefficient type used is T.

[source](#)

### Variable bridge API

MathOptInterface.Bridges.Variable.AbstractBridge - Type.

```
abstract type AbstractBridge <: MOI.Bridges.AbstractBridge end
```

Subtype of `MOI.Bridges.AbstractBridge` for variable bridges.

In addition to the required implementation described in `MOI.Bridges.AbstractBridge`, subtypes of `AbstractBridge` must additionally implement:

- `supports_constrained_variable`
- `concrete_bridge_type`
- `bridge_constrained_variable`

[source](#)

MathOptInterface.Bridges.Variable.SingleBridgeOptimizer - Type.

```
SingleBridgeOptimizer{BT<:AbstractBridge}(model::MOI.ModelLike)
```

Return `MOI.Bridges.AbstractBridgeOptimizer` that always bridges any variables constrained on creation supported by the bridge BT.

This is in contrast with the `MOI.Bridges.LazyBridgeOptimizer`, which only bridges the variables constrained on creation if they are supported by the bridge BT and unsupported by model.

#### Warning

Two `SingleBridgeOptimizer`s cannot be used together as both of them assume that the underlying model only returns variable indices with nonnegative values. Use `MOI.Bridges.LazyBridgeOptimizer` instead.

#### Example

```
julia> struct MyNewBridge{T} <: MOI.Bridges.Variable.AbstractBridge end
julia> bridge = MOI.Bridges.Variable.SingleBridgeOptimizer{MyNewBridge{Float64}}(
    MOI.Utilities.Model{Float64}(),
);
```

### Implementation notes

All bridges should simplify the creation of SingleBridgeOptimizers by defining a constant that wraps the bridge in a SingleBridgeOptimizer.

```
julia> const MyNewBridgeModel{T,OT<:MOI.ModelLike} =
    MOI.Bridges.Variable.SingleBridgeOptimizer{MyNewBridge{T}},OT};
```

This enables users to create bridged models as follows:

```
julia> MyNewBridgeModel{Float64}(MOI.Utilities.Model{Float64}());
```

`source`

`MathOptInterface.Bridges.Variable.supports_constrained_variable` – Function.

```
supports_constrained_variable(
    BT::Type{<:AbstractBridge},
    S::Type{<:MOI.AbstractSet},
) :: Bool
```

Return a `Bool` indicating whether the bridges of type `BT` support bridging constrained variables in `S`. That is, it returns true if the bridge of type `BT` converts constrained variables of type `S` into a form supported by the solver.

### Implementation notes

- This method depends only on the type of the bridge and set, not the runtime values.
- There is a default fallback, so you need only implement this method for sets that the bridge implements.

### Example

```
julia> MOI.Bridges.Variable.supports_constrained_variable(
    MOI.Bridges.Variable.NonposToNonnegBridge{Float64},
    MOI.Nonpositives,
)
true

julia> MOI.Bridges.Variable.supports_constrained_variable(
    MOI.Bridges.Variable.NonposToNonnegBridge{Float64},
    MOI.Nonnegatives,
)
false
```

`source`

`MathOptInterface.Bridges.Variable.concrete_bridge_type` – Function.

```
concrete_bridge_type(
    BT::Type{<:AbstractBridge},
    S::Type{<:MOI.AbstractSet},
) :: Type
```

Return the concrete type of the bridge supporting variables in S constraints.

This function can only be called if MOI.supports\_constrained\_variable(BT, S) is true.

### Example

As a variable in MOI.GreaterThan is bridged into variables in MOI.Nonnegatives by the VectorizeBridge:

```
julia> import MathOptInterface as MOI

julia> MOI.Bridges.Variable.concrete_bridge_type(
    MOI.Bridges.Variable.VectorizeBridge{Float64},
    MOI.GreaterThan{Float64},
)
MathOptInterface.Bridges.Variable.VectorizeBridge{Float64, MathOptInterface.Nonnegatives}
```

`source`

MathOptInterface.Bridges.Variable.bridge\_constrained\_variable - Function.

```
bridge_constrained_variable(
    BT::Type{<:AbstractBridge},
    model::MOI.ModelLike,
    set::MOI.AbstractSet,
)::BT
```

Bridge the constrained variable in set using bridge BT to model and returns a bridge object of type BT.

### Implementation notes

- The bridge type BT must be a concrete type, that is, all the type parameters of the bridge must be set.

`source`

MathOptInterface.Bridges.Variable.add\_all\_bridges - Function.

```
add_all_bridges(model, ::Type{T}) where {T}
```

Add all bridges defined in the Bridges.Variable submodule to model.

The coefficient type used is T.

`source`

MathOptInterface.Bridges.Variable.unbridged\_map - Function.

```
unbridged_map(
    bridge::MOI.Bridges.Variable.AbstractBridge,
    vi::MOI.VariableIndex,
)
```

For a bridged variable in a scalar set, return a tuple of pairs mapping the variables created by the bridge to an affine expression in terms of the bridged variable vi.

```
unbridged_map(
    bridge::MOI.Bridges.Variable.AbstractBridge,
    vis::Vector{MOI.VariableIndex},
)
```

For a bridged variable in a vector set, return a tuple of pairs mapping the variables created by the bridge to an affine expression in terms of the bridged variable vis. If this method is not implemented, it falls back to calling the following method for every variable of vis.

```
unbridged_map(
    bridge::MOI.Bridges.Variable.AbstractBridge,
    vi::MOI.VariableIndex,
    i::MOI.Bridges.IndexInVector,
)
```

For a bridged variable in a vector set, return a tuple of pairs mapping the variables created by the bridge to an affine expression in terms of the bridged variable vi corresponding to the *i*th variable of the vector.

If there is no way to recover the expression in terms of the bridged variable(s) vi(s), return nothing. See [ZerosBridge](#) for an example of bridge returning nothing.

[source](#)

### AbstractBridgeOptimizer API

MathOptInterface.Bridges.AbstractBridgeOptimizer – Type.

```
abstract type AbstractBridgeOptimizer <: MOI.AbstractOptimizer end
```

An abstract type that implements generic functions for bridges.

### Implementation notes

By convention, the inner optimizer should be stored in a `model` field. If not, the optimizer must implement [MOI.optimize!](#).

[source](#)

MathOptInterface.Bridges.bridged\_variable\_function – Function.

```
bridged_variable_function(
    b::AbstractBridgeOptimizer,
    vi::MOI.VariableIndex,
)
```

Return a `MOI.AbstractScalarFunction` of variables of `b.model` that equals `vi`. That is, if the variable `vi` is bridged, it returns its expression in terms of the variables of `b.model`. Otherwise, it returns `vi`.

`source`

`MathOptInterface.Bridges.unbridged_variable_function` – Function.

```
unbridged_variable_function(
    b::AbstractBridgeOptimizer,
    vi::MOI.VariableIndex,
)
```

Return a `MOI.AbstractScalarFunction` of variables of `b` that equals `vi`. That is, if the variable `vi` is an internal variable of `b.model` created by a bridge but not visible to the user, it returns its expression in terms of the variables of bridged variables. Otherwise, it returns `vi`.

`source`

`MathOptInterface.Bridges.bridged_function` – Function.

```
bridged_function(b::AbstractBridgeOptimizer, value)::typeof(value)
```

Substitute any bridged `MOI.VariableIndex` in `value` by an equivalent expression in terms of variables of `b.model`.

`source`

`MathOptInterface.Bridges.supports_constraint_bridges` – Function.

```
supports_constraint_bridges(b::AbstractBridgeOptimizer)::Bool
```

Return a `Bool` indicating if `b` supports `MOI.Bridges.Constraint.AbstractBridge`.

`source`

`MathOptInterface.Bridges.recursive_model` – Function.

```
recursive_model(b::AbstractBridgeOptimizer)
```

If a variable, constraint, or objective is bridged, return the context of the inner variables. For most optimizers, this should be `b.model`.

`source`

`MathOptInterface.Bridges.FirstBridge` – Type.

```
struct FirstBridge <: MOI.AbstractConstraintAttribute end
```

Returns the first bridge used to bridge the constraint.

#### Warning

The indices of the bridge correspond to internal indices and may not correspond to indices of the model this attribute is got from.

[source](#)

#### LazyBridgeOptimizer API

MathOptInterface.Bridges.LazyBridgeOptimizer - Type.

```
LazyBridgeOptimizer(model::MOI.ModelLike)
```

The LazyBridgeOptimizer is a bridge optimizer that supports multiple bridges, and only bridges things which are not supported by the internal model.

Internally, the LazyBridgeOptimizer solves a shortest hyper-path problem to determine which bridges to use.

In general, you should use `full_bridge_optimizer` instead of this constructor because `full_bridge_optimizer` automatically adds a large number of supported bridges.

See also: [add\\_bridge](#), [remove\\_bridge](#), [has\\_bridge](#) and [full\\_bridge\\_optimizer](#).

#### Example

```
julia> model = MOI.Bridges.LazyBridgeOptimizer(MOI.Utilities.Model{Float64}());
julia> MOI.Bridges.add_bridge(model, MOI.Bridges.Variable.FreeBridge{Float64})
julia> MOI.Bridges.has_bridge(model, MOI.Bridges.Variable.FreeBridge{Float64})
true
```

[source](#)

MathOptInterface.Bridges.full\_bridge\_optimizer - Function.

```
full_bridge_optimizer(model::MOI.ModelLike, ::Type{T}) where {T}
```

Returns a `LazyBridgeOptimizer` bridging model for every bridge defined in this package (see below for the few exceptions) and for the coefficient type T, as well as the bridges in the list returned by the `ListOfNonstandardBridges` attribute.

#### Example

```
julia> model = MOI.Utilities.Model{Float64}();
julia> bridged_model = MOI.Bridges.full_bridge_optimizer(model, Float64);
```

### Exceptions

The following bridges are not added by `full_bridge_optimizer`, except if they are in the list returned by the `ListofNonstandardBridges` attribute:

- `Constraint.SOCtoNonConvexQuadBridge`
- `Constraint.RSOCtoNonConvexQuadBridge](@ref)`
- `Constraint.SOCtoPSDBridge`
- If `T` is not a subtype of `AbstractFloat`, subtypes of `Constraint.AbstractToIntervalBridge`
  - `Constraint.GreaterToIntervalBridge`
  - `Constraint.LessToIntervalBridge`)

See the docstring of the each bridge for the reason they are not added.

`source`

`MathOptInterface.Bridges.ListofNonstandardBridges` – Type.

```
ListofNonstandardBridges{T}() <: MOI.AbstractOptimizerAttribute
```

Any optimizer can be wrapped in a `LazyBridgeOptimizer` using `full_bridge_optimizer`. However, by default `LazyBridgeOptimizer` uses a limited set of bridges that are:

1. implemented in `MOI.Bridges`
2. generally applicable for all optimizers.

For some optimizers however, it is useful to add additional bridges, such as those that are implemented in external packages (for example, within the solver package itself) or only apply in certain circumstances (for example, `Constraint.SOCtoNonConvexQuadBridge`).

Such optimizers should implement the `ListofNonstandardBridges` attribute to return a vector of bridge types that are added by `full_bridge_optimizer` in addition to the list of default bridges.

Note that optimizers implementing `ListofNonstandardBridges` may require package-specific functions or sets to be used if the non-standard bridges are not added. Therefore, you are recommended to use `model = MOI.instantiate(Package.Optimizer; with_bridge_type = T)` instead of `model = MOI.instantiate(Package.Optimizer)`. See `MOI.instantiate`.

### Example

#### An optimizer using a non-default bridge in `MOI.Bridges`

Solvers supporting `MOI.ScalarQuadraticFunction` can support `MOI.SecondOrderCone` and `MOI.RotatedSecondOrderCone` by defining:

```
function MOI.get(::MyQuadraticOptimizer, ::ListofNonstandardBridges{Float64})
    return Type[
        MOI.Bridges.Constraint.SOCtoNonConvexQuadBridge{Float64},
        MOI.Bridges.Constraint.RSOCtoNonConvexQuadBridge{Float64},
    ]
end
```

### An optimizer defining an internal bridge

Suppose an optimizer can exploit specific structure of a constraint, for example, it can exploit the structure of the matrix A in the linear system of equations  $A * x = b$ .

The optimizer can define the function:

```
struct MatrixAffineFunction{T} <: MOI.AbstractVectorFunction
    A::SomeStructuredMatrixType{T}
    b::Vector{T}
end
```

and then a bridge

```
struct MatrixAffineFunctionBridge{T} <: MOI.Constraint.AbstractBridge
    # ...
end
# ...
```

from VectorAffineFunction{T} to the MatrixAffineFunction. Finally, it defines:

```
function MOI.get(::Optimizer{T}, ::ListOfNonstandardBridges{T}) where {T}
    return Type[MatrixAffineFunctionBridge{T}]
end
```

`source`

`MathOptInterface.Bridges.add_bridge` - Function.

```
add_bridge(b::LazyBridgeOptimizer, BT::Type{<:AbstractBridge})
```

Enable the use of the bridges of type BT by b.

`source`

`MathOptInterface.Bridges.remove_bridge` - Function.

```
remove_bridge(b::LazyBridgeOptimizer, BT::Type{<:AbstractBridge})
```

Disable the use of the bridges of type BT by b.

`source`

`MathOptInterface.Bridges.has_bridge` - Function.

```
has_bridge(b::LazyBridgeOptimizer, BT::Type{<:AbstractBridge})
```

Return a Bool indicating whether the bridges of type BT are used by b.

`source`

`MathOptInterface.Bridges.print_active_bridges` – Function.

```
print_active_bridges([io::IO=stdout,] b::MOI.Bridges.LazyBridgeOptimizer)
```

Print the set of bridges that are active in the model `b`.

`source`

```
print_active_bridges(
    [io::IO=stdout,]
    b::MOI.Bridges.LazyBridgeOptimizer,
    F::Type{<:MOI.AbstractFunction}
)
```

Print the set of bridges required for an objective function of type `F`.

`source`

```
print_active_bridges(
    [io::IO=stdout,]
    b::MOI.Bridges.LazyBridgeOptimizer,
    F::Type{<:MOI.AbstractFunction},
    S::Type{<:MOI.AbstractSet},
)
```

Print the set of bridges required for a constraint of type `F-in-S`.

`source`

```
print_active_bridges(
    [io::IO=stdout,]
    b::MOI.Bridges.LazyBridgeOptimizer,
    S::Type{<:MOI.AbstractSet}
)
```

Print the set of bridges required for a variable constrained to set `S`.

`source`

`MathOptInterface.Bridges.print_graph` – Function.

```
print_graph([io::IO = stdout,] b::LazyBridgeOptimizer)
```

Print the hyper-graph containing all variable, constraint, and objective types that could be obtained by bridging the variables, constraints, and objectives that are present in the model by all the bridges added to `b`.

Each node in the hyper-graph corresponds to a variable, constraint, or objective type.

- Variable nodes are indicated by [ ]

- Constraint nodes are indicated by ( )
- Objective nodes are indicated by | |

The number inside each pair of brackets is an index of the node in the hyper-graph.

Note that this hyper-graph is the full list of possible transformations. When the bridged model is created, we select the shortest hyper-path from this graph, so many nodes may be un-used.

To see which nodes are used, call `print_active_bridges`.

For more information, see Legat, B., Dowson, O., Garcia, J., and Lubin, M. (2020). "MathOptInterface: a data structure for mathematical optimization problems." [URL](#)

`source`

`MathOptInterface.Bridges.debug_supports_constraint` – Function.

```
debug_supports_constraint(
    b::LazyBridgeOptimizer,
    F::Type{<:MOI.AbstractFunction},
    S::Type{<:MOI.AbstractSet};
    io::IO = Base.stdout,
)
```

Prints to `io` explanations for the value of `MOI.supports_constraint` with the same arguments.

`source`

`MathOptInterface.Bridges.debug_supports` – Function.

```
debug_supports(
    b::LazyBridgeOptimizer,
    ::MOI.ObjectiveFunction{F};
    io::IO = Base.stdout,
) where F
```

Prints to `io` explanations for the value of `MOI.supports` with the same arguments.

`source`

## SetMap API

`MathOptInterface.Bridges.MapNotInvertible` – Type.

```
struct MapNotInvertible <: Exception
    message::String
end
```

An error thrown by `inverse_map_function` or `inverse_adjoint_map_function` indicating that the linear map `A` defined in `Variable.SetMapBridge` and `Constraint.SetMapBridge` is not invertible.

`source`

`MathOptInterface.Bridges.map_set` – Function.

```
map_set(bridge::MOI.Bridges.AbstractBridge, set)
map_set(::Type{BT}, set) where {BT}
```

Return the image of `set` through the linear map `A` defined in `Variable.SetMapBridge` and `Constraint.SetMapBridge`.

This function is used for bridging the constraint and setting the `MOI.ConstraintSet`.

`source`

`MathOptInterface.Bridges.inverse_map_set` – Function.

```
inverse_map_set(bridge::MOI.Bridges.AbstractBridge, set)
inverse_map_set(::Type{BT}, set) where {BT}
```

Return the preimage of `set` through the linear map `A` defined in `Variable.SetMapBridge` and `Constraint.SetMapBridge`.

This function is used for getting the `MOI.ConstraintSet`.

The method can alternatively be defined on the bridge type. This legacy interface is kept for backward compatibility.

`source`

`MathOptInterface.Bridges.map_function` – Function.

```
map_function(bridge::MOI.Bridges.AbstractBridge, func)
map_function(::Type{BT}, func) where {BT}
```

Return the image of `func` through the linear map `A` defined in `Variable.SetMapBridge` and `Constraint.SetMapBridge`.

This function is used for getting the `MOI.ConstraintPrimal` of variable bridges. For constraint bridges, this is used for bridging the constraint, setting the `MOI.ConstraintFunction` and `MOI.ConstraintPrimalStart` and modifying the function with `MOI.modify`.

The default implementation of `Constraint.bridge_constraint` uses `map_function` with the bridge type so if this function is defined on the bridge type, `Constraint.bridge_constraint` does not need to be implemented.

`source`

```
map_function(::Type{BT}, func, i::IndexInVector) where {BT}
```

Return the scalar function at the `i`th index of the vector function that would be returned by `map_function(BT, func)` except that it may compute the `i`th element. This is used by `bridged_function` and for getting the `MOI.VariablePrimal` and `MOI.VariablePrimalStart` of variable bridges.

`source`

`MathOptInterface.Bridges.inverse_map_function` – Function.

```
inverse_map_function(bridge::MOI.Bridges.AbstractBridge, func)
inverse_map_function(::Type{BT}, func) where {BT}
```

Return the image of func through the inverse of the linear map A defined in [Variable.SetMapBridge](#) and [Constraint.SetMapBridge](#).

This function is used by [Variable.unbridged\\_map](#) and for setting the [MOI.VariablePrimalStart](#) of variable bridges and for getting the [MOI.ConstraintFunction](#), the [MOI.ConstraintPrimal](#) and the [MOI.ConstraintPrimalStart](#) of constraint bridges.

If the linear map A is not invertible, the error [MapNotInvertible](#) is thrown.

The method can alternatively be defined on the bridge type. This legacy interface is kept for backward compatibility.

[source](#)

`MathOptInterface.Bridges.adjoint_map_function` – Function.

```
adjoint_map_function(bridge::MOI.Bridges.AbstractBridge, func)
adjoint_map_function(::Type{BT}, func) where {BT}
```

Return the image of func through the adjoint of the linear map A defined in [Variable.SetMapBridge](#) and [Constraint.SetMapBridge](#).

This function is used for getting the [MOI.ConstraintDual](#) and [MOI.ConstraintDualStart](#) of constraint bridges.

The method can alternatively be defined on the bridge type. This legacy interface is kept for backward compatibility.

[source](#)

`MathOptInterface.Bridges.inverse_adjoint_map_function` – Function.

```
inverse_adjoint_map_function(bridge::MOI.Bridges.AbstractBridge, func)
inverse_adjoint_map_function(::Type{BT}, func) where {BT}
```

Return the image of func through the inverse of the adjoint of the linear map A defined in [Variable.SetMapBridge](#) and [Constraint.SetMapBridge](#).

This function is used for getting the [MOI.ConstraintDual](#) of variable bridges and setting the [MOI.ConstraintDualStart](#) of constraint bridges.

If the linear map A is not invertible, the error [MapNotInvertible](#) is thrown.

The method can alternatively be defined on the bridge type. This legacy interface is kept for backward compatibility.

[source](#)

## Bridging graph API

MathOptInterface.Bridges.Graph – Type.

```
Graph()
```

A type-stable datastructure for computing the shortest hyperpath problem.

### Nodes

There are three types of nodes in the graph:

- [VariableNode](#)
- [ConstraintNode](#)
- [ObjectiveNode](#)

Add nodes to the graph using [add\\_node](#).

### Edges

There are two types of edges in the graph:

- [Edge](#)
- [ObjectiveEdge](#)

Add edges to the graph using [add\\_edge](#).

For the ability to add a variable constrained on creation as a free variable followed by a constraint, use [set\\_variable\\_constraint\\_node](#).

### Optimal hyper-edges

Use [bridge\\_index](#) to compute the minimum-cost bridge leaving a node.

Note that [bridge\\_index](#) lazy runs a Bellman-Ford algorithm to compute the set of minimum cost edges. Thus, the first call to [bridge\\_index](#) after adding new nodes or edges will take longer than subsequent calls.

[source](#)

MathOptInterface.Bridges.VariableNode – Type.

```
VariableNode(index::Int)
```

A node in [Graph](#) representing a variable constrained on creation.

[source](#)

MathOptInterface.Bridges.ConstraintNode – Type.

```
ConstraintNode(index::Int)
```

A node in [Graph](#) representing a constraint.

[source](#)

MathOptInterface.Bridges.ObjectiveNode - Type.

```
ObjectiveNode(index::Int)
```

A node in `Graph` representing an objective function.

`source`

MathOptInterface.Bridges.Edge - Type.

```
Edge(
    bridge_index::Int,
    added_variables::Vector{VariableNode},
    added_constraints::Vector{ConstraintNode},
    cost::Float64 = 1.0,
)
```

Return a new datastructure representing an edge in `Graph` that starts at a `VariableNode` or a `ConstraintNode`.

`source`

MathOptInterface.Bridges.ObjectiveEdge - Type.

```
ObjectiveEdge(
    bridge_index::Int,
    added_variables::Vector{VariableNode},
    added_constraints::Vector{ConstraintNode},
)
```

Return a new datastructure representing an edge in `Graph` that starts at an `ObjectiveNode`.

`source`

MathOptInterface.Bridges.add\_node - Function.

```
add_node(graph::Graph, ::Type{VariableNode})::VariableNode
add_node(graph::Graph, ::Type{ConstraintNode})::ConstraintNode
add_node(graph::Graph, ::Type{ObjectiveNode})::ObjectiveNode
```

Add a new node to graph.

`source`

MathOptInterface.Bridges.add\_edge - Function.

```
add_edge(graph::Graph, node::VariableNode, edge::Edge)::Nothing
add_edge(graph::Graph, node::ConstraintNode, edge::Edge)::Nothing
add_edge(graph::Graph, node::ObjectiveNode, edge::ObjectiveEdge)::Nothing
```

Add edge to graph, where edge starts at node and connects to the nodes defined in edge.

`source`

`MathOptInterface.Bridges.set_variable_constraint_node` – Function.

```
set_variable_constraint_node(
    graph::Graph,
    variable_node::VariableNode,
    constraint_node::ConstraintNode,
    cost::Int,
)
```

As an alternative to `variable_node`, add a virtual edge to graph that represents adding a free variable, followed by a constraint of type `constraint_node`, with bridging cost `cost`.

#### Why is this needed?

Variables can either be added as a variable constrained on creation, or as a free variable which then has a constraint added to it.

`source`

`MathOptInterface.Bridges.bridge_index` – Function.

```
bridge_index(graph::Graph, node::VariableNode)::Int
bridge_index(graph::Graph, node::ConstraintNode)::Int
bridge_index(graph::Graph, node::ObjectiveNode)::Int
```

Return the optimal index of the bridge to chose from node.

`source`

`MathOptInterface.Bridges.is_variable_edge_best` – Function.

```
is_variable_edge_best(graph::Graph, node::VariableNode)::Bool
```

Return a `Bool` indicating whether node should be added as a variable constrained on creation, or as a free variable followed by a constraint.

`source`

### 36.3 FileFormats

#### Overview

##### The FileFormats submodule

The `FileFormats` module provides functions for reading and writing MOI models using `write_to_file` and `read_from_file`.

### Supported file types

You must read and write files to a `FileFormats.Model` object. Specific the file-type by passing a `FileFormats.FileFormat` enum. For example:

#### The Conic Benchmark Format

```
julia> model = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_CBF)
MOI.FileFormats.CBF.Model
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

#### The LP file format

```
julia> model = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_LP)
MOI.FileFormats.LP.Model
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

#### The MathOptFormat file format

```
julia> model = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_MOF)
MOI.FileFormats.MOF.Model
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

#### The MPS file format

```
julia> model = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_MPS)
MOI.FileFormats.MPS.Model
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

#### The NL file format

```
julia> model = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_NL)
MOI.FileFormats.NL.Model
├ ObjectiveSense: unknown
├ ObjectiveFunctionType: unknown
├ NumberOfVariables: unknown
└ NumberOfConstraints: unknown
```

### The REW file format

```
julia> model = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_REW)
MOI.FileFormats.MPS.Model
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

Note that the REW format is identical to the MPS file format, except that all names are replaced with generic identifiers.

### The SDPA file format

```
julia> model = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_SDPA)
MOI.FileFormats.SDPA.Model
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

## Write to file

To write a model `src` to a [MathOptFormat](#) file, use:

```
julia> src = MOI.Utilities.Model{Float64}();
julia> MOI.add_variable(src);
julia> dest = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_MOF);

julia> MOI.copy_to(dest, src)
MathOptInterface.Utilities.IndexMap with 1 entry:
MOI.VariableIndex(1) => MOI.VariableIndex(1)

julia> MOI.write_to_file(dest, "file.mof.json")

julia> print(read("file.mof.json", String))
{"name": "MathOptFormat"
  ↪ "Model", "version": {"major": 1, "minor": 7}, "variables": [{"name": "x1"}], "objective": {"sense": "feasibility"}, "constraint"
```

## Read from file

To read a [MathOptFormat](#) file, use:

```
julia> dest = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_MOF);

julia> MOI.read_from_file(dest, "file.mof.json")

julia> MOI.get(dest, MOI.ListOfVariableIndices())
1-element Vector{MathOptInterface.VariableIndex}:
```

```
MOI.VariableIndex(1)

julia> rm("file.mof.json") # Clean up after ourselves.
```

### Detecting the file-type automatically

Instead of the `format` keyword, you can also use the `filename` keyword argument to `FileFormats.Model`. This will attempt to automatically guess the format from the file extension. For example:

```
julia> src = MOI.Utilities.Model{Float64}();
julia> dest = MOI.FileFormats.Model(filename = "file.cbf.gz");
julia> MOI.copy_to(dest, src)
MathOptInterface.Utilities.IndexMap()
julia> MOI.write_to_file(dest, "file.cbf.gz")
julia> src_2 = MOI.FileFormats.Model(filename = "file.cbf.gz");
julia> MOI.read_from_file(src_2, "file.cbf.gz")
julia> rm("file.cbf.gz") # Clean up after ourselves.
```

Note how the compression format (GZip) is also automatically detected from the filename.

### Unsupported constraints

In some cases `src` may contain constraints that are not supported by the file format (for example, the CBF format supports integer variables but not binary). If so, copy `src` to a bridged model using `Bridges.full_bridge_optimizer`:

```
julia> src = MOI.Utilities.Model{Float64}();
julia> x = MOI.add_variable(src);
julia> MOI.add_constraint(src, x, MOI.ZeroOne());
julia> dest = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_CBF);
julia> bridged = MOI.Bridges.full_bridge_optimizer(dest, Float64);
julia> MOI.copy_to(bridged, src);
julia> MOI.write_to_file(dest, "my_model.cbf")
julia> rm("my_model.cbf") # Clean up after ourselves.
```

#### Note

Even after bridging, it may still not be possible to write the model to file because of unsupported constraints (for example, PSD variables in the LP file format).

### Read and write to io

In addition to `write_to_file` and `read_from_file`, you can read and write directly from IO streams using `Base.write` and `Base.read!`:

```
julia> src = MOI.Utilities.Model{Float64}();
julia> dest = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_MPS);
julia> MOI.copy_to(dest, src)
MathOptInterface.Utilities.IndexMap()
julia> io = IOBuffer();
julia> write(io, dest)
julia> seekstart(io);
julia> src_2 = MOI.FileFormats.Model(format = MOI.FileFormats FORMAT_MPS);
julia> read!(io, src_2);
```

### ScalarNonlinearFunction

By default, reading a `.nl` or `.mof.json` that contains nonlinear expressions will create an `NLPBlock`.

To instead read nonlinear expressions as `ScalarNonlinearFunction`, pass the `use_nlp_block = false` keyword argument to the `Model` constructor:

```
julia> model = MOI.FileFormats.Model(
           format = MOI.FileFormats FORMAT_MOF,
           use_nlp_block = false,
       );
julia> model = MOI.FileFormats.Model(
           format = MOI.FileFormats FORMAT_NL,
           use_nlp_block = false,
       );
```

### Validating MOF files

MathOptFormat files are governed by a schema. Use `JSONSchema.jl` to check if a `.mof.json` file satisfies the schema.

First, construct the schema object as follows:

```
julia> import JSON, JSONSchema
julia> schema = JSONSchema.Schema(JSON.parsefile(MOI.FileFormats.MOF.SCHEMA_PATH))
A JSONSchema
```

Then, check if a model file is valid using `isvalid`:

```
julia> good_model = JSON.parse("""
    {
        "version": {
            "major": 1,
            "minor": 5
        },
        "variables": [{"name": "x"}],
        "objective": {"sense": "feasibility"},
        "constraints": []
    }
""");

julia> isvalid(schema, good_model)
true
```

If we construct an invalid file, for example by mis-typing name as NaMe, the validation fails:

```
julia> bad_model = JSON.parse("""
    {
        "version": {
            "major": 1,
            "minor": 5
        },
        "variables": [{"NaMe": "x"}],
        "objective": {"sense": "feasibility"},
        "constraints": []
    }
""");

julia> isvalid(schema, bad_model)
false
```

Use `JSONSchema.validate` to obtain more insight into why the validation failed:

```
julia> JSONSchema.validate(schema, bad_model)
Validation failed:
path:      [variables][1]
instance:   Dict{String, Any}("NaMe" => "x")
schema key: required
schema value: Any["name"]
```

## API Reference

### File Formats

Functions to help read and write MOI models to/from various file formats. See [The FileFormats submodule](#) for more details.

`MathOptInterface.FileFormats.Model` – Function.

```
Model(
    ;
    format::FileFormat = FORMAT_AUTOMATIC,
    filename::Union{Nothing, String} = nothing,
    kwargs...
)
```

Return model corresponding to the `FileFormat` format, or, if `format == FORMAT_AUTOMATIC`, guess the format from `filename`.

The `filename` argument is only needed if `format == FORMAT_AUTOMATIC`.

`kwargs` are passed to the underlying model constructor.

[source](#)

`MathOptInterface.FileFormats.FileFormat` – Type.

```
FileFormat
```

List of accepted export formats.

- `FORMAT_AUTOMATIC`: try to detect the file format based on the file name
- `FORMAT_CBF`: the Conic Benchmark format
- `FORMAT_LP`: the LP file format
- `FORMAT_MOF`: the MathOptFormat file format
- `FORMAT MPS`: the MPS file format
- `FORMAT_NL`: the AMPL .nl file format
- `FORMAT_REW`: the .rew file format, which is MPS with generic names
- `FORMAT_SDPA`: the SemiDefinite Programming Algorithm format

[source](#)

`MathOptInterface.FileFormats.CBF.Model` – Type.

```
Model()
```

Create an empty instance of `FileFormats.CBF.Model`.

[source](#)

`MathOptInterface.FileFormats.LP.Model` – Type.

```
Model(; kwargs...)
```

Create an empty instance of `FileFormats.LP.Model`.

Keyword arguments are:

- `maximum_length::Int=255`: the maximum length for the name of a variable. Ip\_solve 5.0 allows only 16 characters, while CPLEX 12.5+ allow 255.
- `warn::Bool=false`: print a warning when variables or constraints are renamed.

`source`

`MathOptInterface.FileFormats.MOF.Model` – Type.

```
Model(; kwargs...)
```

Create an empty instance of `FileFormats.MOF.Model`.

Keyword arguments are:

- `print_compact::Bool=false`: print the JSON file in a compact format without spaces or newlines.
- `warn::Bool=false`: print a warning when variables or constraints are renamed
- `differentiation_backend::MOI.Nonlinear.AbstractAutomaticDifferentiation = MOI.Nonlinear.SparseReverse`: automatic differentiation backend to use when reading models with nonlinear constraints and objectives.
- `use_nlp_block::Bool=true`: if true parse "ScalarNonlinearFunction" into an `MOI.NLPBlock`. If false, "ScalarNonlinearFunction" are parsed as `MOI.ScalarNonlinearFunction` functions.

`source`

`MathOptInterface.FileFormats.MPS.Model` – Type.

```
Model(; kwargs...)
```

Create an empty instance of `FileFormats.MPS.Model`.

Keyword arguments are:

- `warn::Bool=false`: print a warning when variables or constraints are renamed.
- `print_objsense::Bool=false`: print the OBJSENSE section when writing
- `generic_names::Bool=false`: strip all names in the model and replace them with the generic names `C$i` and `R$i` for the  $i$ 'th column and row respectively.
- `quadratic_format::QuadraticFormat = kQuadraticFormatGurobi`: specify the solver-specific extension used when writing the quadratic components of the model. Options are `kQuadraticFormatGurobi`, `kQuadraticFormatCPLEX`, and `kQuadraticFormatMosek`.

`source`

`MathOptInterface.FileFormats.NL.Model` – Type.

```
Model(; use_nlp_block::Bool = true)
```

Create a new Optimizer object.

`source`

`MathOptInterface.FileFormats.SDPA.Model` – Type.

```
Model(; number_type::Type = Float64)
```

Create an empty instance of `FileFormats.SDPA.Model{number_type}`.

It is important to be aware that the SDPA file format is interpreted in *geometric* form and not *standard conic* form. The *standard conic* form and *geometric conic* form are two dual standard forms for semidefinite programs (SDPs). The *geometric conic* form of an SDP is as follows:

$$\min_{y \in \mathbb{R}^m} b^T y \quad (36.1)$$

$$\text{s.t.} \quad \sum_{i=1}^m A_i y_i - C \in \mathbb{K} \quad (36.2)$$

where  $\mathbb{K}$  is a cartesian product of nonnegative orthant and positive semidefinite matrices that align with a block diagonal structure shared with the matrices `A_i` and `C`.

In other words, the geometric conic form contains free variables and affine constraints in either the nonnegative orthant or the positive semidefinite cone. That is, in the MathOptInterface's terminology, `MOI.VectorAffineFunction-in-MOI.Nonnegatives` and `MOI.VectorAffineFunction-in-MOI.PositiveSemidefiniteConeTriangle` constraints.

The corresponding *standard conic* form of the dual SDP is as follows:

$$\max_{X \in \mathbb{K}} \text{tr}(CX) \quad (36.3)$$

$$\text{s.t.} \quad \text{tr}(A_i X) = b_i \quad i = 1, \dots, m. \quad (36.4)$$

In other words, the standard conic form contains nonnegative and positive semidefinite variables with equality constraints. That is, in the MathOptInterface's terminology, `MOI.VectorOfVariables-in-MOI.Nonnegatives`, `MOI.VectorOfVariables-in-MOI.PositiveSemidefiniteConeTriangle` and `MOI.ScalarAffineFunction-in-MOI.EqualTo` constraints.

If a model is in standard conic form, use `Dualization.jl` to transform it into the geometric conic form before writing it. Otherwise, the nonnegative (resp. positive semidefinite) variables will be bridged into free variables with affine constraints constraining them to belong to the nonnegative orthant (resp. positive semidefinite cone) by the `MOI.Bridges.Constraint.VectorFunctionizeBridge`. Moreover, equality constraints will be bridged into pairs of affine constraints in the nonnegative orthant by the `MOI.Bridges.Constraint.SplitIntegrator` and then the `MOI.Bridges.Constraint.VectorizeBridge`.

If a solver is in standard conic form, use `Dualization.jl` to transform the model read into standard conic form before copying it to the solver. Otherwise, the free variables will be bridged into pairs of variables in the nonnegative orthant by the `MOI.Bridges.Variable.FreeBridge` and affine constraints will be bridged into equality constraints by creating a slack variable by the `MOI.Bridges.Constraint.VectorSlackBridge`.

[source](#)

### Other helpers

`MathOptInterface.FileFormats.NL.SolFileResults` – Type.

```
SolFileResults(
    filename::String,
    model::Model;
    suffix_lower_bound_duals::Vector{String} =
        ["ipopt_zL_out", "lower_bound_duals"],
    suffix_upper_bound_duals::Vector{String} =
        ["ipopt_zU_out", "upper_bound_duals"],
)
```

Parse the .sol file filename created by solving model and return a SolFileResults struct.

The returned struct supports the MOI.get API for querying result attributes such as `MOI.TerminationStatus`, `MOI.VariablePrimal`, and `MOI.ConstraintDual`.

`source`

```
SolFileResults(
    raw_status::String,
    termination_status::MOI.TerminationStatusCode,
)
```

Return a SolFileResults struct with `MOI.RawStatusString` set to raw\_status, `MOI.TerminationStatus` set to termination\_status, and `MOI.PrimalStatus` and `MOI.DualStatus` set to NO\_SOLUTION.

All other attributes are un-set.

`source`

## 36.4 Nonlinear

### Overview

#### Nonlinear

##### Warning

The Nonlinear submodule is experimental. Until this message is removed, breaking changes may be introduced in any minor or patch release of MathOptInterface.

The Nonlinear submodule contains data structures and functions for working with a nonlinear optimization problem in the form of an expression graph. This page explains the API and describes the rationale behind its design.

#### Standard form

Nonlinear programs (NLPs) are a class of optimization problems in which some of the constraints or the objective function are nonlinear:

$$\min_{x \in \mathbb{R}^n} f_0(x) \quad (36.5)$$

$$\text{s.t. } l_j \leq f_j(x) \leq u_j \quad j = 1 \dots m \quad (36.6)$$

There may be additional constraints, as well as things like variable bounds and integrality restrictions, but we do not consider them here because they are best dealt with by other components of MathOptInterface.

### API overview

The core element of the Nonlinear submodule is [Nonlinear.Model](#):

```
julia> const Nonlinear = MOI.Nonlinear;

julia> model = Nonlinear.Model()
A Nonlinear.Model with:
0 objectives
0 parameters
0 expressions
0 constraints
```

[Nonlinear.Model](#) is a mutable struct that stores all of the nonlinear information added to the model.

#### Decision variables

Decision variables are represented by [VariableIndexes](#). The user is responsible for creating these using `MOI.VariableIndex(i)`, where `i` is the column associated with the variable.

#### Expressions

The input data structure is a Julia Expr. The input expressions can incorporate [VariableIndexes](#), but these must be interpolated into the expression with \$:

```
julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> input = :(1 + sin($x)^2)
:(1 + sin(MathOptInterface.VariableIndex(1)) ^ 2)
```

There are a number of restrictions on the input Expr:

- It cannot contain macros
- It cannot contain broadcasting
- It cannot contain splatting (except in limited situations)
- It cannot contain linear algebra, such as matrix-vector products
- It cannot contain generator expressions, including `sum(i for i in S)`

Given an input expression, add an expression using [Nonlinear.add\\_expression](#):

```
julia> expr = Nonlinear.add_expression(model, input)
MathOptInterface.Nonlinear.ExpressionIndex(1)
```

The return value, `expr`, is a `Nonlinear.ExpressionIndex` that can then be interpolated into other input expressions.

Looking again at `model`, we see:

```
julia> model
A Nonlinear.Model with:
0 objectives
0 parameters
1 expression
0 constraints
```

### Parameters

In addition to constant literals like 1 or 1.23, you can create parameters. Parameters are placeholders whose values can change before passing the expression to the solver. Create a parameter using `Nonlinear.add_parameter`, which accepts a default value:

```
julia> p = Nonlinear.add_parameter(model, 1.23)
MathOptInterface.Nonlinearm.ParameterIndex(1)
```

The return value, `p`, is a `Nonlinear.ParameterIndex` that can then be interpolated into other input expressions.

Looking again at `model`, we see:

```
julia> model
A Nonlinear.Model with:
0 objectives
1 parameter
1 expression
0 constraints
```

Update a parameter as follows:

```
julia> model[p]
1.23

julia> model[p] = 4.56
4.56

julia> model[p]
4.56
```

### Objectives

Set a nonlinear objective using `Nonlinear.set_objective`:

```
julia> Nonlinear.set_objective(model, :($p + $expr + $x))

julia> model
```

```
A Nonlinear.Model with:
1 objective
1 parameter
1 expression
0 constraints
```

Clear a nonlinear objective by passing `nothing`:

```
julia> Nonlinear.set_objective(model, nothing)

julia> model
A Nonlinear.Model with:
0 objectives
1 parameter
1 expression
0 constraints
```

But we'll re-add the objective for later:

```
julia> Nonlinear.set_objective(model, :($p + $expr + $x));
```

## Constraints

Add a constraint using `Nonlinear.add_constraint`:

```
julia> c = Nonlinear.add_constraint(model, :(1 + sqrt($x)), MOI.LessThan(2.0))
MathOptInterface.Nonlinearm.ConstraintIndex(1)

julia> model
A Nonlinear.Model with:
1 objective
1 parameter
1 expression
1 constraint
```

The return value, `c`, is a `Nonlinear.ConstraintIndex` that is a unique identifier for the constraint. Interval constraints are also supported:

```
julia> c2 = Nonlinear.add_constraint(model, :(1 + sqrt($x)), MOI.Interval(-1.0, 2.0))
MathOptInterface.Nonlinearm.ConstraintIndex(2)

julia> model
A Nonlinear.Model with:
1 objective
1 parameter
1 expression
2 constraints
```

Delete a constraint using `Nonlinear.delete`:

```
julia> Nonlinear.delete(model, c2)

julia> model
A Nonlinear.Model with:
1 objective
1 parameter
1 expression
1 constraint
```

### User-defined operators

By default, Nonlinear supports a wide range of univariate and multivariate operators. However, you can also define your own operators by *registering* them.

#### Univariate operators

Register a univariate user-defined operator using [Nonlinear.register\\_operator](#):

```
julia> f(x) = 1 + sin(x)^2
f (generic function with 1 method)

julia> Nonlinear.register_operator(model, :my_f, 1, f)
```

Now, you can use `:my_f` in expressions:

```
julia> new_expr = Nonlinear.add_expression(model, :(my_f($x + 1)))
MathOptInterface.Nonlinearity.ExpressionIndex(2)
```

By default, Nonlinear will compute first- and second-derivatives of the registered operator using [ForwardDiff.jl](#). Override this by passing functions which compute the respective derivative:

```
julia> f'(x) = 2 * sin(x) * cos(x)
f' (generic function with 1 method)

julia> Nonlinear.register_operator(model, :my_f2, 1, f, f')
```

or

```
julia> f''(x) = 2 * (cos(x)^2 - sin(x)^2)
f'' (generic function with 1 method)

julia> Nonlinear.register_operator(model, :my_f3, 1, f, f', f'')
```

### Multivariate operators

Register a multivariate user-defined operator using [Nonlinear.register\\_operator](#):

```
julia> g(x...) = x[1]^2 + x[1] * x[2] + x[2]^2
g (generic function with 1 method)

julia> Nonlinear.register_operator(model, :my_g, 2, g)
```

Now, you can use :my\_g in expressions:

```
julia> new_expr = Nonlinear.add_expression(model, :(my_g($x + 1, $x)))
MathOptInterface.Nonlinearity.ExpressionIndex(3)
```

By default, Nonlinear will compute the gradient of the registered operator using [ForwardDiff.jl](#). (Hessian information is not supported.) Override this by passing a function to compute the gradient:

```
julia> function ∇g(ret, x...)
    ret[1] = 2 * x[1] + x[2]
    ret[2] = x[1] + 2 * x[2]
    return
end
∇g (generic function with 1 method)

julia> Nonlinear.register_operator(model, :my_g2, 2, g, ∇g)
```

## MathOptInterface

MathOptInterface communicates the nonlinear portion of an optimization problem to solvers using concrete subtypes of [AbstractNLPEvaluator](#), which implement the [Nonlinear programming API](#).

Create an [AbstractNLPEvaluator](#) from [Nonlinear.Model](#) using [Nonlinear.Evaluator](#).

[Nonlinear.Evaluator](#) requires an [Nonlinear.AbstractAutomaticDifferentiation](#) backend and an ordered list of the variables that are included in the model.

The following backends are available to choose from within MOI, although other packages may add more options by sub-typing [Nonlinear.AbstractAutomaticDifferentiation](#):

- [Nonlinear.ExprGraphOnly](#)
- [Nonlinear.SparseReverseMode](#).

```
julia> evaluator = Nonlinear.Evaluator(model, Nonlinear.ExprGraphOnly(), [x])
Nonlinear.Evaluator with available features:
* :ExprGraph
```

The functions of the [Nonlinear programming API](#) implemented by [Nonlinear.Evaluator](#) depends upon the chosen [Nonlinear.AbstractAutomaticDifferentiation](#) backend.

The :ExprGraph feature means we can call [objective\\_expr](#) and [constraint\\_expr](#) to retrieve the expression graph of the problem. However, we cannot call gradient terms such as [eval\\_objective\\_gradient](#) because [Nonlinear.ExprGraphOnly](#) does not have the capability to differentiate a nonlinear expression.

If, instead, we pass `Nonlinear.SparseReverseMode`, then we get access to `:Grad`, the gradient of the objective function, `:Jac`, the Jacobian matrix of the constraints, `:JacVec`, the ability to compute Jacobian-vector products, and `:ExprGraph`.

```
julia> evaluator = Nonlinear.Evaluator(
    model,
    Nonlinear.SparseReverseMode(),
    [x],
)
Nonlinear.Evaluator with available features:
* :Grad
* :Jac
* :JacVec
* :ExprGraph
```

However, before using the evaluator, we need to call `initialize`:

```
julia> MOI.initialize(evaluator, [:Grad, :Jac, :JacVec, :ExprGraph])
```

Now we can call methods like `eval_objective`:

```
julia> x = [1.0]
1-element Vector{Float64}:
 1.0

julia> MOI.eval_objective(evaluator, x)
7.268073418273571
```

and `eval_objective_gradient`:

```
julia> grad = [0.0]
1-element Vector{Float64}:
 0.0

julia> MOI.eval_objective_gradient(evaluator, grad, x)

julia> grad
1-element Vector{Float64}:
 1.909297426825682
```

Instead of passing `Nonlinear.Evaluator` directly to solvers, solvers query the `NLPBlock` attribute, which returns an `NLPBlockData`. This object wraps an `Nonlinear.Evaluator` and includes other information such as constraint bounds and whether the evaluator has a nonlinear objective. Create and set `NLPBlockData` as follows:

```
julia> block = MOI.NLPBlockData(evaluator);

julia> model = MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}());

julia> MOI.set(model, MOI.NLPBlock(), block);
```

**Warning**

Only call `NLPBlockData` once you have finished modifying the problem in `model`.

Putting everything together, you can create a nonlinear optimization problem in `MathOptInterface` as follows:

```
import MathOptInterface as MOI

function build_model(
    model::MOI.ModelLike;
    backend::MOI.Nonlinear.AbstractAutomaticDifferentiation,
)
    x = MOI.add_variable(model)
    y = MOI.add_variable(model)
    MOI.set(model, MOI.ObjectiveSense(), MOI.MIN_SENSE)
    nl_model = MOI.Nonlinear.Model()
    MOI.Nonlinear.set_objective(nl_model, :($x^2 + $y^2))
    evaluator = MOI.Nonlinear.Evaluator(nl_model, backend, [x, y])
    MOI.set(model, MOI.NLPBlock(), MOI.NLPBlockData(evaluator))
    return
end

# Replace `model` and `backend` with your optimizer and backend of choice.
model = MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}())
build_model(model; backend = MOI.Nonlinear.SparseReverseMode())
```

**Expression-graph representation**

`Nonlinear.Model` stores nonlinear expressions in `Nonlinear.Expressions`. This section explains the design of the expression graph data structure in `Nonlinear.Expression`.

Given a nonlinear function like  $f(x) = \sin(x)^2 + x$ , a conceptual aid for thinking about the graph representation of the expression is to convert it into `Polish prefix notation`:

```
f(x, y) = (+ (^ (sin x) 2) x)
```

This format identifies each operator (function), as well as a list of arguments. Operators can be univariate, like `sin`, or multivariate, like `+`.

A common way of representing Polish prefix notation in code is as follows:

```
julia> x = MOI.VariableIndex(1);

julia> struct ExprNode
           op::Symbol
           children)::Vector{Union{ExprNode,Float64,MOI.VariableIndex}}
       end

julia> expr = ExprNode(:+, [ExprNode(:^, [ExprNode(:sin, [x]), 2.0]), x]);
```

This data structure follows our Polish prefix notation very closely, and we can easily identify the arguments to an operator. However, it has a significant draw-back: each node in the graph requires a `Vector`, which is

heap-allocated and tracked by Julia's garbage collector (GC). For large models, we can expect to have millions of nodes in the expression graph, so this overhead quickly becomes prohibitive for computation.

An alternative is to record the expression as a linear tape:

```
julia> expr = Any[:+, 2, :^, 2, :sin, 1, x, 2.0, x]
9-element Vector{Any}:
  :+
  2
  :^
  2
  :sin
  1
  MOI.VariableIndex(1)
  2.0
  MOI.VariableIndex(1)
```

The Int after each operator Symbol specifies the number of arguments.

This data-structure is a single vector, which resolves our problem with the GC, but each element is the abstract type, Any, and so any operations on it will lead to slower dynamic dispatch. It's also hard to identify the children of each operation without reading the entire tape.

To summarize, representing expression graphs in Julia has the following challenges:

- Nodes in the expression graph should not contain a heap-allocated object
- All data-structures should be concretely typed
- It should be easy to identify the children of a node

### Sketch of the design in Nonlinear

Nonlinear overcomes these problems by decomposing the data structure into a number of different concrete-typed vectors.

First, we create vectors of the supported uni- and multivariate operators.

```
julia> const UNIVARIATE_OPERATORS = [:sin];
julia> const MULTIVARIATE_OPERATORS = [:+, :^];
```

In practice, there are many more supported operations than the ones listed here.

Second, we create an enum to represent the different types of nodes present in the expression graph:

```
julia> @enum(
    NodeType,
    NODE_CALL_MULTIVARIATE,
    NODE_CALL_UNIVARIATE,
    NODE_VARIABLE,
    NODE_VALUE,
)
```

In practice, there are node types other than the ones listed here.

Third, we create two concretely typed structs as follows:

```
julia> struct Node
    type::NodeType
    parent::Int
    index::Int
end

julia> struct Expression
    nodes::Vector{Node}
    values::Vector{Float64}
end
```

For each node `node` in the `.nodes` field, if `node.type` is:

- `NODE_CALL_MULTIVARIATE`, we look up `MULTIVARIATE_OPERATORS[node.index]` to retrieve the operator
- `NODE_CALL_UNIVARIATE`, we look up `UNIVARIATE_OPERATORS[node.index]` to retrieve the operator
- `NODE_VARIABLE`, we create `MOI.VariableIndex(node.index)`
- `NODE_VALUE`, we look up `values[node.index]`

The `.parent` field of each node is the integer index of the parent node in `.nodes`. For the first node, the parent is `-1` by convention.

Therefore, we can represent our function as:

```
julia> expr = Expression(
    [
        Node(NODE_CALL_MULTIVARIATE, -1, 1),
        Node(NODE_CALL_MULTIVARIATE, 1, 2),
        Node(NODE_CALL_UNIVARIATE, 2, 1),
        Node(NODE_VARIABLE, 3, 1),
        Node(NODE_VALUE, 2, 1),
        Node(NODE_VARIABLE, 1, 1),
    ],
    [2.0],
);
```

The ordering of the nodes in the tape must satisfy two rules:

- The children of a node must appear after the parent. This means that the tape is ordered topologically, so that a reverse pass of the nodes evaluates all children nodes before their parent
- The arguments for a CALL node are ordered in the tape based on the order in which they appear in the function call.

### Design goals

This is less readable than the other options, but does this data structure meet our design goals?

Instead of a heap-allocated object for each node, we only have two Vectors for each expression, nodes and values, as well as two constant vectors for the OPERATORS. In addition, all fields are concretely typed, and there are no Union or Any types.

For our third goal, it is not easy to identify the children of a node, but it is easy to identify the *parent* of any node. Therefore, we can use `Nonlinear.adjacency_matrix` to compute a sparse matrix that maps parents to their children.

### The design in practice

In practice, `Node` and `Expression` are exactly `Nonlinear.Node` and `Nonlinear.Expression`. However, `Nonlinear.NodeType` has more fields to account for comparison operators such as `:>=` and `:<=`, logic operators such as `:&&` and `:||`, nonlinear parameters, and nested subexpressions.

Moreover, instead of storing the operators as global constants, they are stored in `Nonlinear.OperatorRegistry`, and it also stores a vector of logic operators and a vector of comparison operators. In addition to `Nonlinear.DEFAULT_UNIVARIATE_OPERATORS` and `Nonlinear.DEFAULT_MULTIVARIATE_OPERATORS`, you can register user-defined functions using `Nonlinear.register_operator`.

`Nonlinear.Model` is a struct that stores the `Nonlinear.OperatorRegistry`, as well as a list of parameters and subexpressions in the model.

## ReverseAD

`Nonlinear.ReverseAD` is a submodule for computing derivatives of a nonlinear optimization problem using sparse reverse-mode automatic differentiation (AD).

This section does not attempt to explain how sparse reverse-mode AD works, but instead explains why MOI contains its own implementation, and highlights notable differences from similar packages.

#### Warning

Don't use the API in ReverseAD to compute derivatives. Instead, create a `Nonlinear.Evaluator` object with `Nonlinear.SparseReverseMode` as the backend, and then query the MOI API methods.

### Design goals

The JuliaDiff organization maintains a [list of packages](#) for doing AD in Julia. At last count, there were at least ten packages—not including ReverseAD—for reverse-mode AD in Julia. ReverseAD exists because it has a different set of design goals.

- **Goal: handle scale and sparsity.** The types of nonlinear optimization problems that MOI represents can be large scale ( $10^5$  or more functions across  $10^5$  or more variables) with very sparse derivatives. The ability to compute a sparse Hessian matrix is essential. To the best of our knowledge, ReverseAD is the only reverse-mode AD system in Julia that handles sparsity by default.
- **Goal: limit the scope to improve robustness.** Most other AD packages accept arbitrary Julia functions as input and then trace an expression graph using operator overloading. This means they must deal (or detect and ignore) with control flow, I/O, and other vagaries of Julia. In contrast, ReverseAD only accepts functions in the form of `Nonlinear.Expression`, which greatly limits the range of syntax that it must deal with. By reducing the scope of what we accept as input to functions relevant for mathematical optimization, we can provide a simpler implementation with various performance optimizations.

- **Goal: provide outputs which match what solvers expect.** Other AD packages focus on differentiating individual Julia functions. In contrast, ReverseAD has a very specific use-case: to generate outputs needed by the MOI nonlinear API. This means it needs to efficiently compute sparse Hessians, and it needs subexpression handling to avoid recomputing subexpressions that are shared between functions.

## History

ReverseAD started life as [ReverseDiffSparse.jl](#), development of which began in early 2014(!). This was well before the other AD packages started development. Because we had a well-tested, working AD in JuMP, there was less motivation to contribute to and explore other AD packages. The lack of historical interaction also meant that other packages were not optimized for the types of problems that JuMP is built for (that is, large-scale sparse problems). When we first created MathOptInterface, we kept the AD in JuMP to simplify the transition, and post-poneed the development of a first-class nonlinear interface in MathOptInterface.

Prior to the introduction of Nonlinear, JuMP's nonlinear implementation was a confusing mix of functions and types spread across the code base and in the private `_Derivatives` submodule. This made it hard to swap the AD system for another. The main motivation for refactoring JuMP to create the Nonlinear submodule in MathOptInterface was to abstract the interface between JuMP and the AD system, allowing us to swap-in and test new AD systems in the future.

## API Reference

### Nonlinear Modeling

More information can be found in the [Nonlinear](#) section of the manual.

`MathOptInterface.Nonlinear` – Module.

Nonlinear

#### Warning

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[source](#)

`MathOptInterface.Nonlinear.Model` – Type.

Model()

The core datastructure for representing a nonlinear optimization problem.

It has the following fields:

- `objective::Union{Nothing, Expression}` : holds the nonlinear objective function, if one exists, otherwise nothing.
- `expressions::Vector{Expression}` : a vector of expressions in the model.
- `constraints::OrderedDict{ConstraintIndex, Constraint}` : a map from `ConstraintIndex` to the corresponding `Constraint`. An `OrderedDict` is used instead of a `Vector` to support constraint deletion.

- `parameters::Vector{Float64}` : holds the current values of the parameters.
- `operators::OperatorRegistry` : stores the operators used in the model.

`source`

## Expressions

`MathOptInterface.Nonlinear.ExpressionIndex` – Type.

`ExpressionIndex`

An index to a nonlinear expression that is returned by `add_expression`.

Given `data::Model` and `ex::ExpressionIndex`, use `data[ex]` to retrieve the corresponding `Expression`.

`source`

`MathOptInterface.Nonlinear.add_expression` – Function.

`add_expression(model::Model, expr)::ExpressionIndex`

Parse `expr` into a `Expression` and add to `model`. Returns an `ExpressionIndex` that can be interpolated into other input expressions.

`expr` must be a type that is supported by `parse_expression`.

## Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Nonlinear.Model();

julia> x = MOI.VariableIndex(1);

julia> ex = MOI.Nonlinear.add_expression(model, :($x^2 + 1))
MathOptInterface.Nonlinear.ExpressionIndex(1)

julia> MOI.Nonlinear.set_objective(model, :(sqrt($ex)))
```

`source`

## Parameters

`MathOptInterface.Nonlinear.ParameterIndex` – Type.

`ParameterIndex`

An index to a nonlinear parameter that is returned by `add_parameter`. Given `data::Model` and `p::ParameterIndex`, use `data[p]` to retrieve the current value of the parameter and `data[p] = value` to set a new value.

`source`

`MathOptInterface.Nonlinear.add_parameter` – Function.

```
add_parameter(model::Model, value::Float64)::ParameterIndex
```

Add a new parameter to `model` with the default value `value`. Returns a `ParameterIndex` that can be interpolated into other input expressions and used to modify the value of the parameter.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Nonlinear.Model()
A Nonlinear.Model with:
0 objectives
0 parameters
0 expressions
0 constraints

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> p = MOI.Nonlinear.add_parameter(model, 1.2)
MathOptInterface.Nonlinear.ParameterIndex(1)

julia> c = MOI.Nonlinear.add_constraint(model, :($x^2 - $p), MOI.LessThan(0.0))
MathOptInterface.Nonlinear.ConstraintIndex(1)
```

[source](#)

### Objectives

`MathOptInterface.Nonlinear.set_objective` – Function.

```
set_objective(model::Model, obj)::Nothing
```

Parse `obj` into a `Expression` and set as the objective function of `model`.

`obj` must be a type that is supported by `parse_expression`.

To remove the objective, pass nothing.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Nonlinear.Model()
A Nonlinear.Model with:
0 objectives
0 parameters
0 expressions
0 constraints
```

```
julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> MOI.Nonlinear.set_objective(model, :($x^2 + 1))

julia> MOI.Nonlinear.set_objective(model, x)

julia> MOI.Nonlinear.set_objective(model, nothing)
```

[source](#)

## Constraints

MathOptInterface.Nonlinear.ConstraintIndex – Type.

ConstraintIndex

An index to a nonlinear constraint that is returned by [add\\_constraint](#).

Given `data::Model` and `c::ConstraintIndex`, use `data[c]` to retrieve the corresponding [Constraint](#).

[source](#)

MathOptInterface.Nonlinear.add\_constraint – Function.

```
add_constraint(
    model::Model,
    func,
    set::Union{
        MOI.GreaterThan{Float64},
        MOI.LessThan{Float64},
        MOI.Interval{Float64},
        MOI.EqualTo{Float64},
    },
)
```

Parse `func` and `set` into a [Constraint](#) and add to `model`. Returns a [ConstraintIndex](#) that can be used to delete the constraint or query solution information.

## Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Nonlinear.Model();

julia> x = MOI.VariableIndex(1);

julia> c = MOI.Nonlinear.add_constraint(model, :($x^2), MOI.LessThan(1.0))
MathOptInterface.Nonlinear.ConstraintIndex(1)
```

[source](#)

`MathOptInterface.Nonlinear.delete` – Function.

```
delete(model::Model, c::ConstraintIndex)::Nothing
```

Delete the constraint index `c` from `model`.

### Example

```
julia> import MathOptInterface as MOI

julia> model = MOI.Nonlinear.Model()
A Nonlinear.Model with:
0 objectives
0 parameters
0 expressions
0 constraints

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> c = MOI.Nonlinear.add_constraint(model, :($x^2), MOI.LessThan(1.0))
MathOptInterface.Nonlinear.ConstraintIndex(1)

julia> model
A Nonlinear.Model with:
0 objectives
0 parameters
0 expressions
1 constraint

julia> MOI.Nonlinear.delete(model, c)

julia> model
A Nonlinear.Model with:
0 objectives
0 parameters
0 expressions
0 constraints
```

`source`

### User-defined operators

`MathOptInterface.Nonlinear.OperatorRegistry` – Type.

```
OperatorRegistry()
```

Create a new `OperatorRegistry` to store and evaluate univariate and multivariate operators.

`source`

`MathOptInterface.Nonlinear.DEFAULT_UNIVARIATE_OPERATORS` – Constant.

**DEFAULT\_UNIVARIATE\_OPERATORS**

The list of univariate operators that are supported by default.

**Example**

```
julia> import MathOptInterface as MOI

julia> MOI.Nonlinear.DEFAULT_UNIVARIATE_OPERATORS
73-element Vector{Symbol}:
:+
:-
:abs
:sign
:sqrt
:cbrt
:abs2
:inv
:log
:log10
[]
:airybi
:airyaiprime
:airybiprime
:besselj0
:besselj1
:bessely0
:bessely1
:erfcx
:dawson
```

[source](#)

`MathOptInterface.Nonlinear.DEFAULT_MULTIVARIATE_OPERATORS` – Constant.

**DEFAULT\_MULTIVARIATE\_OPERATORS**

The list of multivariate operators that are supported by default.

**Example**

```
julia> import MathOptInterface as MOI

julia> MOI.Nonlinear.DEFAULT_MULTIVARIATE_OPERATORS
9-element Vector{Symbol}:
:+
:-
:*
:^
:/
:ifelse
```

```
:atan
:min
:max
```

`source`

`MathOptInterface.Nonlineар.register_operator - Function.`

```
register_operator(
    model::Model,
    op::Symbol,
    nargs::Int,
    f::Function,
    [∇f::Function],
    [∇²f::Function],
)
```

Register the user-defined operator `op` with `nargs` input arguments in `model`.

### Univariate functions

- `f(x::T)::T` must be a function that takes a single input argument `x` and returns the function evaluated at `x`. If  $\nabla f$  and  $\nabla^2 f$  are not provided, `f` must support any Real input type `T`.
- `∇f(x::T)::T` is a function that takes a single input argument `x` and returns the first derivative of `f` with respect to `x`. If  $\nabla^2 f$  is not provided,  $\nabla f$  must support any Real input type `T`.
- `∇²f(x::T)::T` is a function that takes a single input argument `x` and returns the second derivative of `f` with respect to `x`.

### Multivariate functions

- `f(x::T...)::T` must be a function that takes `nargs` input arguments `x` and returns the function evaluated at `x`. If  $\nabla f$  and  $\nabla^2 f$  are not provided, `f` must support any Real input type `T`.
- `∇f(g::AbstractVector{T}, x::T...)::T` is a function that takes a cache vector `g` of length `length(x)`, and fills each element `g[i]` with the partial derivative of `f` with respect to `x[i]`.
- `∇²f(H::AbstractMatrix, x::T...)::T` is a function that takes a matrix `H` and fills the lower-triangular components `H[i, j]` with the Hessian of `f` with respect to `x[i]` and `x[j]` for `i >= j`.

### Notes for multivariate Hessians

- `H` has `size(H) == (length(x), length(x))`, but you must not access elements `H[i, j]` for `i > j`.
- `H` is dense, but you do not need to fill structural zeros.

`source`

`MathOptInterface.Nonlineар.register_operator_if_needed - Function.`

```
register_operator_if_needed(
    registry::OperatorRegistry,
    op::Symbol,
    nargs::Int,
    f::Function;
)
```

Similar to `register_operator`, but this function warns if the function is not registered, and skips silently if it already is.

`source`  
`MathOptInterface.Nonlineар.assert_registered` – Function.

```
assert_registered(registry::OperatorRegistry, op::Symbol, nargs::Int)
```

Throw an error if op is not registered in registry with nargs arguments.

`source`  
`MathOptInterface.Nonlineар.check_return_type` – Function.

```
check_return_type(::Type{T}, ret::S) where {T,S}
```

Overload this method for new types S to throw an informative error if a user-defined function returns the type S instead of T.

`source`  
`MathOptInterface.Nonlineар.eval_univariate_function` – Function.

```
eval_univariate_function(
    registry::OperatorRegistry,
    op::Symbol,
    x::T,
) where {T}
```

Evaluate the operator  $op(x)::T$ , where op is a univariate function in registry.

`source`  
`MathOptInterface.Nonlineар.eval_univariate_gradient` – Function.

```
eval_univariate_gradient(
    registry::OperatorRegistry,
    op::Symbol,
    x::T,
) where {T}
```

Evaluate the first-derivative of the operator  $\text{op}(x) : \mathbb{T}$ , where  $\text{op}$  is a univariate function in registry.

`source`  
`MathOptInterface.Nonlinear.eval_univariate_hessian - Function.`

```
eval_univariate_hessian(
    registry::OperatorRegistry,
    op::Symbol,
    x::T,
) where {T}
```

Evaluate the second-derivative of the operator  $\text{op}(x) : \mathbb{T}$ , where  $\text{op}$  is a univariate function in registry.

`source`  
`MathOptInterface.Nonlinear.eval_multivariate_function - Function.`

```
eval_multivariate_function(
    registry::OperatorRegistry,
    op::Symbol,
    x::AbstractVector{T},
) where {T}
```

Evaluate the operator  $\text{op}(x) : \mathbb{T}$ , where  $\text{op}$  is a multivariate function in registry.

`source`  
`MathOptInterface.Nonlinear.eval_multivariate_gradient - Function.`

```
eval_multivariate_gradient(
    registry::OperatorRegistry,
    op::Symbol,
    g::AbstractVector{T},
    x::AbstractVector{T},
) where {T}
```

Evaluate the gradient of operator  $\text{g} := \nabla \text{op}(x)$ , where  $\text{op}$  is a multivariate function in registry.

`source`  
`MathOptInterface.Nonlinear.eval_multivariate_hessian - Function.`

```
eval_multivariate_hessian(
    registry::OperatorRegistry,
    op::Symbol,
    H::AbstractMatrix,
    x::AbstractVector{T},
) where {T}
```

Evaluate the Hessian of operator  $\nabla^2 \text{op}(x)$ , where  $\text{op}$  is a multivariate function in registry.

The Hessian is stored in the lower-triangular part of the matrix  $H$ .

#### Note

Implementations of the Hessian operators will not fill structural zeros. Therefore, before calling this function you should pre-populate the matrix  $H$  with 0.

[source](#)

`MathOptInterface.Nonlinear.eval_logic_function` – Function.

```
eval_logic_function(
    registry::OperatorRegistry,
    op::Symbol,
    lhs::T,
    rhs::T,
)::Bool where {T}
```

Evaluate  $(\text{lhs} \text{ op } \text{rhs})::\text{Bool}$ , where  $\text{op}$  is a logic operator in registry.

[source](#)

`MathOptInterface.Nonlinear.eval_comparison_function` – Function.

```
eval_comparison_function(
    registry::OperatorRegistry,
    op::Symbol,
    lhs::T,
    rhs::T,
)::Bool where {T}
```

Evaluate  $(\text{lhs} \text{ op } \text{rhs})::\text{Bool}$ , where  $\text{op}$  is a comparison operator in registry.

[source](#)

#### Automatic-differentiation backends

`MathOptInterface.Nonlinear.Evaluator` – Type.

```
Evaluator(
    model::Model,
    backend::AbstractAutomaticDifferentiation,
    ordered_variables::Vector{MOI.VariableIndex},
)
```

Create `Evaluator`, a subtype of `MOI.AbstractNLPEvaluator`, from `Model`.

[source](#)

`MathOptInterface.Nonlinear.AbstractAutomaticDifferentiation` – Type.

```
AbstractAutomaticDifferentiation
```

An abstract type for extending [Evaluator](#).

[source](#)

MathOptInterface.Nonlinear.ExprGraphOnly – Type.

```
ExprGraphOnly() <: AbstractAutomaticDifferentiation
```

The default implementation of `AbstractAutomaticDifferentiation`. The only supported feature is :`ExprGraph`.

[source](#)

MathOptInterface.Nonlinear.SparseReverseMode – Type.

```
SparseReverseMode() <: AbstractAutomaticDifferentiation
```

An implementation of `AbstractAutomaticDifferentiation` that uses sparse reverse-mode automatic differentiation to compute derivatives. Supports all features in the MOI nonlinear interface.

[source](#)

### Data-structure

MathOptInterface.Nonlinear.Node – Type.

```
struct Node
    type::NodeType
    index::Int
    parent::Int
end
```

A single node in a nonlinear expression tree. Used by [Expression](#).

See the [MathOptInterface](#) documentation for information on how the nodes and values form an expression tree.

[source](#)

MathOptInterface.Nonlinear.NodeType – Type.

```
NodeType
```

An enum describing the possible node types. Each `Node` has a `.index` field, which should be interpreted as follows:

- `NODE_CALL_MULTIVARIATE`: the index into `operators.multivariate_operators`

- NODE\_CALL\_UNIVARIATE: the index into operators.univariate\_operators
- NODE\_LOGIC: the index into operators.logic\_operators
- NODE\_COMPARISON: the index into operators.comparison\_operators
- NODE\_MOI\_VARIABLE: the value of MOI.VariableIndex(index) in the user's space of the model.
- NODE\_VARIABLE: the 1-based index of the internal vector
- NODE\_VALUE: the index into the .values field of Expression
- NODE\_PARAMETER: the index into data.parameters
- NODE\_SUBEXPRESSION: the index into data.expressions

`source`

MathOptInterface.Nonlineар.Expression – Type.

```
struct Expression
    nodes::Vector{Node}
    values::Vector{Float64}
end
```

The core type that represents a nonlinear expression. See the MathOptInterface documentation for information on how the nodes and values form an expression tree.

`source`

MathOptInterface.Nonlineар.Constraint – Type.

```
struct Constraint
    expression::Expression
    set::Union{
        MOI.LessThan{Float64},
        MOI.GreaterThan{Float64},
        MOI.EqualTo{Float64},
        MOI.Interval{Float64},
    }
end
```

A type to hold information relating to the nonlinear constraint  $f(x)$  in  $S$ , where  $f(x)$  is defined by .expression, and  $S$  is .set.

`source`

MathOptInterface.Nonlineар.adjacency\_matrix – Function.

```
adjacency_matrix(nodes::Vector{Node})
```

Compute the sparse adjacency matrix describing the parent-child relationships in nodes.

The element  $(i, j)$  is true if there is an edge from node[j] to node[i]. Since we get a column-oriented matrix, this gives us a fast way to look up the edges leaving any node (that is, the children).

`source`

`MathOptInterface.Nonlineар.parse_expression` – Function.

```
parse_expression(data::Model, input)::Expression
```

Parse input into a `Expression`.

`source`

```
parse_expression(
    data::Model,
    expr::Expression,
    input::Any,
    parent_index::Int,
)::Expression
```

Parse input into a `Expression`, and add it to `expr` as a child of `expr.nodes[parent_index]`. Existing subexpressions and parameters are stored in `data`.

You can extend parsing support to new types of objects by overloading this method with a different type on `input::Any`.

`source`

`MathOptInterface.Nonlineар.convert_to_expr` – Function.

```
convert_to_expr(data::Model, expr::Expression)
```

Convert the `Expression` `expr` into a Julia Expr.

- subexpressions are represented by a `ExpressionIndex` object.
- parameters are represented by a `ParameterIndex` object.
- variables are represented by an `MOI.VariableIndex` object.

`source`

```
convert_to_expr(
    evaluator::Evaluator,
    expr::Expression;
    moi_output_format::Bool,
)
```

Convert the `Expression` `expr` into a Julia Expr.

If `moi_output_format = true`:

- subexpressions will be converted to Julia Expr and substituted into the output expression.
- the current value of each parameter will be interpolated into the expression
- variables will be represented in the form `x[MOI.VariableIndex(i)]`

```
If moi_output_format = false:
    • subexpressions will be represented by a ExpressionIndex object.
    • parameters will be represented by a ParameterIndex object.
    • variables will be represented by an MOI.VariableIndex object.
```

**Warning**

To use `moi_output_format = true`, you must have first called `MOI.initialize` with `:ExprGraph` as a requested feature.

`source`

`MathOptInterface.Nonlinear.ordinal_index` - Function.

```
ordinal_index(evaluator::Evaluator, c::ConstraintIndex)::Int
```

Return the 1-indexed value of the constraint index `c` in `evaluator`.

**Example**

```
julia> import MathOptInterface as MOI

julia> model = MOI.Nonlinear.Model()
A Nonlinear.Model with:
0 objectives
0 parameters
0 expressions
0 constraints

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> c1 = MOI.Nonlinear.add_constraint(model, :($x^2), MOI.LessThan(1.0))
MathOptInterface.Nonlinear.ConstraintIndex(1)

julia> c2 = MOI.Nonlinear.add_constraint(model, :($x^2), MOI.LessThan(1.0))
MathOptInterface.Nonlinear.ConstraintIndex(2)

julia> evaluator = MOI.Nonlinear.Evaluator(model)
Nonlinear.Evaluator with available features:
 * :ExprGraph

julia> MOI.initialize(evaluator, Symbol[])
julia> MOI.Nonlinear.ordinal_index(evaluator, c2) # Returns 2
2

julia> MOI.Nonlinear.delete(model, c1)

julia> evaluator = MOI.Nonlinear.Evaluator(model)
Nonlinear.Evaluator with available features:
```

```
* :ExprGraph

julia> MOI.initialize(evaluator, Symbol[])
julia> MOI.Nonlinear.ordinal_index(evaluator, c2) # Returns 1
1
```

[source](#)

## 36.5 Utilities

### Overview

#### The Utilities submodule

The Utilities submodule provides a variety of functions and datastructures for managing MOI.ModelLike objects.

#### Utilities.Model

`Utilities.Model` provides an implementation of a `ModelLike` that efficiently supports all functions and sets defined within MOI. However, given the extensibility of MOI, this might not cover all use cases.

Create a model as follows:

```
julia> model = MOI.Utilities.Model{Float64}()
MOIU.Model{Float64}
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

#### Utilities.UniversalFallback

`Utilities.UniversalFallback` is a layer that sits on top of any `ModelLike` and provides non-specialized (slower) fallbacks for constraints and attributes that the underlying `ModelLike` does not support.

For example, `Utilities.Model` doesn't support some variable attributes like `VariablePrimalStart`, so JuMP uses a combination of Universal fallback and `Utilities.Model` as a generic problem cache:

```
julia> model = MOI.Utilities.UniversalFallback(MOI.Utilities.Model{Float64}())
MOIU.UniversalFallback{MOIU.Model{Float64}}
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberOfConstraints: 0
```

#### Warning

Adding a `UniversalFallback` means that your model will now support all constraints, even if the inner-model does not. This can lead to unexpected behavior.

**Utilities.@model**

For advanced use cases that need efficient support for functions and sets defined outside of MOI (but still known at compile time), we provide the `Utilities.@model` macro.

The `@model` macro takes a name (for a new type, which must not exist yet), eight tuples specifying the types of constraints that are supported, and then a Bool indicating the type is a subtype of `MOI.AbstractOptimizer` (if true) or `MOI.ModelLike` (if false).

The eight tuples are in the following order:

1. Un-typed scalar sets, for example, `Integer`
2. Typed scalar sets, for example, `LessThan`
3. Un-typed vector sets, for example, `Nonnegatives`
4. Typed vector sets, for example, `PowerCone`
5. Un-typed scalar functions, for example, `VariableIndex`
6. Typed scalar functions, for example, `ScalarAffineFunction`
7. Un-typed vector functions, for example, `VectorOfVariables`
8. Typed vector functions, for example, `VectorAffineFunction`

The tuples can contain more than one element. Typed-sets must be specified without their type parameter, for example, `MOI.LessThan`, not `MOI.LessThan{Float64}`.

Here is an example:

```
julia> MOI.Utilities.@model(
    MyNewModel,
    (MOI.Integer,),                      # Un-typed scalar sets
    (MOI.GreaterThan,),                  # Typed scalar sets
    (MOI.Nonnegatives,),                # Un-typed vector sets
    (MOI.PowerCone,),                   # Typed vector sets
    (MOI.VariableIndex,),                # Un-typed scalar functions
    (MOI.ScalarAffineFunction,),        # Typed scalar functions
    (MOI.VectorOfVariables,),          # Un-typed vector functions
    (MOI.VectorAffineFunction,),        # Typed vector functions
    true,                                # <:MOI.AbstractOptimizer?
)
MathOptInterface.Utilities.GenericOptimizer{T, MathOptInterface.Utilities.ObjectiveContainer{T},
                                         → MathOptInterface.Utilities.VariablesContainer{T}, MyNewModelFunctionConstraints{T}} where T

julia> model = MyNewModel{Float64}()
MOIU.GenericOptimizer{Float64, MOIU.ObjectiveContainer{Float64}, MOIU.VariablesContainer{Float64},
                     → MyNewModelFunctionConstraints{Float64}}
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberOfVariables: 0
└ NumberofConstraints: 0
```

**Warning**

MyNewModel supports every VariableIndex-in-Set constraint, as well as VariableIndex, ScalarAffineFunction, and ScalarQuadraticFunction objective functions. Implement MOI.supports as needed to forbid constraint and objective function combinations.

As another example, PATHSolver, which only supports VectorAffineFunction-in-Complements defines its optimizer as:

```
julia> MOI.Utilities.@model(
    PathOptimizer,
    (), # Scalar sets
    (), # Typed scalar sets
    (MOI.Complements,), # Vector sets
    (), # Typed vector sets
    (), # Scalar functions
    (), # Typed scalar functions
    (), # Vector functions
    (MOI.VectorAffineFunction,), # Typed vector functions
    true, # is_optimizer
)
MathOptInterface.Utilities.GenericOptimizer{T, MathOptInterface.Utilities.ObjectiveContainer{T}},
→ MathOptInterface.Utilities.VariablesContainer{T},
→ MathOptInterface.Utilities.VectorOfConstraints{MathOptInterface.VectorAffineFunction{T}},
→ MathOptInterface.Complements}} where T
```

However, PathOptimizer does not support some VariableIndex-in-Set constraints, so we must explicitly define:

```
julia> function MOI.supports_constraint(
    ::PathOptimizer,
    ::Type{MOI.VariableIndex},
    ::Type{Union{<:MOI.Semiinteger, MOI.Semicontinuous, MOI.ZeroOne, MOI.Integer}})
    )
        return false
    end
```

Finally, PATH doesn't support an objective function, so we need to add:

```
julia> MOI.supports(::PathOptimizer, ::MOI.ObjectiveFunction) = false
```

**Warning**

This macro creates a new type, so it must be called from the top-level of a module, for example, it cannot be called from inside a function.

**Utilities.CachingOptimizer**

A [Utilities.CachingOptimizer] is an MOI layer that abstracts the difference between solvers that support incremental modification (for example, they support adding variables one-by-one), and solvers that require the entire problem in a single API call (for example, they only accept the A, b and c matrices of a linear program).

It has two parts:

1. A cache, where the model can be built and modified incrementally
2. An optimizer, which is used to solve the problem

```
julia> model = MOI.Utilities.CachingOptimizer(
    MOI.Utilities.Model{Float64}(),
    PathOptimizer{Float64}(),
)
MOIU.CachingOptimizer
├ state: EMPTY_OPTIMIZER
├ mode: AUTOMATIC
├ model_cache: MOIU.Model{Float64}
| ├ ObjectiveSense: FEASIBILITY_SENSE
| ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
| ├ NumberOfVariables: 0
| └ NumberofConstraints: 0
└ optimizer: MOIU.GenericOptimizer{Float64, MOIU.ObjectiveContainer{Float64},
  ↳ MOIU.VariablesContainer{Float64}, MOIU.VectorOfConstraints{MOI.VectorAffineFunction{Float64}},
  ↳ MOI.Complements}
    ├ ObjectiveSense: FEASIBILITY_SENSE
    ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
    ├ NumberofVariables: 0
    └ NumberofConstraints: 0
```

A `Utilities.CachingOptimizer` may be in one of three possible states:

- `NO_OPTIMIZER`: The CachingOptimizer does not have any optimizer.
- `EMPTY_OPTIMIZER`: The CachingOptimizer has an empty optimizer, and it is not synchronized with the cached model. Modifications are forwarded to the cache, but *not* to the optimizer.
- `ATTACHED_OPTIMIZER`: The CachingOptimizer has an optimizer, and it is synchronized with the cached model. Modifications are forwarded to the optimizer. If the optimizer does not support modifications, an error will be thrown.

Use `Utilities.attach_optimizer` to go from `EMPTY_OPTIMIZER` to `ATTACHED_OPTIMIZER`:

```
julia> MOI.Utilities.attach_optimizer(model)

julia> MOI.Utilities.state(model)
ATTACHED_OPTIMIZER::CachingOptimizerState = 2
```

### Info

You must be in `ATTACHED_OPTIMIZER` to use `optimize!`.

Use `Utilities.reset_optimizer` to go from `ATTACHED_OPTIMIZER` to `EMPTY_OPTIMIZER`:

```
julia> MOI.Utilities.reset_optimizer(model)

julia> MOI.Utilities.state(model)
EMPTY_OPTIMIZER::CachingOptimizerState = 1
```

**Info**

Calling `MOI.empty!(model)` also resets the state to `EMPTY_OPTIMIZER`. So after emptying a model, the modification will only be applied to the cache.

Use `Utilities.drop_optimizer` to go from any state to `NO_OPTIMIZER`:

```
julia> MOI.Utilities.drop_optimizer(model)

julia> MOI.Utilities.state(model)
NO_OPTIMIZER::CachingOptimizerState = 0

julia> model
MOIU.CachingOptimizer
├ state: NO_OPTIMIZER
├ mode: AUTOMATIC
├ model_cache: MOIU.Model{Float64}
| ├ ObjectiveSense: FEASIBILITY_SENSE
| ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
| ├ NumberOfVariables: 0
| └ NumberOfConstraints: 0
└ optimizer: nothing
```

Pass an empty optimizer to `Utilities.reset_optimizer` to go from `NO_OPTIMIZER` to `EMPTY_OPTIMIZER`:

```
julia> MOI.Utilities.reset_optimizer(model, PathOptimizer{Float64}())

julia> MOI.Utilities.state(model)
EMPTY_OPTIMIZER::CachingOptimizerState = 1

julia> model
MOIU.CachingOptimizer
├ state: EMPTY_OPTIMIZER
├ mode: AUTOMATIC
├ model_cache: MOIU.Model{Float64}
| ├ ObjectiveSense: FEASIBILITY_SENSE
| ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
| ├ NumberOfVariables: 0
| └ NumberOfConstraints: 0
└ optimizer: MOIU.GenericOptimizer{Float64, MOIU.ObjectiveContainer{Float64},
  ↵ MOIU.VariablesContainer{Float64}, MOIU.VectorOfConstraints{MOI.VectorAffineFunction{Float64}},
  ↵ MOI.Complements}}
  ├ ObjectiveSense: FEASIBILITY_SENSE
  ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
  ├ NumberOfVariables: 0
  └ NumberOfConstraints: 0
```

Deciding when to attach and reset the optimizer is tedious, and you will often write code like this:

```
try
    # modification
catch
    MOI.Utilities.reset_optimizer(model)
    # Re-try modification
end
```

To make this easier, `Utilities.CachingOptimizer` has two modes of operation:

- AUTOMATIC: The CachingOptimizer changes its state when necessary. Attempting to add a constraint or perform a modification not supported by the optimizer results in a drop to EMPTY\_OPTIMIZER mode.
- MANUAL: The user must change the state of the CachingOptimizer. Attempting to perform an operation in the incorrect state results in an error.

By default, AUTOMATIC mode is chosen. However, you can create a CachingOptimizer in MANUAL mode as follows:

```
julia> model = MOI.Utilities.CachingOptimizer(
        MOI.Utilities.Model{Float64}(),
        MOI.Utilities.MANUAL,
    )
MOIU.CachingOptimizer
├ state: NO_OPTIMIZER
├ mode: MANUAL
├ model_cache: MOIU.Model{Float64}
| ├ ObjectiveSense: FEASIBILITY_SENSE
| ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
| ├ NumberOfVariables: 0
| └ NumberOfConstraints: 0
└ optimizer: nothing

julia> MOI.Utilities.reset_optimizer(model, PathOptimizer{Float64}())

julia> model
MOIU.CachingOptimizer
├ state: EMPTY_OPTIMIZER
├ mode: MANUAL
├ model_cache: MOIU.Model{Float64}
| ├ ObjectiveSense: FEASIBILITY_SENSE
| ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
| ├ NumberOfVariables: 0
| └ NumberOfConstraints: 0
└ optimizer: MOIU.GenericOptimizer{Float64, MOIU.ObjectiveContainer{Float64}},
  ↵ MOIU.VariablesContainer{Float64}, MOIU.VectorOfConstraints{MOI.VectorAffineFunction{Float64}},
  ↵ MOI.Complements}
    ├ ObjectiveSense: FEASIBILITY_SENSE
    ├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
    ├ NumberOfVariables: 0
    └ NumberOfConstraints: 0
```

### Printing

Use `print` to print the formulation of the model.

```
julia> model = MOI.Utilities.Model{Float64}();
julia> x = MOI.add_variable(model)
MOI.VariableIndex(1)

julia> MOI.set(model, MOI.VariableName(), x, "x_var")

julia> MOI.add_constraint(model, x, MOI.ZeroOne())
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex, MathOptInterface.ZeroOne}(1)

julia> MOI.set(model, MOI.ObjectiveFunction{typeof(x)}(), x)

julia> MOI.set(model, MOI.ObjectiveSense(), MOI.MAX_SENSE)

julia> print(model)
Maximize VariableIndex:
    x_var

Subject to:

VariableIndex-in-ZeroOne
    x_var ∈ {0, 1}
```

Use `Utilities.latex_formulation` to display the model in LaTeX form:

```
julia> MOI.Utilities.latex_formulation(model)
$$ \begin{aligned}
&\max\quad &x\_var \\
&\text{Subject to} \\
&\quad &\text{VariableIndex-in-ZeroOne} \\
&\quad &x\_var \in \{0, 1\} \\
\end{aligned} $$
```

#### Tip

In IJulia, calling `print` or ending a cell with `Utilities.latex_formulation` will render the model in LaTeX.

### Utilities.PenaltyRelaxation

Pass `Utilities.PenaltyRelaxation` to `modify` to relax the problem by adding penalized slack variables to the constraints. This is helpful when debugging sources of infeasible models.

```
julia> model = MOI.Utilities.Model{Float64}();
julia> x = MOI.add_variable(model);
julia> MOI.set(model, MOI.VariableName(), x, "x")
```

```

julia> c = MOI.add_constraint(model, 1.0 * x, MOI.LessThan(2.0));

julia> map = MOI.modify(model, MOI.Utilities.PenaltyRelaxation(Dict(c => 2.0)));

julia> print(model)
Minimize ScalarAffineFunction{Float64}:
  0.0 + 2.0 v[2]

Subject to:

ScalarAffineFunction{Float64}-in-LessThan{Float64}
  0.0 + 1.0 x - 1.0 v[2] <= 2.0

VariableIndex-in-GreaterThan{Float64}
  v[2] >= 0.0

julia> map[c]
0.0 + 1.0 MOI.VariableIndex(2)

```

You can also modify a single constraint using `Utilities.ScalarPenaltyRelaxation`:

```

julia> model = MOI.Utilities.Model{Float64}();

julia> x = MOI.add_variable(model);

julia> MOI.set(model, MOI.VariableName(), x, "x")

julia> c = MOI.add_constraint(model, 1.0 * x, MOI.LessThan(2.0));

julia> f = MOI.modify(model, c, MOI.Utilities.ScalarPenaltyRelaxation(2.0));

julia> print(model)
Minimize ScalarAffineFunction{Float64}:
  0.0 + 2.0 v[2]

Subject to:

ScalarAffineFunction{Float64}-in-LessThan{Float64}
  0.0 + 1.0 x - 1.0 v[2] <= 2.0

VariableIndex-in-GreaterThan{Float64}
  v[2] >= 0.0

julia> f
0.0 + 1.0 MOI.VariableIndex(2)

```

### **Utilities.MatrixOfConstraints**

The constraints of `Utilities.Model` are stored as a vector of tuples of function and set in a `Utilities.VectorOfConstraints`. Other representations can be used by parameterizing the type `Utilities.GenericModel` (resp. `Utilities.GenericOptimizer`). For example, if all non-`VariableIndex` constraints are affine, the coefficients of all the constraints can be stored in a single sparse matrix using `Utilities.MatrixOfConstraints`.

The constraints storage can even be customized up to a point where it exactly matches the storage of the solver of interest, in which case `copy_to` can be implemented for the solver by calling `copy_to` to this custom model.

For example, `Clp.jl` defines the following model:

```
julia> MOI.Utilities.@product_of_sets(
    SupportedSets,
    MOI.EqualTo{T},
    MOI.LessThan{T},
    MOI.GreaterThan{T},
    MOI.Interval{T},
);

julia> const OptimizerCache = MOI.Utilities.GenericModel{
    Float64,
    MOI.Utilities.ObjectiveContainer{Float64},
    MOI.Utilities.VariablesContainer{Float64},
    MOI.Utilities.MatrixOfConstraints{
        Float64,
        MOI.Utilities.MutableSparseMatrixCSC{
            # The data type of the coefficients
            Float64,
            # The data type of the variable indices
            Cint,
            # Can also be MOI.Utilities.OneBasedIndexing
            MOI.Utilities.ZeroBasedIndexing,
        },
        MOI.Utilities.Hyperrectangle{Float64},
        SupportedSets{Float64},
    },
};
```

Given the input model:

```
julia> src = MOI.Utilities.Model{Float64}();

julia> MOI.Utilities.loadfromstring!(
    src,
    """
    variables: x, y, z
    maxobjective: x + 2.0 * y + -3.1 * z
    x + y <= 1.0
    2.0 * y >= 3.0
    -4.0 * x + z == 5.0
    x in Interval(0.0, 1.0)
    y <= 10.0
    z == 5.0
    """,
)
```

We can construct a new cached model and copy `src` to it:

```
julia> dest = OptimizerCache();
julia> index_map = MOI.copy_to(dest, src);
```

From dest, we can access the A matrix in sparse matrix form:

```
julia> A = dest.constraints.coefficients;
julia> A.n
3
julia> A.m
3
julia> A.colptr
4-element Vector{Int32}:
0
2
4
5
julia> A.rowval
5-element Vector{Int32}:
0
1
1
2
0
julia> A.nzval
5-element Vector{Float64}:
-4.0
1.0
1.0
2.0
1.0
```

The lower and upper row bounds:

```
julia> row_bounds = dest.constraints.constants;
julia> row_bounds.lower
3-element Vector{Float64}:
5.0
-Inf
3.0
julia> row_bounds.upper
3-element Vector{Float64}:
5.0
1.0
Inf
```

The lower and upper variable bounds:

```
julia> dest.variables.lower
3-element Vector{Float64}:
 0.0
-Inf
 5.0

julia> dest.variables.upper
3-element Vector{Float64}:
 1.0
10.0
 5.0
```

Because of larger variations between solvers, the objective can be queried using the standard MOI methods:

```
julia> MOI.get(dest, MOI.ObjectiveSense())
MAX_SENSE::OptimizationSense = 1

julia> F = MOI.get(dest, MOI.ObjectiveFunctionType())
MathOptInterface.ScalarAffineFunction{Float64}

julia> F = MOI.get(dest, MOI.ObjectiveFunction{F}())
0.0 + 1.0 MOI.VariableIndex(1) + 2.0 MOI.VariableIndex(2) - 3.1 MOI.VariableIndex(3)
```

Thus, Clp.jl implements `copy_to` methods similar to the following:

```
# This method copies from the cache to the `Clp.Optimizer` object.
function MOI.copy_to(dest::Optimizer, src::OptimizerCache)
    @assert MOI.is_empty(dest)
    A = src.constraints.coefficients
    row_bounds = src.constraints.constants
    Clp_loadProblem(
        dest,
        A.n,
        A.m,
        A.colptr,
        A.rowval,
        A.nzval,
        src.lower_bound,
        src.upper_bound,
        # (...) objective vector (omitted),
        row_bounds.lower,
        row_bounds.upper,
    )
    return MOI.Utilities.identity_index_map(src)
end

# This method copies from an arbitrary model to the optimizer, by the
# intermediate `OptimizerCache` representation.
function MOI.copy_to(dest::Optimizer, src::MOI.ModelLike)
    cache = OptimizerCache()
    index_map = MOI.copy_to(cache, src)
    MOI.copy_to(dest, cache)
```

```

    return index_map
end

# This is a special method that gets called in some cases when `OptimizerCache`
# is used as the backing data structure in a `MOI.Utilities.CachingOptimizer`.
# It is needed for performance, but not correctness.
function MOI.copy_to(
    dest::Optimizer,
    src::MOI.Utilities.UniversalFallback{OptimizerCache},
)
    MOI.Utilities.throw_unsupported(src)
    return MOI.copy_to(dest, src.model)
end

```

**Tip**

For other examples of `Utilities.MatrixOfConstraints`, see:

- [Cbc.jl](#)
- [ECOS.jl](#)
- [SCS.jl](#)

**ModelFilter**

Utilities provides `Utilities.ModelFilter` as a useful tool to copy a subset of a model. For example, given an infeasible model, we can copy the irreducible infeasible subsystem (for models implementing `ConstraintConflictStatus`) as follows:

```

my_filter(::Any) = true
function my_filter(ci::MOI.ConstraintIndex)
    status = MOI.get(dest, MOI.ConstraintConflictStatus(), ci)
    return status != MOI.NOT_IN_CONFLICT
end
filtered_src = MOI.Utilities.ModelFilter(my_filter, src)
index_map = MOI.copy_to(dest, filtered_src)

```

**Fallbacks**

The value of some attributes can be inferred from the value of other attributes.

For example, the value of `ObjectiveValue` can be computed using `ObjectiveFunction` and `VariablePrimal`.

When a solver gives direct access to an attribute, it is better to return this value. However, if this is not the case, `Utilities.get_fallback` can be used instead. For example:

```

function MOI.get(model::Optimizer, attr::MOI.ObjectiveFunction)
    return MOI.Utilities.get_fallback(model, attr)
end

```

### DoubleDicts

When writing MOI interfaces, we often need to handle situations in which we map `ConstraintIndex`s to different values. For example, to a string for `ConstraintName`.

One option is to use a dictionary like `Dict{MOI.ConstraintIndex, String}`. However, this incurs a performance cost because the key is not a concrete type.

The DoubleDicts submodule helps this situation by providing two types main types `Utilities.DoubleDicts.DoubleDict` and `Utilities.DoubleDicts.IndexDoubleDict`. These types act like normal dictionaries, but internally they use more efficient dictionaries specialized to the type of the function-set pair.

The most common usage of a DoubleDict is in the `index_map` returned by `copy_to`. Performance can be improved, by using a function barrier. That is, instead of code like:

```
index_map = MOI.copy_to(dest, src)
for (F, S) in MOI.get(src, MOI.ListOfConstraintTypesPresent())
    for ci in MOI.get(src, MOI.ListOfConstraintIndices{F,S}())
        dest_ci = index_map[ci]
        #
    end
end
```

use instead:

```
function function_barrier(
    dest,
    src,
    index_map::MOI.Utilities.DoubleDicts.IndexDoubleDictInner{F,S},
) where {F,S}
    for ci in MOI.get(src, MOI.ListOfConstraintIndices{F,S}())
        dest_ci = index_map[ci]
        #
    end
    return
end

index_map = MOI.copy_to(dest, src)
for (F, S) in MOI.get(src, MOI.ListOfConstraintTypesPresent())
    function_barrier(dest, src, index_map[F, S])
end
```

## API Reference

### Utilities.Model

`MathOptInterface.Utilities.Model` - Type.

```
MOI.Utilities.Model{T}() where {T}
```

An implementation of `ModelLike` that supports all functions and sets defined in MOI. It is parameterized by the coefficient type.

**Example**

```
julia> import MathOptInterface as MOI

julia> model = MOI.Utilities.Model{Float64}()
MOIU.Model{Float64}
├ ObjectiveSense: FEASIBILITY_SENSE
├ ObjectiveFunctionType: MOI.ScalarAffineFunction{Float64}
├ NumberofVariables: 0
└ NumberofConstraints: 0
```

[source](#)**Utilities.UniversalFallback**

MathOptInterface.Utilities.UniversalFallback – Type.

[UniversalFallback](#)

The UniversalFallback can be applied on a [MOI.ModelLike](#) model to create the model `UniversalFallback(model)` supporting *any* constraint and attribute. This allows to have a specialized implementation in `model` for performance critical constraints and attributes while still supporting other attributes with a small performance penalty. Note that `model` is unaware of constraints and attributes stored by `UniversalFallback` so this is not appropriate if `model` is an optimizer (for this reason, [MOI.optimize!](#) has not been implemented). In that case, optimizer bridges should be used instead.

[source](#)**Utilities.@model**

MathOptInterface.Utilities.@model – Macro.

```
macro model(
    model_name,
    scalar_sets,
    typed_scalar_sets,
    vector_sets,
    typed_vector_sets,
    scalar_functions,
    typed_scalar_functions,
    vector_functions,
    typed_vector_functions,
    is_optimizer = false
)
```

Creates a type `model_name` implementing the MOI model interface and supporting all combinations of the provided functions and sets.

Each `typed_` scalar/vector sets/functions argument is a tuple of types. A type is "typed" if it has a coefficient  $\{T\}$  as the first type parameter.

**Tuple syntax**

To give no set/function, write `()`. To give one set or function X, write `(X,)`.

### `is_optimizer`

If `is_optimizer = true`, the resulting struct is a of `GenericOptimizer`, which is a subtype of `MOI.AbstractOptimizer`, otherwise, it is a `GenericModel`, which is a subtype of `MOI.ModelLike`.

### `VariableIndex`

- The function `MOI.VariableIndex` must not be given in `scalar_functions`.
- The model supports `MOI.VariableIndex`-in-S constraints where S is `MOI.EqualTo`, `MOI.GreaterThan`, `MOI.LessThan`, `MOI.Interval`, `MOI.Integer`, `MOI.ZeroOne`, `MOI.Semicontinuous` or `MOI.Semiinteger`.
- The sets supported with `MOI.VariableIndex` cannot be controlled from the macro; use `UniversalFallback` to support more sets.

### **Example**

The model describing a linear program would be:

```
@model(
    LPMModel,                                # model_name
    (),                                         # untyped scalar sets
    (MOI.EqualTo, MOI.GreaterThan, MOI.LessThan, MOI.Interval), # typed scalar sets
    (MOI.Zeros, MOI.Nonnegatives, MOI.Nonpositives), # untyped vector sets
    (),                                         # typed vector sets
    (),                                         # untyped scalar functions
    (MOI.ScalarAffineFunction,),                # typed scalar functions
    (MOI.VectorOfVariables,),                  # untyped vector functions
    (MOI.VectorAffineFunction,),                # typed vector functions
    false,                                       # is_optimizer
)
```

`source`

`MathOptInterface.Utilities.GenericModel` – Type.

```
mutable struct GenericModel{T,O,V,C} <: AbstractModelLike{T}
```

Implements a model supporting coefficients of type T and:

- An objective function stored in `.objective::O`
- Variables and `VariableIndex` constraints stored in `.variable_bounds::V`
- F-in-S constraints (excluding `VariableIndex` constraints) stored in `.constraints::C`

All interactions take place via the MOI interface, so the types O, V, and C must implement the API as needed for their functionality.

`source`

`MathOptInterface.Utilities.GenericOptimizer` – Type.

```
mutable struct GenericOptimizer{T,O,V,C} <: AbstractOptimizer{T}
```

Implements a model supporting coefficients of type T and:

- An objective function stored in .objective::O
- Variables and VariableIndex constraints stored in .variable\_bounds::V
- F-in-S constraints (excluding VariableIndex constraints) stored in .constraints::C

All interactions take place via the MOI interface, so the types O, V, and C must implement the API as needed for their functionality.

```
source  
.objective  
MathOptInterface.Utilities.ObjectiveContainer - Type.
```

```
ObjectiveContainer{T}
```

A helper struct to simplify the handling of objective functions in Utilities.Model.

```
source  
.variables  
MathOptInterface.Utilities.VariablesContainer - Type.
```

```
struct VariablesContainer{T} <: AbstractVectorBounds  
    set_mask::Vector{UInt16}  
    lower::Vector{T}  
    upper::Vector{T}  
end
```

A struct for storing variables and VariableIndex-related constraints. Used in MOI.Utilities.Model by default.

```
source  
MathOptInterface.Utilities.FreeVariables - Type.
```

```
mutable struct FreeVariables <: MOI.ModelLike  
    n::Int64  
    FreeVariables() = new(0)  
end
```

A struct for storing free variables that can be used as the variables field of [GenericModel](#) or [GenericModel](#). It represents a model that does not support any constraint nor objective function.

### Example

The following model type represents a conic model in geometric form. As opposed to `VariablesContainer`, `FreeVariables` does not support constraint bounds so they are bridged into an affine constraint in the `MOI.Nonnegatives` cone as expected for the geometric conic form.

```
julia> MOI.Utilities.@product_of_sets(
    Cones,
    MOI.Zeros,
    MOI.Nonnegatives,
    MOI.SecondOrderCone,
    MOI.PositiveSemidefiniteConeTriangle,
)
;

julia> const ConicModel{T} = MOI.Utilities.GenericOptimizer{
    T,
    MOI.Utilities.ObjectiveContainer{T},
    MOI.Utilities.FreeVariables,
    MOI.Utilities.MatrixOfConstraints{
        T,
        MOI.Utilities.MutableSparseMatrixCSC{
            T,
            Int,
            MOI.Utilities.OneBasedIndexing,
        },
        Vector{T},
        Cones{T},
    },
}
;

julia> model = MOI.instantiate(ConicModel{Float64}, with_bridge_type=Float64);

julia> x = MOI.add_variable(model)
MathOptInterface.VariableIndex(1)

julia> c = MOI.add_constraint(model, x, MOI.GreaterThan(1.0))
MathOptInterface.ConstraintIndex{MathOptInterface.VariableIndex,
    MathOptInterface.GreaterThan{Float64}}(1)

julia> MOI.Bridges.is_bridged(model, c)
true

julia> bridge = MOI.Bridges.bridge(model, c)
MathOptInterface.Bridges.Constraint.VectorizeBridge{Float64,
    MathOptInterface.VectorAffineFunction{Float64}, MathOptInterface.Nonnegatives,
    MathOptInterface.VariableIndex}(MathOptInterface.ConstraintIndex{MathOptInterface.VectorAffineFunction{Float64}},
    MathOptInterface.Nonnegatives}(1), 1.0)

julia> bridge.vector_constraint
MathOptInterface.ConstraintIndex{MathOptInterface.VectorAffineFunction{Float64},
    MathOptInterface.Nonnegatives}(1)

julia> MOI.Bridges.is_bridged(model, bridge.vector_constraint)
false
```

[source](#)

```
.constraints
MathOptInterface.Utilities.VectorOfConstraints - Type.
```

```
mutable struct VectorOfConstraints{
    F<:MOI.AbstractFunction,
    S<:MOI.AbstractSet,
} <: MOI.ModelLike
    constraints::CleverDicts.CleverDict{
        MOI.ConstraintIndex{F,S},
        Tuple{F,S},
        typeof(CleverDicts.key_to_index),
        typeof(CleverDicts.index_to_key),
    }
end
```

A struct storing F-in-S constraints as a mapping between the constraint indices to the corresponding tuple of function and set.

```
source
MathOptInterface.Utilities.StructOfConstraints - Type.
```

```
abstract type StructOfConstraints <: MOI.ModelLike end
```

A struct storing a subfields other structs storing constraints of different types.

See [Utilities.@struct\\_of\\_constraints\\_by\\_function\\_types](#) and [Utilities.@struct\\_of\\_constraints\\_by\\_set\\_types](#).

```
source
```

MathOptInterface.Utilities.@struct\_of\_constraints\_by\_function\_types - Macro.

```
Utilities.@struct_of_constraints_by_function_types(name, func_types...)
```

Given a vector of n function types ( $F_1, F_2, \dots, F_n$ ) in func\_types, defines a subtype of StructOfConstraints of name name and which type parameters  $\{T, C_1, C_2, \dots, C_n\}$ . It contains n field where the i<sup>th</sup> field has type  $C_i$  and stores the constraints of function type  $F_i$ .

The expression  $F_i$  can also be a union in which case any constraint for which the function type is in the union is stored in the field with type  $C_i$ .

```
source
MathOptInterface.Utilities.@struct_of_constraints_by_set_types - Macro.
```

```
Utilities.@struct_of_constraints_by_set_types(name, func_types...)
```

Given a vector of n set types ( $S_1, S_2, \dots, S_n$ ) in func\_types, defines a subtype of StructOfConstraints of name name and which type parameters  $\{T, C_1, C_2, \dots, C_n\}$ . It contains n field where the i<sup>th</sup> field

has type  $C_i$  and stores the constraints of set type  $S_i$ . The expression  $S_i$  can also be a union in which case any constraint for which the set type is in the union is stored in the field with type  $C_i$ . This can be useful if  $C_i$  is a [MatrixOfConstraints](#) in order to concatenate the coefficients of constraints of several different set types in the same matrix.

[source](#)

MathOptInterface.Utilities.struct\_of\_constraint\_code - Function.

```
struct_of_constraint_code(struct_name, types, field_types = nothing)
```

Given a vector of  $n$   $\text{Union}\{\text{SymbolFun}, \text{_UnionSymbolFS}\{\text{SymbolFun}\}\}$  or  $\text{Union}\{\text{SymbolSet}, \text{_UnionSymbolFS}\{\text{SymbolSet}\}\}$  in  $\text{types}$ , defines a subtype of  $\text{StructOfConstraints}$  of name  $\text{name}$  and which type parameters  $\{T, F_1, F_2, \dots, F_n\}$  if  $\text{field\_types}$  is `nothing` and a  $\{T\}$  otherwise. It contains  $n$  field where the  $i$ th field has type  $C_i$  if  $\text{field\_types}$  is `nothing` and type  $\text{field\_types}[i]$  otherwise. If  $\text{types}$  is vector of  $\text{Union}\{\text{SymbolFun}, \text{_UnionSymbolFS}\{\text{SymbolFun}\}\}$  (resp.  $\text{Union}\{\text{SymbolSet}, \text{_UnionSymbolFS}\{\text{SymbolSet}\}\}$ ) then the constraints of that function (resp. set) type are stored in the corresponding field.

This function is used by the macros [@model](#), [@struct\\_of\\_constraints\\_by\\_function\\_types](#) and [@struct\\_of\\_constraints\\_by\\_set\\_type](#).

[source](#)

## Caching optimizer

MathOptInterface.Utilities.CachingOptimizer - Type.

```
CachingOptimizer
```

`CachingOptimizer` is an intermediate layer that stores a cache of the model and links it with an optimizer. It supports incremental model construction and modification even when the optimizer doesn't.

### Constructors

```
CachingOptimizer(cache::MOI.ModelLike, optimizer::AbstractOptimizer)
```

Creates a `CachingOptimizer` in `AUTOMATIC` mode, with the optimizer `optimizer`.

The type of the optimizer returned is `CachingOptimizer{typeof(optimizer), typeof(cache)}` so it does not support the function `reset_optimizer(::CachingOptimizer, new_optimizer)` if the type of `new_optimizer` is different from the type of `optimizer`.

```
CachingOptimizer(cache::MOI.ModelLike, mode::CachingOptimizerMode)
```

Creates a `CachingOptimizer` in the `NO_OPTIMIZER` state and mode `mode`.

The type of the optimizer returned is `CachingOptimizer{MOI.AbstractOptimizer, typeof(cache)}` so it *does* support the function `reset_optimizer(::CachingOptimizer, new_optimizer)` if the type of `new_optimizer` is different from the type of `optimizer`.

### About the type

#### States

A `CachingOptimizer` may be in one of three possible states (`CachingOptimizerState`):

- NO\_OPTIMIZER: The CachingOptimizer does not have any optimizer.
- EMPTY\_OPTIMIZER: The CachingOptimizer has an empty optimizer. The optimizer is not synchronized with the cached model.
- ATTACHED\_OPTIMIZER: The CachingOptimizer has an optimizer, and it is synchronized with the cached model.

### Modes

A CachingOptimizer has two modes of operation (CachingOptimizerMode):

- MANUAL: The only methods that change the state of the CachingOptimizer are `Utilities.reset_optimizer`, `Utilities.drop_optimizer`, and `Utilities.attach_optimizer`. Attempting to perform an operation in the incorrect state results in an error.
- AUTOMATIC: The CachingOptimizer changes its state when necessary. For example, `optimize!` will automatically call `attach_optimizer` (an optimizer must have been previously set). Attempting to add a constraint or perform a modification not supported by the optimizer results in a drop to EMPTY\_OPTIMIZER mode.

`source`

`MathOptInterface.Utilities.attach_optimizer` – Function.

```
attach_optimizer(model::CachingOptimizer)
```

Attaches the optimizer to `model`, copying all model data into it. Can be called only from the EMPTY\_OPTIMIZER state. If the copy succeeds, the CachingOptimizer will be in state ATTACHED\_OPTIMIZER after the call, otherwise an error is thrown; see `MOI.copy_to` for more details on which errors can be thrown.

`source`

```
MOIU.attach_optimizer(model::GenericModel)
```

Call `MOIU.attach_optimizer` on the backend of `model`.

Cannot be called in direct mode.

`source`

`MathOptInterface.Utilities.reset_optimizer` – Function.

```
reset_optimizer(m::CachingOptimizer, optimizer::MOI.AbstractOptimizer)
```

Sets or resets `m` to have the given empty optimizer `optimizer`.

Can be called from any state. An assertion error will be thrown if `optimizer` is not empty.

The CachingOptimizer `m` will be in state EMPTY\_OPTIMIZER after the call.

`source`

```
reset_optimizer(m::CachingOptimizer)
```

Detaches and empties the current optimizer. Can be called from ATTACHED\_OPTIMIZER or EMPTY\_OPTIMIZER state. The CachingOptimizer will be in state EMPTY\_OPTIMIZER after the call.

[source](#)

```
MOIU.reset_optimizer(model::GenericModel, optimizer::MOI.AbstractOptimizer)
```

Call MOIU.reset\_optimizer on the backend of model.

Cannot be called in direct mode.

[source](#)

```
MOIU.reset_optimizer(model::GenericModel)
```

Call MOIU.reset\_optimizer on the backend of model.

Cannot be called in direct mode.

[source](#)

MathOptInterface.Utilities.drop\_optimizer – Function.

```
drop_optimizer(m::CachingOptimizer)
```

Drops the optimizer, if one is present. Can be called from any state. The CachingOptimizer will be in state NO\_OPTIMIZER after the call.

[source](#)

```
MOIU.drop_optimizer(model::GenericModel)
```

Call MOIU.drop\_optimizer on the backend of model.

Cannot be called in direct mode.

[source](#)

MathOptInterface.Utilities.state – Function.

```
state(m::CachingOptimizer)::CachingOptimizerState
```

Returns the state of the CachingOptimizer m. See [Utilities.CachingOptimizer](#).

[source](#)

MathOptInterface.Utilities.mode – Function.

```
mode(m::CachingOptimizer)::CachingOptimizerMode
```

Returns the operating mode of the CachingOptimizer `m`. See [Utilities.CachingOptimizer](#).

[source](#)

### Mock optimizer

`MathOptInterface.Utilities.MockOptimizer` – Type.

```
MockOptimizer
```

`MockOptimizer` is a fake optimizer especially useful for testing. Its main feature is that it can store the values that should be returned for each attribute.

[source](#)

### Printing

`MathOptInterface.Utilities.latex_formulation` – Function.

```
latex_formulation(model::MOI.ModelLike; kwargs...)
```

Wrap model in a type so that it can be pretty-printed as text/latex in a notebook like IJulia, or in Documenter.

To render the model, end the cell with `latex_formulation(model)`, or call `display(latex_formulation(model))` in to force the display of the model from inside a function.

Possible keyword arguments are:

- `simplify_coefficients` : Simplify coefficients if possible by omitting them or removing trailing zeros.
- `default_name` : The name given to variables with an empty name.
- `print_types` : Print the MOI type of each function and set for clarity.

[source](#)

### Copy utilities

`MathOptInterface.Utilities.default_copy_to` – Function.

```
default_copy_to(dest::MOI.ModelLike, src::MOI.ModelLike)
```

A default implementation of `MOI.copy_to(dest, src)` for models that implement the incremental interface, that is, `MOI.supports_incremental_interface` returns `true`.

[source](#)

`MathOptInterface.Utilities.IndexMap` – Type.

```
IndexMap()
```

The dictionary-like object returned by `MOI.copy_to`.

`source`

`MathOptInterface.Utilities.identity_index_map` – Function.

```
identity_index_map(model::MOI.ModelLike)
```

Return an `IndexMap` that maps all variable and constraint indices of `model` to themselves.

`source`

`MathOptInterface.Utilities.ModelFilter` – Type.

```
ModelFilter(filter::Function, model::MOI.ModelLike)
```

A layer to filter out various components of `model`.

The filter function takes a single argument, which is each element from the list returned by the attributes below. It returns true if the element should be visible in the filtered model and false otherwise.

The components that are filtered are:

- Entire constraint types via:
  - `MOI.ListOfConstraintTypesPresent`
- Individual constraints via:
  - `MOI.ListOfConstraintIndices{F,S}`
- Specific attributes via:
  - `MOI.ListOfModelAttributeSet`
  - `MOI.ListOfConstraintAttributesSet`
  - `MOI.ListOfVariableAttributesSet`

#### Warning

The list of attributes filtered may change in a future release. You should write functions that are generic and not limited to the five types listed above. Thus, you should probably define a fallback `filter(::Any) = true`.

See below for examples of how this works.

#### Note

This layer has a limited scope. It is intended to be used in conjunction with `MOI.copy_to`.

**Example: copy model excluding integer constraints**

Use the do syntax to provide a single function.

```
filtered_src = MOI.Utilities.ModelFilter(src) do item
    return item != (MOI.VariableIndex, MOI.Integer)
end
MOI.copy_to(dest, filtered_src)
```

**Example: copy model excluding names**

Use type dispatch to simplify the implementation:

```
my_filter(::Any) = true # Note the generic fallback
my_filter(::MOI.VariableName) = false
my_filter(::MOI.ConstraintName) = false
filtered_src = MOI.Utilities.ModelFilter(my_filter, src)
MOI.copy_to(dest, filtered_src)
```

**Example: copy irreducible infeasible subsystem**

```
my_filter(::Any) = true # Note the generic fallback
function my_filter(ci::MOI.ConstraintIndex)
    status = MOI.get(dest, MOI.ConstraintConflictStatus(), ci)
    return status != MOI.NOT_IN_CONFLICT
end
filtered_src = MOI.Utilities.ModelFilter(my_filter, src)
MOI.copy_to(dest, filtered_src)
```

`source`

`MathOptInterface.Utilities.loadfromstring!` – Function.

```
loadfromstring!(model, s)
```

A utility function to aid writing tests.

**Warning**

This function is not intended for widespread use. It is mainly used as a tool to simplify writing tests in `MathOptInterface`. Do not use it as an exchange format for storing or transmitting problem instances. Use the `FileFormats` submodule instead.

**Example**

```
julia> model = MOI.Utilities.Model{Float64}();
julia> MOI.Utilities.loadfromstring!(model, """
variables: x, y, z
constrainedvariable: [a, b, c] in Nonnegatives(3)
```

```

minobjective::Float64: 2x + 3y
con1: x + y <= 1.0
con2: [x, y] in Nonnegatives(2)
x >= 0.0
""")

```

**Notes**

Special labels are:

- variables
- minobjective
- maxobjectives

Everything else denotes a constraint with a name.

Append `::T` to use an element type of `T` when parsing the function.

Do not name `VariableIndex` constraints.

**Exceptions**

- `x - y` does NOT currently parse. Instead, write `x + -1.0 * y`.
- `x^2` does NOT currently parse. Instead, write `x * x`.

`source`

**Penalty relaxation**

`MathOptInterface.Utilities.PenaltyRelaxation` - Type.

```

PenaltyRelaxation(
    penalties = Dict{MOI.ConstraintIndex,Float64}();
    default::Union{Nothing,T} = 1.0,
)

```

A problem modifier that, when passed to `MOI.modify`, destructively modifies the model in-place to create a penalized relaxation of the constraints.

**Warning**

This is a destructive routine that modifies the model in-place. If you don't want to modify the original model, use `JuMP.copy_model` to create a copy before calling `MOI.modify`.

**Reformulation**

See `Utilities.ScalarPenaltyRelaxation` for details of the reformulation.

For each constraint `ci`, the penalty passed to `Utilities.ScalarPenaltyRelaxation` is `get(penalties, ci, default)`. If the value is nothing, because `ci` does not exist in `penalties` and `default = nothing`, then the constraint is skipped.

**Return value**

`MOI.modify(model, PenaltyRelaxation())` returns a `Dict{MOI.ConstraintIndex, MOI.ScalarAffineFunction}` that maps each constraint index to the corresponding  $y + z$  as a `MOI.ScalarAffineFunction`. In an optimal solution, query the value of these functions to compute the violation of each constraint.

**Relax a subset of constraints**

To relax a subset of constraints, pass a `penalties` dictionary and set `default = nothing`.

**Supported constraint types**

The penalty relaxation is currently limited to modifying `MOI.ScalarAffineFunction` and `MOI.ScalarQuadraticFunction` constraints in the linear sets `MOI.LessThan`, `MOI.GreaterThan`, `MOI.EqualTo` and `MOI.Interval`.

It does not include variable bound or integrality constraints, because these cannot be modified in-place.

To modify variable bounds, rewrite them as linear constraints.

**Example**

```
julia> model = MOI.Utilities.Model{Float64}();
julia> x = MOI.add_variable(model);
julia> c = MOI.add_constraint(model, 1.0 * x, MOI.LessThan(2.0));
julia> map = MOI.modify(model, MOI.Utilities.PenaltyRelaxation(default = 2.0));
julia> print(model)
Minimize ScalarAffineFunction{Float64}:
 0.0 + 2.0 v[2]
Subject to:
  ScalarAffineFunction{Float64}-in-LessThan{Float64}
  0.0 + 1.0 v[1] - 1.0 v[2] <= 2.0
  VariableIndex-in-GreaterThan{Float64}
  v[2] >= 0.0
julia> map[c] isa MOI.ScalarAffineFunction{Float64}
true
```

```
julia> model = MOI.Utilities.Model{Float64}();
julia> x = MOI.add_variable(model);
julia> c = MOI.add_constraint(model, 1.0 * x, MOI.LessThan(2.0));
julia> map = MOI.modify(model, MOI.Utilities.PenaltyRelaxation(Dict(c => 3.0)));
julia> print(model)
Minimize ScalarAffineFunction{Float64}:
  0.0 + 3.0 v[2]
Subject to:
```

```

ScalarAffineFunction{Float64}-in-LessThan{Float64}
0.0 + 1.0 v[1] - 1.0 v[2] <= 2.0

VariableIndex-in-GreaterThan{Float64}
v[2] >= 0.0

julia> map[c] isa MOI.ScalarAffineFunction{Float64}
true

```

[source](#)

MathOptInterface.Utilities.ScalarPenaltyRelaxation – Type.

```
ScalarPenaltyRelaxation(penalty::T) where {T}
```

A problem modifier that, when passed to `MOI.modify`, destructively modifies the constraint in-place to create a penalized relaxation of the constraint.

### Warning

This is a destructive routine that modifies the constraint in-place. If you don't want to modify the original model, use `JuMP.copy_model` to create a copy before calling `MOI.modify`.

### Reformulation

The penalty relaxation modifies constraints of the form  $f(x) \in S$  into  $f(x) + y - z \in S$ , where  $y, z \geq 0$ , and then it introduces a penalty term into the objective of  $a \times (y + z)$  (if minimizing, else  $-a$ ), where  $a$  is `penalty`

When  $S$  is `MOI.LessThan` or `MOI.GreaterThan`, we omit  $y$  or  $z$  respectively as a performance optimization.

### Return value

`MOI.modify(model, ci, ScalarPenaltyRelaxation(penalty))` returns  $y + z$  as a `MOI.ScalarAffineFunction`. In an optimal solution, query the value of this function to compute the violation of the constraint.

### Example

```

julia> model = MOI.Utilities.Model{Float64}();
julia> x = MOI.add_variable(model);
julia> c = MOI.add_constraint(model, 1.0 * x, MOI.LessThan(2.0));
julia> f = MOI.modify(model, c, MOI.Utilities.ScalarPenaltyRelaxation(2.0));
julia> print(model)
Minimize ScalarAffineFunction{Float64}:
0.0 + 2.0 v[2]
Subject to:

```

```

ScalarAffineFunction{Float64}-in-LessThan{Float64}
0.0 + 1.0 v[1] - 1.0 v[2] <= 2.0

VariableIndex-in-GreaterThan{Float64}
v[2] >= 0.0

julia> f isa MOI.ScalarAffineFunction{Float64}
true

```

[source](#)

## MatrixOfConstraints

MathOptInterface.Utilities.MatrixOfConstraints – Type.

```

mutable struct MatrixOfConstraints{T,AT,BT,ST} <: MOI.ModelLike
    coefficients::AT
    constants::BT
    sets::ST
    caches::Vector{Any}
    are_indices_mapped::Vector{BitSet}
    final_touch::Bool
end

```

Represent ScalarAffineFunction and VectorAffinefunction constraints in a matrix form where the linear coefficients of the functions are stored in the coefficients field, the constants of the functions or sets are stored in the constants field. Additional information about the sets are stored in the sets field.

This model can only be used as the constraints field of a MOI.Utilities.AbstractModel.

When the constraints are added, they are stored in the caches field. They are only loaded in the coefficients and constants fields once MOI.Utilities.final\_touch is called. For this reason, MatrixOfConstraints should not be used by an incremental interface. Use MOI.copy\_to instead.

The constraints can be added in two different ways:

1. With add\_constraint, in which case a canonicalized copy of the function is stored in caches.
2. With pass\_nonvariable\_constraints, in which case the functions and sets are stored themselves in caches without mapping the variable indices. The corresponding index in caches is added in are\_indices\_mapped. This avoids doing a copy of the function in case the getter of CanonicalConstraintFunction does not make a copy for the source model, for example, this is the case of VectorOfConstraints.

We illustrate this with an example. Suppose a model is copied from a `src::MOI.Utilities.Model` to a bridged model with a MatrixOfConstraints. For all the types that are not bridged, the constraints will be copied with `pass_nonvariable_constraints`. Hence the functions stored in caches are exactly the same as the ones stored in `src`. This is ok since this is only during the `copy_to` operation during which `src` cannot be modified. On the other hand, for the types that are bridged, the functions added may contain duplicates even if the functions did not contain duplicates in `src` so duplicates are removed with `MOI.Utilities.canonical`.

## Interface

The `.coefficients::AT` type must implement:

- AT()
- MOI.empty(::AT)!
- MOI.Utilities.add\_column
- MOI.Utilities.set\_number\_of\_rows
- MOI.Utilities.allocate\_terms
- MOI.Utilities.load\_terms
- MOI.Utilities.final\_touch

The .constants::BT type must implement:

- BT()
- Base.empty!(::BT)
- Base.resize(::BT)
- MOI.Utilities.load\_constants
- MOI.Utilities.function\_constants
- MOI.Utilities.set\_from\_constants

The .sets::ST type must implement:

- ST()
- MOI.is\_empty(::ST)
- MOI.empty(::ST)
- MOI.dimension(::ST)
- MOI.is\_valid(::ST, ::MOI.ConstraintIndex)
- MOI.get(::ST, ::MOI.ListOfConstraintTypesPresent)
- MOI.get(::ST, ::MOI.NumberOfConstraints)
- MOI.get(::ST, ::MOI.ListOfConstraintIndices)
- MOI.Utilities.set\_types
- MOI.Utilities.set\_index
- MOI.Utilities.add\_set
- MOI.Utilities.rows
- MOI.Utilities.final\_touch

`source`

#### `.coefficients`

`MathOptInterface.Utilities.add_column` - Function.

```
add_column(coefficients)::Nothing
```

Tell `coefficients` to pre-allocate datastructures as needed to store one column.

`source`

`MathOptInterface.Utilities.allocate_terms` - Function.

```
allocate_terms(coefficients, index_map, func)::Nothing
```

Tell coefficients that the terms of the function func where the variable indices are mapped with index\_map will be loaded with [load\\_terms](#).

The function func must be canonicalized before calling `allocate_terms`. See [is\\_canonical](#).

[source](#)

`MathOptInterface.Utilities.set_number_of_rows` - Function.

```
set_number_of_rows(coefficients, n)::Nothing
```

Tell coefficients to pre-allocate datastructures as needed to store n rows.

[source](#)

`MathOptInterface.Utilities.load_terms` - Function.

```
load_terms(coefficients, index_map, func, offset)::Nothing
```

Loads the terms of func to coefficients, mapping the variable indices with index\_map.

The i<sup>th</sup> dimension of func is loaded at the (offset + i)<sup>th</sup> row of coefficients.

The function must be allocated first with [allocate\\_terms](#).

The function func must be canonicalized, see [is\\_canonical](#).

[source](#)

`MathOptInterface.Utilities.final_touch` - Function.

```
final_touch(coefficients)::Nothing
```

Informs the coefficients that all functions have been added with `load_terms`. No more modification is allowed unless `MOI.empty!` is called.

```
final_touch(sets)::Nothing
```

Informs the sets that all functions have been added with `add_set`. No more modification is allowed unless `MOI.empty!` is called.

[source](#)

`MathOptInterface.Utilities.extract_function` - Function.

```
extract_function(coefficients, row::Integer, constant::T) where {T}
```

Return the MOI.ScalarAffineFunction{T} function corresponding to row row in coefficients.

```
extract_function(
    coefficients,
    rows::UnitRange,
    constants::Vector{T},
) where{T}
```

Return the MOI.VectorAffineFunction{T} function corresponding to rows rows in coefficients.

`source`  
MathOptInterface.Utilities.MutableSparseMatrixCSC - Type.

```
mutable struct MutableSparseMatrixCSC{Tv,Ti<:Integer,I<:AbstractIndexing}
    indexing::I
    m::Int
    n::Int
    colptr::Vector{Ti}
    rowval::Vector{Ti}
    nzval::Vector{Tv}
    nz_added::Vector{Ti}
end
```

Matrix type loading sparse matrices in the Compressed Sparse Column format. The indexing used is `indexing`, see [AbstractIndexing](#). The other fields have the same meaning than for `SparseArrays.SparseMatrixCSC` except that the indexing is different unless `indexing` is `OneBasedIndexing`. In addition, `nz_added` is used to cache the number of non-zero terms that have been added to each column due to the incremental nature of `load_terms`.

The matrix is loaded in 5 steps:

1. `MOI.empty!` is called.
2. `MOI.Utilities.add_column` and `MOI.Utilities.allocate_terms` are called in any order.
3. `MOI.Utilities.set_number_of_rows` is called.
4. `MOI.Utilities.load_terms` is called for each affine function.
5. `MOI.Utilities.final_touch` is called.

`source`  
MathOptInterface.Utilities.AbstractIndexing - Type.

```
abstract type AbstractIndexing end
```

Indexing to be used for storing the row and column indices of `MutableSparseMatrixCSC`. See [ZeroBasedIndexing](#) and [OneBasedIndexing](#).

`source`  
MathOptInterface.Utilities.ZeroBasedIndexing - Type.

```
struct ZeroBasedIndexing <: AbstractIndexing end
```

Zero-based indexing: the  $i$ th row or column has index  $i - 1$ . This is useful when the vectors of row and column indices need to be communicated to a library using zero-based indexing such as C libraries.

[source](#)  
`MathOptInterface.Utilities.OneBasedIndexing - Type.`

```
struct ZeroBasedIndexing <: AbstractIndexing end
```

One-based indexing: the  $i$ th row or column has index  $i$ . This enables an allocation-free conversion of `MutableSparseMatrixCSC` to `SparseArrays.SparseMatrixCSC`.

[source](#)  
`.constants`  
`MathOptInterface.Utilities.load_constants - Function.`

```
load_constants(constants, offset, func_or_set)::Nothing
```

This function loads the constants of `func_or_set` in `constants` at an offset of `offset`. Where `offset` is the sum of the dimensions of the constraints already loaded. The storage should be preallocated with `resize!` before calling this function.

This function should be implemented to be usable as storage of constants for `MatrixOfConstraints`.

The constants are loaded in three steps:

1. `Base.empty!` is called.
2. `Base.resize!` is called with the sum of the dimensions of all constraints.
3. `MOI.Utilities.load_constants` is called for each function for vector constraint or set for scalar constraint.

[source](#)  
`MathOptInterface.Utilities.function_constants - Function.`

```
function_constants(constants, rows)
```

This function returns the function constants that were loaded with `load_constants` at the rows `rows`.

This function should be implemented to be usable as storage of constants for `MatrixOfConstraints`.

[source](#)  
`MathOptInterface.Utilities.set_from_constants - Function.`

```
set_from_constants(constants, S::Type, rows)::S
```

This function returns an instance of the set S for which the constants where loaded with `load_constants` at the rows rows.

This function should be implemented to be usable as storage of constants for `MatrixOfConstraints`.

`source`

`MathOptInterface.Utilities.modify_constants` - Function.

```
modify_constants(constants, row::Integer, new_constant::T) where {T}
modify_constants(
    constants,
    rows::AbstractVector{<: Integer},
    new_constants::AbstractVector{T},
) where {T}
```

Modify constants in-place to store new\_constant in the row row, or rows rows.

This function must be implemented to enable `MOI.ScalarConstantChange` and `MOI.VectorConstantChange` for `MatrixOfConstraints`.

`source`

`MathOptInterface.Utilities.Hyperrectangle` - Type.

```
struct Hyperrectangle{T} <: AbstractVectorBounds
    lower::Vector{T}
    upper::Vector{T}
end
```

A struct for the .constants field in `MatrixOfConstraints`.

`source`

`.sets`

`MathOptInterface.Utilities.set_index` - Function.

```
set_index(sets, ::Type{S})::Union{Int,Nothing} where {S<:MOI.AbstractSet}
```

Return an integer corresponding to the index of the set type in the list given by `set_types`.

If S is not part of the list, return nothing.

`source`

`MathOptInterface.Utilities.set_types` - Function.

```
set_types(sets)::Vector{Type}
```

Return the list of the types of the sets allowed in sets.

[source](#)

MathOptInterface.Utilities.add\_set - Function.

```
add_set(sets, i)::Int64
```

Add a scalar set of type index i.

```
add_set(sets, i, dim)::Int64
```

Add a vector set of type index i and dimension dim.

Both methods return a unique Int64 of the set that can be used to reference this set.

[source](#)

MathOptInterface.Utilities.rows - Function.

```
rows(sets, ci::MOI.ConstraintIndex)::Union{Int,UnitRange{Int}}
```

Return the rows in 1:MOI.dimension(sets) corresponding to the set of id ci.value.

For scalar sets, this returns an Int. For vector sets, this returns an UnitRange{Int}.

[source](#)

MathOptInterface.Utilities.num\_rows - Function.

```
num_rows(sets)::OrderedProductOfSets, ::Type{S}) where {S}
```

Return the number of rows corresponding to a set of type S. That is, it is the sum of the dimensions of the sets of type S.

[source](#)

MathOptInterface.Utilities.set\_with\_dimension - Function.

```
set_with_dimension(::Type{S}, dim) where {S<:MOI.AbstractVectorSet}
```

Returns the instance of S of MOI.dimension dim. This needs to be implemented for sets of type S to be useable with [MatrixOfConstraints](#).

[source](#)

MathOptInterface.Utilities.ProductOfSets - Type.

```
abstract type ProductOfSets{T} end
```

Represents a cartesian product of sets of given types.

[source](#)

MathOptInterface.Utilities.MixOfScalarSets - Type.

```
abstract type MixOfScalarSets{T} <: ProductOfSets{T} end
```

Product of scalar sets in the order the constraints are added, mixing the constraints of different types.

Use `@mix_of_scalar_sets` to generate a new subtype.

[source](#)

MathOptInterface.Utilities.@mix\_of\_scalar\_sets - Macro.

```
@mix_of_scalar_sets(name, set_types...)
```

Generate a new `MixOfScalarSets` subtype.

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.Utilities.@mix_of_scalar_sets(
    MixedIntegerLinearProgramSets,
    MOI.GreaterThan{T},
    MOI.LessThan{T},
    MOI.EqualTo{T},
    MOI.Integer,
)
```

[source](#)

MathOptInterface.Utilities.OrderedProductOfSets - Type.

```
abstract type OrderedProductOfSets{T} <: ProductOfSets{T} end
```

Product of sets in the order the constraints are added, grouping the constraints of the same types contiguously.

Use `@product_of_sets` to generate new subtypes.

[source](#)

MathOptInterface.Utilities.@product\_of\_sets - Macro.

```
@product_of_sets(name, set_types...)
```

Generate a new `OrderedProductOfSets` subtype.

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.Utilities.@product_of_sets(
    LinearOrthants,
    MOI.Zeros,
    MOI.Nonnegatives,
    MOI.Nonpositives,
    MOI.ZeroOne,
)
```

`source`

### Fallbacks

`MathOptInterface.Utilities.get_fallback` – Function.

```
getFallback(model::MOI.ModelLike, ::MOI.ObjectiveValue)
```

Compute the objective function value using the `VariablePrimal` results and the `ObjectiveFunction` value.

`source`

```
getFallback(
    model::MOI.ModelLike,
    ::MOI.DualObjectiveValue,
    ::Type{T},
) where {T}
```

Compute the dual objective value of type `T` using the `ConstraintDual` results and the `ConstraintFunction` and `ConstraintSet` values.

Note that the nonlinear part of the model is ignored.

`source`

```
getFallback(
    model::MOI.ModelLike,
    ::MOI.ConstraintPrimal,
    constraint_index::MOI.ConstraintIndex,
)
```

Compute the value of the function of the constraint of index `constraint_index` using the `VariablePrimal` results and the `ConstraintFunction` values.

```
source

getFallback(
    model::MOI.ModelLike,
    attr::MOI.ConstraintDual,
    ci::MOI.ConstraintIndex{Union{MOI.VariableIndex, MOI.VectorOfVariables}},
    ::Type{T} = Float64,
) where {T}
```

Compute the dual of the constraint of index `ci` using the `ConstraintDual` of other constraints and the `ConstraintFunction` values.

Throws an error if some constraints are quadratic or if there is one another `MOI.VariableIndex`-in-S or `MOI.VectorOfVariables`-in-S constraint with one of the variables in the function of the constraint `ci`.

`source`

### Function utilities

The following utilities are available for functions:

`MathOptInterface.Utilities.eval_variables` – Function.

```
eval_variables(value_fn::Function, f::MOI.AbstractFunction)
```

Returns the value of function `f` if each variable index `vi` is evaluated as `value_fn(vi)`.

Note that `value_fn` must return a `Number`. See `substitute_variables` for a similar function where `value_fn` returns an `MOI.AbstractScalarFunction`.

#### Warning

The two-argument version of `eval_variables` is deprecated and may be removed in MOI v2.0.0. Use the three-argument method `eval_variables(::Function, ::MOI.ModelLike, ::MOI.AbstractFunction)` instead.

`source`

`MathOptInterface.Utilities.map_indices` – Function.

```
map_indices(index_map::Function, attr::MOI.AnyAttribute, x::X)::X where {X}
```

Substitute any `MOI.VariableIndex` (resp. `MOI.ConstraintIndex`) in `x` by the `MOI.VariableIndex` (resp. `MOI.ConstraintIndex`) of the same type given by `index_map(x)`.

#### When to implement this method for new types X

This function is used by implementations of `MOI.copy_to` on constraint functions, attribute values and submittable values. If you define a new attribute whose values `x::X` contain variable or constraint indices, you must also implement this function.

`source`

```
map_indices(
    variable_map::AbstractDict{T,T},
    x::X,
)>::X where {T<:MOI.Index,X}
```

Shortcut for `map_indices(vi -> variable_map[vi], x)`.

`source`

`MathOptInterface.Utilities.substitute_variables` - Function.

```
substitute_variables(variable_map::Function, x)
```

Substitute any `MOI.VariableIndex` in `x` by `variable_map(x)`. The `variable_map` function returns either `MOI.VariableIndex` or `MOI.ScalarAffineFunction`, see `eval_variables` for a similar function where `variable_map` returns a number.

This function is used by bridge optimizers on constraint functions, attribute values and submittable values when at least one variable bridge is used hence it needs to be implemented for custom types that are meant to be used as attribute or submittable value.

#### Note

When implementing a new method, don't use `substitute_variables(::Function)`, because Julia will not specialize on it. Use instead `substitute_variables(::F, ...)` where `{F<:Function}`.

`source`

`MathOptInterface.Utilities.filter_variables` - Function.

```
filter_variables(keep::Function, f::AbstractFunction)
```

Return a new function `f` with the variable `vi` such that `!keep(vi)` removed.

WARNING: Don't define `filter_variables(::Function, ...)` because Julia will not specialize on this. Define instead `filter_variables(::F, ...)` where `{F<:Function}`.

`source`

`MathOptInterface.Utilities.remove_variable` - Function.

```
remove_variable(f::AbstractFunction, vi::VariableIndex)
```

Return a new function `f` with the variable `vi` removed.

`source`

```
remove_variable(
    f::MOI.AbstractFunction,
    s::MOI.AbstractSet,
    vi::MOI.VariableIndex,
)
```

Return a tuple  $(g, t)$  representing the constraint  $f$ -in- $s$  with the variable  $v_i$  removed. That is, the terms containing the variable  $v_i$  in the function  $f$  are removed and the dimension of the set  $s$  is updated if needed (for example, when  $f$  is a `VectorOfVariables` with  $v_i$  being one of the variables).

[source](#)

`MathOptInterface.Utilities.all_coefficients` - Function.

```
all_coefficients(p::Function, f::MOI.AbstractFunction)
```

Determine whether predicate  $p$  returns true for all coefficients of  $f$ , returning false as soon as the first coefficient of  $f$  for which  $p$  returns false is encountered (short-circuiting). Similar to `all`.

[source](#)

`MathOptInterface.Utilities.unsafe_add` - Function.

```
unsafe_add(t1::MOI.ScalarAffineTerm, t2::MOI.ScalarAffineTerm)
```

Sums the coefficients of  $t_1$  and  $t_2$  and returns an output `MOI.ScalarAffineTerm`. It is unsafe because it uses the variable of  $t_1$  as the variable of the output without checking that it is equal to that of  $t_2$ .

[source](#)

```
unsafe_add(t1::MOI.ScalarQuadraticTerm, t2::MOI.ScalarQuadraticTerm)
```

Sums the coefficients of  $t_1$  and  $t_2$  and returns an output `MOI.ScalarQuadraticTerm`. It is unsafe because it uses the variable's of  $t_1$  as the variable's of the output without checking that they are the same (up to permutation) to those of  $t_2$ .

[source](#)

```
unsafe_add(t1::MOI.VectorAffineTerm, t2::MOI.VectorAffineTerm)
```

Sums the coefficients of  $t_1$  and  $t_2$  and returns an output `MOI.VectorAffineTerm`. It is unsafe because it uses the `output_index` and `variable` of  $t_1$  as the `output_index` and `variable` of the output term without checking that they are equal to those of  $t_2$ .

[source](#)

`MathOptInterface.Utilities.isapprox_zero` - Function.

```
isapprox_zero(f::MOI.AbstractFunction, tol)
```

Return a `Bool` indicating whether the function  $f$  is approximately zero using  $\text{tol}$  as a tolerance.

#### Important note

This function assumes that  $f$  does not contain any duplicate terms, you might want to first call `canonical` if that is not guaranteed.

#### Example

```
julia> import MathOptInterface as MOI

julia> x = MOI.VariableIndex(1)
MOI.VariableIndex(1)

julia> f = MOI.ScalarAffineFunction(MOI.ScalarAffineTerm.([1, -1], [x, x]), 0)
(0) + (1) MOI.VariableIndex(1) - (1) MOI.VariableIndex(1)

julia> MOI.Utilities.isapprox_zero(f, 1e-8)
false

julia> MOI.Utilities.isapprox_zero(MOI.Utilities.canonical(f), 1e-8)
true
```

[source](#)

MathOptInterface.Utilities.modify\_function – Function.

```
modify_function(f::AbstractFunction, change::AbstractFunctionModification)
```

Return a copy of the function `f`, modified according to `change`.

[source](#)

MathOptInterface.Utilities.zero\_with\_output\_dimension – Function.

```
zero_with_output_dimension(::Type{T}, output_dimension::Integer) where {T}
```

Create an instance of type `T` with the output dimension `output_dimension`.

This is mostly useful in Bridges, when code needs to be agnostic to the type of vector-valued function that is passed in.

[source](#)

The following functions can be used to canonicalize a function:

MathOptInterface.Utilities.is\_canonical – Function.

```
is_canonical(f::Union{ScalarAffineFunction, VectorAffineFunction})
```

Returns a Bool indicating whether the function is in canonical form. See [canonical](#).

[source](#)

```
is_canonical(f::Union{ScalarQuadraticFunction, VectorQuadraticFunction})
```

Returns a Bool indicating whether the function is in canonical form. See [canonical](#).

[source](#)

`MathOptInterface.Utilities.canonical` – Function.

```
canonical(f::MOI.AbstractFunction)
```

Returns the function in a canonical form, that is,

- A term appear only once.
- The coefficients are nonzero.
- The terms appear in increasing order of variable where there the order of the variables is the order of their value.
- For a `AbstractVectorFunction`, the terms are sorted in ascending order of output index.

The output of `canonical` can be assumed to be a copy of `f`, even for `VectorOfVariables`.

### Example

```
julia> import MathOptInterface as MOI

julia> x, y, z = MOI.VariableIndex.(1:3);

julia> f = MOI.ScalarAffineFunction(
        MOI.ScalarAffineTerm.(Float64[2, 1, 3, -2, -3], [y, x, z, x, z]),
        5.0,
    )
5.0 + 2.0 MOI.VariableIndex(2) + 1.0 MOI.VariableIndex(1) + 3.0 MOI.VariableIndex(3) - 2.0
→ MOI.VariableIndex(1) - 3.0 MOI.VariableIndex(3)

julia> MOI.Utilities.canonical(f)
5.0 - 1.0 MOI.VariableIndex(1) + 2.0 MOI.VariableIndex(2)
```

`source`

`MathOptInterface.Utilities.canonical!` – Function.

```
canonicalize!(f::Union{ScalarAffineFunction, VectorAffineFunction})
```

Convert a function to canonical form in-place, without allocating a copy to hold the result. See [canonical](#).

`source`

```
canonicalize!(f::Union{ScalarQuadraticFunction, VectorQuadraticFunction})
```

Convert a function to canonical form in-place, without allocating a copy to hold the result. See [canonical](#).

`source`

The following functions can be used to manipulate functions with basic algebra:

`MathOptInterface.Utilities.scalar_type` – Function.

```
scalar_type(F::Type{<:MOI.AbstractVectorFunction})
```

Type of functions obtained by indexing objects obtained by calling eachscalar on functions of type F.

[source](#)

MathOptInterface.Utilities.scalarize - Function.

```
scalarize(func::MOI.VectorOfVariables, ignore_constants::Bool = false)
```

Returns a vector of scalar functions making up the vector function in the form of a Vector{MOI.SingleVariable}.

See also [eachscalar](#).

[source](#)

```
scalarize(func::MOI.VectorAffineFunction{T}, ignore_constants::Bool = false)
```

Returns a vector of scalar functions making up the vector function in the form of a Vector{MOI.ScalarAffineFunction{T}}.

See also [eachscalar](#).

[source](#)

```
scalarize(func::MOI.VectorQuadraticFunction{T}, ignore_constants::Bool = false)
```

Returns a vector of scalar functions making up the vector function in the form of a Vector{MOI.ScalarQuadraticFunction{T}}

See also [eachscalar](#).

[source](#)

MathOptInterface.Utilities.eachscalar - Function.

```
eachscalar(f::MOI.AbstractVectorFunction)
```

Returns an iterator for the scalar components of the vector function.

See also [scalarize](#).

[source](#)

```
eachscalar(f::MOI.AbstractVector)
```

Returns an iterator for the scalar components of the vector.

[source](#)

MathOptInterface.Utilities.promote\_operation - Function.

```

promote_operation(
    op::Function,
    ::Type{T},
    ArgsTypes::Type{<:Union{T,AbstractVector{T},MOI.AbstractFunction}...},
) where {T<:Number}

```

Compute the return type of the call `operate(op, T, args...)`, where the types of the arguments `args` are `ArgsTypes`.

One assumption is that the element type `T` is invariant under each operation. That is, `op(::T, ::T)::T` where `op` is a `+`, `-`, `*`, and `/`.

There are six methods for which we implement `Utilities.promote_operation`:

1. `+ a. promote_operation(::typeof(+), ::Type{T}, ::Type{F1}, ::Type{F2})`
2. `- a. promote_operation(::typeof(-), ::Type{T}, ::Type{F}) b. promote_operation(::typeof(-), ::Type{T}, ::Type{F1}, ::Type{F2})`
3. `* a. promote_operation(::typeof(*), ::Type{T}, ::Type{T}, ::Type{F}) b. promote_operation(::typeof(*), ::Type{T}, ::Type{F1}, ::Type{F2}), ::Type{T}, ::Type{F}, ::Type{T}) c. promote_operation(::typeof(*), ::Type{T}, ::Type{F1}, ::Type{F2}) where F1 and F2 are VariableIndex or ScalarAffineFunction d. promote_operation(::typeof(*), ::Type{T}, ::Type{<:Diagonal{T}}), ::Type{F}`
4. `/ a. promote_operation(::typeof(/), ::Type{T}, ::Type{F}, ::Type{T})`
5. `vcat a. promote_operation(::typeof(vcat), ::Type{T}, ::Type{F}...)`
6. `imag a. promote_operation(::typeof(imag), ::Type{T}, ::Type{F}) where F is VariableIndex or VectorOfVariables`

In each case, `F` (or `F1` and `F2`) is one of the ten supported types, with a restriction that the mathematical operation makes sense, for example, we don't define `promote_operation(-, T, F1, F2)` where `F1` is a scalar-valued function and `F2` is a vector-valued function. The ten supported types are:

1. `::T`
2. `::VariableIndex`
3. `::ScalarAffineFunction{T}`
4. `::ScalarQuadraticFunction{T}`
5. `::ScalarNonlinearFunction`
6. `::AbstractVector{T}`
7. `::VectorOfVariables`
8. `::VectorAffineFunction{T}`
9. `::VectorQuadraticFunction{T}`
10. `::VectorNonlinearFunction`

`source`

`MathOptInterface.Utilities.operate` – Function.

```
operate(
    op::Function,
    ::Type{T},
    args::Union{T, MOI.AbstractFunction}...,
) ::MOI.AbstractFunction where {T<:Number}
```

Returns an `MOI.AbstractFunction` representing the function resulting from the operation `op(args...)` on functions of coefficient type `T`.

No argument can be modified.

### Methods

1. + a. `operate(::typeof(+), ::Type{T}, ::F1)` b. `operate(::typeof(+), ::Type{T}, ::F1, ::F2)`  
c. `operate(::typeof(+), ::Type{T}, ::F1...)`
2. - a. `operate(::typeof(-), ::Type{T}, ::F)` b. `operate(::typeof(-), ::Type{T}, ::F1, ::F2)`
3. \* a. `operate(::typeof(*), ::Type{T}, ::T, ::F)` b. `operate(::typeof(*), ::Type{T}, ::F, ::T)` c. `operate(::typeof(*), ::Type{T}, ::F1, ::F2)` where `F1` and `F2` are `VariableIndex` or `ScalarAffineFunction` d. `operate(::typeof(*), ::Type{T}, ::Diagonal{T}, ::F)`
4. / a. `operate(::typeof(/), ::Type{T}, ::F, ::T)`
5. `vcat` a. `operate(::typeof(vcat), ::Type{T}, ::F...)`
6. `imag` a. `operate(::typeof(imag), ::Type{T}, ::F)` where `F` is `VariableIndex` or `VectorOfVariables`

One assumption is that the element type `T` is invariant under each operation. That is, `op(::T, ::T)::T` where `op` is a `+`, `-`, `*`, and `/`.

In each case, `F` (or `F1` and `F2`) is one of the ten supported types, with a restriction that the mathematical operation makes sense, for example, we don't define `promote_operation(-, T, F1, F2)` where `F1` is a scalar-valued function and `F2` is a vector-valued function. The ten supported types are:

1. `::T`
2. `::VariableIndex`
3. `::ScalarAffineFunction{T}`
4. `::ScalarQuadraticFunction{T}`
5. `::ScalarNonlinearFunction`
6. `::AbstractVector{T}`
7. `::VectorOfVariables`
8. `::VectorAffineFunction{T}`
9. `::VectorQuadraticFunction{T}`
10. `::VectorNonlinearFunction`

[source](#)

`MathOptInterface.Utilities.operate!` – Function.

```
operate!(
    op::Function,
    ::Type{T},
    args::Union{T, MOI.AbstractFunction}...,
) ::MOI.AbstractFunction where {T<:Number}
```

Returns an MOI.AbstractFunction representing the function resulting from the operation `op(args...)` on functions of coefficient type `T`.

The first argument may be modified, in which case the return value is identical to the first argument. For operations which cannot be implemented in-place, this function returns a new object.

[source](#)

`MathOptInterface.Utilities.operate_output_index!` – Function.

```
operate_output_index!(
    op::Union{typeof(+), typeof(-)},
    ::Type{T},
    output_index::Integer,
    f::Union{AbstractVector{T}, MOI.AbstractVectorFunction},
    g::Union{T, MOI.AbstractScalarFunction}...
) where {T<:Number}
```

Return an MOI.AbstractVectorFunction in which the scalar function in row `output_index` is the result of `op(f[output_index], g)`.

The functions at output index different to `output_index` are the same as the functions at the same output index in `func`. The first argument may be modified.

### Methods

1. `+ a. operate_output_index!(+, ::Type{T}, ::Int, ::VectorF, ::ScalarF)`
2. `- a. operate_output_index!(-, ::Type{T}, ::Int, ::VectorF, ::ScalarF)`

[source](#)

`MathOptInterface.Utilities.vectorize` – Function.

```
vectorize(x::AbstractVector{<:Number})
```

Returns `x`.

[source](#)

```
vectorize(x::AbstractVector{MOI.VariableIndex})
```

Returns the vector of scalar affine functions in the form of a MOI.VectorAffineFunction{T}.

[source](#)

```
vectorize(funcs::AbstractVector{MOI.ScalarAffineFunction{T}}) where T
```

Returns the vector of scalar affine functions in the form of a MOI.VectorAffineFunction{T}.

[source](#)

```
vectorize(funcs::AbstractVector{MOI.ScalarQuadraticFunction{T}}) where T
```

Returns the vector of scalar quadratic functions in the form of a MOI.VectorQuadraticFunction{T}.

[source](#)

### Constraint utilities

The following utilities are available for moving the function constant to the set for scalar constraints:

`MathOptInterface.Utilities.shift_constant` - Function.

```
shift_constant(set::MOI.AbstractScalarSet, offset)
```

Returns a new scalar set `new_set` such that `func-in-set` is equivalent to `func + offset-in-new_set`.

Use `supports_shift_constant` to check if the set supports shifting:

```
if MOI.Utilities.supports_shift_constant(typeof(set))
    new_set = MOI.Utilities.shift_constant(set, -func.constant)
    func.constant = 0
    MOI.add_constraint(model, func, new_set)
else
    MOI.add_constraint(model, func, set)
end
```

### Note for developers

Only define this function if it makes sense and you have implemented `supports_shift_constant` to return true.

### Example

```
julia> import MathOptInterface as MOI

julia> set = MOI.Interval(-2.0, 3.0)
MathOptInterface.Interval{Float64}(-2.0, 3.0)

julia> MOI.Utilities.supports_shift_constant(typeof(set))
true

julia> MOI.Utilities.shift_constant(set, 1.0)
MathOptInterface.Interval{Float64}(-1.0, 4.0)
```

[source](#)

`MathOptInterface.Utilities.supports_shift_constant` - Function.

```
supports_shift_constant(::Type{S}) where {S<:MOI.AbstractSet}
```

Return true if `shift_constant` is defined for set S.

See also `shift_constant`.

### Example

```
julia> import MathOptInterface as MOI

julia> MOI.Utilities.supports_shift_constant(MOI.Interval{Float64})
true

julia> MOI.Utilities.supports_shift_constant(MOI.ZeroOne)
false
```

[source](#)

`MathOptInterface.Utilities.normalize_and_add_constraint` - Function.

```
normalize_and_add_constraint(
    model::MOI.ModelLike,
    func::MOI.AbstractScalarFunction,
    set::MOI.AbstractScalarSet;
    allow_modify_function::Bool = false,
)
```

Adds the scalar constraint obtained by moving the constant term in `func` to the set in `model`. If `allow_modify_function` is true then the function `func` can be modified.

[source](#)

`MathOptInterface.Utilities.normalize_constant` - Function.

```
normalize_constant(
    func::MOI.AbstractScalarFunction,
    set::MOI.AbstractScalarSet;
    allow_modify_function::Bool = false,
)
```

Return the `func`-in-set constraint in normalized form. That is, if `func` is `MOI.ScalarQuadraticFunction` or `MOI.ScalarAffineFunction`, the constant is moved to the set. If `allow_modify_function` is true then the function `func` can be modified.

[source](#)

The following utility identifies those constraints imposing bounds on a given variable, and returns those bound values:

`MathOptInterface.Utilities.get_bounds` - Function.

```
get_bounds(model::MOI.ModelLike, ::Type{T}, x::MOI.VariableIndex)
```

Return a tuple (lb, ub) of type Tuple{T, T}, where lb and ub are lower and upper bounds, respectively, imposed on x in model.

[source](#)

```
get_bounds(
    model::MOI.ModelLike,
    bounds_cache::Dict{MOI.VariableIndex,NTuple{2,T}},
    f::MOI.ScalarAffineFunction{T},
) where {T} --> Union{Nothing,NTuple{2,T}}
```

Return the lower and upper bound of f as a tuple. If the domain is not bounded, return nothing.

[source](#)

```
get_bounds(
    model::MOI.ModelLike,
    bounds_cache::Dict{MOI.VariableIndex,NTuple{2,T}},
    x::MOI.VariableIndex,
) where {T} --> Union{Nothing,NTuple{2,T}}
```

Return the lower and upper bound of x as a tuple. If the domain is not bounded, return nothing.

Similar to get\_bounds(::MOI.ModelLike, ::Type{T}, ::MOI.VariableIndex), except that the second argument is a cache which maps variables to their bounds and avoids repeated lookups.

[source](#)

The following utilities are useful when working with symmetric matrix cones.

`MathOptInterface.Utilities.is_diagonal_vectorized_index` – Function.

```
is_diagonal_vectorized_index(index::Base.Integer)
```

Return whether index is the index of a diagonal element in a `MOI.AbstractSymmetricMatrixSetTriangle` set.

[source](#)

`MathOptInterface.Utilities.side_dimension_for_vectorized_dimension` – Function.

```
side_dimension_for_vectorized_dimension(n::Integer)
```

Return the dimension d such that `MOI.dimension(MOI.PositiveSemidefiniteConeTriangle(d))` is n.

[source](#)

### Set utilities

The following utilities are available for sets:

`MathOptInterface.Utilities.AbstractDistance` – Type.

```
abstract type AbstractDistance end
```

An abstract type used to enable dispatch of `Utilities.distance_to_set`.

`source`

`MathOptInterface.Utilities.ProjectionUpperBoundDistance` – Type.

```
ProjectionUpperBoundDistance() <: AbstractDistance
```

An upper bound on the minimum distance between point and the closest feasible point in set.

#### Definition of distance

The minimum distance is computed as:

$$d(x, \mathcal{K}) = \min_{y \in \mathcal{K}} \|x - y\|$$

where  $x$  is point and  $\mathcal{K}$  is set. The norm is computed as:

$$\|x\| = \sqrt{f(x, x, \mathcal{K})}$$

where  $f$  is `Utilities.set_dot`.

In the default case, where the set does not have a specialized method for `Utilities.set_dot`, the norm is equivalent to the Euclidean norm  $\|x\| = \sqrt{\sum x_i^2}$ .

#### Why an upper bound?

In most cases, `distance_to_set` should return the smallest upper bound, but it may return a larger value if the smallest upper bound is expensive to compute.

For example, given an epigraph from of a conic set,  $\{(t, x) | f(x) \leq t\}$ , it may be simpler to return  $\delta$  such that  $f(x) \leq t + \delta$ , rather than computing the nearest projection onto the set.

If the distance is not the smallest upper bound, the docstring of the appropriate `distance_to_set` method *must* describe the way that the distance is computed.

`source`

`MathOptInterface.Utilities.distance_to_set` – Function.

```
distance_to_set(
    [d::AbstractDistance = ProjectionUpperBoundDistance(),],
    point::T,
    set::MOI.AbstractScalarSet,
```

```
) where {T}

distance_to_set(
    [d::AbstractDistance = ProjectionUpperBoundDistance(),]
    point::AbstractVector{T},
    set::MOI.AbstractVectorSet,
) where {T}
```

Compute the distance between point and set using the distance metric d. If point is in the set set, this function *must* return zero(T).

If d is omitted, the default distance is `Utilities.ProjectionUpperBoundDistance`.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.RotatedSecondOrderCone)
```

Let  $(t, u, y\dots) = x$ . Return the 2-norm of the vector d such that in  $x + d$ , u is projected to 1 if  $u \leq 0$ , and t is increased such that  $x + d$  belongs to the set.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.ExponentialCone)
```

Let  $(u, v, w) = x$ . If  $v > 0$ , return the epigraph distance d such that  $(u, v, w + d)$  belongs to the set.

If  $v \leq 0$  return the 2-norm of the vector d such that  $x + d = (u, 1, z)$  where z satisfies the constraints.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.DualExponentialCone)
```

Let  $(u, v, w) = x$ . If  $u < 0$ , return the epigraph distance d such that  $(u, v, w + d)$  belongs to the set.

If  $u \geq 0$  return the 2-norm of the vector d such that  $x + d = (u, -1, z)$  where z satisfies the constraints.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.GeometricMeanCone)
```

Let  $(t, y\dots) = x$ . If all y are non-negative, return the epigraph distance d such that  $(t + d, y\dots)$  belongs to the set.

If any y are strictly negative, return the 2-norm of the vector d that projects negative y elements to 0 and t to  $\mathbb{R}_-$ .

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.PowerCone)
```

Let  $(a, b, c) = x$ . If a and b are non-negative, return the epigraph distance required to increase c such that the constraint is satisfied.

If  $a$  or  $b$  is strictly negative, return the 2-norm of the vector  $d$  such that in the vector  $x + d$ :  $c$ , and any negative  $a$  and  $b$  are projected to 0.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.DualPowerCone)
```

Let  $(a, b, c) = x$ . If  $a$  and  $b$  are non-negative, return the epigraph distance required to increase  $c$  such that the constraint is satisfied.

If  $a$  or  $b$  is strictly negative, return the 2-norm of the vector  $d$  such that in the vector  $x + d$ :  $c$ , and any negative  $a$  and  $b$  are projected to 0.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.NormOneCone)
```

Let  $(t, y...) = x$ . Return the epigraph distance  $d$  such that  $(t + d, y...)$  belongs to the set.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.NormInfinityCone)
```

Let  $(t, y...) = x$ . Return the epigraph distance  $d$  such that  $(t + d, y...)$  belongs to the set.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, ::MOI.RelativeEntropyCone)
```

Let  $(u, v..., w...) = x$ . If  $v$  and  $w$  are strictly positive, return the epigraph distance required to increase  $u$  such that the constraint is satisfied.

If any elements in  $v$  or  $w$  are non-positive, return the 2-norm of the vector  $d$  such that in the vector  $x + d$ : any non-positive elements in  $v$  and  $w$  are projected to 1, and  $u$  is projected such that the epigraph constraint holds.

`source`

```
distance_to_set(::ProjectionUpperBoundDistance, x, set::MOI.NormCone)
```

Let  $(t, y...) = x$ . Return the epigraph distance  $d$  such that  $(t + d, y...)$  belongs to the set.

`source`

`MathOptInterface.Utilities.set_dot` - Function.

```
set_dot(x::AbstractVector, y::AbstractVector, set::AbstractVectorSet)
```

Return the scalar product between a vector  $x$  of the set  $set$  and a vector  $y$  of the dual of the set  $s$ .

`source`

```
set_dot(x, y, set::AbstractScalarSet)
```

Return the scalar product between a number x of the set set and a number y of the dual of the set s.

[source](#)

### DoubleDicts

MathOptInterface.Utilities.DoubleDicts.DoubleDict - Type.

```
DoubleDict{V}
```

An optimized dictionary to map MOI.ConstraintIndex to values of type V.

Works as a AbstractDict{MOI.ConstraintIndex,V} with minimal differences.

If V is also a MOI.ConstraintIndex, use [IndexDoubleDict](#).

Note that MOI.ConstraintIndex is not a concrete type, opposed to MOI.ConstraintIndex{MOI.VariableIndex, MOI.Integers}, which is a concrete type.

When looping through multiple keys of the same Function-in-Set type, use

```
inner = dict[F, S]
```

to return a type-stable [DoubleDictInner](#).

[source](#)

MathOptInterface.Utilities.DoubleDicts.DoubleDictInner - Type.

```
DoubleDictInner{F,S,V}
```

A type stable inner dictionary of [DoubleDict](#).

[source](#)

MathOptInterface.Utilities.DoubleDicts.IndexDoubleDict - Type.

```
IndexDoubleDict
```

A specialized version of [DoubleDict] in which the values are of type MOI.ConstraintIndex

When looping through multiple keys of the same Function-in-Set type, use

```
inner = dict[F, S]
```

to return a type-stable [IndexDoubleDictInner](#).

[source](#)

`MathOptInterface.Utilities.DoubleDicts.IndexDoubleDictInner` – Type.

```
IndexDoubleDictInner{F,S}
```

A type stable inner dictionary of `IndexDoubleDict`.

[source](#)

`MathOptInterface.Utilities.DoubleDicts.outer_keys` – Function.

```
outer_keys(d::AbstractDoubleDict)
```

Return an iterator over the outer keys of the `AbstractDoubleDict` `d`. Each outer key is a `Tuple{Type,Type}` so that a double loop can be easily used:

```
for (F, S) in DoubleDicts.outer_keys(dict)
    for (k, v) in dict[F, S]
        # ...
    end
end
```

For performance, it is recommended that the inner loop lies in a separate function to guarantee type-stability. Some outer keys (`F, S`) might lead to an empty `dict[F, S]`. If you want only nonempty `dict[F, S]`, use `nonempty_outer_keys`.

[source](#)

`MathOptInterface.Utilities.DoubleDicts.nonempty_outer_keys` – Function.

```
nonempty_outer_keys(d::AbstractDoubleDict)
```

Return a vector of outer keys of the `AbstractDoubleDict` `d`.

Only outer keys that have a nonempty set of inner keys will be returned.

Each outer key is a `Tuple{Type,Type}` so that a double loop can be easily used

```
for (F, S) in DoubleDicts.nonempty_outer_keys(dict)
    for (k, v) in dict[F, S]
        # ...
    end
end
```

For performance, it is recommended that the inner loop lies `in` a separate `function` to guarantee type-stability.

If you want an iterator of all current outer keys, use `[`outer_keys`](@ref)`.

[source](#)

## 36.6 Test

### Overview

#### The Test submodule

The Test submodule provides tools to help solvers implement unit tests in order to ensure they implement the MathOptInterface API correctly, and to check for solver-correctness.

We use a centralized repository of tests, so that if we find a bug in one solver, instead of adding a test to that particular repository, we add it here so that all solvers can benefit.

#### How to test a solver

The skeleton below can be used for the wrapper test file of a solver named FooBar.

```
# ===== /test/MOI_wrapper.jl =====
module TestFooBar

import FooBar
using Test

import MathOptInterface as MOI

const OPTIMIZER = MOI.instantiate(
    MOI.OptimizerWithAttributes(FooBar.Optimizer, MOI.Silent() => true),
)

const BRIDGED = MOI.instantiate(
    MOI.OptimizerWithAttributes(FooBar.Optimizer, MOI.Silent() => true),
    with_bridge_type = Float64,
)

# See the docstring of MOI.Test.Config for other arguments.
const CONFIG = MOI.Test.Config(
    # Modify tolerances as necessary.
    atol = 1e-6,
    rtol = 1e-6,
    # Use MOI.LOCALLY_SOLVED for local solvers.
    optimal_status = MOI.OPTIMAL,
    # Pass attributes or MOI functions to `exclude` to skip tests that
    # rely on this functionality.
    exclude = Any[MOI.VariableName, MOI.delete],
)

"""
    runtests()

```

This function runs all functions in the this Module starting with `test\_`.

```
"""
function runtests()
    for name in names(@__MODULE__; all = true)
        if startswith("$(name)", "test_")
            @testset "$(name)" begin
                getfield(@__MODULE__, name)()
            end
        end
    end
end
```

```

    end
end

"""

test_runtests()

This function runs all the tests in MathOptInterface.Test.

Pass arguments to `exclude` to skip tests for functionality that is not
implemented or that your solver doesn't support.

"""

function test_runtests()
    MOI.Test.runtests(
        BRIDGED,
        CONFIG,
        exclude = [
            "test_attribute_NumberOfThreads",
            "test_quadratic_",
        ],
        # This argument is useful to prevent tests from failing on future
        # releases of MOI that add new tests. Don't let this number get too far
        # behind the current MOI release though. You should periodically check
        # for new tests to fix bugs and implement new features.
        exclude_tests_after = v"0.10.5",
    )
    return
end

"""

test_SolverName()

You can also write new tests for solver-specific functionality. Write each new
test as a function with a name beginning with `test_`.

"""

function test_SolverName()
    @test MOI.get(FooBar.Optimizer(), MOI.SolverName()) == "FooBar"
    return
end

end # module TestFooBar

# This line at the end of the file runs all the tests!
TestFooBar.runtests()

```

Then modify your runtests.jl file to include the MOI\_wrapper.jl file:

```

# ===== /test/runtests.jl =====

using Test

@testset "MOI" begin
    include("test/MOI_wrapper.jl")
end

```

**Info**

The optimizer BRIDGED constructed with `instantiate` automatically bridges constraints that are not supported by OPTIMIZER using the bridges listed in [Bridges](#). It is recommended for an implementation of MOI to only support constraints that are natively supported by the solver and let bridges transform the constraint to the appropriate form. For this reason it is expected that tests may not pass if OPTIMIZER is used instead of BRIDGED.

**How to debug a failing test**

When writing a solver, it's likely that you will initially fail many tests. Some failures will be bugs, but other failures you may choose to exclude.

There are two ways to exclude tests:

- Exclude tests whose names contain a string using:

```
MOI.Test.runitests(
    model,
    config;
    exclude = String["test_to_exclude", "test_conic_"],
)
```

This will exclude tests whose name contains either of the two strings provided.

- Exclude tests which rely on specific functionality using:

```
MOI.Test.Config(exclude = Any[MOI.VariableName, MOI.optimize!])
```

This will exclude tests which use the `MOI.VariableName` attribute, or which call `MOI.optimize!`.

Each test that fails can be independently called as:

```
model = FooBar.Optimizer()
config = MOI.Test.Config()
MOI.empty!(model)
MOI.Test.test_category_name_that_failed(model, config)
```

You can look-up the source code of the test that failed by searching for it in the `src/Test/test_category.jl` file.

**Tip**

Each test function also has a docstring that explains what the test is for. Use `? MOI.Test.test_category_name_that_failed` from the REPL to read it.

Periodically, you should re-run excluded tests to see if they now pass. The easiest way to do this is to swap the `exclude` keyword argument of `runitests` to `include`. For example:

```
MOI.Test.runtests(
    model,
    config;
    exclude = String["test_to_exclude", "test_conic_"],
)
```

becomes

```
MOI.Test.runtests(
    model,
    config;
    include = String["test_to_exclude", "test_conic_"],
)
```

## How to add a test

To detect bugs in solvers, we add new tests to MOI.Test.

As an example, ECOS errored calling `optimize!` twice in a row. (See [ECOS.jl PR #72](#).) We could add a test to ECOS.jl, but that would only stop us from re-introducing the bug to ECOS.jl in the future, but it would not catch other solvers in the ecosystem with the same bug. Instead, if we add a test to MOI.Test, then all solvers will also check that they handle a double optimize call.

For this test, we care about correctness, rather than performance. therefore, we don't expect solvers to efficiently decide that they have already solved the problem, only that calling `optimize!` twice doesn't throw an error or give the wrong answer.

### Step 1

Install the MathOptInterface julia package in `dev mode`:

```
julia> ]
(@v1.6) pkg> dev MathOptInterface
```

### Step 2

From here on, proceed with making the following changes in the `~/ .julia/dev/MathOptInterface` folder (or equivalent dev path on your machine).

### Step 3

Since the double-optimize error involves solving an optimization problem, add a new test to [src/Test/test\\_solve.jl](#):

```
"""
    test_unit_optimize!_twice(model::MOI.ModelLike, config::Config)

Test that calling `MOI.optimize!` twice does not error.

This problem was first detected in ECOS.jl PR#72:
https://github.com/jump-dev/ECOS.jl/pull/72
"""

function test_unit_optimize!_twice(
    model::MOI.ModelLike,
```

```

config)::Config{T},
) where {T}
    # Use the `@requires` macro to check conditions that the test function
    # requires to run. Models failing this `@requires` check will silently skip
    # the test.
    @requires MOI.supports_constraint(
        model,
        MOI.VariableIndex,
        MOI.GreaterThan{Float64},
    )
    @requires _supports(config, MOI.optimize!)
    # If needed, you can test that the model is empty at the start of the test.
    # You can assume that this will be the case for tests run via `runtests`.
    # User's calling tests individually need to call `MOI.empty!` themselves.
    @test MOI.is_empty(model)
    # Create a simple model. Try to make this as simple as possible so that the
    # majority of solvers can run the test.
    x = MOI.add_variable(model)
    MOI.add_constraint(model, x, MOI.GreaterThan(one(T)))
    MOI.set(model, MOI.ObjectiveSense(), MOI.MIN_SENSE)
    MOI.set(
        model,
        MOI.ObjectiveFunction{MOI.VariableIndex}(),
        x,
    )
    # The main component of the test: does calling `optimize!` twice error?
    MOI.optimize!(model)
    MOI.optimize!(model)
    # Check we have a solution.
    @test MOI.get(model, MOI.TerminationStatus()) == MOI.OPTIMAL
    # There is a three-argument version of `Base.isapprox` for checking
    # approximate equality based on the tolerances defined in `config`:
    @test isapprox(MOI.get(model, MOI.VariablePrimal()), x), one(T), config)
    # For code-style, these tests should always `return` `nothing`.
    return
end

```

**Info**

Make sure the function is agnostic to the number type T; don't assume it is a Float64 capable solver.

We also need to write a test for the test. Place this function immediately below the test you just wrote in the same file:

```

function setup_test(
    ::typeof(test_unit_optimize!_twice),
    model::MOI.Utilities.MockOptimizer,
    ::Config,
)
    MOI.Utilities.set_mock_optimize!(
        model,
        (mock::MOI.Utilities.MockOptimizer) -> MOIU.mock_optimize!(
            mock,
            MOI.OPTIMAL,

```

```

        (MOI.FEASIBLE_POINT, [1.0]),
    ),
)
return
end

```

Finally, you also need to implement `Test.version_added`. If we added this test when the latest released version of MOI was v0.10.5, define:

```
version_added(::typeof(test_unit_optimize!_twice)) = v"0.10.6"
```

## Step 6

Commit the changes to git from `~/ .julia/dev/MathOptInterface` and submit the PR for review.

### Tip

If you need help writing a test, [open an issue on GitHub](#), or ask the [Developer Chatroom](#).

## API Reference

### The Test submodule

Functions to help test implementations of MOI. See [The Test submodule](#) for more details.

`MathOptInterface.Test.Config` - Type.

```

Config(
    ::Type{T} = Float64;
    atol::Real = Base.rtoldefault(T),
    rtol::Real = Base.rtoldefault(T),
    optimal_status::MOI.TerminationStatusCode = MOI.OPTIMAL,
    infeasible_status::MOI.TerminationStatusCode = MOI.INFEASIBLE,
    exclude::Vector{Any} = Any[],
) where {T}

```

Return an object that is used to configure various tests.

### Configuration arguments

- `atol::Real = Base.rtoldefault(T)`: Control the absolute tolerance used when comparing solutions.
- `rtol::Real = Base.rtoldefault(T)`: Control the relative tolerance used when comparing solutions.
- `optimal_status = MOI.OPTIMAL`: Set to `MOI.LOCALLY_SOLVED` if the solver cannot prove global optimality.
- `infeasible_status = MOI.INFEASIBLE`: Set to `MOI.LOCALLY_INFEASIBLE` if the solver cannot prove global infeasibility.
- `exclude = Vector{Any}`: Pass attributes or functions to `exclude` to skip parts of tests that require certain functionality. Common arguments include:

- MOI.delete to skip deletion-related tests
- MOI.optimize! to skip optimize-related tests
- MOI.ConstraintDual to skip dual-related tests
- MOI.VariableName to skip setting variable names
- MOI.ConstraintName to skip setting constraint names

### Example

For a nonlinear solver that finds local optima and does not support finding dual variables or constraint names:

```
julia> import MathOptInterface as MOI

julia> config = MOI.Test.Config(
        Float64;
        optimal_status = MOI.LOCALLY_SOLVED,
        exclude = Any[
            MOI.ConstraintDual,
            MOI.VariableName,
            MOI.ConstraintName,
            MOI.delete,
        ],
    );
;
```

[source](#)

MathOptInterface.Test.runtests – Function.

```
runtests(
    model::MOI.ModelLike,
    config::Config;
    include::Vector{Union{String,Regex}} = String[],
    exclude::Vector{Union{String,Regex}} = String[],
    warn_unsupported::Bool = false,
    exclude_tests_after::VersionNumber = v"999.0.0",
    verbose::Bool = false,
)
```

Run all tests in MathOptInterface.Test on model.

### Configuration arguments

- config is a `Test.Config` object that can be used to modify the behavior of tests.
- If include is not empty, only run tests if an element from include occurs in the name of the test.
- If exclude is not empty, skip tests if an element from exclude occurs in the name of the test.
- exclude takes priority over include.
- If warn\_unsupported is false, runtests will silently skip tests that fail with a `MOI.NotAllowedError`, `MOI.UnsupportedError`, or `RequirementUnmet` error. (The latter is thrown when an @requires statement returns false.) When warn\_unsupported is true, a warning will be printed. For most cases the default behavior, false, is what you want, since these tests likely test functionality that is not supported by model. However, it can be useful to run warn\_unsupported = true to check you are not skipping tests due to a missing `supports_constraint` method or equivalent.

- `exclude_tests_after` is a version number that excludes any tests to MOI added after that version number. This is useful for solvers who can declare a fixed set of tests, and not cause their tests to break if a new patch of MOI is released with a new test.
- `verbose` is a Bool that controls whether the name of the test is printed before executing it. This can be helpful when debugging.

See also: [setup\\_test](#).

### Example

```
config = MathOptInterface.Test.Config()
MathOptInterface.Test.runtests(
    model,
    config;
    include = ["test_linear_", r"^\$test_model_Name\$"],
    exclude = ["VariablePrimalStart"],
    warn_unsupported = true,
    verbose = true,
    exclude_tests_after = v"0.10.5",
)
```

[source](#)

`MathOptInterface.Test.setup_test` - Function.

```
setup_test(::typeof(f), model::MOI.ModelLike, config::Config)
```

Overload this method to modify `model` before running the test function `f` on `model` with `config`. You can also modify the fields in `config` (for example, to loosen the default tolerances).

This function should either return nothing, or return a function which, when called with zero arguments, undoes the setup to return the model to its previous state. You do not need to undo any modifications to `config`.

This function is most useful when writing new tests of the tests for MOI, but it can also be used to set test-specific tolerances, etc.

See also: [runtests](#)

### Example

```
function MOI.Test.setup_test(
    ::typeof(MOI.Test.test_linear_VariablePrimalStart_partial),
    mock::MOIU.MockOptimizer,
    ::MOI.Test.Config,
)
    MOIU.set_mock_optimize!(
        mock,
        (mock::MOIU.MockOptimizer) -> MOIU.mock_optimize!(mock, [1.0, 0.0]),
    )
    mock.eval_variable_constraint_dual = false

    function reset_function()
```

```

        mock.eval_variable_constraint_dual = true
    return
end
return reset_function
end

```

`source`  
`MathOptInterface.Test.version_added - Function.`

```
version_added(::typeof(function_name))
```

Returns the version of MOI in which the test `function_name` was added.

This method should be implemented for all new tests.

See the `exclude_tests_after` keyword of `runtests` for more details.

`source`  
`MathOptInterface.Test.@requires - Macro.`

```
@requires(x)
```

Check that the condition `x` is `true`. Otherwise, throw an `RequirementUnmet` error to indicate that the model does not support something required by the test function.

### Example

```
@requires MOI.supports(model, MOI.Silent())
@test MOI.get(model, MOI.Silent())
```

`source`  
`MathOptInterface.Test.RequirementUnmet - Type.`

```
RequirementUnmet(msg::String) <: Exception
```

An error for throwing in tests to indicate that the model does not support some requirement expected by the test function.

`source`  
`MathOptInterface.Test.HS071 - Type.`

```
HS071(
    enable_hessian::Bool,
    enable_hessian_vector_product::Bool = false,
)
```

An `MOI.AbstractNLPEvaluator` for the problem:

$$\begin{aligned} & \min x_1 * x_4 * (x_1 + x_2 + x_3) + x_3 \\ & \text{subject to } x_1 * x_2 * x_3 * x_4 \geq 25 \\ & \quad x_1^2 + x_2^2 + x_3^2 + x_4^2 = 40 \\ & \quad 1 \leq x_1, x_2, x_3, x_4 \leq 5 \end{aligned}$$

The optimal solution is [1.000, 4.743, 3.821, 1.379].

`source`

## Chapter 37

# Developer Docs

### 37.1 Checklists

The purpose of this page is to collate a series of checklists for commonly performed changes to the source code of MathOptInterface.

In each case, copy the checklist into the description of the pull request.

#### Making a release

Use this checklist when making a release of the MathOptInterface repository.

```
## Basic

- [ ] `version` field of `Project.toml` has been updated
  - If a breaking change, increment the MAJOR field and reset others to 0
  - If adding new features, increment the MINOR field and reset PATCH to 0
  - If adding bug fixes or documentation changes, increment the PATCH field

## Documentation

- [ ] Add a new entry to `docs/src/changelog.md`, following existing style

## Tests

- [ ] The `solver-tests.yml` GitHub action does not have unexpected failures.
  To run the action, go to:
  https://github.com/jump-dev/MathOptInterface.jl/actions/workflows/solver-tests.yml
  and click "Run workflow"
```

#### Adding a new set

Use this checklist when adding a new set to the MathOptInterface repository.

```
## Basic

- [ ] Add a new `AbstractScalarSet` or `AbstractVectorSet` to `src/sets.jl`
- [ ] If `isbitstype(S) == false`, implement `Base.copy(set::S)`
- [ ] If `isbitstype(S) == false`, implement `Base.:(==)(x::S, y::S)`
```

```

- [ ] If an `AbstractVectorSet`, implement `dimension(set::S)`, unless the
      dimension is given by `set.dimension`.

## Utilities

- [ ] If an `AbstractVectorSet`, implement `Utilities.set_dot`,
      unless the dot product between two vectors in the set is equivalent to
      `LinearAlgebra.dot`
- [ ] If an `AbstractVectorSet`, implement `Utilities.set_with_dimension` in
      `src/Utilities/matrix_of_constraints.jl`
- [ ] Add the set to the `@model` macro at the bottom of `src/Utilities.model.jl`

## Documentation

- [ ] Add a docstring, which gives the mathematical definition of the set,
      along with an `## Example` block containing a `jldoctest`
- [ ] Add the docstring to `docs/src/reference/standard_form.md`
- [ ] Add the set to the relevant table in `docs/src/manual/standard_form.md`

## Tests

- [ ] Define a new `_set(::Type{S})` method in `src/Test/test_basic_constraint.jl`
      and add the name of the set to the list at the bottom of that file
- [ ] If the set has any checks in its constructor, add tests to `test/sets.jl`

## MathOptFormat

- [ ] Open an issue at `https://github.com/jump-dev/MathOptFormat` to add
      support for the new set {{ replace with link to the issue }}

## Optional

- [ ] Implement `dual_set(::S)` and `dual_set_type(::Type{S})`
- [ ] Add new tests to the `Test` submodule exercising your new set
- [ ] Add new bridges to convert your set into more commonly used sets

```

## Adding a new bridge

Use this checklist when adding a new bridge to the MathOptInterface repository.

The steps are mostly the same, but locations depend on whether the bridge is a `Constraint`, `Objective`, or `Variable` bridge. In each case below, replace XXX with the appropriate type of bridge.

```

## Basic

- [ ] Create a new file in `src/Bridges/XXX/bridges` named after the type of
      the bridge
- [ ] Define the bridge, following existing examples. The name of the bridge
      struct must end in `Bridge`
- [ ] Check if your bridge can be a subtype of [`MOI.Bridges.Constraint.SetMapBridge`](@ref)
- [ ] Define a new `const` that is a `SingleBridgeOptimizer` wrapping the
      new bridge. The name of the const must be the name of the bridge, less
      the `Bridge` suffix
- [ ] If the bridge should be enabled by default, add the bridge to

```

```

`add_all_bridges` at the bottom of `src/Bridges/XXX/XXX.jl`

## Tests

- [ ] Create a new file in the appropriate subdirectory of `tests/Bridges/XXX`
      named after the type of the bridge
- [ ] Use `MOI.Bridges.runitests` to test various inputs and outputs of the
      bridge
- [ ] If, after opening the pull request to add the bridge, some lines are not
      covered by the tests, add additional bridge-specific tests to cover the
      untested lines.

## Documentation

- [ ] Add a docstring which uses the same template as existing bridges.

## Final touch

If the bridge depends on run-time values of other variables and constraints in
the model:

- [ ] Implement `MOI.Utilities.needs_final_touch(::Bridge)`
- [ ] Implement `MOI.Utilities.final_touch(::Bridge, ::MOI.ModelLike)`
- [ ] Ensure that `final_touch` can be called multiple times in a row

```

## Updating MathOptFormat

Use this checklist when updating the version of MathOptFormat.

```

## Basic

- [ ] The file at `src/FileFormats/MOF/mof.schema.json` is updated
- [ ] The constant `_SUPPORTED VERSIONS` is updated in
      `src/FileFormats/MOF/MOF.jl`

## New sets

- [ ] New sets are added to the `@model` in `src/FileFormats/MOF/MOF.jl`
- [ ] New sets are added to the `@enum` in `src/FileFormats/MOF/read.jl`
- [ ] `set_to_moi` is defined for each set in `src/FileFormats/MOF/read.jl`
- [ ] `head_name` is defined for each set in `src/FileFormats/MOF/write.jl`
- [ ] A new unit test calling `test_model_equality` is added to
      `test/FileFormats/MOF/MOF.jl`

## Tests

- [ ] The version field in `test/FileFormats/MOF/nlp.mof.json` is updated

## Documentation

- [ ] The version fields are updated in `docs/src/submodules/FileFormats/overview.md`

```