# sasoptpy Documentation

***Release 1.0.0-alpha***

**SAS Institute Inc.**

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# CONTENTS

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*sasoptpy* is a Python package that provides a modeling interface for SAS Viya and SAS/OR optimization solvers. It provides a quick way for users to deploy optimization models and solve them by using the SAS Viya Optimization Action Set.

*sasoptpy* can handle linear, mixed integer linear, nonlinear, and black-box optimization problems. You can use native Python structures like dictionaries, tuples, and lists to define an optimization problem. *sasoptpy* supports Pandas objects extensively.

Under the hood, *sasoptpy* uses the swat package to communicate with SAS Viya, and uses the saspy package to communicate with SAS 9.4 installations.

*sasoptpy* is an interface to SAS Optimization solvers. Check SAS/OR and PROC OPTMODEL for more details about optimization tools provided by SAS and an interface to model optimization problems inside SAS.

See the SAS Global Forum paper: Optimization Modeling with Python and SAS Viya

CHAPTER

ONE

# OVERVIEW

## 1.1 About sasoptpy

**sasoptpy** is a Python package that provides easy and integrated ways of working with SAS Optimization and SAS/OR optimization solvers. It enables developers to model optimization problems with ease by providing high-level building blocks.

### 1.1.1 Capabilities

sasoptpy is very flexible in terms of optimization problem types it supports and workflow alternatives.

#### Solvers

It currently supports the following model types:

- Linear problems
- Integer linear problems / Mixed integer linear problems
- Quadratic problems
- Nonlinear / Black-box problems

#### Data

It supports working with both client-side data and server-side data. When data are available on the client-side, it populates the model with integrated data and brings the solution back to the client. When data are available on the server-side, it generates the code to be able to populate the model on the server. You can retrieve the final solution after the solve.

#### Platforms

sasoptpy can be used with SAS Viya 3.3 or later and SAS 9.4, in all the supporting operating systems.

### 1.1.2 Road map

sasoptpy has the broader goal of supporting all the functionality of the SAS Optimization and SAS/OR solvers, and providing a high-level set of tools for easily working with models.

### 1.1.3 Versioning

sasoptpy follows Semantic Versioning as of version 1.0.0.

- Any backwards incompatible changes increase the major version number (X.y.z).
- Minor changes and improvements increase the the minor version number (x.Y.z).
- Patches increase the patch version number (x.y.Z).
- Pre-releases are marked by using *alpha* and *beta*, and release candidates are marked using *rc* identifiers.

### 1.1.4 License

sasoptpy is an open-source package and uses the standard *Apache 2.0 license*.

### 1.1.5 Support

Have any questions?

- If you have a package-related issue, feel free to report it on GitHub.
- If you have an optimization-related question, consider asking it on SAS Communities.
- For further technical support, reach SAS Technical Support.

### 1.1.6 Contribution

Contributions are always welcome. Clone the project to your working environment and submit pull requests as you see fit. For more details, see the guidelines at the GitHub repository.

### 1.1.7 Highlighted Works

A list of highlighted projects and blog posts:

- Fastest, cheapest, greenest: How will football fans choose which matches to attend?
- 1 tournament, 12 countries: A logistical maze?
- Using SAS Optimization with Python and containers
- Bringing Analytics to the Soccer Transfer Season
- Visiting all 30 Major League Baseball Stadiums - with Python and SAS Viya

## 1.2 What's New

### 1.2.1 v1.0.0-alpha (TBD)

#### New Features

- Added workspaces; see more info in *User Guide* and *example*
- Added *configurations*
- Added *abstract actions* that allow server-side operations. Highlights include:
  - `actions.read_data()` and `actions.create_data()`
  - `actions.for_loop()` and `actions.cofor_loop()`
  - `actions.print_item()`
  - `actions.solve()`
- Added structure decorators for better control of submissions

#### Changes

- Refactored the entire package. sasoptpy now has *core*, *abstract*, *interface*, *session*, and *util* directories
- Experimental RESTful API was dropped
- *get_obj_by_name* function was removed
- *lso* solver was renamed to *blackbox*
- Because of the use of literal strings (**PEP 498**), only Python 3.6 or later versions are supported

#### Bug Fixes

- Fixed: Arithmetic operations with powers are generating incorrect results
- Fixed: Variable groups with space in their index are not getting values
- Fixed: Constraints without directions do not produce an error
- Fixed: Documentation does not mention conda-forge library requirement
- Fixed: Single-dimensional parameters are hard to access

## 1.3 License

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CHAPTER

TWO

# INSTALLATION

## 2.1 Python version support and dependencies

*sasoptpy* is developed and tested for Python version 3.6+.

It requires the following packages:

- numpy
- saspy
- swat
- pandas

## 2.2 Getting sasoptpy

You can install *sasoptpy* by using *pip* or *conda*:

```
pip install sasoptpy

conda install -c sas-institute sasoptpy
```

Any dependencies should be installed automatically.

Depending on your installation, you might need to add *conda-forge* channel to *conda* by using:

```
conda config --append channels conda-forge
```

### 2.2.1 GitHub repository

You can also get stable and development versions of *sasoptpy* from the GitHub repository. To get the latest version, call:

```
git clone https://github.com/sassoftware/sasoptpy.git
```

Then inside the sasoptpy folder, call:

```
pip install .
```

Alternatively, you can use:

```
python setup.py install
```

CHAPTER

# THREE

# USER GUIDE

## 3.1 Introduction to Optimization

Optimization is an umbrella term for maximizing or minimizing a given target, which can be represented as a function. It is often used in real-life problems from finance to aviation, from chemistry to sports analytics.

Optimization problems can describe a business problem or a physical concept. Any phenomena that can be represented as a function can be optimized by several algorithms. It lies at the heart of several tools we use every day, from routing to Machine Learning.

### 3.1.1 Steps of Optimization

Optimization problems often consists of the following steps[1,2]:

1. Observe the system and define the problem
2. Gather relevant data
3. Develop a formulation
4. Solve the model
5. Interpret the solution

Often, a process is observed by the modeler to identify the problems. Several examples are finding the shortest path between two locations, maximizing a profit, and maximizing the accuracy of a handwriting recognition algorithm.

Collecting data is often the most daunting process. In the age of big data, it is often difficult to distinguish noise from relevant data. After data are gathered, you can write a formulation. A proper formulation is critical because features such as linearity and convexity greatly impact the performance of solution algorithms, especially for large problems.

Solving a model requires an optimization algorithm. SAS Optimization provides several optimization algorithms to solve a variety of different formulations. See *types of optimization* for more information on this topic.

Finally, the modeler should decide whether the result of an optimization process is valid. If not, the process should be repeated by adding the missing pieces until a satisfactory result is obtained.

[1] Hillier, Frederick S., and Gerald J. Lieberman. Introduction to operations research. McGraw-Hill Science, Engineering & Mathematics, 1995.

[2] SAS Institute. SAS/OR 15.1 User's Guide: Mathematical Programming Examples. SAS institute, 2018.

### 3.1.2 Basic Elements

There might be several elements in the definition of an optimization formulation. To clarify these elements, consider an optimization problem of finding a route from your home to the airport.

1. **Variables**: Variables are parameters that the optimization algorithm tunes. In the example, the decisions of which roads to be used are decision variables. An optimization algorithm determines optimal values for variables in the problem.
2. **Objective**: An objective is the measure of performance that is to be maximized or minimized. An objective is a function of variables in a problem, meaning an objective value is obtained for given values of variables in an optimization problem. In the example, the objective function is the time to reach the airport. The optimization algorithm should decide which roads to use in order to minimize the travel time.
3. **Constraints**: Constraints are restrictions on variables that prevent illogical solutions. In the example, the amount of fuel in the car places a restriction on how far you can drive. You can the force optimization algorithm to find a solution under a certain mileage, even if there are other solutions which could be shorter in terms of travel time.

In short, *optimization* is choosing **variable** values to maximize or minimize an **objective** function subject to certain **constraints**.

### 3.1.3 Simple Problem

Let us consider a simple example. The following problem (Brewer's Dilemma) is a simplified Resource Allocation problem, presented by Robert G. Bland[3].

In the problem, a brewer has limited corn, hops, and barley malt inventory. The brewer wants to produce Ale and Beer that will maximize the total profit. Each product requires a certain amount of these three ingredients, as follows:

| (per barrel) | Amount Required | | | |
|---|---|---|---|---|
| Product | Corn | Hops | Barley Malt | Profit |
| Ale | 5 pounds | 4 ounces | 35 pounds | $13 |
| Beer | 15 pounds | 4 ounces | 20 pounds | $23 |
| (Total Available) | 480 pounds | 160 ounces | 1,190 pounds | |

The **variables** in this problem are to decide how many barrels of ale and beer to produce. Let us call them *ale* and *beer*. It might be intuitive to prefer beer to ale due to its higher profit rate. However, doing so might deplete all the resources faster and might leave you with excess amount of hops and barley malt.

The **objective** in this problem is to maximize the total profit function, which is $13 \cdot \text{ale} + 23 \cdot \text{beer}$.

Each limitation on ingredients is a **constraint**. For corn, hops, and barley malt, the following constrains apply:

$$5 \cdot \text{ale} + 15 \cdot \text{beer} \leq 480$$
$$4 \cdot \text{ale} + 4 \cdot \text{beer} \leq 160$$
$$35 \cdot \text{ale} + 20 \cdot \text{beer} \leq 1,190$$

Combining all items, the optimization formulation is written as follows:

$$\begin{array}{lllll}
\text{maximize:} & 13 \cdot \text{ale} & +23 \cdot \text{beer} & & \\
\text{subject to:} & & & & \\
 & 5 \cdot \text{ale} & + 15 \cdot \text{beer} & \leq & 480 \\
 & 4 \cdot \text{ale} & + 4 \cdot \text{beer} & \leq & 160 \\
 & 35 \cdot \text{ale} & + 20 \cdot \text{beer} & \leq & 1,190 \\
 & & \text{ale} & \geq & 0 \\
 & & \text{beer} & \geq & 0
\end{array}$$

[3] Bland, Robert G. "The Allocation of Resources by Linear Programming." Scientific American 244 (1981): 126-144.

This problem is small enough to be solved by hand, but let us consider some alternatives.

| | Barrels produced | | |
|---|---|---|---|
| # | Ale | Beer | Profit |
| 1 | 34 | 0 | $442 |
| 2 | 0 | 32 | $736 |
| 3 | 15 | 25 | $770 |
| 4 | 12 | 28 | $800 |

Producing only ale or beer is inferior to producing a combination of the two, for obvious reasons. Finding the exact ratio that will maximize the profit might be tricky, as seen in solutions 3 and 4. Indeed, solution 4 gives the optimal values that maximize the profit in this example.

Some additional examples of problems that can be formulated as optimization problems are as follows:

- Scheduling project steps to minimize total completion, where tasks might depend on completion of earlier tasks
- Choosing distribution centers for retailers to minimize total cost while satisfying customer demands on time
- Assigning soccer players to a squad to maximize the total rating of the team under foreign player rules
- Finding the cheapest travel option and shortest route between two cities
- Blending chemical products to minimize the total cost while achieving a certain efficiency of detergents
- Choosing a price that will maximize the total profit in a competitive market

See the related section of SAS Optimization 8.5 Mathematical Optimization Procedures[4] for more information about optimization problems and examples.

### 3.1.4 Types of Optimization

The structure of a formulation affects which algorithms can be deployed to solve a problem. The most common optimization types are as follows:

- **Linear optimization**: If the objective function and all constraints of a problem can be described by linear mathematical relations, and if all decision variables are continuous, the formulation is called a Linear problem (LP). LPs are one of the easiest problems in terms of solution time and well-studied in literature.
- **Mixed integer linear optimization**: If a linear formulation involves binary (on/off type decisions) or integer variables, that problem is an Integer Linear Problem (ILP) or Mixed Integer Linear Problem (MILP) depending on variables. MILPs are very popular as many real-life problems can be represented as MILPs.
- **Nonlinear optimization**: If a problem involves nonlinear objectives or constraints (such as exponential, polynomial, absolute values) the problem is called a nonlinear problem (NLP).

[4] https://go.documentation.sas.com/?cdcId=pgmsascdc&cdcVersion=9.4_3.5&docsetId=casmopt&docsetTarget=casmopt_intro_toc.htm&locale=en

## 3.2 Basic Functionality

Solving an optimization problem via *sasoptpy* starts with having a running CAS (SAS Viya) Server or having a SAS 9.4 installation. It is possible to model a problem without a connection but solving a problem requires access to SAS Optimization or SAS/OR solvers at runtime.

### 3.2.1 Creating a session

#### Creating a SAS Viya session

*sasoptpy* uses the CAS connection provided by the swat package. After installation simply use:

```
In [1]: from swat import CAS

In [2]: s = CAS(hostname, port, userid, password)
```

The last two parameters are optional for some use cases. See swat Documentation for more details.

#### Creating a SAS 9.4 session

To create a SAS 9.4 session, see saspy Documentation. After customizing the configurations for your setup, you can create a session as follows:

```
import saspy
s = saspy.SASsession(cfgname='winlocal')
```

### 3.2.2 Initializing a model

After creating an active CAS or SAS session, you can create an empty model as follows:

```
In [3]: import sasoptpy as so

In [4]: m = so.Model(name='my_first_model', session=s)
NOTE: Initialized model my_first_model.
```

This command creates an empty model.

### 3.2.3 Processing input data

The easiest way to work with *sasoptpy* is to define problem inputs as Pandas DataFrames. You can define objective and cost coefficients, and lower and upper bounds by using the DataFrame and Series objects. See Pandas Documentation to learn more.

```
In [5]: import pandas as pd

In [6]: prob_data = pd.DataFrame([
   ...:     ['Period1', 30, 5],
   ...:     ['Period2', 15, 5],
   ...:     ['Period3', 25, 0]
   ...:     ], columns=['period', 'demand', 'min_prod']).set_index(['period'])
   ...:
```

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```
In [7]: price_per_product = 10

In [8]: capacity_cost = 10
```

You can extract the set `PERIODS` and the other fields `demand` and `min_production` as follows:

```
In [9]: PERIODS = prob_data.index.tolist()

In [10]: demand = prob_data['demand']

In [11]: min_production = prob_data['min_prod']
```

### 3.2.4 Adding variables

You can add a single variable or a set of variables to *Model* objects.

- *Model.add_variable()* method is used to add a single variable.

  ```
  In [12]: production_cap = m.add_variable(vartype=so.INT, name='production_cap',␣
  ↪lb=0)
  ```

  When working with multiple models, you can create a variable independent of the model, such as

  ```
  >>> production_cap = so.Variable(name='production_cap', vartype=so.INT, lb=0)
  ```

  and add it to an existing model by using

  ```
  >>> m.include(production_cap)
  ```

- The *Model.add_variables()* method is used to add a set of variables.

  ```
  In [13]: production = m.add_variables(PERIODS, vartype=so.INT, name='production',
     ....:                                lb=min_production)
     ....:
  ```

  When passed as a set of variables, you can retrieve individual variables by using individual keys, such as `production['Period1']`. To create multidimensional variables, simply list all the keys as follows:

  ```
  >>> multivar = m.add_variables(KEYS1, KEYS2, KEYS3, name='multivar')
  ```

### 3.2.5 Creating expressions

*Expression* objects hold mathematical expressions. Although these objects are mostly used under the hood when defining a model, it is possible to define a custom *Expression* to use later.

```
In [14]: totalRevenue = production.sum('*')*price_per_product

In [15]: totalCost = production_cap * capacity_cost
```

Note the use of the *VariableGroup.sum()* method over a variable group. This method returns the sum of variables inside the group as an *Expression* object. Its multiplication with a scalar `price_per_product` gives the final expression.

Similarly, `totalCost` is simply multiplication of a *Variable* object with a scalar.

### 3.2.6 Setting an objective function

You can define objective functions in terms of expressions. In this problem, the objective is to maximize the profit, so the *Model.set_objective()* method is used as follows:

```
In [16]: m.set_objective(totalRevenue-totalCost, sense=so.MAX, name='totalProfit')
Out[16]: sasoptpy.Expression(exp = 10 * production[Period1] + 10 *␣
↪production[Period2] + 10 * production[Period3] - 10 * production_cap, name=
↪'totalProfit')
```

Notice that you can define the same objective by using:

```
>>> m.set_objective(production.sum('*')*price_per_product - production_cap*capacity_
↪cost, sense=so.MAX, name='totalProfit')
```

The mandatory argument `sense` should be assigned the value of either `so.MIN` or `so.MAX` for minimization or maximization problems, respectively.

### 3.2.7 Adding constraints

In *sasoptpy*, constraints are simply expressions with a direction. It is possible to define an expression and add it to a model by defining which direction the linear relation should have.

There are two methods to add constraints. The first one is *Model.add_constraint()* where a single constraint can be added to a model.

The second one is *Model.add_constraints()* where multiple constraints can be added to a model.

```
In [17]: m.add_constraints((production[i] <= production_cap for i in PERIODS),
   ....:                    name='capacity')
   ....:
Out[17]: sasoptpy.ConstraintGroup([production[Period1] - production_cap <=  0,␣
↪production[Period2] - production_cap <=  0, production[Period3] - production_cap <=␣
↪ 0], name='capacity')
```

```
In [18]: m.add_constraints((production[i] <= demand[i] for i in PERIODS),
   ....:                    name='demand')
   ....:
Out[18]: sasoptpy.ConstraintGroup([production[Period1] <=  30, production[Period2] <=␣
↪ 15, production[Period3] <=  25], name='demand')
```

Here, the first term provides a Python generator, which then gets translated into constraints in the problem. The symbols <=, >=, and == are used for less than or equal to, greater than or equal to, and equal to constraints, respectively. You can define range constraints by using == symbol and a list of two values that represent lower and upper bounds.

```
In [19]: m.add_constraint(production['Period1'] == [10, 100], name='production_bounds
↪')
Out[19]: sasoptpy.Constraint(production[Period1] ==  [10, 100], name='production_
↪bounds')
```

### 3.2.8 Solving a problem

After a problem is defined, you can send it to the CAS server or SAS session by calling the *Model.solve()* method. The *Model.solve()* method returns the primal solution when available, and None otherwise.

```
In [20]: m.solve()
NOTE: Added action set 'optimization'.
NOTE: Converting model my_first_model to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 4 variables (0 free, 0 fixed).
NOTE: The problem has 0 binary and 4 integer variables.
NOTE: The problem has 7 linear constraints (6 LE, 0 EQ, 0 GE, 1 range).
NOTE: The problem has 10 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed all variables and constraints.
NOTE: Optimal.
NOTE: Objective = 400.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 4 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 7 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
Out[20]:
Selected Rows from Table SOLUTION

     i                  var  value   lb             ub  rc
0  1.0       production_cap   25.0 -0.0  1.797693e+308 NaN
1  2.0  production[Period1]   25.0  5.0  1.797693e+308 NaN
2  3.0  production[Period2]   15.0  5.0  1.797693e+308 NaN
3  4.0  production[Period3]   25.0 -0.0  1.797693e+308 NaN
```

At the end of the solve operation, the solver returns both Problem Summary and Solution Summary tables. These tables can later be accessed by using m.get_problem_summary() and m.get_solution_summary().

```
In [21]: print(m.get_solution_summary())
Selected Rows from Table SOLUTIONSUMMARY

                                Value
Label
Solver                           MILP
Algorithm              Branch and Cut
Objective Function        totalProfit
Solution Status               Optimal
Objective Value                   400

Relative Gap                        0
Absolute Gap                        0
Primal Infeasibility                0
Bound Infeasibility                 0
Integer Infeasibility               0

Best Bound                        400
```

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```
Nodes                               0
Solutions Found                     3
Iterations                          0
Presolve Time                    0.00
Solution Time                    0.02
```

### 3.2.9 Printing solutions

You can retrieve the solutions by using the `sasoptpy.get_solution_table()` method. It is strongly suggested to group variables and expressions that share the same keys in a call.

```
In [22]: print(so.get_solution_table(demand, production))
        demand  production
period
Period1     30        25.0
Period2     15        15.0
Period3     25        25.0
```

As seen, a Pandas Series and a Variable object that have the same index keys are printed in this example.

### 3.2.10 Initializing a workspace

If you would like to use extensive abstract modeling capabilities of *sasoptpy*, you can create a workspace. Workspaces support features like server-side for loops, cofor loops (parallel), read data, and create data. You can initialize a `sasoptpy.Workspace` by using Python's *with* keyword. As an example, you can create a workspace with a set and a variable group as follows:

```
In [23]: def create_workspace():
   ....:     with so.Workspace(name='my_workspace', session=s) as w:
   ....:         I = so.Set(name='I', value=range(1, 11))
   ....:         x = so.VariableGroup(I, name='x', lb=0)
   ....:     return w
   ....:
```

```
In [24]: workspace = create_workspace()

In [25]: print(so.to_optmodel(workspace))
proc optmodel;
   set I = 1..10;
   var x {{I}} >= 0;
quit;
```

You can submit a workspace to a CAS server and retrieve the response by using:

```
In [26]: workspace.submit()
NOTE: Added action set 'optimization'.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 10 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 0 rows and 4 columns.
Out[26]:
Selected Rows from Table SOLUTION

      i    var  value   lb              ub  rc
```

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```
0   1.0   x[1]    0.0  0.0  1.797693e+308 NaN
1   2.0   x[2]    0.0  0.0  1.797693e+308 NaN
2   3.0   x[3]    0.0  0.0  1.797693e+308 NaN
3   4.0   x[4]    0.0  0.0  1.797693e+308 NaN
4   5.0   x[5]    0.0  0.0  1.797693e+308 NaN
5   6.0   x[6]    0.0  0.0  1.797693e+308 NaN
6   7.0   x[7]    0.0  0.0  1.797693e+308 NaN
7   8.0   x[8]    0.0  0.0  1.797693e+308 NaN
8   9.0   x[9]    0.0  0.0  1.797693e+308 NaN
9  10.0  x[10]    0.0  0.0  1.797693e+308 NaN
```

### 3.2.11 Package configurations

You can change the default options regarding problem representation as follows:

```
In [27]: x = so.Variable(name='x')

In [28]: c = so.Constraint(10 / 3 * x + 1e-20 * x ** 2 <= 30 + 1e-11, name='c')

In [29]: print(so.to_definition(c))
con c : 3.333333333333 * x + 0.0 * ((x) ^ (2)) <= 30.00000000001;
```

```
In [30]: so.config['max_digits'] = 2
```

```
In [31]: print(so.to_definition(c))
con c : 3.33 * x + 0.0 * ((x) ^ (2)) <= 30.0;
```

```
In [32]: so.config['max_digits'] = None
```

```
In [33]: print(so.to_definition(c))
con c : 3.3333333333333335 * x + 1e-20 * ((x) ^ (2)) <= 30.00000000001;
```

You can reset the options as follows:

```
In [34]: del so.config['max_digits']
```

You can also create a new configuration to be used globally:

```
In [35]: so.config['myvalue'] = 2
```

All default configuration options are as follows:

- verbosity (default 3)
- max_digits (default 12)
- print_digits (default 6)
- default_sense (default so.minimization)
- default_bounds
- valid_outcomes

## 3.3 Sessions

### 3.3.1 CAS Sessions

A `swat.cas.connection.CAS` session is needed to solve optimization problems with *sasoptpy* by using SAS Viya optimization solvers. See the SAS documentation to learn more about CAS sessions and SAS Viya.

You can create a sample CAS Session as follows:

```
>>> import sasoptpy as so
>>> from swat import CAS
>>> s = CAS(hostname=cas_host, username=cas_username, password=cas_password, port=cas_
↪port)
>>> m = so.Model(name='demo', session=s)
>>> print(repr(m))
sasoptpy.Model(name='demo', session=CAS(hostname, port, username, protocol='cas',␣
↪name='py-session-1', session=session-no))
```

You can end the session and close the connection as follows:

```
>>> s.terminate()
```

### 3.3.2 SAS Sessions

A `saspy.SASsession` session is needed to solve optimization problems with *sasoptpy* by using SAS/OR solvers on SAS 9.4 clients.

You can create a sample SAS session as follows:

```
>>> import sasoptpy as so
>>> import saspy
>>> sas_session = saspy.SASsession(cfgname='winlocal')
>>> m = so.Model(name='demo', session=sas_session)
>>> print(repr(m))
sasoptpy.Model(name='demo', session=saspy.SASsession(cfgname='winlocal'))
```

It is possible to connect to a SAS session by using a configuration file

```
In [1]: sas = saspy.SASsession(cfgfile=config_file)
Using SAS Config named: sshsas
SAS Connection established. Subprocess id is 8722
```

```
In [2]: m = so.Model(name='demo', session=sas)
NOTE: Initialized model demo.
```

```
In [3]: print(m.get_session().sasver)
9.04.01M6P11072018
```

You can terminate the SAS session as follows:

```
In [4]: sas.endsas()
SAS Connection terminated. Subprocess id was 8722
```

## 3.4 Models

### 3.4.1 Creating a model

You can create an empty model by using the *Model* constructor:

```
In [1]: import sasoptpy as so

In [2]: m = so.Model(name='model1')
NOTE: Initialized model model1.
```

### 3.4.2 Adding new components to a model

Adding a variable:

```
In [3]: x = m.add_variable(name='x', vartype=so.BIN)

In [4]: print(m)
Model: [
  Name: model1
  Objective: MIN [0]
  Variables (1): [
    x
  ]
  Constraints (0): [
  ]
]

In [5]: y = m.add_variable(name='y', lb=1, ub=10)

In [6]: print(m)
Model: [
  Name: model1
  Objective: MIN [0]
  Variables (2): [
    x
    y
  ]
  Constraints (0): [
  ]
]
```

Adding a constraint:

```
In [7]: c1 = m.add_constraint(x + 2 * y <= 10, name='c1')

In [8]: print(m)
Model: [
  Name: model1
  Objective: MIN [0]
  Variables (2): [
    x
    y
  ]
  Constraints (1): [
```

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```
    x + 2 * y <=  10
  ]
]
```

### 3.4.3 Adding existing components to a model

A new model can use existing variables. The typical way to include a variable is to use the *Model.include()* method:

```
In [9]: new_model = so.Model(name='new_model')
NOTE: Initialized model new_model.

In [10]: new_model.include(x, y)

In [11]: print(new_model)
Model: [
  Name: new_model
  Objective: MIN [0]
  Variables (2): [
    x
    y
  ]
  Constraints (0): [
  ]
]

In [12]: new_model.include(c1)

In [13]: print(new_model)
Model: [
  Name: new_model
  Objective: MIN [0]
  Variables (2): [
    x
    y
  ]
  Constraints (1): [
    x + 2 * y <=  10
  ]
]

In [14]: z = so.Variable(name='z', vartype=so.INT, lb=3)

In [15]: new_model.include(z)

In [16]: print(new_model)
Model: [
  Name: new_model
  Objective: MIN [0]
  Variables (3): [
    x
    y
    z
  ]
  Constraints (1): [
```

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```
    x + 2 * y <=  10
  ]
]
```

Note that variables are added to `Model` objects by reference. Therefore, after `Model.solve()` is called, the values of variables are replaced with optimal values.

### 3.4.4 Accessing components

You can get a list of model variables by using the `Model.get_variables()` method:

```
In [17]: print(m.get_variables())
[sasoptpy.Variable(name='x', lb=0, ub=1,  vartype='BIN'), sasoptpy.Variable(name='y',␣
↪lb=1, ub=10,  vartype='CONT')]
```

Similarly, you can access a list of constraints by using the `Model.get_constraints()` method:

```
In [18]: c2 = m.add_constraint(2 * x - y >= 1, name='c2')

In [19]: print(m.get_constraints())
[sasoptpy.Constraint(x + 2 * y <=  10, name='c1'), sasoptpy.Constraint(2 * x - y >= ␣
↪1, name='c2')]
```

To access a certain constraint by using its name, you can use the `Model.get_constraint()` method:

```
In [20]: print(m.get_constraint('c2'))
2 * x - y >=  1
```

### 3.4.5 Dropping components

You can drop a variable inside a model by using `Model.drop_variable()` method. Similarly, you can drop a set of variables by using the `Model.drop_variables()` method.

```
In [21]: m.drop_variable(y)

In [22]: print(m)
Model: [
  Name: model1
  Objective: MIN [0]
  Variables (1): [
    x
  ]
  Constraints (2): [
    x + 2 * y <=  10
    2 * x - y >=  1
  ]
]
```

```
In [23]: m.include(y)

In [24]: print(m)
Model: [
  Name: model1
```

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```
  Objective: MIN [0]
  Variables (2): [
    x
    y
  ]
  Constraints (2): [
    x + 2 * y <=  10
    2 * x - y >=  1
  ]
]
```

You can drop a constraint by using the `Model.drop_constraint()` method. Similarly, you can drop a set of constraints by using the `Model.drop_constraints()` method.

```
In [25]: m.drop_constraint(c1)

In [26]: m.drop_constraint(c2)

In [27]: print(m)
Model: [
  Name: model1
  Objective: MIN [0]
  Variables (2): [
    x
    y
  ]
  Constraints (0): [
  ]
]
```

```
In [28]: m.include(c1)

In [29]: print(m)
Model: [
  Name: model1
  Objective: MIN [0]
  Variables (2): [
    x
    y
  ]
  Constraints (1): [
    x + 2 * y <=  10
  ]
]
```

### 3.4.6 Copying a model

You can copy an existing model by including the `Model` object itself.

```
In [30]: copy_model = so.Model(name='copy_model')
NOTE: Initialized model copy_model.

In [31]: copy_model.include(m)

In [32]: print(copy_model)
Model: [
  Name: copy_model
  Objective: MIN [0]
  Variables (2): [
    x
    y
  ]
  Constraints (1): [
    x + 2 * y <=  10
  ]
]
```

Note that all variables and constraints are included by reference.

### 3.4.7 Solving a model

A model is solved by using the `Model.solve()` method. This method converts Python definitions into an MPS file and uploads it to a CAS server for the optimization action. The type of the optimization problem is determined based on the variable types and expressions.

```
>>> m.solve()
NOTE: Initialized model model_1
NOTE: Converting model model_1 to DataFrame
NOTE: Added action set 'optimization'.
...
NOTE: Optimal.
NOTE: Objective = 124.343.
NOTE: The Dual Simplex solve time is 0.01 seconds.
```

### 3.4.8 Solve options

#### Solver Options

You can pass both PROC OPTMODEL solve options and `solveLp`, `solveMilp` action options by using the `options` argument of the `Model.solve()` method.

```
>>> m.solve(options={'with': 'milp', 'maxtime': 600})
>>> m.solve(options={'with': 'lp', 'algorithm': 'ipm'})
```

The only special option for the `Model.solve()` method is `with`. If not passed, PROC OPTMODEL chooses a solver that depends on the problem type. Possible `with` options are listed in the SAS/OR documentation.

You can find specific solver options in the SAS Optimization documentation:

- LP solver options

- MILP solver options
- NLP solver options
- QP solver options
- BLACKBOX solver options

The `options` argument can also pass `solveLp` and `solveMilp` action options when `frame=True` is used when calling the `Model.solve()` method.

- solveLp options
- solveMilp options

#### Package Options

Besides the `options` argument, you can pass following arguments into the `Model.solve()` method:

- name: Name of the uploaded problem information
- drop: Option for dropping the data from server after the solve
- replace: Option for replacing an existing data with the same name
- primalin: Option for using the current values of the variables as an initial solution
- submit: Option for calling the CAS / SAS action
- frame: Option for using frame (MPS) method (if False, it uses OPTMODEL)
- verbose: Option for printing the generated OPTMODEL code before solve

When `primalin` argument is `True`, it grabs `Variable` objects `_init` field. You can modify this field by using the `Variable.set_init()` method.

### 3.4.9 Getting solutions

After the solve is completed, all variable and constraint values are parsed automatically. You can access a summary of the problem by using the `Model.get_problem_summary()` method, and a summary of the solution by using the `Model.get_solution_summary()` method.

To print the values of any object, you can use the `get_solution_table()` method:

```
>>> print(so.get_solution_table(x, y))
```

All variables and constraints passed into this method are returned based on their indices. See *Examples* for more details.

### 3.4.10 Tuning MILP model parameters

SAS Optimization solvers provide a variety of settings. However, it might be difficult to find the best settings for a given model. In order to compare and obtain a good choice of parameters, you can use the *optimization.tune* action for mixed-integer linear optimization problems.

The `Model.tune_parameters()` method is a wrapper for the tune action. Consider the following knapsack problem example:

```
In [33]: def get_model():
   ....:     m = so.Model(name='knapsack_with_tuner', session=cas_conn)
   ....:     data = [
   ....:         ['clock', 8, 4, 3],
   ....:         ['mug', 10, 6, 5],
   ....:         ['headphone', 15, 7, 2],
   ....:         ['book', 20, 12, 10],
   ....:         ['pen', 1, 1, 15]
   ....:     ]
   ....:     df = pd.DataFrame(data, columns=['item', 'value', 'weight', 'limit']).set_
↪index(['item'])
   ....:     ITEMS = df.index
   ....:     value = df['value']
   ....:     weight = df['weight']
   ....:     limit = df['limit']
   ....:     total_weight = 55
   ....:     get = m.add_variables(ITEMS, name='get', vartype=so.INT)
   ....:     m.add_constraints((get[i] <= limit[i] for i in ITEMS), name='limit_con')
   ....:     m.add_constraint(so.quick_sum(weight[i] * get[i] for i in ITEMS) <= total_
↪weight, name='weight_con')
   ....:     total_value = so.quick_sum(value[i] * get[i] for i in ITEMS)
   ....:     m.set_objective(total_value, name='total_value', sense=so.MAX)
   ....:     return m
   ....:

In [34]: m = get_model()
NOTE: Initialized model knapsack_with_tuner.
```

For this problem, you can compare configurations as follows:

```
In [35]: results = m.tune_parameters(tunerParameters={'maxConfigs': 10})
NOTE: Added action set 'optimization'.
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table KNAPSACK_WITH_
↪TUNER in caslib CASUSER(casuser).
NOTE: The table KNAPSACK_WITH_TUNER has been created in caslib CASUSER(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Start to tune the MILP
         SolveCalls  Configurations    BestTime        Time
                  1               1       0.19*        0.26
                  2               2       0.19*        0.46
                  3               3       0.19*        0.65
                  4               4       0.19*        0.85
                  5               5       0.19*        1.04
                  6               6       0.19*        1.23
                  7               7       0.19*        1.43
                  8               8       0.19*        1.62
                  9               9       0.19*        1.81
                 10              10       0.19*        2.01
NOTE: Configuration limit reached.
NOTE: The tuning time is 2.01 seconds.
```

```
In [36]: print(results)
   Configuration conflictSearch  cutGomory cutMiLifted cutStrategy  \
0            0.0      automatic  automatic   automatic   automatic
1            1.0       moderate       none   automatic   automatic
2            2.0           none       none    moderate  aggressive
```

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```
3           3.0      automatic       none        none    moderate
4           4.0     aggressive       none  aggressive        none
5           5.0     aggressive       none        none  aggressive
6           6.0       moderate       none   automatic    moderate
7           7.0           none   moderate    moderate        none
8           8.0           none   moderate  aggressive        none
9           9.0           none   moderate  aggressive        none

  cutZeroHalf heuristics           nodelSel  presolver      probe   restarts  \
0   automatic  automatic          automatic  automatic  automatic  automatic
1        none  automatic          automatic       none       none      basic
2        none  automatic  bestEstimatedepth   moderate       none      basic
3    moderate  automatic          automatic       none  automatic       none
4    moderate  automatic          bestBound   moderate  automatic       none
5    moderate       none              depth  automatic  automatic       none
6  aggressive       none          bestBound   moderate  automatic       none
7  aggressive       none              depth  automatic  automatic  automatic
8  aggressive  automatic              depth      basic      basic   moderate
9  aggressive  automatic              depth   moderate      basic   moderate

     symmetry      varSel  Mean of Run Times  Sum of Run Times  \
0   automatic   automatic               0.18              0.18
1   automatic      pseudo               0.16              0.16
2        none   automatic               0.17              0.17
3       basic   minInfeas               0.16              0.16
4    moderate  ryanFoster               0.17              0.17
5  aggressive   minInfeas               0.17              0.17
6   automatic  ryanFoster               0.16              0.16
7        none   minInfeas               0.16              0.16
8       basic   minInfeas               0.17              0.17
9       basic   minInfeas               0.17              0.17

   Percentage Successful
0                    0.0
1                    0.0
2                    0.0
3                    0.0
4                    0.0
5                    0.0
6                    0.0
7                    0.0
8                    0.0
9                    0.0
```

`Model.tune_parameters()` accepts three main arguments

- milpParameters
- tunerParameters
- tuningParameters

For a full set of tuning parameters and acceptable values of these arguments, see the SAS Optimization documentation[1].

For the example problem, you can tune the *presolver*, *cutStrategy*, and *strongIter* settings, by using initial values and candidate values, and limit the maximum number of configurations and maximum running time as follows:

[1] https://go.documentation.sas.com/?cdcId=pgmsascdc&cdcVersion=9.4_3.5&docsetId=casactmopt&docsetTarget=casactmopt_optimization_details37.htm

```
In [37]: results = m.tune_parameters(
   ....:     milpParameters={'maxtime': 10},
   ....:     tunerParameters={'maxConfigs': 20, 'logfreq': 5},
   ....:     tuningParameters=[
   ....:         {'option': 'presolver', 'initial': 'none', 'values': ['basic',
↪'aggressive', 'none']},
   ....:         {'option': 'cutStrategy'},
   ....:         {'option': 'strongIter', 'initial': -1, 'values': [-1, 100, 1000]}
   ....:     ])
   ....:
NOTE: Added action set 'optimization'.
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table KNAPSACK_WITH_
↪TUNER in caslib CASUSER(casuser).
NOTE: The table KNAPSACK_WITH_TUNER has been created in caslib CASUSER(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Start to tune the MILP
         SolveCalls  Configurations    BestTime        Time
                  5               5        0.17*       1.00
                 10              10        0.17*       2.03
                 15              15        0.17*       3.00
                 20              20        0.17*       3.98
NOTE: Configuration limit reached.
NOTE: The tuning time is 3.98 seconds.
```

```
In [38]: print(results)
    Configuration conflictSearch  cutGomory cutMiLifted cutStrategy  \
0             0.0      automatic  automatic   automatic   automatic
1             1.0       moderate       none   automatic   automatic
2             2.0           none       none    moderate  aggressive
3             3.0      automatic       none        none    moderate
4             4.0     aggressive       none  aggressive        none
5             5.0     aggressive       none        none  aggressive
6             6.0       moderate       none   automatic    moderate
7             7.0           none   moderate    moderate        none
8             8.0     aggressive   moderate  aggressive   automatic
9             9.0     aggressive   moderate  aggressive   automatic
10           10.0     aggressive   moderate    moderate   automatic
11           11.0     aggressive   moderate  aggressive   automatic
12           12.0     aggressive   moderate  aggressive   automatic
13           13.0     aggressive  automatic  aggressive   automatic
14           14.0     aggressive   moderate  aggressive   automatic
15           15.0     aggressive   moderate  aggressive   automatic
16           16.0     aggressive   moderate  aggressive   automatic
17           17.0      automatic  automatic   automatic   automatic
18           18.0      automatic  automatic   automatic   automatic
19           19.0      automatic  automatic   automatic   automatic

   cutZeroHalf  heuristics           nodelSel  presolver      probe  \
0    automatic   automatic          automatic  automatic  automatic
1         none   automatic          automatic       none       none
2         none   automatic  bestEstimatedepth   moderate       none
3     moderate   automatic          automatic       none  automatic
4     moderate   automatic          bestBound   moderate  automatic
5     moderate        none              depth  automatic  automatic
6   aggressive        none          bestBound   moderate  automatic
7   aggressive        none              depth  automatic  automatic
```

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```
8         none    moderate            depth   moderate       none
9   aggressive    moderate        bestBound   moderate       none
10        none    moderate        bestBound   moderate       none
11        none    moderate        bestBound   moderate       none
12        none    moderate        bestBound   moderate      basic
13        none    moderate        bestBound   moderate       none
14        none    moderate        automatic   moderate       none
15        none    moderate        bestBound      basic       none
16        none    moderate        bestBound   moderate       none
17   automatic   automatic        bestBound  automatic  automatic
18   automatic  aggressive        automatic  automatic  automatic
19   automatic   automatic        automatic  automatic  automatic

     restarts    symmetry      varSel  Mean of Run Times  Sum of Run Times  \
0   automatic   automatic   automatic               0.17              0.17
1       basic   automatic      pseudo               0.17              0.17
2       basic        none   automatic               0.17              0.17
3        none       basic   minInfeas               0.17              0.17
4        none    moderate  ryanFoster               0.16              0.16
5        none  aggressive   minInfeas               0.17              0.17
6        none   automatic  ryanFoster               0.17              0.17
7   automatic        none   minInfeas               0.17              0.17
8       basic   automatic      pseudo               0.16              0.16
9       basic   automatic      pseudo               0.17              0.17
10      basic   automatic      pseudo               0.16              0.16
11      basic   automatic   maxInfeas               0.17              0.17
12      basic   automatic      pseudo               0.17              0.17
13      basic   automatic      pseudo               0.16              0.16
14      basic   automatic      pseudo               0.16              0.16
15      basic   automatic      pseudo               0.17              0.17
16      basic   automatic      pseudo               0.17              0.17
17  automatic   automatic   automatic               0.17              0.17
18  automatic   automatic   automatic               0.17              0.17
19  automatic        none   automatic               0.17              0.17

    Percentage Successful
0                     0.0
1                     0.0
2                     0.0
3                     0.0
4                     0.0
5                     0.0
6                     0.0
7                     0.0
8                     0.0
9                     0.0
10                    0.0
11                    0.0
12                    0.0
13                    0.0
14                    0.0
15                    0.0
16                    0.0
17                    0.0
18                    0.0
19                    0.0
```

You can retrieve full details by using the `Model.get_tuner_results()` method.

## 3.5 Model components

In this section, several model components are discussed with examples. See *Examples* to learn more about how you can use these components to define optimization models.

### 3.5.1 Expressions

`Expression` objects represent linear and nonlinear mathematical expressions in *sasoptpy*.

#### Creating expressions

You can create an `Expression` object as follows:

```
In [1]: profit = so.Expression(5 * sales - 3 * material, name='profit')

In [2]: print(repr(profit))
sasoptpy.Expression(exp = 5 * sales - 3 * material, name='profit')
```

#### Nonlinear expressions

`Expression` objects are linear by default. It is possible to create nonlinear expressions, but there are some limitations.

```
In [3]: nonexp = sales ** 2 + (1 / material) ** 3

In [4]: print(nonexp)
(sales) ** (2) + ((1) / (material)) ** (3)
```

Currently, it is not possible to get or print values of nonlinear expressions. Moreover, if your model includes a nonlinear expression, you need to use SAS Viya 3.4 or later or any SAS version for solving your problem.

To use mathematical operations, you need to import *sasoptpy.math* functions.

#### Mathematical expressions

*sasoptpy* provides mathematical functions for generating mathematical expressions to be used in optimization models.

You need to import *sasoptpy.math* to your code to start by using these functions. Available mathematical functions are listed in *Math Functions*.

```
In [5]: import sasoptpy.math as sm

In [6]: newexp = sm.max(sales, 10) ** 2

In [7]: print(newexp._expr())
(max(sales , 10)) ^ (2)
```

```
In [8]: import sasoptpy.math as sm

In [9]: angle = so.Variable(name='angle')

In [10]: newexp = sm.sin(angle) ** 2 + sm.cos(angle) ** 2

In [11]: print(newexp._expr())
(sin(angle)) ^ (2) + (cos(angle)) ^ (2)
```

## Operations

### Getting the current value

After the solve is completed, you can obtain the current value of an expression by using the *Expression.get_value()* method:

```
>>> print(profit.get_value())
42.0
```

### Getting the dual value

You can retrieve the dual values of *Expression* objects by using *Variable.get_dual()* and Constraint.get_dual() methods.

```
>>> m.solve()
>>> ...
>>> print(x.get_dual())
1.0
```

### Addition

There are two ways to add elements to an expression. The first and simpler way creates a new expression at the end:

```
In [12]: tax = 0.5

In [13]: profit_after_tax = profit - tax
```

```
In [14]: print(repr(profit_after_tax))
sasoptpy.Expression(exp = 5 * sales - 3 * material - 0.5, name=None)
```

The second way, *Expression.add()* method, takes two arguments: the element to be added and the sign (1 or -1):

```
In [15]: profit_after_tax = profit.add(tax, sign=-1)
```

```
In [16]: print(profit_after_tax)
5 * sales - 3 * material - 0.5
```

```
In [17]: print(repr(profit_after_tax))
sasoptpy.Expression(exp = 5 * sales - 3 * material - 0.5, name=None)
```

If the expression is a temporary one, the addition is performed in place.

### Multiplication

You can multiply expressions with scalar values:

```
In [18]: investment = profit.mult(0.2)

In [19]: print(investment)
sales - 0.6 * material
```

**Summation**

For faster summations compared to Python's native `sum` function, *sasoptpy* provides `sasoptpy.quick_sum()`.

```
In [20]: import time

In [21]: x = m.add_variables(1000, name='x')
```

```
In [22]: t0 = time.time()

In [23]: e = so.quick_sum(2 * x[i] for i in range(1000))

In [24]: print(time.time()-t0)
0.13680672645568848
```

```
In [25]: t0 = time.time()

In [26]: f = sum(2 * x[i] for i in range(1000))

In [27]: print(time.time()-t0)
0.955230712890625
```

### Renaming an expression

You can rename expressions by using the `Expression.set_name()` method:

```
In [28]: e = so.Expression(x[5] + 2 * x[6], name='e1')

In [29]: print(repr(e))
sasoptpy.Expression(exp = x[5] + 2 * x[6], name='e1')
```

```
In [30]: e.set_name('e2');

In [31]: print(repr(e))
sasoptpy.Expression(exp = x[5] + 2 * x[6], name='e2')
```

### Copying an expression

You can copy an `Expression` by using the `Expression.copy()` method:

```
In [32]: copy_profit = profit.copy(name='copy_profit')

In [33]: print(repr(copy_profit))
sasoptpy.Expression(exp = 5 * sales - 3 * material, name='copy_profit')
```

### 3.5.2 Objective Functions

#### Setting and getting an objective function

You can use any valid `Expression` as the objective function of a model. You can also use an existing expression as an objective function by using the `Model.set_objective()` method. The objective function of a model can be obtained by using the `Model.get_objective()` method.

```
>>> profit = so.Expression(5 * sales - 2 * material, name='profit')
>>> m.set_objective(profit, so.MAX)
>>> print(m.get_objective())
 -  2.0 * material  +  5.0 * sales
```

#### Getting the value

After a solve, you can retrieve the objective value by using the `Model.get_objective_value()` method.

```
>>> m.solve()
>>> print(m.get_objective_value())
42.0
```

### 3.5.3 Variables

#### Creating variables

You can create variables either standalone or inside a model.

**Creating a variable outside a model**

The first way to create a variable uses the default constructor.

```
>>> x = so.Variable(vartype=so.INT, ub=5, name='x')
```

When created separately, a variable needs to be included (or added) inside the model:

```
>>> y = so.Variable(name='y', lb=5)
>>> m.add_variable(y)
```

Equivalently, you could do this in one step:

```
>>> y = m.add_variable(name='y', lb=5)
```

**Creating a variable inside a model**

The second way is to use `Model.add_variable()`. This method creates a `Variable` object and returns a pointer.

```
>>> x = m.add_variable(vartype=so.INT, ub=5, name='x')
```

#### Arguments

There are three types of variables: continuous variables, integer variables, and binary variables. Continuous variables are the default type and you can specify it by using the `vartype=so.CONT` argument. You can create Integer variables and binary variables by using the `vartype=so.INT` and `vartype=so.BIN` arguments, respectively.

The default lower bound for variables is 0, and the upper bound is infinity. Name is a required argument.

#### Changing bounds

The `Variable.set_bounds()` method changes the bounds of a variable.

```
>>> x = so.Variable(name='x', lb=0, ub=20)
>>> print(repr(x))
sasoptpy.Variable(name='x', lb=0, ub=20, vartype='CONT')
>>> x.set_bounds(lb=5, ub=15)
>>> print(repr(x))
sasoptpy.Variable(name='x', lb=5, ub=15, vartype='CONT')
```

#### Setting initial values

You can pass the initial values of variables to the solvers for certain problems. The `Variable.set_init()` method changes the initial value for variables. You can set this value at the creation of the variable as well.

```
>>> x.set_init(5)
>>> print(repr(x))
sasoptpy.Variable(name='x', ub=20, init=5,  vartype='CONT')
```

#### Working with a set of variables

You can create a set of variables by using single or multiple indices. Valid index sets include list, dict, and `pandas.Index` objects. See *Handling Data* for more information about allowed index types.

**Creating a set of variables outside a model**

```
>>> production = VariableGroup(PERIODS, vartype=so.INT, name='production',
                               lb=min_production)
>>> print(repr(production))
sasoptpy.VariableGroup(['Period1', 'Period2', 'Period3'], name='production')
>>> m.include(production)
```

**Creating a set of variables inside a model**

```
>>> production = m.add_variables(PERIODS, vartype=so.INT,
                                 name='production', lb=min_production)
>>> print(production)
>>> print(repr(production))
Variable Group (production) [
  [Period1: production['Period1',]]
  [Period2: production['Period2',]]
  [Period3: production['Period3',]]
]
sasoptpy.VariableGroup(['Period1', 'Period2', 'Period3'],
name='production')
```

### 3.5.4 Constraints

#### Creating constraints

Similar to `Variable` objects, you can create `Constraint` objects inside or outside optimization models.

**Creating a constraint outside a model**

```
>>> c1 = so.Constraint(3 * x - 5 * y <= 10, name='c1')
>>> print(repr(c1))
sasoptpy.Constraint( - 5.0 * y  +  3.0 * x  <=  10, name='c1')
```

**Creating a constraint inside a model**

```
>>> c1 = m.add_constraint(3 * x - 5 * y <= 10, name='c1')
>>> print(repr(c1))
sasoptpy.Constraint( - 5.0 * y  +  3.0 * x  <=  10, name='c1')
```

#### Modifying variable coefficients

You can update the coefficient of a variable inside a constraint by using the `Constraint.update_var_coef()` method:

```
>>> c1 = so.Constraint(exp=3 * x - 5 * y <= 10, name='c1')
>>> print(repr(c1))
sasoptpy.Constraint( - 5.0 * y  +  3.0 * x  <=  10, name='c1')
>>> c1.update_var_coef(x, -1)
>>> print(repr(c1))
sasoptpy.Constraint( - 5.0 * y  -  x  <=  10, name='c1')
```

#### Working with a set of constraints

You can add a set of constraints by using single or multiple indices. Valid index sets include list, dict, and `pandas.Index` objects. See *Handling Data* for more information about allowed index types.

**Creating a set of constraints outside a model**

```
>>> z = so.VariableGroup(2, ['a', 'b', 'c'], name='z', lb=0, ub=10)
>>> cg = so.ConstraintGroup((2 * z[i, j] + 3 * z[i-1, j] >= 2 for i in
                             [1] for j in ['a', 'b', 'c']), name='cg')
>>> print(cg)
Constraint Group (cg) [
  [(1, 'a'):  3.0 * z[0, 'a']  +  2.0 * z[1, 'a']  >=  2]
  [(1, 'b'):  3.0 * z[0, 'b']  +  2.0 * z[1, 'b']  >=  2]
  [(1, 'c'):  2.0 * z[1, 'c']  +  3.0 * z[0, 'c']  >=  2]
]
```

**Creating a set of constraints inside a model**

```
>>> z = so.VariableGroup(2, ['a', 'b', 'c'], name='z', lb=0, ub=10)
>>> cg2 = m.add_constraints((2 * z[i, j] + 3 * z[i-1, j] >= 2 for i in
                              [1] for j in ['a', 'b', 'c']), name='cg2')
>>> print(cg2)
Constraint Group (cg2) [
  [(1, 'a'):  2.0 * z[1, 'a']  +  3.0 * z[0, 'a']  >=  2]
```

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```
  [(1, 'b'):  3.0 * z[0, 'b']  +  2.0 * z[1, 'b']  >=  2]
  [(1, 'c'):  2.0 * z[1, 'c']  +  3.0 * z[0, 'c']  >=  2]
]
```

#### Range constraints

You can give a range for an expression by using a list of two value (lower and upper bound) with an == sign:

```
>>> x = m.add_variable(name='x')
>>> y = m.add_variable(name='y')
>>> c1 = m.add_constraint(x + 2*y == [2,9], name='c1')
>>> print(repr(c1))
sasoptpy.Constraint( x + 2.0 * y  ==  [2, 9], name='c1')
```

## 3.6 Workspaces

One of the most powerful features of SAS Optimization and PROC OPTMODEL is the ability to combine several optimization models in a single call. You can read a common data set once, or parallelize solve steps for similar subproblems by using this ability.

The newly introduced *Workspace* provides this ability in a familiar syntax. Compared to *Model* objects, a *Workspace* can consist of several models and is able to use server-side data and OPTMODEL statements in a more detailed way.

### 3.6.1 Creating a workspace

A *Workspace* should be called by using the *with* keyword of Python as follows:

```
>>> with so.Workspace('my_workspace') as w:
>>>     ...
```

You can define several models in the same workspace, and solve problems multiple times. All the statements are sent to the server after *Workspace.submit()* is called.

### 3.6.2 Adding components

Unlike *Model* objects, where components are added explicitly, objects defined inside a *Workspace* are added automatically.

For example, adding a new variable is performed as follows:

```
In [1]: with so.Workspace(name='my_workspace') as w:
   ...:     x = so.Variable(name='x', vartype=so.integer)
   ...:
```

You can display contents of a workspace by using the *Workspace.to_optmodel()* method:

```
In [2]: print(w.to_optmodel())
proc optmodel;
   var x integer;
quit;
```

See the following full example where data are loaded into the server, and a problem is solved by using a Workspace:

Create CAS session:

```
In [3]: import os

In [4]: hostname = os.getenv('CASHOST')

In [5]: port = os.getenv('CASPORT')

In [6]: from swat import CAS

In [7]: cas_conn = CAS(hostname, port)

In [8]: import sasoptpy as so

In [9]: import pandas as pd
```

Upload data:

```
In [10]: def send_data():
   ....:     data = [
   ....:         ['clock', 8, 4, 3],
   ....:         ['mug', 10, 6, 5],
   ....:         ['headphone', 15, 7, 2],
   ....:         ['book', 20, 12, 10],
   ....:         ['pen', 1, 1, 15]
   ....:     ]
   ....:     df = pd.DataFrame(data, columns=['item', 'value', 'weight', 'limit'])
   ....:     cas_conn.upload_frame(df, casout={'name': 'mydata', 'replace': True})
   ....: send_data()
   ....:
NOTE: Cloud Analytic Services made the uploaded file available as table MYDATA in␣
↪caslib CASUSER(casuser).
NOTE: The table MYDATA has been created in caslib CASUSER(casuser) from binary data␣
↪uploaded to Cloud Analytic Services.
```

Model workspace:

```
In [11]: from sasoptpy.actions import read_data, solve

In [12]: def create_workspace():
   ....:     with so.Workspace('my_knapsack', session=cas_conn) as w:
   ....:         items = so.Set(name='ITEMS', settype=so.string)
   ....:         value = so.ParameterGroup(items, name='value')
   ....:         weight = so.ParameterGroup(items, name='weight')
   ....:         limit = so.ParameterGroup(items, name='limit')
   ....:         total_weight = so.Parameter(name='total_weight', value=55)
   ....:         read_data(
   ....:             table='mydata', index={'target': items, 'key': ['item']},
   ....:             columns=[value, weight, limit]
   ....:         )
   ....:         get = so.VariableGroup(items, name='get', vartype=so.integer, lb=0)
   ....:         limit_con = so.ConstraintGroup((get[i] <= limit[i] for i in items),
   ....:                                        name='limit_con')
   ....:         weight_con = so.Constraint(
   ....:             so.expr_sum(weight[i] * get[i] for i in items) <= total_weight,
   ....:             name='weight_con')
```

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```
   ....:       total_value = so.Objective(
   ....:          so.expr_sum(value[i] * get[i] for i in items), name='total_value',
   ....:          sense=so.maximize)
   ....:       solve()
   ....:    return w
   ....:

In [13]: my_workspace = create_workspace()
```

Print content:

```
In [14]: print(so.to_optmodel(my_workspace))
proc optmodel;
   set <str> ITEMS;
   num value {ITEMS};
   num weight {ITEMS};
   num limit {ITEMS};
   num total_weight = 55;
   read data mydata into ITEMS=[item] value weight limit;
   var get {{ITEMS}} integer >= 0;
   con limit_con {o72 in ITEMS} : get[o72] - limit[o72] <= 0;
   con weight_con : total_weight - (sum {i in ITEMS} (weight[i] * get[i])) >= 0;
   max total_value = sum {i in ITEMS} (value[i] * get[i]);
   solve;
quit;
```

Submit:

```
In [15]: my_workspace.submit()
NOTE: Added action set 'optimization'.
NOTE: There were 5 rows read from table 'MYDATA' in caslib 'CASUSER(casuser)'.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 5 variables (0 free, 0 fixed).
NOTE: The problem has 0 binary and 5 integer variables.
NOTE: The problem has 6 linear constraints (5 LE, 0 EQ, 1 GE, 0 range).
NOTE: The problem has 10 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 5 constraints.
NOTE: The MILP presolver removed 5 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 5 variables, 1 constraints, and 5 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      4     99.0000000    199.0000000   50.25%       0
                0        1      4     99.0000000    102.3333333    3.26%       0
                0        0      4     99.0000000     99.0000000    0.00%       0
NOTE: Optimal.
NOTE: Objective = 99.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 5 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 6 rows and 4 columns.
```

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```
Out[15]:
Selected Rows from Table SOLUTION

     i            var  value   lb            ub  rc
0  1.0      get[book]    2.0 -0.0  1.797693e+308 NaN
1  2.0     get[clock]    3.0 -0.0  1.797693e+308 NaN
2  3.0 get[headphone]    2.0 -0.0  1.797693e+308 NaN
3  4.0       get[mug]   -0.0 -0.0  1.797693e+308 NaN
4  5.0       get[pen]    5.0 -0.0  1.797693e+308 NaN
```

### 3.6.3 Abstract actions

As shown in the previous example, a *Workspace* can have statements such as *actions.read_data()* and *actions.solve()*.

These statements are called “Abstract Statements” and are fully supported inside *Workspace* objects.

#### Adding abstract actions

You can import abstract actions through *sasoptpy.actions* as follows:

```
>>> from sasoptpy.actions import read_data, create_data
```

These abstract actions are performed on the server side by generating equivalent OPTMODEL code at execution.

#### Grabbing results

In order to solve a problem, you need to use the *actions.solve()* function explicitly. Because *Workspace* objects allow several models and solve statements to be included, each of these solve statements are retrieved separately. You can return the solution after each solve by using the `actions.print()` function or creating a table by using the *actions.create_data()* function.

See the following example where a parameter is changed and the same problem solved twice:

```
In [16]: from sasoptpy.actions import read_data, solve, print_item

In [17]: def create_multi_solve_workspace():
   ....:     with so.Workspace('my_knapsack', session=cas_conn) as w:
   ....:         items = so.Set(name='ITEMS', settype=so.string)
   ....:         value = so.ParameterGroup(items, name='value')
   ....:         weight = so.ParameterGroup(items, name='weight')
   ....:         limit = so.ParameterGroup(items, name='limit')
   ....:         total_weight = so.Parameter(name='total_weight', init=55)
   ....:         read_data(table='mydata', index={'target': items, 'key': ['item']},␣
↪columns=[value, weight, limit])
   ....:         get = so.VariableGroup(items, name='get', vartype=so.integer, lb=0)
   ....:         limit_con = so.ConstraintGroup((get[i] <= limit[i] for i in items),␣
↪name='limit_con')
   ....:         weight_con = so.Constraint(
   ....:             so.expr_sum(weight[i] * get[i] for i in items) <= total_weight,␣
↪name='weight_con')
   ....:         total_value = so.Objective(so.expr_sum(value[i] * get[i] for i in␣
↪items), name='total_value', sense=so.MAX)
```

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```
   ....:         s1 = solve()
   ....:         p1 = print_item(get)
   ....:         total_weight.set_value(40)
   ....:         s2 = solve()
   ....:         p2 = print_item(get)
   ....:     return w, s1, p1, s2, p2
   ....:

In [18]: (my_workspace, solve1, print1, solve2, print2) = create_multi_solve_
↪workspace()
```

Submit:

```
In [19]: my_workspace.submit()
NOTE: Added action set 'optimization'.
NOTE: There were 5 rows read from table 'MYDATA' in caslib 'CASUSER(casuser)'.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 5 variables (0 free, 0 fixed).
NOTE: The problem has 0 binary and 5 integer variables.
NOTE: The problem has 6 linear constraints (5 LE, 0 EQ, 1 GE, 0 range).
NOTE: The problem has 10 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 5 constraints.
NOTE: The MILP presolver removed 5 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 5 variables, 1 constraints, and 5 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      4     99.0000000    199.0000000   50.25%       0
                0        1      4     99.0000000    102.3333333    3.26%       0
                0        0      4     99.0000000     99.0000000    0.00%       0
NOTE: Optimal.
NOTE: Objective = 99.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 5 variables (0 free, 0 fixed).
NOTE: The problem has 0 binary and 5 integer variables.
NOTE: The problem has 6 linear constraints (5 LE, 0 EQ, 1 GE, 0 range).
NOTE: The problem has 10 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 5 constraints.
NOTE: The MILP presolver removed 5 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 5 variables, 1 constraints, and 5 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
```

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```
                0        1      4     76.0000000    179.0000000   57.54%        0
                0        1      4     76.0000000     77.3333333    1.72%        0
                0        0      4     76.0000000     76.0000000    0.00%        0
NOTE: Optimal.
NOTE: Objective = 76.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 5 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 6 rows and 4 columns.
Out[19]:
Selected Rows from Table SOLUTION

     i            var  value   lb            ub  rc
0  1.0      get[book]    1.0 -0.0  1.797693e+308 NaN
1  2.0     get[clock]    3.0 -0.0  1.797693e+308 NaN
2  3.0  get[headphone]   2.0 -0.0  1.797693e+308 NaN
3  4.0        get[mug]  -0.0 -0.0  1.797693e+308 NaN
4  5.0        get[pen]   2.0 -0.0  1.797693e+308 NaN
```

Print results:

```
In [20]: print(solve1.get_solution_summary())
Solution Summary

                                Value
Label
Solver                           MILP
Algorithm              Branch and Cut
Objective Function        total_value
Solution Status               Optimal
Objective Value                    99

Relative Gap                        0
Absolute Gap                        0
Primal Infeasibility                0
Bound Infeasibility                 0
Integer Infeasibility               0

Best Bound                         99
Nodes                               1
Solutions Found                     4
Iterations                          7
Presolve Time                    0.00
Solution Time                    0.20
```

```
In [21]: print(print1.get_response())
        COL1  get
0       book  2.0
1      clock  3.0
2  headphone  2.0
3        mug -0.0
4        pen  5.0
```

```
In [22]: print(solve2.get_solution_summary())
Solution Summary

                                Value
```

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```
Label
Solver                          MILP
Algorithm              Branch and Cut
Objective Function       total_value
Solution Status              Optimal
Objective Value                   76

Relative Gap                       0
Absolute Gap                       0
Primal Infeasibility               0
Bound Infeasibility                0
Integer Infeasibility              0

Best Bound                        76
Nodes                              1
Solutions Found                    4
Iterations                         3
Presolve Time                   0.00
Solution Time                   0.18
```

```
In [23]: print(print2.get_response())
        COL1  get
0       book  1.0
1      clock  3.0
2  headphone  2.0
3        mug -0.0
4        pen  2.0
```

#### List of abstract actions

A list of abstract actions is available in the *API section*.

## 3.7 Handling Data

*sasoptpy* can work with native Python types and *pandas* objects for all data operations. Among *pandas* object types, *sasoptpy* works with `pandas.DataFrame` and `pandas.Series` objects to construct and manipulate model components.

### 3.7.1 Indices

Methods like *`Model.add_variables()`* can utilize native Python object types like list and range as variable and constraint indices. You can use `pandas.Index` objects as indices as well.

### List

```
In [1]: m = so.Model(name='demo')
NOTE: Initialized model demo.

In [2]: SEASONS = ['Fall', 'Winter', 'Spring', 'Summer']

In [3]: prod_lb = {'Fall': 100, 'Winter': 200, 'Spring': 100, 'Summer': 400}

In [4]: production = m.add_variables(SEASONS, lb=prod_lb, name='production')

In [5]: print(production)
Variable Group (production) [
  [Fall: production[Fall]]
  [Winter: production[Winter]]
  [Spring: production[Spring]]
  [Summer: production[Summer]]
]
```

```
In [6]: print(repr(production['Summer']))
sasoptpy.Variable(name='production[Summer]', lb=400,  vartype='CONT')
```

Note that if a list is being used as the index set, associated fields like *lb*, *ub* should be accessible by using the index keys. Accepted types are dict and `pandas.Series`.

### Range

```
In [7]: link = m.add_variables(range(3), range(2), vartype=so.BIN, name='link')

In [8]: print(link)
Variable Group (link) [
  [(0, 0): link[0, 0]]
  [(0, 1): link[0, 1]]
  [(1, 0): link[1, 0]]
  [(1, 1): link[1, 1]]
  [(2, 0): link[2, 0]]
  [(2, 1): link[2, 1]]
]
```

```
In [9]: print(repr(link[2, 1]))
sasoptpy.Variable(name='link[2,1]', lb=0, ub=1,  vartype='BIN')
```

### pandas.Index

```
In [10]: import pandas as pd

In [11]: p_data = [[3, 5, 9],
   ....:            [0, -1, 14],
   ....:            [5, 6, 20]]
   ....:

In [12]: df = pd.DataFrame(p_data, columns=['c1', 'col_lb', 'col_ub'])

In [13]: x = m.add_variables(df.index, lb=df['c1'], vartype=so.INT, name='x')
```

```
In [14]: print(x)
Variable Group (x) [
  [0: x[0]]
  [1: x[1]]
  [2: x[2]]
]
```

```
In [15]: df2 = df.set_index([['r1', 'r2', 'r3']])

In [16]: y = m.add_variables(df2.index, lb=df2['col_lb'], ub=df2['col_ub'], name='y')
```

```
In [17]: print(y)
Variable Group (y) [
  [r1: y[r1]]
  [r2: y[r2]]
  [r3: y[r3]]
]
```

```
In [18]: print(repr(y['r1']))
sasoptpy.Variable(name='y[r1]', lb=5, ub=9,  vartype='CONT')
```

### Set

*sasoptpy* can work with data on the server and generate abstract expressions. For this purpose, you can use `Set` objects to represent PROC OPTMODEL sets.

```
In [19]: m2 = so.Model(name='m2')
NOTE: Initialized model m2.

In [20]: I = m2.add_set(name='I')

In [21]: u = m2.add_variables(I, name='u')

In [22]: print(I, u)
I Variable Group (u) [
]
```

See *Workflows* for more information on working with server-side models.

### 3.7.2 Data

*sasoptpy* can work with both client-side and server-side data. Here are some options to load data into the optimization models.

#### pandas DataFrame

`pandas.DataFrame` is the preferred object type when passing data into *sasoptpy* models.

```
In [23]: data = [
   ....:     ['clock', 8, 4, 3],
   ....:     ['mug', 10, 6, 5],
   ....:     ['headphone', 15, 7, 2],
   ....:     ['book', 20, 12, 10],
   ....:     ['pen', 1, 1, 15]
   ....:     ]
   ....:

In [24]: df = pd.DataFrame(data, columns=['item', 'value', 'weight', 'limit']).set_
↪index(['item'])

In [25]: get = so.VariableGroup(df.index, ub=df['limit'], name='get')

In [26]: print(get)
Variable Group (get) [
  [clock: get[clock]]
  [mug: get[mug]]
  [headphone: get[headphone]]
  [book: get[book]]
  [pen: get[pen]]
]
```

#### Dictionaries

You can use lists and dictionaries in expressions and when creating variables.

```
In [27]: items = ['clock', 'mug', 'headphone', 'book', 'pen']

In [28]: limits = {'clock': 3, 'mug': 5, 'headphone': 2, 'book': 10, 'pen': 15}

In [29]: get2 = so.VariableGroup(items, ub=limits, name='get2')

In [30]: print(get2)
Variable Group (get2) [
  [clock: get2[clock]]
  [mug: get2[mug]]
  [headphone: get2[headphone]]
  [book: get2[book]]
  [pen: get2[pen]]
]
```

### CASTable

When data are available on the server-side, you can pass a reference to the object. Note that, using `swat.cas.table.CASTable` and Abstract Data requires SAS Viya version 3.4 or later.

```
In [31]: m2 = so.Model(name='m2', session=session)
NOTE: Initialized model m2.
```

```
In [32]: table = session.upload_frame(df)
NOTE: Cloud Analytic Services made the uploaded file available as table TMPXL9K6KGX␣
↪in caslib CASUSER(casuser).
NOTE: The table TMPXL9K6KGX has been created in caslib CASUSER(casuser) from binary␣
↪data uploaded to Cloud Analytic Services.
```

```
In [33]: print(type(table), table)
<class 'swat.cas.table.CASTable'> CASTable('TMPXL9K6KGX', caslib='CASUSER(casuser)')
```

```
In [34]: df = pd.DataFrame(data, columns=['item', 'value', 'weight', 'limit'])

In [35]: ITEMS = m.add_set(name='ITEMS')

In [36]: value = m.add_parameter(ITEMS, name='value')

In [37]: weight = m.add_parameter(ITEMS, name='weight')

In [38]: limit = m.add_parameter(ITEMS, name='limit')

In [39]: from sasoptpy.actions import read_data

In [40]: m.include(read_data(table=table, index={'target': ITEMS, 'key': None},
   ....:                         columns=[value, weight, limit]))
   ....:

In [41]: get3 = m2.add_variables(ITEMS, name='get3')

In [42]: print(get3)
Variable Group (get3) [
]
```

### Abstract Data

If you would like to model your problem first and then load data, you can pass a string for the data sets that will be available later.

```
In [43]: from sasoptpy.actions import read_data

In [44]: m3 = so.Model(name='m3', session=session)
NOTE: Initialized model m3.

In [45]: ITEMS = m.add_set(name='ITEMS')

In [46]: limit = m.add_parameter(ITEMS, name='limit')

In [47]: m3.include(read_data(table='DF', index=['item'], columns=[limit]))
```

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```
In [48]: print(type(ITEMS), ITEMS)
<class 'sasoptpy.abstract.set.Set'> ITEMS
```

Note that the key set is created as a reference. You can later solve the problem after having the data available with the same name; for example, by using the *upload_frame* function.

```
In [49]: session.upload_frame(df, casout='DF')
NOTE: Cloud Analytic Services made the uploaded file available as table DF in caslib␣
↪CASUSER(casuser).
NOTE: The table DF has been created in caslib CASUSER(casuser) from binary data␣
↪uploaded to Cloud Analytic Services.
Out[49]: CASTable('DF', caslib='CASUSER(casuser)')
```

### 3.7.3 Operations

You can use lists, `pandas.Series`, and `pandas.DataFrame` objects for mathematical operations such as `VariableGroup.mult()`.

```
In [50]: sd = [3, 5, 6]

In [51]: z = m.add_variables(3, name='z')
```

```
In [52]: print(z)
Variable Group (z) [
  [0: z[0]]
  [1: z[1]]
  [2: z[2]]
]
```

```
In [53]: print(repr(z))
sasoptpy.VariableGroup([0, 1, 2], name='z')
```

```
In [54]: e1 = z.mult(sd)

In [55]: print(e1)
3 * z[0] + 5 * z[1] + 6 * z[2]
```

```
In [56]: ps = pd.Series(sd)

In [57]: e2 = z.mult(ps)

In [58]: print(e2)
3 * z[0] + 5 * z[1] + 6 * z[2]
```

## 3.8 Workflows

*sasoptpy* can work with both client-side data and server-side data. Some limitations to the functionalities might apply in terms of which workflow is being used. In this section, the overall flow of the package is explained.

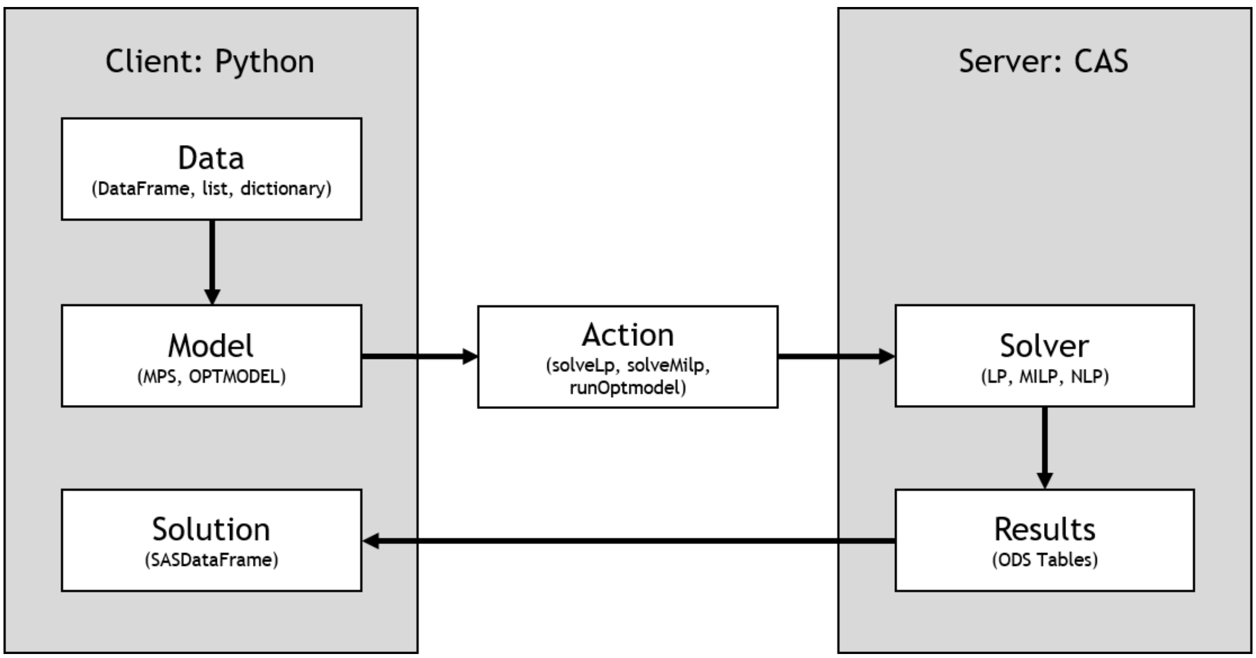
### 3.8.1 Client-side models

If the data are on the client-side (Python), then a concrete model is generated on the client-side and uploaded by using one of the available CAS actions.

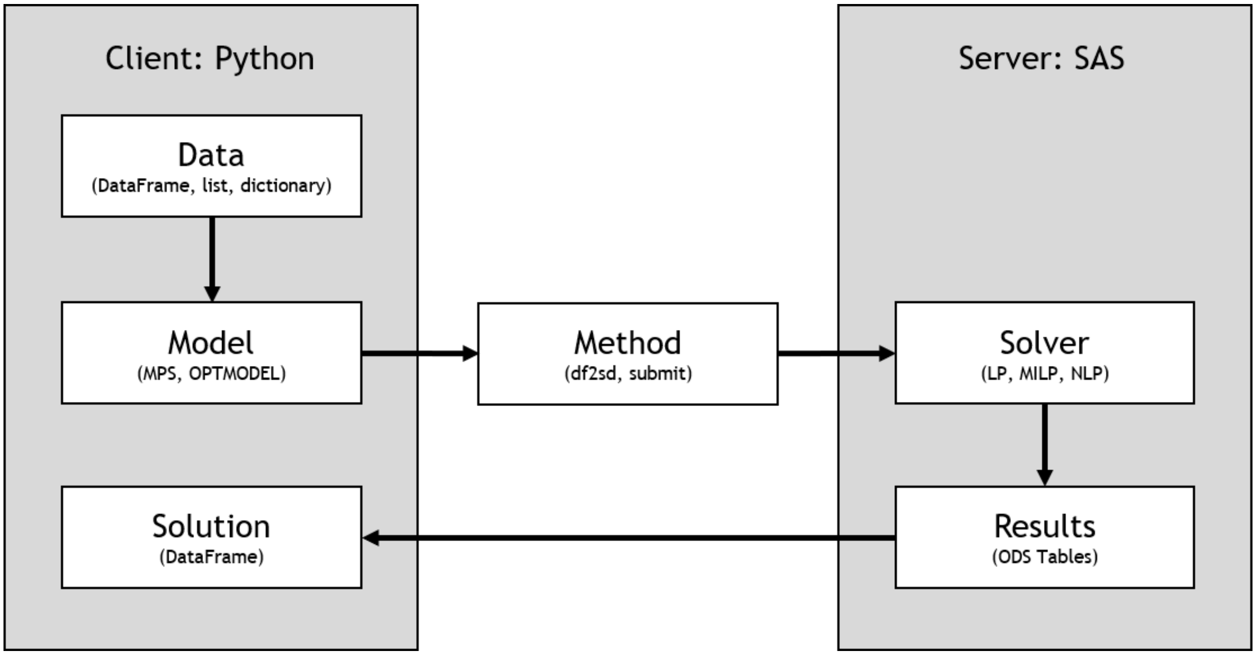
Using a client-side model brings several advantages, such as accessing variables, expressions, and constraints directly. You can do more intensive operations like filter data, sort values, change variable values, and print expressions more easily.

There are two main disadvantages of working with client-side models. First, if your model is relatively large, the generated MPS DataFrame or OPTMODEL code might allocate a large memory on your machine. Second, the information that needs to be passed from client to server might be larger compared to using a server-side model.

See the following representation of the client-side model workflow for CAS (Viya) servers:




See the following representation of the client-side model workflow for SAS clients:




Steps of modeling a simple knapsack problem are shown in the following subsections.

### Reading data

```
In [1]: import sasoptpy as so

In [2]: import pandas as pd

In [3]: from swat import CAS

In [4]: session = CAS(hostname, port)

In [5]: m = so.Model(name='client_CAS', session=session)
NOTE: Initialized model client_CAS.

In [6]: data = [
   ...:     ['clock', 8, 4, 3],
   ...:     ['mug', 10, 6, 5],
   ...:     ['headphone', 15, 7, 2],
   ...:     ['book', 20, 12, 10],
   ...:     ['pen', 1, 1, 15]
   ...:     ]
   ...:

In [7]: df = pd.DataFrame(data, columns=['item', 'value', 'weight', 'limit'])

In [8]: ITEMS = df.index

In [9]: value = df['value']

In [10]: weight = df['weight']

In [11]: limit = df['limit']
```

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```
In [12]: total_weight = 55
```

```
In [13]: print(type(ITEMS), ITEMS)
<class 'pandas.core.indexes.range.RangeIndex'> RangeIndex(start=0, stop=5, step=1)
```

```
In [14]: print(type(total_weight), total_weight)
<class 'int'> 55
```

Here, you can obtain the column values one by one:

```
>>> df = df.set_index('item')
>>> ITEMS = df.index.tolist()
>>> value = df['value']
>>> weight = df['weight']
>>> limit = df['limit']
```

### Model

```
# Variables
In [15]: get = m.add_variables(ITEMS, name='get', vartype=so.INT, lb=0)

# Constraints
In [16]: m.add_constraints((get[i] <= limit[i] for i in ITEMS), name='limit_con');

In [17]: m.add_constraint(
   ....:     so.quick_sum(weight[i] * get[i] for i in ITEMS) <= total_weight,
   ....:     name='weight_con');
   ....:

# Objective
In [18]: total_value = so.expr_sum(value[i] * get[i] for i in ITEMS)

In [19]: m.set_objective(total_value, name='total_value', sense=so.MAX);

# Solve
In [20]: m.solve(verbose=True)
NOTE: Added action set 'optimization'.
NOTE: Converting model client_CAS to OPTMODEL.
   var get {{0,1,2,3,4}} integer >= 0;
   con limit_con_0 : get[0] <= 3;
   con limit_con_1 : get[1] <= 5;
   con limit_con_2 : get[2] <= 2;
   con limit_con_3 : get[3] <= 10;
   con limit_con_4 : get[4] <= 15;
   con weight_con : 4 * get[0] + 6 * get[1] + 7 * get[2] + 12 * get[3] + get[4] <= 55;
   max total_value = 8 * get[0] + 10 * get[1] + 15 * get[2] + 20 * get[3] + get[4];
   solve;
   create data solution from [i]= {1.._NVAR_} var=_VAR_.name value=_VAR_ lb=_VAR_.lb␣
↪ub=_VAR_.ub rc=_VAR_.rc;
   create data dual from [j] = {1.._NCON_} con=_CON_.name value=_CON_.body dual=_CON_.
↪dual;

NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
```

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```
NOTE: The problem has 5 variables (0 free, 0 fixed).
NOTE: The problem has 0 binary and 5 integer variables.
NOTE: The problem has 6 linear constraints (6 LE, 0 EQ, 0 GE, 0 range).
NOTE: The problem has 10 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 5 constraints.
NOTE: The MILP presolver removed 5 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 5 variables, 1 constraints, and 5 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      4     99.0000000    199.0000000   50.25%       0
                0        1      4     99.0000000    102.3333333    3.26%       0
                0        1      4     99.0000000    102.3333333    3.26%       0
NOTE: The MILP presolver is applied again.
                0        1      4     99.0000000    102.3333333    3.26%       0
NOTE: Optimal.
NOTE: Objective = 99.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 5 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 6 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
Out[20]:
Selected Rows from Table SOLUTION

     i     var  value   lb             ub  rc
0  1.0  get[0]    2.0 -0.0  1.797693e+308 NaN
1  2.0  get[1]    5.0 -0.0  1.797693e+308 NaN
2  3.0  get[2]    2.0 -0.0  1.797693e+308 NaN
3  4.0  get[3]   -0.0 -0.0  1.797693e+308 NaN
4  5.0  get[4]    3.0 -0.0  1.797693e+308 NaN
```

You can display the generated OPTMODEL code at runtime by using the `verbose` option. Here, you can see the coefficient values of the parameters inside the model.

### Parsing results

After the solve, the primal and dual solution tables are obtained. You can print the solution tables by using the *`Model.get_solution()`* method.

It is also possible to print the optimal solution by using the *`get_solution_table()`* function.

```
In [21]: print(m.get_solution())
Selected Rows from Table SOLUTION

     i     var  value   lb             ub  rc
0  1.0  get[0]    2.0 -0.0  1.797693e+308 NaN
```

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```
1  2.0  get[1]    5.0 -0.0  1.797693e+308 NaN
2  3.0  get[2]    2.0 -0.0  1.797693e+308 NaN
3  4.0  get[3]   -0.0 -0.0  1.797693e+308 NaN
4  5.0  get[4]    3.0 -0.0  1.797693e+308 NaN
```

```
In [22]: print(so.get_solution_table(get, key=ITEMS))
   get
0  2.0
1  5.0
2  2.0
3 -0.0
4  3.0
```

```
In [23]: print('Total value:', total_value.get_value())
Total value: 99.0
```

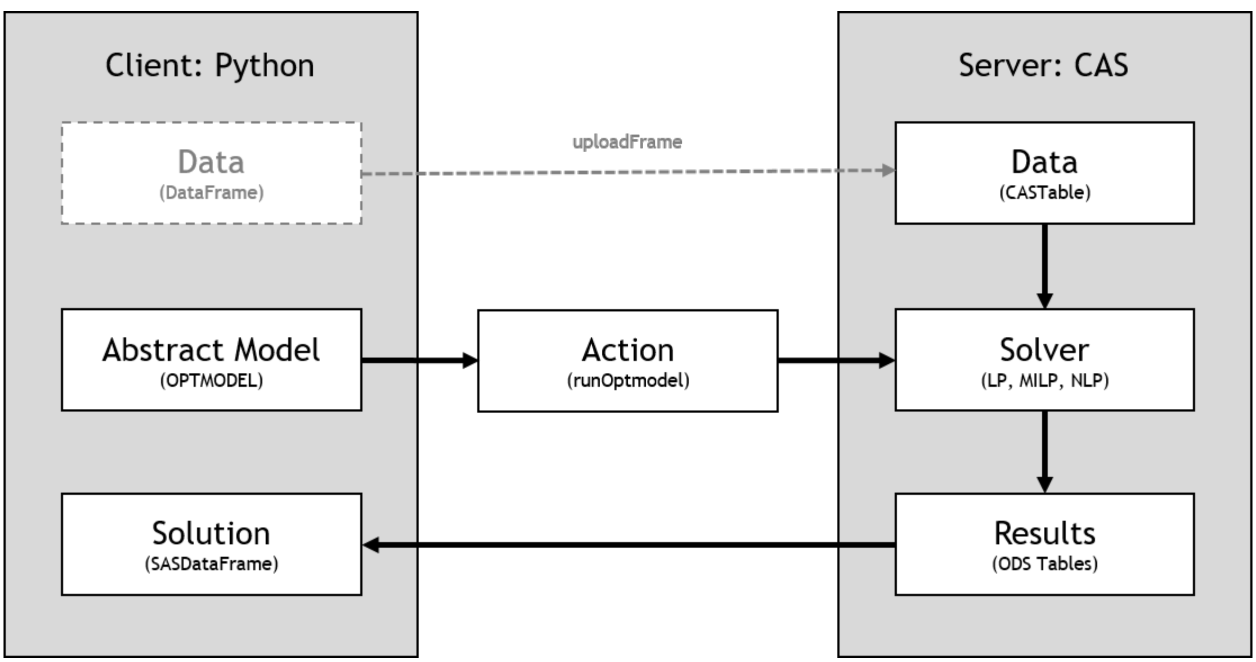
### 3.8.2 Server-side models

If the data are on the server-side (CAS or SAS), then an abstract model is generated on the client-side. This abstract model is later converted to PROC OPTMODEL code, which reads the data on the server.

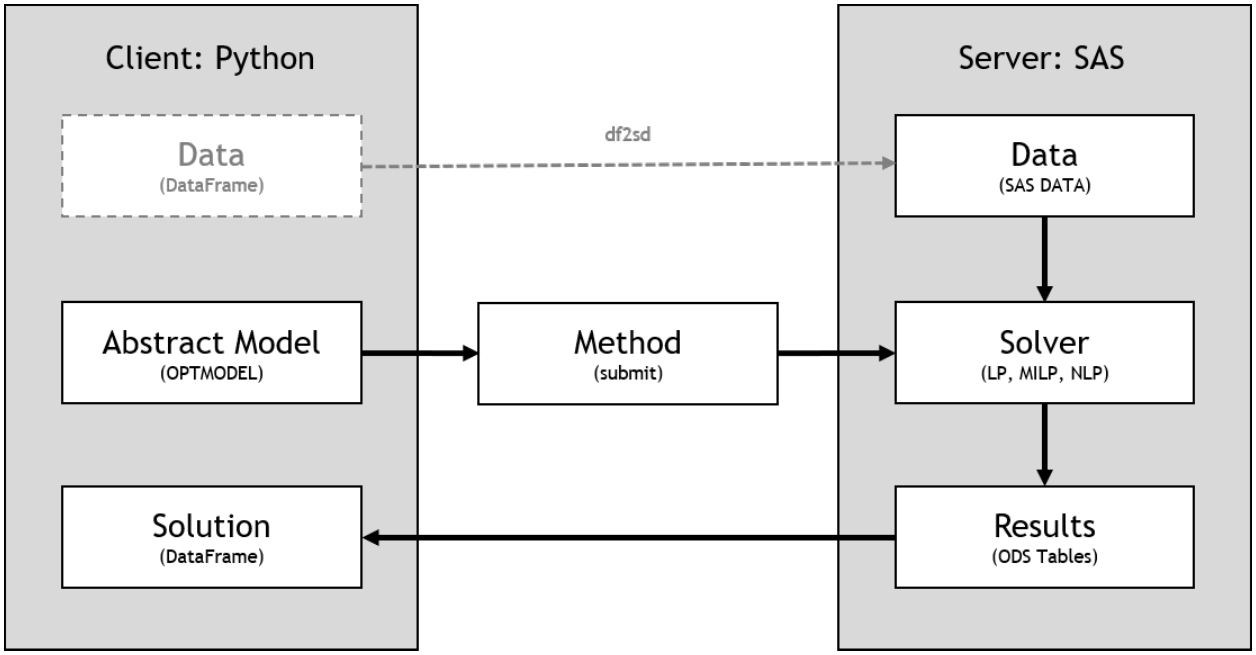
The main advantage of the server-side models is faster upload times compared to client-side. This is especially noticeable when using large numbers of variable and constraint groups.

The only disadvantage of using server-side models is that variables often need to be accessed directly from the resulting SASDataFrame objects. Because components of the models are abstract, accessing objects directly is often not possible.

See the following representation of the server-side model workflow for CAS (Viya) servers:




See the following representation of the server-side model workflow for SAS clients:




In the following subsections, the same example is solved by using server-side data.

## Model

```
In [24]: from sasoptpy.actions import read_data

In [25]: m = so.Model(name='client_CAS', session=session)
NOTE: Initialized model client_CAS.
```

```
In [26]: cas_table = session.upload_frame(df, casout='data')
NOTE: Cloud Analytic Services made the uploaded file available as table DATA in␣
↪caslib CASUSER(casuser).
NOTE: The table DATA has been created in caslib CASUSER(casuser) from binary data␣
↪uploaded to Cloud Analytic Services.
```

```
In [27]: ITEMS = m.add_set(name='ITEMS', settype=so.STR)

In [28]: value = m.add_parameter(ITEMS, name='value')

In [29]: weight = m.add_parameter(ITEMS, name='weight')

In [30]: limit = m.add_parameter(ITEMS, name='limit')

In [31]: m.include(read_data(
   ....:     table=cas_table, index={'target':ITEMS, 'key': 'item'},
   ....:     columns=[value, weight, limit]))
   ....:

# Variables
In [32]: get = m.add_variables(ITEMS, name='get', vartype=so.INT, lb=0)

# Constraints
In [33]: m.add_constraints((get[i] <= limit[i] for i in ITEMS), name='limit_con');
```

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```
In [34]: m.add_constraint(
   ....:     so.quick_sum(weight[i] * get[i] for i in ITEMS) <= total_weight,
   ....:     name='weight_con');
   ....:
```

```
# Objective
In [35]: total_value = so.quick_sum(value[i] * get[i] for i in ITEMS)

In [36]: m.set_objective(total_value, name='total_value', sense=so.MAX);

# Solve
In [37]: m.solve(verbose=True)
NOTE: Added action set 'optimization'.
NOTE: Converting model client_CAS to OPTMODEL.
   set <str> ITEMS;
   num value {{ITEMS}};
   num weight {{ITEMS}};
   num limit {{ITEMS}};
   read data DATA into ITEMS=[item] value weight limit;
   var get {{ITEMS}} integer >= 0;
   con limit_con {o37 in ITEMS} : get[o37] - limit[o37] <= 0;
   con weight_con : sum {i in ITEMS} (weight[i] * get[i]) <= 55;
   max total_value = sum {i in ITEMS} (value[i] * get[i]);
   solve;
   create data solution from [i]= {1.._NVAR_} var=_VAR_.name value=_VAR_ lb=_VAR_.lb␣
↪ub=_VAR_.ub rc=_VAR_.rc;
   create data dual from [j] = {1.._NCON_} con=_CON_.name value=_CON_.body dual=_CON_.
↪dual;

NOTE: Submitting OPTMODEL code to CAS server.
NOTE: There were 5 rows read from table 'DATA' in caslib 'CASUSER(casuser)'.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 5 variables (0 free, 0 fixed).
NOTE: The problem has 0 binary and 5 integer variables.
NOTE: The problem has 6 linear constraints (6 LE, 0 EQ, 0 GE, 0 range).
NOTE: The problem has 10 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 5 constraints.
NOTE: The MILP presolver removed 5 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 5 variables, 1 constraints, and 5 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      4     99.0000000    199.0000000   50.25%       0
                0        1      4     99.0000000    102.3333333    3.26%       0
                0        0      4     99.0000000     99.0000000    0.00%       0
NOTE: Optimal.
NOTE: Objective = 99.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 5 rows and 6␣
↪columns.
```

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```
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 6 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
Out[37]:
Selected Rows from Table SOLUTION

     i              var  value   lb             ub  rc
0  1.0        get[book]    2.0 -0.0  1.797693e+308 NaN
1  2.0       get[clock]    3.0 -0.0  1.797693e+308 NaN
2  3.0   get[headphone]    2.0 -0.0  1.797693e+308 NaN
3  4.0         get[mug]   -0.0 -0.0  1.797693e+308 NaN
4  5.0         get[pen]    5.0 -0.0  1.797693e+308 NaN
```

### Parsing results

```
# Print results
In [38]: print(m.get_solution())
Selected Rows from Table SOLUTION

     i              var  value   lb             ub  rc
0  1.0        get[book]    2.0 -0.0  1.797693e+308 NaN
1  2.0       get[clock]    3.0 -0.0  1.797693e+308 NaN
2  3.0   get[headphone]    2.0 -0.0  1.797693e+308 NaN
3  4.0         get[mug]   -0.0 -0.0  1.797693e+308 NaN
4  5.0         get[pen]    5.0 -0.0  1.797693e+308 NaN
```

```
In [39]: print('Total value:', m.get_objective_value())
Total value: 99.0
```

Because there is no direct access to expressions and variables, the optimal solution is printed by using the server response.

## 3.8.3 Limitations

- In SAS Viya, nonlinear models can be solved only by using the runOptmodel action, which requires the SAS Viya version to be 3.4 or later.
- User-defined decomposition blocks are available only in MPS mode, and therefore only work with client-side data.
- Mixed usage (client-side and server-side data) might not work in some cases. A quick fix would be transferring the data in either direction.

CHAPTER

# FOUR

# EXAMPLES

Examples are provided from SAS/OR documentation.

## 4.1 Viya Examples / Concrete

### 4.1.1 Food Manufacture 1

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex1_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex01.html

#### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    # Problem data
    OILS = ['veg1', 'veg2', 'oil1', 'oil2', 'oil3']
    PERIODS = range(1, 7)
    cost_data = [
        [110, 120, 130, 110, 115],
        [130, 130, 110, 90, 115],
        [110, 140, 130, 100,  95],
        [120, 110, 120, 120, 125],
        [100, 120, 150, 110, 105],
        [90, 100, 140,  80, 135]]
    cost = pd.DataFrame(cost_data, columns=OILS, index=PERIODS).transpose()
    hardness_data = [8.8, 6.1, 2.0, 4.2, 5.0]
    hardness = {OILS[i]: hardness_data[i] for i in range(len(OILS))}

    revenue_per_ton = 150
    veg_ub = 200
    nonveg_ub = 250
    store_ub = 1000
    storage_cost_per_ton = 5
```

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```
    hardness_lb = 3
    hardness_ub = 6
    init_storage = 500

    # Problem initialization
    m = so.Model(name='food_manufacture_1', session=cas_conn)

    # Problem definition
    buy = m.add_variables(OILS, PERIODS, lb=0, name='buy')
    use = m.add_variables(OILS, PERIODS, lb=0, name='use')
    manufacture = m.add_implicit_variable((use.sum('*', p) for p in PERIODS),
                                          name='manufacture')
    last_period = len(PERIODS)
    store = m.add_variables(OILS, [0] + list(PERIODS), lb=0, ub=store_ub,
                            name='store')
    for oil in OILS:
        store[oil, 0].set_bounds(lb=init_storage, ub=init_storage)
        store[oil, last_period].set_bounds(lb=init_storage, ub=init_storage)
    VEG = [i for i in OILS if 'veg' in i]
    NONVEG = [i for i in OILS if i not in VEG]
    revenue = so.quick_sum(revenue_per_ton * manufacture[p] for p in PERIODS)
    rawcost = so.quick_sum(cost.at[o, p] * buy[o, p]
                           for o in OILS for p in PERIODS)
    storagecost = so.quick_sum(storage_cost_per_ton * store[o, p]
                               for o in OILS for p in PERIODS)
    m.set_objective(revenue - rawcost - storagecost, sense=so.MAX,
                    name='profit')

    # Constraints
    m.add_constraints((use.sum(VEG, p) <= veg_ub for p in PERIODS),
                      name='veg_ub')
    m.add_constraints((use.sum(NONVEG, p) <= nonveg_ub for p in PERIODS),
                      name='nonveg_ub')
    m.add_constraints((store[o, p-1] + buy[o, p] == use[o, p] + store[o, p]
                      for o in OILS for p in PERIODS),
                      name='flow_balance')
    m.add_constraints((so.quick_sum(hardness[o]*use[o, p] for o in OILS) >=
                      hardness_lb * manufacture[p] for p in PERIODS),
                      name='hardness_ub')
    m.add_constraints((so.quick_sum(hardness[o]*use[o, p] for o in OILS) <=
                      hardness_ub * manufacture[p] for p in PERIODS),
                      name='hardness_lb')

    # Solver call
    res = m.solve()

    # With other solve options
    m.solve(options={'with': 'lp', 'algorithm': 'PS'})
    m.solve(options={'with': 'lp', 'algorithm': 'IP'})
    m.solve(options={'with': 'lp', 'algorithm': 'NS'})

    if res is not None:
        print(so.get_solution_table(buy, use, store))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.food_manufacture_1 import test

In [8]: test(cas_conn)
NOTE: Initialized model food_manufacture_1.
NOTE: Added action set 'optimization'.
NOTE: Converting model food_manufacture_1 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 95 variables (0 free, 10 fixed).
NOTE: The problem has 54 linear constraints (18 LE, 30 EQ, 6 GE, 0 range).
NOTE: The problem has 210 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 44 variables and 4 constraints.
NOTE: The LP presolver removed 48 constraint coefficients.
NOTE: The presolved problem has 51 variables, 50 constraints, and 162 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    4.755480E+05         0
          P 2         49    1.078426E+05         0
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 95 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 54 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: Added action set 'optimization'.
NOTE: Converting model food_manufacture_1 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 95 variables (0 free, 10 fixed).
NOTE: The problem has 54 linear constraints (18 LE, 30 EQ, 6 GE, 0 range).
NOTE: The problem has 210 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
```

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```
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 44 variables and 4 constraints.
NOTE: The LP presolver removed 48 constraint coefficients.
NOTE: The presolved problem has 51 variables, 50 constraints, and 162 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Primal Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          P 1          1    1.749040E+03         0
          P 2         32    3.638889E+04         0
          D 2         51    1.078426E+05         0
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: The Primal Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 95 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 54 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: Added action set 'optimization'.
NOTE: Converting model food_manufacture_1 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 95 variables (0 free, 10 fixed).
NOTE: The problem has 54 linear constraints (18 LE, 30 EQ, 6 GE, 0 range).
NOTE: The problem has 210 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 44 variables and 4 constraints.
NOTE: The LP presolver removed 48 constraint coefficients.
NOTE: The LP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 51 variables, 50 constraints, and 162 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Interior Point algorithm is used.
NOTE: The deterministic parallel mode is enabled.
NOTE: The Interior Point algorithm is using up to 8 threads.
                                             Primal        Bound         Dual
         Iter   Complement Duality Gap        Infeas        Infeas        Infeas    Time
            0   1.1003E+04   1.3994E+01   2.0602E-02   1.1145E-02   1.2444E+00       0
            1   1.0498E+04   4.1015E+01   1.7385E-02   9.4051E-03   1.0928E+00       0
            2   7.2084E+03   7.4551E+00   5.6703E-03   3.0675E-03   6.8365E-01       0
            3   1.7518E+03   1.1221E+00   1.5798E-03   8.5465E-04   1.1852E-01       0
            4   4.1038E+02   2.5544E-01   5.6092E-04   3.0344E-04   1.1852E-03       0
            5   3.9774E+01   2.2775E-02   7.2994E-05   3.9488E-05   1.9281E-05       0
            6   9.9400E-01   5.6526E-04   7.9112E-07   4.2798E-07   7.7185E-07       0
            7   9.9572E-03   5.6615E-06   7.9420E-09   4.2964E-09   7.7239E-09       0
            8   0.0000E+00   1.8686E-08   1.6613E-07   1.1864E-10   6.2833E-07       0
NOTE: The Interior Point solve time is 0.02 seconds.
NOTE: The CROSSOVER option is enabled.
NOTE: The crossover basis contains 11 primal and 3 dual superbasic variables.
                              Objective
```

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```
         Phase Iteration        Value         Time
          P C          1    1.014226E+03         0
          D C         13    9.697429E+00         0
          D 2         16    1.078426E+05         0
          P 2         17    1.078426E+05         0
          D 2         18    1.078426E+05         0
NOTE: The Crossover time is 0.01 seconds.
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 95 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 54 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 16 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: Added action set 'optimization'.
NOTE: Converting model food_manufacture_1 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 95 variables (0 free, 10 fixed).
NOTE: The problem has 54 linear constraints (18 LE, 30 EQ, 6 GE, 0 range).
NOTE: The problem has 210 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 44 variables and 4 constraints.
NOTE: The LP presolver removed 48 constraint coefficients.
NOTE: The presolved problem has 51 variables, 50 constraints, and 162 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Network Simplex algorithm is used.
NOTE: The network has 20 rows (40.00%), 29 columns (56.86%), and 1 component.
NOTE: The network extraction and setup time is 0.01 seconds.
                          Primal         Primal           Dual
         Iteration      Objective  Infeasibility  Infeasibility     Time
                 1    3.750000E+03   5.000000E+02   1.551000E+03     0.01
                24    7.125000E+04   0.000000E+00   0.000000E+00     0.01
NOTE: The Network Simplex solve time is 0.00 seconds.
NOTE: The total Network Simplex solve time is 0.01 seconds.
NOTE: The Dual Simplex algorithm is used.
                             Objective
         Phase Iteration        Value         Time
          D 2          1    2.240180E+05         0
          P 2         43    1.078426E+05         0
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: The Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 95 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 54 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 14 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
                 buy            use         store
veg1 1  0.000000e+00  8.518519e+01  4.148148e+02
```

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```
veg1 2  0.000000e+00  1.592593e+02  2.555556e+02
veg1 3  2.842171e-14  0.000000e+00  2.555556e+02
veg1 4 -1.421085e-14  1.592593e+02  9.629630e+01
veg1 5  7.105427e-14  9.629630e+01  0.000000e+00
veg1 6  6.592593e+02  1.592593e+02  5.000000e+02
veg2 1 -5.684342e-14  1.148148e+02  3.851852e+02
veg2 2  0.000000e+00  4.074074e+01  3.444444e+02
veg2 3  2.842171e-14  2.000000e+02  1.444444e+02
veg2 4 -2.842171e-14  4.074074e+01  1.037037e+02
veg2 5  0.000000e+00  1.037037e+02  0.000000e+00
veg2 6  5.407407e+02  4.074074e+01  5.000000e+02
oil1 1  0.000000e+00  0.000000e+00  5.000000e+02
oil1 2  0.000000e+00  0.000000e+00  5.000000e+02
oil1 3  0.000000e+00  0.000000e+00  5.000000e+02
oil1 4  0.000000e+00 -1.744059e-14  5.000000e+02
oil1 5  0.000000e+00  0.000000e+00  5.000000e+02
oil1 6  0.000000e+00  0.000000e+00  5.000000e+02
oil2 1  0.000000e+00  0.000000e+00  5.000000e+02
oil2 2  2.500000e+02  2.500000e+02  5.000000e+02
oil2 3  0.000000e+00  2.273737e-13  5.000000e+02
oil2 4  2.842171e-14  2.500000e+02  2.500000e+02
oil2 5  0.000000e+00  2.500000e+02  0.000000e+00
oil2 6  7.500000e+02  2.500000e+02  5.000000e+02
oil3 1  0.000000e+00  2.500000e+02  2.500000e+02
oil3 2  0.000000e+00  0.000000e+00  2.500000e+02
oil3 3 -5.048710e-29  2.500000e+02 -2.842171e-13
oil3 4  2.842171e-13  0.000000e+00  0.000000e+00
oil3 5  5.000000e+02  0.000000e+00  5.000000e+02
oil3 6  0.000000e+00  0.000000e+00  5.000000e+02
veg1 0           NaN           NaN  5.000000e+02
veg2 0           NaN           NaN  5.000000e+02
oil1 0           NaN           NaN  5.000000e+02
oil2 0           NaN           NaN  5.000000e+02
oil3 0           NaN           NaN  5.000000e+02
Out[8]: 107842.59259259264
```

### 4.1.2 Food Manufacture 2

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex2_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex02.html

### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    # Problem data
    OILS = ['veg1', 'veg2', 'oil1', 'oil2', 'oil3']
    PERIODS = range(1, 7)
    cost_data = [
        [110, 120, 130, 110, 115],
        [130, 130, 110, 90, 115],
        [110, 140, 130, 100,  95],
        [120, 110, 120, 120, 125],
        [100, 120, 150, 110, 105],
        [90, 100, 140,  80, 135]]
    cost = pd.DataFrame(cost_data, columns=OILS, index=PERIODS).transpose()
    hardness_data = [8.8, 6.1, 2.0, 4.2, 5.0]
    hardness = {OILS[i]: hardness_data[i] for i in range(len(OILS))}

    revenue_per_ton = 150
    veg_ub = 200
    nonveg_ub = 250
    store_ub = 1000
    storage_cost_per_ton = 5
    hardness_lb = 3
    hardness_ub = 6
    init_storage = 500
    max_num_oils_used = 3
    min_oil_used_threshold = 20

    # Problem initialization
    m = so.Model(name='food_manufacture_2', session=cas_conn)

    # Problem definition
    buy = m.add_variables(OILS, PERIODS, lb=0, name='buy')
    use = m.add_variables(OILS, PERIODS, lb=0, name='use')
    manufacture = m.add_implicit_variable((use.sum('*', p) for p in PERIODS),
                                          name='manufacture')
    last_period = len(PERIODS)
    store = m.add_variables(OILS, [0] + list(PERIODS), lb=0, ub=store_ub,
                            name='store')
    for oil in OILS:
        store[oil, 0].set_bounds(lb=init_storage, ub=init_storage)
        store[oil, last_period].set_bounds(lb=init_storage, ub=init_storage)
    VEG = [i for i in OILS if 'veg' in i]
    NONVEG = [i for i in OILS if i not in VEG]
    revenue = so.quick_sum(revenue_per_ton * manufacture[p] for p in PERIODS)
    rawcost = so.quick_sum(cost.at[o, p] * buy[o, p]
                           for o in OILS for p in PERIODS)
    storagecost = so.quick_sum(storage_cost_per_ton * store[o, p]
                               for o in OILS for p in PERIODS)
    m.set_objective(revenue - rawcost - storagecost, sense=so.MAX,
                    name='profit')
```

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```
    # Constraints
    m.add_constraints((use.sum(VEG, p) <= veg_ub for p in PERIODS),
                      name='veg_ub')
    m.add_constraints((use.sum(NONVEG, p) <= nonveg_ub for p in PERIODS),
                      name='nonveg_ub')
    m.add_constraints((store[o, p-1] + buy[o, p] == use[o, p] + store[o, p]
                      for o in OILS for p in PERIODS),
                      name='flow_balance')
    m.add_constraints((so.quick_sum(hardness[o]*use[o, p] for o in OILS) >=
                      hardness_lb * manufacture[p] for p in PERIODS),
                      name='hardness_ub')
    m.add_constraints((so.quick_sum(hardness[o]*use[o, p] for o in OILS) <=
                      hardness_ub * manufacture[p] for p in PERIODS),
                      name='hardness_lb')

    # Additions to the first problem
    isUsed = m.add_variables(OILS, PERIODS, vartype=so.BIN, name='is_used')
    for p in PERIODS:
        for o in VEG:
            use[o, p].set_bounds(ub=veg_ub)
        for o in NONVEG:
            use[o, p].set_bounds(ub=nonveg_ub)
    m.add_constraints((use[o, p] <= use[o, p]._ub * isUsed[o, p]
                      for o in OILS for p in PERIODS), name='link')
    m.add_constraints((isUsed.sum('*', p) <= max_num_oils_used
                      for p in PERIODS), name='logical1')
    m.add_constraints((use[o, p] >= min_oil_used_threshold * isUsed[o, p]
                      for o in OILS for p in PERIODS), name='logical2')
    m.add_constraints((isUsed[o, p] <= isUsed['oil3', p]
                      for o in ['veg1', 'veg2'] for p in PERIODS),
                      name='logical3')

    res = m.solve()
    if res is not None:
        print(so.get_solution_table(buy, use, store, isUsed))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.food_manufacture_2 import test
```

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```
In [8]: test(cas_conn)
NOTE: Initialized model food_manufacture_2.
NOTE: Added action set 'optimization'.
NOTE: Converting model food_manufacture_2 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 125 variables (0 free, 10 fixed).
NOTE: The problem has 30 binary and 0 integer variables.
NOTE: The problem has 132 linear constraints (66 LE, 30 EQ, 36 GE, 0 range).
NOTE: The problem has 384 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 50 variables and 10 constraints.
NOTE: The MILP presolver removed 66 constraint coefficients.
NOTE: The MILP presolver modified 6 constraint coefficients.
NOTE: The presolved problem has 75 variables, 122 constraints, and 318 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      5  36900.0000000         343250   89.25%       0
                0        1      5  36900.0000000         107333   65.62%       0
                0        1      5  36900.0000000         105799   65.12%       0
                0        1      5  36900.0000000         105650   65.07%       0
                0        1      5  36900.0000000         105650   65.07%       0
                0        1      5  36900.0000000         105650   65.07%       0
                0        1      5  36900.0000000         105650   65.07%       0
                0        1      5  36900.0000000         105650   65.07%       0
                0        1      6  99491.6666667         105650    5.83%       0
NOTE: The MILP solver added 15 cuts with 77 cut coefficients at the root.
               10        6      7  99683.3343492         105090    5.15%       0
               28       19      8  99908.3333333         104782    4.65%       0
               68       45      9  99908.3333333         104564    4.45%       0
              139       80     10         100054         104225    4.00%       0
              145       75     11         100192         103683    3.37%       0
              177       86     12         100192         103516    3.21%       0
              183       87     13         100214         103516    3.19%       0
              189       85     14         100279         103268    2.89%       0
              283       40     15         100279         102053    1.74%       0
              284       40     16         100279         102053    1.74%       0
              333        0     16         100279         100279    0.00%       0
NOTE: Optimal.
NOTE: Objective = 100278.70577.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 125 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 132 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
                 buy           use         store       is_used
veg1 1  0.000000e+00  8.518519e+01  4.148148e+02  1.000000e+00
veg1 2  0.000000e+00  8.518519e+01  3.296296e+02  1.000000e+00
veg1 3  0.000000e+00  0.000000e+00  3.296296e+02  0.000000e+00
```

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```
veg1 4  0.000000e+00  1.550000e+02  1.746296e+02  9.999948e-01
veg1 5  0.000000e+00  1.550000e+02  1.962960e+01  1.000000e+00
veg1 6  4.803704e+02  0.000000e+00  5.000000e+02  0.000000e+00
veg2 1  0.000000e+00  1.148148e+02  3.851852e+02  1.000000e+00
veg2 2  0.000000e+00  1.148148e+02  2.703704e+02  1.000000e+00
veg2 3  0.000000e+00  2.000000e+02  7.037037e+01  1.000000e+00
veg2 4 -1.421085e-14  0.000000e+00  7.037037e+01 -1.949310e-15
veg2 5  0.000000e+00  0.000000e+00  7.037037e+01 -0.000000e+00
veg2 6  6.296296e+02  2.000000e+02  5.000000e+02  1.000000e+00
oil1 1  0.000000e+00  0.000000e+00  5.000000e+02  0.000000e+00
oil1 2 -5.684342e-14  0.000000e+00  5.000000e+02  0.000000e+00
oil1 3  0.000000e+00  0.000000e+00  5.000000e+02 -0.000000e+00
oil1 4  5.684342e-14  0.000000e+00  5.000000e+02  0.000000e+00
oil1 5  0.000000e+00  0.000000e+00  5.000000e+02  0.000000e+00
oil1 6  0.000000e+00  0.000000e+00  5.000000e+02  0.000000e+00
oil2 1  0.000000e+00  0.000000e+00  5.000000e+02 -0.000000e+00
oil2 2  1.900001e+02  2.273737e-13  6.900001e+02  9.094947e-16
oil2 3  0.000000e+00  2.300000e+02  4.600001e+02  1.000000e+00
oil2 4 -2.842171e-14  2.300001e+02  2.300000e+02  1.000000e+00
oil2 5  2.842171e-14  2.300000e+02  0.000000e+00  1.000000e+00
oil2 6  7.300000e+02  2.300000e+02  5.000000e+02  1.000000e+00
oil3 1  0.000000e+00  2.500000e+02  2.500000e+02  1.000000e+00
oil3 2  0.000000e+00  2.500000e+02  2.557954e-13  1.000000e+00
oil3 3  5.799999e+02  2.000000e+01  5.599999e+02  1.000000e+00
oil3 4  0.000000e+00  1.999990e+01  5.400000e+02  9.999948e-01
oil3 5  0.000000e+00  2.000000e+01  5.200000e+02  1.000000e+00
oil3 6  0.000000e+00  2.000000e+01  5.000000e+02  1.000000e+00
veg1 0           NaN           NaN  5.000000e+02           NaN
veg2 0           NaN           NaN  5.000000e+02           NaN
oil1 0           NaN           NaN  5.000000e+02           NaN
oil2 0           NaN           NaN  5.000000e+02           NaN
oil3 0           NaN           NaN  5.000000e+02           NaN
Out[8]: 100278.70576513262
```

### 4.1.3 Factory Planning 1

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex3_toc.htm&docsetVersion=15.1&locale=en

https://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex03.html

#### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    m = so.Model(name='factory_planning_1', session=cas_conn)
```

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```
    # Input data
    product_list = ['prod{}'.format(i) for i in range(1, 8)]
    product_data = pd.DataFrame([10, 6, 8, 4, 11, 9, 3],
                                columns=['profit'], index=product_list)
    demand_data = [
        [500, 1000, 300, 300,  800, 200, 100],
        [600,  500, 200,   0,  400, 300, 150],
        [300,  600,   0,   0,  500, 400, 100],
        [200,  300, 400, 500,  200,   0, 100],
        [0,    100, 500, 100, 1000, 300,   0],
        [500,  500, 100, 300, 1100, 500,  60]]
    demand_data = pd.DataFrame(
        demand_data, columns=product_list, index=range(1, 7))
    machine_types_data = [
        ['grinder', 4],
        ['vdrill', 2],
        ['hdrill', 3],
        ['borer', 1],
        ['planer', 1]]
    machine_types_data = pd.DataFrame(machine_types_data, columns=[
        'machine_type', 'num_machines']).set_index(['machine_type'])
    machine_type_period_data = [
        ['grinder', 1, 1],
        ['hdrill',  2, 2],
        ['borer',   3, 1],
        ['vdrill',  4, 1],
        ['grinder', 5, 1],
        ['vdrill',  5, 1],
        ['planer',  6, 1],
        ['hdrill',  6, 1]]
    machine_type_period_data = pd.DataFrame(machine_type_period_data, columns=[
        'machine_type', 'period', 'num_down'])
    machine_type_product_data = [
        ['grinder', 0.5,  0.7,  0,    0,    0.3,  0.2, 0.5],
        ['vdrill',  0.1,  0.2,  0,    0.3,  0,    0.6, 0],
        ['hdrill',  0.2,  0,    0.8,  0,    0,    0,   0.6],
        ['borer',   0.05, 0.03, 0,    0.07, 0.1,  0,   0.08],
        ['planer',  0,    0,    0.01, 0,    0.05, 0,   0.05]]
    machine_type_product_data = \
        pd.DataFrame(machine_type_product_data, columns=['machine_type'] +
                     product_list).set_index(['machine_type'])
    store_ub = 100
    storage_cost_per_unit = 0.5
    final_storage = 50
    num_hours_per_period = 24 * 2 * 8

    # Problem definition
    PRODUCTS = product_list
    PERIODS = range(1, 7)
    MACHINE_TYPES = machine_types_data.index.values

    num_machine_per_period = pd.DataFrame()
    for i in range(1, 7):
        num_machine_per_period[i] = machine_types_data['num_machines']
    for _, row in machine_type_period_data.iterrows():
        num_machine_per_period.at[row['machine_type'],
                                  row['period']] -= row['num_down']
```

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```
    make = m.add_variables(PRODUCTS, PERIODS, lb=0, name='make')
    sell = m.add_variables(PRODUCTS, PERIODS, lb=0, ub=demand_data.transpose(),
                           name='sell')

    store = m.add_variables(PRODUCTS, PERIODS, lb=0, ub=store_ub, name='store')
    for p in PRODUCTS:
        store[p, 6].set_bounds(lb=final_storage, ub=final_storage+1)

    storageCost = storage_cost_per_unit * store.sum('*', '*')
    revenue = so.quick_sum(product_data.at[p, 'profit'] * sell[p, t]
                           for p in PRODUCTS for t in PERIODS)
    m.set_objective(revenue-storageCost, sense=so.MAX, name='total_profit')

    production_time = machine_type_product_data
    m.add_constraints((
        so.quick_sum(production_time.at[mc, p] * make[p, t] for p in PRODUCTS)
        <= num_hours_per_period * num_machine_per_period.at[mc, t]
        for mc in MACHINE_TYPES for t in PERIODS), name='machine_hours')
    m.add_constraints(((store[p, t-1] if t-1 in PERIODS else 0) + make[p, t] ==
                       sell[p, t] + store[p, t] for p in PRODUCTS
                       for t in PERIODS),
                      name='flow_balance')

    res = m.solve()
    if res is not None:
        print(so.get_solution_table(make, sell, store))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.factory_planning_1 import test

In [8]: test(cas_conn)
NOTE: Initialized model factory_planning_1.
NOTE: Added action set 'optimization'.
NOTE: Converting model factory_planning_1 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 126 variables (0 free, 6 fixed).
NOTE: The problem has 72 linear constraints (30 LE, 42 EQ, 0 GE, 0 range).
```

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```
NOTE: The problem has 281 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 60 variables and 46 constraints.
NOTE: The LP presolver removed 178 constraint coefficients.
NOTE: The presolved problem has 66 variables, 26 constraints, and 103 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    9.478510E+04         0
          P 2         21    9.371518E+04         0
NOTE: Optimal.
NOTE: Objective = 93715.178571.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 126 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 72 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
                   make         sell  store
(prod1, 1)   500.000000   500.000000    0.0
(prod1, 2)   700.000000   600.000000  100.0
(prod1, 3)     0.000000   100.000000    0.0
(prod1, 4)   200.000000   200.000000    0.0
(prod1, 5)     0.000000     0.000000    0.0
(prod1, 6)   550.000000   500.000000   50.0
(prod2, 1)   888.571429   888.571429    0.0
(prod2, 2)   600.000000   500.000000  100.0
(prod2, 3)     0.000000   100.000000    0.0
(prod2, 4)   300.000000   300.000000    0.0
(prod2, 5)   100.000000   100.000000    0.0
(prod2, 6)   550.000000   500.000000   50.0
(prod3, 1)   382.500000   300.000000   82.5
(prod3, 2)   117.500000   200.000000    0.0
(prod3, 3)     0.000000     0.000000    0.0
(prod3, 4)   400.000000   400.000000    0.0
(prod3, 5)   600.000000   500.000000  100.0
(prod3, 6)     0.000000    50.000000   50.0
(prod4, 1)   300.000000   300.000000    0.0
(prod4, 2)     0.000000     0.000000    0.0
(prod4, 3)     0.000000     0.000000    0.0
(prod4, 4)   500.000000   500.000000    0.0
(prod4, 5)   100.000000   100.000000    0.0
(prod4, 6)   350.000000   300.000000   50.0
(prod5, 1)   800.000000   800.000000    0.0
(prod5, 2)   500.000000   400.000000  100.0
(prod5, 3)     0.000000   100.000000    0.0
(prod5, 4)   200.000000   200.000000    0.0
(prod5, 5)  1100.000000  1000.000000  100.0
(prod5, 6)     0.000000    50.000000   50.0
(prod6, 1)   200.000000   200.000000    0.0
```

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```
(prod6, 2)   300.000000   300.000000    0.0
(prod6, 3)   400.000000   400.000000    0.0
(prod6, 4)     0.000000     0.000000    0.0
(prod6, 5)   300.000000   300.000000    0.0
(prod6, 6)   550.000000   500.000000   50.0
(prod7, 1)     0.000000     0.000000    0.0
(prod7, 2)   250.000000   150.000000  100.0
(prod7, 3)     0.000000   100.000000    0.0
(prod7, 4)   100.000000   100.000000    0.0
(prod7, 5)   100.000000     0.000000  100.0
(prod7, 6)     0.000000    50.000000   50.0
Out[8]: 93715.17857142858
```

### 4.1.4 Factory Planning 2

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex4_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex04.html

#### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    m = so.Model(name='factory_planning_2', session=cas_conn)

    # Input data
    product_list = ['prod{}'.format(i) for i in range(1, 8)]
    product_data = pd.DataFrame([10, 6, 8, 4, 11, 9, 3],
                                columns=['profit'], index=product_list)
    demand_data = [
        [500, 1000, 300, 300,  800, 200, 100],
        [600,  500, 200,   0,  400, 300, 150],
        [300,  600,   0,   0,  500, 400, 100],
        [200,  300, 400, 500,  200,   0, 100],
        [0,    100, 500, 100, 1000, 300,   0],
        [500,  500, 100, 300, 1100, 500,  60]]
    demand_data = pd.DataFrame(
        demand_data, columns=product_list, index=range(1, 7))
    machine_type_product_data = [
        ['grinder', 0.5,  0.7,  0,    0,    0.3,  0.2, 0.5],
        ['vdrill',  0.1,  0.2,  0,    0.3,  0,    0.6, 0],
        ['hdrill',  0.2,  0,    0.8,  0,    0,    0,   0.6],
        ['borer',   0.05, 0.03, 0,    0.07, 0.1,  0,   0.08],
        ['planer',  0,    0,    0.01, 0,    0.05, 0,   0.05]]
    machine_type_product_data = \
        pd.DataFrame(machine_type_product_data, columns=['machine_type'] +
```

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```
                    product_list).set_index(['machine_type'])
    machine_types_data = [
        ['grinder', 4, 2],
        ['vdrill',  2, 2],
        ['hdrill',  3, 3],
        ['borer',   1, 1],
        ['planer',  1, 1]]
    machine_types_data = pd.DataFrame(machine_types_data, columns=[
        'machine_type', 'num_machines', 'num_machines_needing_maintenance'])\
        .set_index(['machine_type'])

    store_ub = 100
    storage_cost_per_unit = 0.5
    final_storage = 50
    num_hours_per_period = 24 * 2 * 8

    # Problem definition
    PRODUCTS = product_list
    profit = product_data['profit']
    PERIODS = range(1, 7)
    MACHINE_TYPES = machine_types_data.index.tolist()

    num_machines = machine_types_data['num_machines']

    make = m.add_variables(PRODUCTS, PERIODS, lb=0, name='make')
    sell = m.add_variables(PRODUCTS, PERIODS, lb=0, ub=demand_data.transpose(),
                           name='sell')

    store = m.add_variables(PRODUCTS, PERIODS, lb=0, ub=store_ub, name='store')
    for p in PRODUCTS:
        store[p, 6].set_bounds(lb=final_storage, ub=final_storage)

    storageCost = so.quick_sum(
        storage_cost_per_unit * store[p, t] for p in PRODUCTS for t in PERIODS)
    revenue = so.quick_sum(profit[p] * sell[p, t]
                           for p in PRODUCTS for t in PERIODS)
    m.set_objective(revenue-storageCost, sense=so.MAX, name='total_profit')

    num_machines_needing_maintenance = \
        machine_types_data['num_machines_needing_maintenance']
    numMachinesDown = m.add_variables(MACHINE_TYPES, PERIODS, vartype=so.INT,
                                      lb=0, name='numMachinesDown')

    production_time = machine_type_product_data
    m.add_constraints((
        so.quick_sum(production_time.at[mc, p] * make[p, t] for p in PRODUCTS)
        <= num_hours_per_period *
        (num_machines[mc] - numMachinesDown[mc, t])
        for mc in MACHINE_TYPES for t in PERIODS), name='machine_hours_con')

    m.add_constraints((so.quick_sum(numMachinesDown[mc, t] for t in PERIODS) ==
                       num_machines_needing_maintenance[mc]
                       for mc in MACHINE_TYPES), name='maintenance_con')

    m.add_constraints(((store[p, t-1] if t-1 in PERIODS else 0) + make[p, t] ==
                      sell[p, t] + store[p, t]
                      for p in PRODUCTS for t in PERIODS),
```

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```
                        name='flow_balance_con')

    res = m.solve()
    if res is not None:
        print(so.get_solution_table(make, sell, store))
        print(so.get_solution_table(numMachinesDown).unstack(level=-1))

    print(m.get_solution_summary())
    print(m.get_problem_summary())

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.factory_planning_2 import test

In [8]: test(cas_conn)
NOTE: Initialized model factory_planning_2.
NOTE: Added action set 'optimization'.
NOTE: Converting model factory_planning_2 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 156 variables (0 free, 13 fixed).
NOTE: The problem has 0 binary and 30 integer variables.
NOTE: The problem has 77 linear constraints (30 LE, 47 EQ, 0 GE, 0 range).
NOTE: The problem has 341 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 27 variables and 15 constraints.
NOTE: The MILP presolver removed 63 constraint coefficients.
NOTE: The MILP presolver modified 16 constraint coefficients.
NOTE: The presolved problem has 129 variables, 62 constraints, and 278 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      2  92755.0000000         116455   20.35%       0
                0        1      2  92755.0000000         116455   20.35%       0
```

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```
                0        1      2  92755.0000000        116141   20.14%       0
                0        1      2  92755.0000000        115660   19.80%       0
                0        1      2  92755.0000000        114136   18.73%       0
                0        1      2  92755.0000000        113334   18.16%       0
                0        1      2  92755.0000000        112487   17.54%       0
                0        1      2  92755.0000000        111392   16.73%       0
                0        1      2  92755.0000000        111136   16.54%       0
                0        1      2  92755.0000000        110056   15.72%       0
                0        1      2  92755.0000000        109718   15.46%       0
                0        1      2  92755.0000000        109122   15.00%       0
                0        1      2  92755.0000000        108904   14.83%       0
                0        1      2  92755.0000000        108868   14.80%       0
                0        1      2  92755.0000000        108855   14.79%       0
                0        1      3         108855        108855    0.00%       0
NOTE: The MILP solver added 38 cuts with 136 cut coefficients at the root.
NOTE: Optimal within relative gap.
NOTE: Objective = 108855.00961.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 156 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 77 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
                   make         sell       store
(prod1, 1)   500.000000   500.000000    0.000000
(prod1, 2)   600.000200   600.000000    0.000200
(prod1, 3)   399.999201   300.000000   99.999401
(prod1, 4)     0.001198   100.000599    0.000000
(prod1, 5)     0.000000     0.000000    0.000000
(prod1, 6)   550.000000   500.000000   50.000000
(prod2, 1)  1000.000000  1000.000000    0.000000
(prod2, 2)   500.000188   500.000000    0.000188
(prod2, 3)   699.998215   599.999002   99.999401
(prod2, 4)     0.001797   100.001198    0.000000
(prod2, 5)   100.002196   100.000000    0.002196
(prod2, 6)   549.997804   500.000000   50.000000
(prod3, 1)   300.000000   300.000000    0.000000
(prod3, 2)   200.000000   200.000000    0.000000
(prod3, 3)   100.000000     0.000000  100.000000
(prod3, 4)     0.001283   100.001283    0.000000
(prod3, 5)   500.000072   500.000000    0.000072
(prod3, 6)   149.999928   100.000000   50.000000
(prod4, 1)   300.000000   300.000000    0.000000
(prod4, 2)     0.000000     0.000000    0.000000
(prod4, 3)    99.999401     0.000000   99.999401
(prod4, 4)     0.002994   100.002396    0.000000
(prod4, 5)   100.000000   100.000000    0.000000
(prod4, 6)   350.000000   300.000000   50.000000
(prod5, 1)   800.000522   800.000000    0.000522
(prod5, 2)   399.999338   399.999460    0.000399
(prod5, 3)   599.998374   499.999201   99.999572
(prod5, 4)     0.001027   100.000599    0.000000
(prod5, 5)  1000.006512  1000.000000    0.006512
(prod5, 6)  1149.992981  1099.999493   50.000000
(prod6, 1)   200.000000   200.000000    0.000000
(prod6, 2)   300.000000   300.000000    0.000000
```

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```
(prod6, 3)   400.000000   400.000000    0.000000
(prod6, 4)     0.000000     0.000000    0.000000
(prod6, 5)   300.000000   300.000000    0.000000
(prod6, 6)   550.000000   500.000000   50.000000
(prod7, 1)   100.000000   100.000000    0.000000
(prod7, 2)   150.000000   150.000000    0.000000
(prod7, 3)   199.999572   100.000000   99.999572
(prod7, 4)     0.000428   100.000000    0.000000
(prod7, 5)     0.000000     0.000000    0.000000
(prod7, 6)   110.000000    60.000000   50.000000
numMachinesDown  (grinder, 1)   -0.000000e+00
numMachinesDown  (grinder, 2)   -0.000000e+00
numMachinesDown  (grinder, 3)   -0.000000e+00
numMachinesDown  (grinder, 4)    2.000000e+00
numMachinesDown  (grinder, 5)   -0.000000e+00
numMachinesDown  (grinder, 6)   -0.000000e+00
numMachinesDown  (vdrill, 1)     0.000000e+00
numMachinesDown  (vdrill, 2)    -0.000000e+00
numMachinesDown  (vdrill, 3)    -0.000000e+00
numMachinesDown  (vdrill, 4)     1.999994e+00
numMachinesDown  (vdrill, 5)     3.955573e-06
numMachinesDown  (vdrill, 6)     2.033239e-06
numMachinesDown  (hdrill, 1)     1.000000e+00
numMachinesDown  (hdrill, 2)     2.000000e+00
numMachinesDown  (hdrill, 3)    -0.000000e+00
numMachinesDown  (hdrill, 4)    -0.000000e+00
numMachinesDown  (hdrill, 5)    -0.000000e+00
numMachinesDown  (hdrill, 6)    -0.000000e+00
numMachinesDown  (borer, 1)      0.000000e+00
numMachinesDown  (borer, 2)     -0.000000e+00
numMachinesDown  (borer, 3)      1.996271e-06
numMachinesDown  (borer, 4)      9.999940e-01
numMachinesDown  (borer, 5)     -0.000000e+00
numMachinesDown  (borer, 6)      3.992541e-06
numMachinesDown  (planer, 1)     0.000000e+00
numMachinesDown  (planer, 2)     1.798545e-06
numMachinesDown  (planer, 3)     1.996271e-06
numMachinesDown  (planer, 4)     9.999957e-01
numMachinesDown  (planer, 5)     8.120488e-16
numMachinesDown  (planer, 6)     4.829074e-07
dtype: float64
Selected Rows from Table SOLUTIONSUMMARY

                                                 Value
Label
Solver                                            MILP
Algorithm                                Branch and Cut
Objective Function                        total_profit
Solution Status        Optimal within Relative Gap
Objective Value                           108855.00961

Relative Gap                              3.0634424E-6
Absolute Gap                              0.3334720743
Primal Infeasibility                      5.684342E-14
Bound Infeasibility                                  0
Integer Infeasibility                     5.9888119E-6
```

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```
Best Bound                           108855.34308
Nodes                                           1
Solutions Found                                 3
Iterations                                    377
Presolve Time                                0.00
Solution Time                                0.31
Selected Rows from Table PROBLEMSUMMARY

                                Value
Label
Objective Sense           Maximization
Objective Function        total_profit
Objective Type                  Linear

Number of Variables                156
Bounded Above                        0
Bounded Below                       72
Bounded Below and Above             71
Free                                 0
Fixed                               13
Binary                               0
Integer                             30

Number of Constraints               77
Linear LE (<=)                      30
Linear EQ (=)                       47
Linear GE (>=)                       0
Linear Range                         0

Constraint Coefficients            341
Out[8]: 108855.00960810453
```

### 4.1.5 Manpower Planning

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex5_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex05.html

#### Model

```
import sasoptpy as so
import pandas as pd
import math


def test(cas_conn):
    # Input data
    demand_data = pd.DataFrame([
        [0, 2000, 1500, 1000],
        [1, 1000, 1400, 1000],
```

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```
        [2, 500, 2000, 1500],
        [3, 0, 2500, 2000]
        ], columns=['period', 'unskilled', 'semiskilled', 'skilled'])\
        .set_index(['period'])
    worker_data = pd.DataFrame([
        ['unskilled',   0.25, 0.10, 500, 200, 1500, 50, 500],
        ['semiskilled', 0.20, 0.05, 800, 500, 2000, 50, 400],
        ['skilled',     0.10, 0.05, 500, 500, 3000, 50, 400]
        ], columns=['worker', 'waste_new', 'waste_old', 'recruit_ub',
                    'redundancy_cost', 'overmanning_cost', 'shorttime_ub',
                    'shorttime_cost']).set_index(['worker'])
    retrain_data = pd.DataFrame([
        ['unskilled', 'semiskilled', 200, 400],
        ['semiskilled', 'skilled', math.inf, 500],
        ], columns=['worker1', 'worker2', 'retrain_ub', 'retrain_cost']).\
        set_index(['worker1', 'worker2'])
    downgrade_data = pd.DataFrame([
        ['semiskilled', 'unskilled'],
        ['skilled', 'semiskilled'],
        ['skilled', 'unskilled']
        ], columns=['worker1', 'worker2'])

    semiskill_retrain_frac_ub = 0.25
    downgrade_leave_frac = 0.5
    overmanning_ub = 150
    shorttime_frac = 0.5

    # Sets
    WORKERS = worker_data.index.tolist()
    PERIODS0 = demand_data.index.tolist()
    PERIODS = PERIODS0[1:]
    RETRAIN_PAIRS = [i for i, _ in retrain_data.iterrows()]
    DOWNGRADE_PAIRS = [(row['worker1'], row['worker2'])
                       for _, row in downgrade_data.iterrows()]

    waste_old = worker_data['waste_old']
    waste_new = worker_data['waste_new']
    redundancy_cost = worker_data['redundancy_cost']
    overmanning_cost = worker_data['overmanning_cost']
    shorttime_cost = worker_data['shorttime_cost']
    retrain_cost = retrain_data['retrain_cost'].unstack(level=-1)

    # Initialization
    m = so.Model(name='manpower_planning', session=cas_conn)

    # Variables
    numWorkers = m.add_variables(WORKERS, PERIODS0, name='numWorkers', lb=0)
    demand0 = demand_data.loc[0]
    for w in WORKERS:
        numWorkers[w, 0].set_bounds(lb=demand0[w], ub=demand0[w])
    numRecruits = m.add_variables(WORKERS, PERIODS, name='numRecruits', lb=0)
    worker_ub = worker_data['recruit_ub']
    for w in WORKERS:
        for p in PERIODS:
            numRecruits[w, p].set_bounds(ub=worker_ub[w])
    numRedundant = m.add_variables(WORKERS, PERIODS, name='numRedundant', lb=0)
    numShortTime = m.add_variables(WORKERS, PERIODS, name='numShortTime', lb=0)
```

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```
    shorttime_ub = worker_data['shorttime_ub']
    for w in WORKERS:
        for p in PERIODS:
            numShortTime.set_bounds(ub=shorttime_ub[w])
    numExcess = m.add_variables(WORKERS, PERIODS, name='numExcess', lb=0)

    retrain_ub = pd.DataFrame()
    for i in PERIODS:
        retrain_ub[i] = retrain_data['retrain_ub']
    numRetrain = m.add_variables(RETRAIN_PAIRS, PERIODS, name='numRetrain',
                                 lb=0, ub=retrain_ub)

    numDowngrade = m.add_variables(DOWNGRADE_PAIRS, PERIODS,
                                   name='numDowngrade', lb=0)
    # Constraints
    m.add_constraints((numWorkers[w, p]
                       - (1-shorttime_frac) * numShortTime[w, p]
                       - numExcess[w, p] == demand_data.loc[p, w]
                       for w in WORKERS for p in PERIODS), name='demand')
    m.add_constraints((numWorkers[w, p] ==
                       (1 - waste_old[w]) * numWorkers[w, p-1]
                       + (1 - waste_new[w]) * numRecruits[w, p]
                       + (1 - waste_old[w]) * numRetrain.sum('*', w, p)
                       + (1 - downgrade_leave_frac) *
                       numDowngrade.sum('*', w, p)
                       - numRetrain.sum(w, '*', p)
                       - numDowngrade.sum(w, '*', p)
                       - numRedundant[w, p]
                       for w in WORKERS for p in PERIODS),
                       name='flow_balance')
    m.add_constraints((numRetrain['semiskilled', 'skilled', p] <=
                       semiskill_retrain_frac_ub * numWorkers['skilled', p]
                       for p in PERIODS), name='semiskill_retrain')
    m.add_constraints((numExcess.sum('*', p) <= overmanning_ub
                       for p in PERIODS), name='overmanning')
    # Objectives
    redundancy = so.Expression(numRedundant.sum('*', '*'), name='redundancy')
    cost = so.Expression(so.quick_sum(redundancy_cost[w] * numRedundant[w, p] +
                                      shorttime_cost[w] * numShortTime[w, p] +
                                      overmanning_cost[w] * numExcess[w, p]
                                      for w in WORKERS for p in PERIODS)
                         + so.quick_sum(
                             retrain_cost.loc[i, j] * numRetrain[i, j, p]
                             for i, j in RETRAIN_PAIRS for p in PERIODS),
                         name='cost')

    m.set_objective(redundancy, sense=so.MIN, name='redundancy_obj')
    res = m.solve()
    if res is not None:
        print('Redundancy:', redundancy.get_value())
        print('Cost:', cost.get_value())
        print(so.get_solution_table(
            numWorkers, numRecruits, numRedundant, numShortTime, numExcess))
        print(so.get_solution_table(numRetrain))
        print(so.get_solution_table(numDowngrade))

    m.set_objective(cost, sense=so.MIN, name='cost_obj')
```

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```
    res = m.solve()
    if res is not None:
        print('Redundancy:', redundancy.get_value())
        print('Cost:', cost.get_value())
        print(so.get_solution_table(numWorkers, numRecruits, numRedundant,
                                    numShortTime, numExcess))
        print(so.get_solution_table(numRetrain))
        print(so.get_solution_table(numDowngrade))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.manpower_planning import test

In [8]: test(cas_conn)
NOTE: Initialized model manpower_planning.
NOTE: Added action set 'optimization'.
NOTE: Converting model manpower_planning to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 63 variables (0 free, 3 fixed).
NOTE: The problem has 24 linear constraints (6 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 108 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.01 seconds.
NOTE: The LP presolver removed 36 variables and 12 constraints.
NOTE: The LP presolver removed 52 constraint coefficients.
NOTE: The presolved problem has 27 variables, 12 constraints, and 56 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    -1.032250E+03         0
          P 2         17     8.417969E+02         0
NOTE: Optimal.
NOTE: Objective = 841.796875.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 63 rows and 6␣
↪columns.
```

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```
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 24 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
Redundancy: 841.796875
Cost: 1668750.0
               numWorkers  numRecruits  numRedundant  numShortTime  numExcess
unskilled   0  2000.00000          NaN           NaN           NaN        NaN
unskilled   1  1157.03125          0.0    442.968750          50.0  132.03125
unskilled   2   675.00000          0.0    166.328125          50.0  150.00000
unskilled   3   175.00000          0.0    232.500000          50.0  150.00000
semiskilled 0  1500.00000          NaN           NaN           NaN        NaN
semiskilled 1  1442.96875          0.0      0.000000          50.0   17.96875
semiskilled 2  2025.00000        800.0      0.000000          50.0    0.00000
semiskilled 3  2500.00000        800.0      0.000000           0.0    0.00000
skilled     0  1000.00000          NaN           NaN           NaN        NaN
skilled     1  1025.00000          0.0      0.000000          50.0    0.00000
skilled     2  1500.00000        500.0      0.000000           0.0    0.00000
skilled     3  2000.00000        500.0      0.000000           0.0    0.00000
                             numRetrain
(unskilled, semiskilled, 1)  200.000000
(unskilled, semiskilled, 2)  200.000000
(unskilled, semiskilled, 3)  200.000000
(semiskilled, skilled, 1)    256.250000
(semiskilled, skilled, 2)    262.276786
(semiskilled, skilled, 3)    364.285714
                             numDowngrade
(semiskilled, unskilled, 1)  0.000000e+00
(semiskilled, unskilled, 2) -1.421085e-14
(semiskilled, unskilled, 3)  0.000000e+00
(skilled, semiskilled, 1)    1.684375e+02
(skilled, semiskilled, 2)    1.729129e+02
(skilled, semiskilled, 3)    2.210714e+02
(skilled, unskilled, 1)      0.000000e+00
(skilled, unskilled, 2)      0.000000e+00
(skilled, unskilled, 3)      0.000000e+00
NOTE: Added action set 'optimization'.
NOTE: Converting model manpower_planning to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 63 variables (0 free, 3 fixed).
NOTE: The problem has 24 linear constraints (6 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 108 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 38 variables and 13 constraints.
NOTE: The LP presolver removed 56 constraint coefficients.
NOTE: The presolved problem has 25 variables, 11 constraints, and 52 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1   -4.018114E+04         0
```

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```
          D 2          6    4.986773E+05         0
NOTE: Optimal.
NOTE: Objective = 498677.28532.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 63 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 24 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
Redundancy: 1423.7188365650968
Cost: 498677.2853185596
               numWorkers  numRecruits  numRedundant  numShortTime  numExcess
unskilled   0      2000.0          NaN           NaN           NaN        NaN
unskilled   1      1000.0     0.000000    812.500000           0.0        0.0
unskilled   2       500.0     0.000000    257.617729           0.0        0.0
unskilled   3         0.0     0.000000    353.601108           0.0        0.0
semiskilled 0      1500.0          NaN           NaN           NaN        NaN
semiskilled 1      1400.0     0.000000      0.000000           0.0        0.0
semiskilled 2      2000.0   800.000000      0.000000           0.0        0.0
semiskilled 3      2500.0   800.000000      0.000000           0.0        0.0
skilled     0      1000.0          NaN           NaN           NaN        NaN
skilled     1      1000.0    55.555556      0.000000           0.0        0.0
skilled     2      1500.0   500.000000      0.000000           0.0        0.0
skilled     3      2000.0   500.000000      0.000000           0.0        0.0
                             numRetrain
(unskilled, semiskilled, 1)    0.000000
(unskilled, semiskilled, 2)  142.382271
(unskilled, semiskilled, 3)   96.398892
(semiskilled, skilled, 1)      0.000000
(semiskilled, skilled, 2)    105.263158
(semiskilled, skilled, 3)    131.578947
                             numDowngrade
(semiskilled, unskilled, 1)  2.500000e+01
(semiskilled, unskilled, 2)  2.842171e-14
(semiskilled, unskilled, 3) -2.842171e-14
(skilled, semiskilled, 1)    0.000000e+00
(skilled, semiskilled, 2)    0.000000e+00
(skilled, semiskilled, 3)    0.000000e+00
(skilled, unskilled, 1)      0.000000e+00
(skilled, unskilled, 2)      1.136868e-13
(skilled, unskilled, 3)      1.421085e-14
Out[8]: 498677.2853185596
```

### 4.1.6 Refinery Optimization

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex6_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex06.html

### Model

```
import sasoptpy as so
import pandas as pd
import numpy as np


def test(cas_conn, **kwargs):

    m = so.Model(name='refinery_optimization', session=cas_conn)

    crude_data = pd.DataFrame([
        ['crude1', 20000],
        ['crude2', 30000]
        ], columns=['crude', 'crude_ub']).set_index(['crude'])

    arc_data = pd.DataFrame([
        ['source', 'crude1', 6],
        ['source', 'crude2', 6],
        ['crude1', 'light_naphtha', 0.1],
        ['crude1', 'medium_naphtha', 0.2],
        ['crude1', 'heavy_naphtha', 0.2],
        ['crude1', 'light_oil', 0.12],
        ['crude1', 'heavy_oil', 0.2],
        ['crude1', 'residuum', 0.13],
        ['crude2', 'light_naphtha', 0.15],
        ['crude2', 'medium_naphtha', 0.25],
        ['crude2', 'heavy_naphtha', 0.18],
        ['crude2', 'light_oil', 0.08],
        ['crude2', 'heavy_oil', 0.19],
        ['crude2', 'residuum', 0.12],
        ['light_naphtha', 'regular_petrol', np.nan],
        ['light_naphtha', 'premium_petrol', np.nan],
        ['medium_naphtha', 'regular_petrol', np.nan],
        ['medium_naphtha', 'premium_petrol', np.nan],
        ['heavy_naphtha', 'regular_petrol', np.nan],
        ['heavy_naphtha', 'premium_petrol', np.nan],
        ['light_naphtha', 'reformed_gasoline', 0.6],
        ['medium_naphtha', 'reformed_gasoline', 0.52],
        ['heavy_naphtha', 'reformed_gasoline', 0.45],
        ['light_oil', 'jet_fuel', np.nan],
        ['light_oil', 'fuel_oil', np.nan],
        ['heavy_oil', 'jet_fuel', np.nan],
        ['heavy_oil', 'fuel_oil', np.nan],
        ['light_oil', 'light_oil_cracked', 2],
        ['light_oil_cracked', 'cracked_oil', 0.68],
        ['light_oil_cracked', 'cracked_gasoline', 0.28],
        ['heavy_oil', 'heavy_oil_cracked', 2],
        ['heavy_oil_cracked', 'cracked_oil', 0.75],
        ['heavy_oil_cracked', 'cracked_gasoline', 0.2],
        ['cracked_oil', 'jet_fuel', np.nan],
        ['cracked_oil', 'fuel_oil', np.nan],
        ['reformed_gasoline', 'regular_petrol', np.nan],
        ['reformed_gasoline', 'premium_petrol', np.nan],
        ['cracked_gasoline', 'regular_petrol', np.nan],
        ['cracked_gasoline', 'premium_petrol', np.nan],
        ['residuum', 'lube_oil', 0.5],
```

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```
        ['residuum', 'jet_fuel', np.nan],
        ['residuum', 'fuel_oil', np.nan],
        ], columns=['i', 'j', 'multiplier']).set_index(['i', 'j'])

    octane_data = pd.DataFrame([
        ['light_naphtha', 90],
        ['medium_naphtha', 80],
        ['heavy_naphtha', 70],
        ['reformed_gasoline', 115],
        ['cracked_gasoline', 105],
        ], columns=['i', 'octane']).set_index(['i'])

    petrol_data = pd.DataFrame([
        ['regular_petrol', 84],
        ['premium_petrol', 94],
        ], columns=['petrol', 'octane_lb']).set_index(['petrol'])

    vapour_pressure_data = pd.DataFrame([
        ['light_oil', 1.0],
        ['heavy_oil', 0.6],
        ['cracked_oil', 1.5],
        ['residuum', 0.05],
        ], columns=['oil', 'vapour_pressure']).set_index(['oil'])

    fuel_oil_ratio_data = pd.DataFrame([
        ['light_oil', 10],
        ['cracked_oil', 4],
        ['heavy_oil', 3],
        ['residuum', 1],
        ], columns=['oil', 'coefficient']).set_index(['oil'])

    final_product_data = pd.DataFrame([
        ['premium_petrol', 700],
        ['regular_petrol', 600],
        ['jet_fuel', 400],
        ['fuel_oil', 350],
        ['lube_oil', 150],
        ], columns=['product', 'profit']).set_index(['product'])

    vapour_pressure_ub = 1
    crude_total_ub = 45000
    naphtha_ub = 10000
    cracked_oil_ub = 8000
    lube_oil_lb = 500
    lube_oil_ub = 1000
    premium_ratio = 0.40

    ARCS = arc_data.index.tolist()
    arc_mult = arc_data['multiplier'].fillna(1)

    FINAL_PRODUCTS = final_product_data.index.tolist()
    final_product_data['profit'] = final_product_data['profit'] / 100
    profit = final_product_data['profit']

    ARCS = ARCS + [(i, 'sink') for i in FINAL_PRODUCTS]
    flow = m.add_variables(ARCS, name='flow', lb=0)
    NODES = np.unique([i for j in ARCS for i in j])
```

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```
m.set_objective(so.quick_sum(profit[i] * flow[i, 'sink']
                             for i in FINAL_PRODUCTS
                             if (i, 'sink') in ARCS),
                name='totalProfit', sense=so.MAX)

m.add_constraints((so.quick_sum(flow[a] for a in ARCS if a[0] == n) ==
                  so.quick_sum(arc_mult[a] * flow[a]
                               for a in ARCS if a[1] == n)
                  for n in NODES if n not in ['source', 'sink']),
                  name='flow_balance')

CRUDES = crude_data.index.tolist()
crudeDistilled = m.add_variables(CRUDES, name='crudesDistilled', lb=0)
crudeDistilled.set_bounds(ub=crude_data['crude_ub'])
m.add_constraints((flow[i, j] == crudeDistilled[i]
                  for (i, j) in ARCS if i in CRUDES), name='distillation')

OILS = ['light_oil', 'heavy_oil']
CRACKED_OILS = [i+'_cracked' for i in OILS]
oilCracked = m.add_variables(CRACKED_OILS, name='oilCracked', lb=0)
m.add_constraints((flow[i, j] == oilCracked[i] for (i, j) in ARCS
                  if i in CRACKED_OILS), name='cracking')

octane = octane_data['octane']
PETROLS = petrol_data.index.tolist()
octane_lb = petrol_data['octane_lb']
vapour_pressure = vapour_pressure_data['vapour_pressure']

m.add_constraints((so.quick_sum(octane[a[0]] * arc_mult[a] * flow[a]
                                for a in ARCS if a[1] == p)
                   >= octane_lb[p] *
                  so.quick_sum(arc_mult[a] * flow[a]
                               for a in ARCS if a[1] == p)
                  for p in PETROLS), name='blending_petrol')

m.add_constraint(so.quick_sum(vapour_pressure[a[0]] * arc_mult[a] * flow[a]
                              for a in ARCS if a[1] == 'jet_fuel') <=
                 vapour_pressure_ub *
                 so.quick_sum(arc_mult[a] * flow[a]
                              for a in ARCS if a[1] == 'jet_fuel'),
                 name='blending_jet_fuel')

fuel_oil_coefficient = fuel_oil_ratio_data['coefficient']
sum_fuel_oil_coefficient = sum(fuel_oil_coefficient)
m.add_constraints((sum_fuel_oil_coefficient * flow[a] ==
                  fuel_oil_coefficient[a[0]] * flow.sum('*', ['fuel_oil'])
                  for a in ARCS if a[1] == 'fuel_oil'),
                  name='blending_fuel_oil')

m.add_constraint(crudeDistilled.sum('*') <= crude_total_ub,
                 name='crude_total_ub')

m.add_constraint(so.quick_sum(flow[a] for a in ARCS
                              if a[0].find('naphtha') > -1 and
                              a[1] == 'reformed_gasoline')
                 <= naphtha_ub, name='naphtba_ub')
```

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```
    m.add_constraint(so.quick_sum(flow[a] for a in ARCS if a[1] ==
                                  'cracked_oil') <=
                     cracked_oil_ub, name='cracked_oil_ub')

    m.add_constraint(flow['lube_oil', 'sink'] == [lube_oil_lb, lube_oil_ub],
                     name='lube_oil_range')

    m.add_constraint(flow.sum('premium_petrol', '*') >= premium_ratio *
                     flow.sum('regular_petrol', '*'), name='premium_ratio')

    res = m.solve(**kwargs)
    if res is not None:
        print(so.get_solution_table(crudeDistilled))
        print(so.get_solution_table(oilCracked))
        print(so.get_solution_table(flow))

        octane_sol = []
        for p in PETROLS:
            octane_sol.append(so.quick_sum(octane[a[0]] * arc_mult[a] *
                                           flow[a].get_value() for a in ARCS
                                           if a[1] == p) /
                              sum(arc_mult[a] * flow[a].get_value()
                                  for a in ARCS if a[1] == p))
        octane_sol = pd.Series(octane_sol, name='octane_sol', index=PETROLS)
        print(so.get_solution_table(octane_sol, octane_lb))
        print(so.get_solution_table(vapour_pressure))
        vapour_pressure_sol = sum(vapour_pressure[a[0]] *
                                  arc_mult[a] *
                                  flow[a].get_value() for a in ARCS
                                  if a[1] == 'jet_fuel') /\
            sum(arc_mult[a] * flow[a].get_value() for a in ARCS
                if a[1] == 'jet_fuel')
        print('Vapour_pressure_sol: {:.4f}'.format(vapour_pressure_sol))

        num_fuel_oil_ratio_sol = [arc_mult[a] * flow[a].get_value() /
                                  sum(arc_mult[b] *
                                      flow[b].get_value()
                                      for b in ARCS if b[1] == 'fuel_oil')
                                  for a in ARCS if a[1] == 'fuel_oil']
        num_fuel_oil_ratio_sol = pd.Series(num_fuel_oil_ratio_sol,
                                           name='num_fuel_oil_ratio_sol',
                                           index=[a[0] for a in ARCS
                                                  if a[1] == 'fuel_oil'])
        print(so.get_solution_table(fuel_oil_coefficient,
                                    num_fuel_oil_ratio_sol))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.refinery_optimization import test

In [8]: test(cas_conn)
NOTE: Initialized model refinery_optimization.
NOTE: Added action set 'optimization'.
NOTE: Converting model refinery_optimization to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 51 variables (0 free, 0 fixed).
NOTE: The problem has 46 linear constraints (4 LE, 38 EQ, 3 GE, 1 range).
NOTE: The problem has 158 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 29 variables and 30 constraints.
NOTE: The LP presolver removed 86 constraint coefficients.
NOTE: The presolved problem has 22 variables, 16 constraints, and 72 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    9.878656E+05         0
          P 2         18    2.113651E+05         0
NOTE: Optimal.
NOTE: Objective = 211365.13477.
NOTE: The Dual Simplex solve time is 0.02 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 51 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 46 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
        crudesDistilled
crude1          15000.0
crude2          30000.0
                   oilCracked
light_oil_cracked      4200.0
heavy_oil_cracked      3800.0
                                                flow
(source, crude1)                        15000.000000
```

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```
(source, crude2)                          30000.000000
(crude1, light_naphtha)                   15000.000000
(crude1, medium_naphtha)                  15000.000000
(crude1, heavy_naphtha)                   15000.000000
(crude1, light_oil)                       15000.000000
(crude1, heavy_oil)                       15000.000000
(crude1, residuum)                        15000.000000
(crude2, light_naphtha)                   30000.000000
(crude2, medium_naphtha)                  30000.000000
(crude2, heavy_naphtha)                   30000.000000
(crude2, light_oil)                       30000.000000
(crude2, heavy_oil)                       30000.000000
(crude2, residuum)                        30000.000000
(light_naphtha, regular_petrol)            3293.112993
(light_naphtha, premium_petrol)            2706.887007
(medium_naphtha, regular_petrol)          10500.000000
(medium_naphtha, premium_petrol)              0.000000
(heavy_naphtha, regular_petrol)            1315.334140
(heavy_naphtha, premium_petrol)            1677.804016
(light_naphtha, reformed_gasoline)            0.000000
(medium_naphtha, reformed_gasoline)           0.000000
(heavy_naphtha, reformed_gasoline)         5406.861844
(light_oil, jet_fuel)                         0.000000
(light_oil, fuel_oil)                         0.000000
(heavy_oil, jet_fuel)                      4900.000000
(heavy_oil, fuel_oil)                         0.000000
(light_oil, light_oil_cracked)             4200.000000
(light_oil_cracked, cracked_oil)           4200.000000
(light_oil_cracked, cracked_gasoline)      4200.000000
(heavy_oil, heavy_oil_cracked)             3800.000000
(heavy_oil_cracked, cracked_oil)           3800.000000
(heavy_oil_cracked, cracked_gasoline)      3800.000000
(cracked_oil, jet_fuel)                    5706.000000
(cracked_oil, fuel_oil)                       0.000000
(reformed_gasoline, regular_petrol)           0.000000
(reformed_gasoline, premium_petrol)        2433.087830
(cracked_gasoline, regular_petrol)         1936.000000
(cracked_gasoline, premium_petrol)            0.000000
(residuum, lube_oil)                       1000.000000
(residuum, jet_fuel)                       4550.000000
(residuum, fuel_oil)                          0.000000
(premium_petrol, sink)                     6817.778853
(regular_petrol, sink)                    17044.447133
(jet_fuel, sink)                          15156.000000
(fuel_oil, sink)                              0.000000
(lube_oil, sink)                            500.000000
                octane_sol octane_lb
petrol
regular_petrol        84.0        84
premium_petrol        94.0        94
            vapour_pressure
oil
light_oil               1.0
heavy_oil               0.6
cracked_oil             1.5
residuum               0.05
Vapour_pressure_sol: 0.7737
```

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```
            coefficient num_fuel_oil_ratio_sol
light_oil            10                    nan
cracked_oil           4                    nan
heavy_oil             3                    nan
residuum              1                    nan
Out[8]: 211365.13476893297
```

### 4.1.7 Mining Optimization

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex7_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex07.html

#### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    m = so.Model(name='mining_optimization', session=cas_conn)

    mine_data = pd.DataFrame([
        ['mine1', 5, 2, 1.0],
        ['mine2', 4, 2.5, 0.7],
        ['mine3', 4, 1.3, 1.5],
        ['mine4', 5, 3, 0.5],
        ], columns=['mine', 'cost', 'extract_ub', 'quality']).\
        set_index(['mine'])

    year_data = pd.DataFrame([
        [1, 0.9],
        [2, 0.8],
        [3, 1.2],
        [4, 0.6],
        [5, 1.0],
        ], columns=['year', 'quality_required']).set_index(['year'])

    max_num_worked_per_year = 3
    revenue_per_ton = 10
    discount_rate = 0.10

    MINES = mine_data.index.tolist()
    cost = mine_data['cost']
    extract_ub = mine_data['extract_ub']
    quality = mine_data['quality']
    YEARS = year_data.index.tolist()
    quality_required = year_data['quality_required']
```

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```
    isOpen = m.add_variables(MINES, YEARS, vartype=so.BIN, name='isOpen')
    isWorked = m.add_variables(MINES, YEARS, vartype=so.BIN, name='isWorked')
    extract = m.add_variables(MINES, YEARS, lb=0, name='extract')
    [extract[i, j].set_bounds(ub=extract_ub[i]) for i in MINES for j in YEARS]

    extractedPerYear = {j: extract.sum('*', j) for j in YEARS}
    discount = {j: 1 / (1+discount_rate) ** (j-1) for j in YEARS}

    totalRevenue = revenue_per_ton *\
        so.quick_sum(discount[j] * extractedPerYear[j] for j in YEARS)
    totalCost = so.quick_sum(discount[j] * cost[i] * isOpen[i, j]
                             for i in MINES for j in YEARS)
    m.set_objective(totalRevenue-totalCost, sense=so.MAX, name='totalProfit')

    m.add_constraints((extract[i, j] <= extract[i, j]._ub * isWorked[i, j]
                      for i in MINES for j in YEARS), name='link')

    m.add_constraints((isWorked.sum('*', j) <= max_num_worked_per_year
                      for j in YEARS), name='cardinality')

    m.add_constraints((isWorked[i, j] <= isOpen[i, j] for i in MINES
                      for j in YEARS), name='worked_implies_open')

    m.add_constraints((isOpen[i, j] <= isOpen[i, j-1] for i in MINES
                      for j in YEARS if j != 1), name='continuity')

    m.add_constraints((so.quick_sum(quality[i] * extract[i, j] for i in MINES)
                      == quality_required[j] * extractedPerYear[j]
                      for j in YEARS), name='quality_con')

    res = m.solve()
    if res is not None:
        print(so.get_solution_table(isOpen, isWorked, extract))
        quality_sol = {j: so.quick_sum(quality[i] * extract[i, j].get_value()
                                       for i in MINES)
                       / extractedPerYear[j].get_value() for j in YEARS}
        qs = so.dict_to_frame(quality_sol, ['quality_sol'])
        epy = so.dict_to_frame(extractedPerYear, ['extracted_per_year'])
        print(so.get_solution_table(epy, qs, quality_required))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.mining_optimization import test

In [8]: test(cas_conn)
NOTE: Initialized model mining_optimization.
NOTE: Added action set 'optimization'.
NOTE: Converting model mining_optimization to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 60 variables (0 free, 0 fixed).
NOTE: The problem has 40 binary and 0 integer variables.
NOTE: The problem has 66 linear constraints (61 LE, 5 EQ, 0 GE, 0 range).
NOTE: The problem has 151 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 8 variables and 8 constraints.
NOTE: The MILP presolver removed 16 constraint coefficients.
NOTE: The MILP presolver modified 8 constraint coefficients.
NOTE: The presolved problem has 52 variables, 58 constraints, and 135 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1     14     96.5802313    157.7309278   38.77%       0
                0        1     14     96.5802313    150.9548680   36.02%       0
                0        1     14     96.5802313    147.3693449   34.46%       0
                0        1     15    146.8619974    146.8619974    0.00%       0
                0        0     15    146.8619974    146.8619974    0.00%       0
NOTE: The MILP solver added 7 cuts with 34 cut coefficients at the root.
NOTE: Optimal.
NOTE: Objective = 146.86199735.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 60 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 66 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
              isOpen  isWorked       extract
(mine1, 1)  1.000000  1.000000  2.000000e+00
(mine1, 2)  0.999994  0.000006  1.252000e-05
(mine1, 3)  0.999994  0.999994  1.950000e+00
(mine1, 4)  0.999994  0.999994  1.250007e-01
(mine1, 5)  0.999994  0.999994  1.999987e+00
(mine2, 1)  1.000000  0.000000  0.000000e+00
(mine2, 2)  1.000000  0.999995  2.499988e+00
(mine2, 3)  0.999998 -0.000000  0.000000e+00
(mine2, 4)  0.999998  0.999998  2.499994e+00
(mine2, 5)  0.999998  0.999998  2.166667e+00
(mine3, 1)  1.000000  1.000000  1.300000e+00
(mine3, 2)  1.000000  0.999998  1.299997e+00
(mine3, 3)  1.000000  1.000000  1.300000e+00
(mine3, 4)  1.000000  0.000001  3.477765e-07
(mine3, 5)  1.000000  1.000000  1.300000e+00
(mine4, 1)  1.000000  1.000000  2.450000e+00
```

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```
(mine4, 2)  1.000000  1.000000  2.200005e+00
(mine4, 3)  1.000000 -0.000000  0.000000e+00
(mine4, 4)  1.000000  1.000000  3.000000e+00
(mine4, 5) -0.000000 -0.000000  0.000000e+00
   extracted_per_year  quality_sol  quality_required
1            5.750000          0.9               0.9
2            6.000003          0.8               0.8
3            3.250000          1.2               1.2
4            5.624995          0.6               0.6
5            5.466654          1.0               1.0
Out[8]: 146.861997350257
```

### 4.1.8 Farm Planning

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex8_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex08.html

#### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    m = so.Model(name='farm_planning', session=cas_conn)

    # Input Data

    cow_data_raw = []
    for age in range(12):
        if age < 2:
            row = {'age': age,
                   'init_num_cows': 10,
                   'acres_needed': 2/3.0,
                   'annual_loss': 0.05,
                   'bullock_yield': 0,
                   'heifer_yield': 0,
                   'milk_revenue': 0,
                   'grain_req': 0,
                   'sugar_beet_req': 0,
                   'labour_req': 10,
                   'other_costs': 50}
        else:
            row = {'age': age,
                   'init_num_cows': 10,
                   'acres_needed': 1,
                   'annual_loss': 0.02,
                   'bullock_yield': 1.1/2,
```

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```
                    'heifer_yield': 1.1/2,
                    'milk_revenue': 370,
                    'grain_req': 0.6,
                    'sugar_beet_req': 0.7,
                    'labour_req': 42,
                    'other_costs': 100}
        cow_data_raw.append(row)
    cow_data = pd.DataFrame(cow_data_raw).set_index(['age'])
    grain_data = pd.DataFrame([
        ['group1', 20, 1.1],
        ['group2', 30, 0.9],
        ['group3', 20, 0.8],
        ['group4', 10, 0.65]
        ], columns=['group', 'acres', 'yield']).set_index(['group'])
    num_years = 5
    num_acres = 200
    bullock_revenue = 30
    heifer_revenue = 40
    dairy_cow_selling_age = 12
    dairy_cow_selling_revenue = 120
    max_num_cows = 130
    sugar_beet_yield = 1.5
    grain_cost = 90
    grain_revenue = 75
    grain_labour_req = 4
    grain_other_costs = 15
    sugar_beet_cost = 70
    sugar_beet_revenue = 58
    sugar_beet_labour_req = 14
    sugar_beet_other_costs = 10
    nominal_labour_cost = 4000
    nominal_labour_hours = 5500
    excess_labour_cost = 1.2
    capital_outlay_unit = 200
    num_loan_years = 10
    annual_interest_rate = 0.15
    max_decrease_ratio = 0.50
    max_increase_ratio = 0.75

    # Sets

    AGES = cow_data.index.tolist()
    init_num_cows = cow_data['init_num_cows']
    acres_needed = cow_data['acres_needed']
    annual_loss = cow_data['annual_loss']
    bullock_yield = cow_data['bullock_yield']
    heifer_yield = cow_data['heifer_yield']
    milk_revenue = cow_data['milk_revenue']
    grain_req = cow_data['grain_req']
    sugar_beet_req = cow_data['sugar_beet_req']
    cow_labour_req = cow_data['labour_req']
    cow_other_costs = cow_data['other_costs']

    YEARS = list(range(1, num_years+1))
    YEARS0 = [0] + YEARS

    # Variables
```

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```
numCows = m.add_variables(AGES + [dairy_cow_selling_age], YEARS0, lb=0,
                          name='numCows')
for age in AGES:
    numCows[age, 0].set_bounds(lb=init_num_cows[age],
                               ub=init_num_cows[age])
numCows[dairy_cow_selling_age, 0].set_bounds(lb=0, ub=0)

numBullocksSold = m.add_variables(YEARS, lb=0, name='numBullocksSold')
numHeifersSold = m.add_variables(YEARS, lb=0, name='numHeifersSold')

GROUPS = grain_data.index.tolist()
acres = grain_data['acres']
grain_yield = grain_data['yield']
grainAcres = m.add_variables(GROUPS, YEARS, lb=0, name='grainAcres')
for group in GROUPS:
    for year in YEARS:
        grainAcres[group, year].set_bounds(ub=acres[group])
grainBought = m.add_variables(YEARS, lb=0, name='grainBought')
grainSold = m.add_variables(YEARS, lb=0, name='grainSold')

sugarBeetAcres = m.add_variables(YEARS, lb=0, name='sugarBeetAcres')
sugarBeetBought = m.add_variables(YEARS, lb=0, name='sugarBeetBought')
sugarBeetSold = m.add_variables(YEARS, lb=0, name='sugarBeetSold')

numExcessLabourHours = m.add_variables(YEARS, lb=0,
                                       name='numExcessLabourHours')
capitalOutlay = m.add_variables(YEARS, lb=0, name='capitalOutlay')

yearly_loan_payment = (annual_interest_rate * capital_outlay_unit) /\
                      (1 - (1+annual_interest_rate)**(-num_loan_years))

# Objective function

revenue = {year:
           bullock_revenue * numBullocksSold[year] +
           heifer_revenue * numHeifersSold[year] +
           dairy_cow_selling_revenue * numCows[dairy_cow_selling_age,
                                               year] +
           so.quick_sum(milk_revenue[age] * numCows[age, year]
                        for age in AGES) +
           grain_revenue * grainSold[year] +
           sugar_beet_revenue * sugarBeetSold[year]
           for year in YEARS}

cost = {year:
        grain_cost * grainBought[year] +
        sugar_beet_cost * sugarBeetBought[year] +
        nominal_labour_cost +
        excess_labour_cost * numExcessLabourHours[year] +
        so.quick_sum(cow_other_costs[age] * numCows[age, year]
                     for age in AGES) +
        so.quick_sum(grain_other_costs * grainAcres[group, year]
                     for group in GROUPS) +
        sugar_beet_other_costs * sugarBeetAcres[year] +
        so.quick_sum(yearly_loan_payment * capitalOutlay[y]
                     for y in YEARS if y <= year)
```

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```
        for year in YEARS}
profit = {year: revenue[year] - cost[year] for year in YEARS}

totalProfit = so.quick_sum(profit[year] -
                           yearly_loan_payment * (num_years - 1 + year) *
                           capitalOutlay[year] for year in YEARS)

m.set_objective(totalProfit, sense=so.MAX, name='totalProfit')

# Constraints

m.add_constraints((
    so.quick_sum(acres_needed[age] * numCows[age, year] for age in AGES) +
    so.quick_sum(grainAcres[group, year] for group in GROUPS) +
    sugarBeetAcres[year] <= num_acres
    for year in YEARS), name='num_acres')

m.add_constraints((
    numCows[age+1, year+1] == (1-annual_loss[age]) * numCows[age, year]
    for age in AGES if age != dairy_cow_selling_age
    for year in YEARS0 if year != num_years), name='aging')

m.add_constraints((
    numBullocksSold[year] == so.quick_sum(
        bullock_yield[age] * numCows[age, year] for age in AGES)
    for year in YEARS), name='numBullocksSold_def')

m.add_constraints((
    numCows[0, year] == so.quick_sum(
        heifer_yield[age] * numCows[age, year]
        for age in AGES) - numHeifersSold[year]
    for year in YEARS), name='numHeifersSold_def')

m.add_constraints((
    so.quick_sum(numCows[age, year] for age in AGES) <= max_num_cows +
    so.quick_sum(capitalOutlay[y] for y in YEARS if y <= year)
    for year in YEARS), name='max_num_cows_def')

grainGrown = {(group, year): grain_yield[group] * grainAcres[group, year]
              for group in GROUPS for year in YEARS}
m.add_constraints((
    so.quick_sum(grain_req[age] * numCows[age, year] for age in AGES) <=
    so.quick_sum(grainGrown[group, year] for group in GROUPS)
    + grainBought[year] - grainSold[year]
    for year in YEARS), name='grain_req_def')

sugarBeetGrown = {(year): sugar_beet_yield * sugarBeetAcres[year]
                  for year in YEARS}
m.add_constraints((
    so.quick_sum(sugar_beet_req[age] * numCows[age, year] for age in AGES)
    <=
    sugarBeetGrown[year] + sugarBeetBought[year] - sugarBeetSold[year]
    for year in YEARS), name='sugar_beet_req_def')

m.add_constraints((
    so.quick_sum(cow_labour_req[age] * numCows[age, year]
                 for age in AGES) +
```

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```
        so.quick_sum(grain_labour_req * grainAcres[group, year]
                     for group in GROUPS) +
        sugar_beet_labour_req * sugarBeetAcres[year] <=
        nominal_labour_hours + numExcessLabourHours[year]
        for year in YEARS), name='labour_req_def')
    m.add_constraints((profit[year] >= 0 for year in YEARS), name='cash_flow')

    m.add_constraint(so.quick_sum(numCows[age, num_years] for age in AGES
                                  if age >= 2) /
                     sum(init_num_cows[age] for age in AGES if age >= 2) ==
                     [1-max_decrease_ratio, 1+max_increase_ratio],
                     name='final_dairy_cows_range')

    res = m.solve()

    if res is not None:
        so.pd.display_all()
        print(so.get_solution_table(numCows))
        revenue_df = so.dict_to_frame(revenue, cols=['revenue'])
        cost_df = so.dict_to_frame(cost, cols=['cost'])
        profit_df = so.dict_to_frame(profit, cols=['profit'])
        print(so.get_solution_table(numBullocksSold, numHeifersSold,
                                    capitalOutlay, numExcessLabourHours,
                                    revenue_df, cost_df, profit_df))
        gg_df = so.dict_to_frame(grainGrown, cols=['grainGrown'])
        print(so.get_solution_table(grainAcres, gg_df))
        sbg_df = so.dict_to_frame(sugarBeetGrown, cols=['sugerBeetGrown'])
        print(so.get_solution_table(
            grainBought, grainSold, sugarBeetAcres,
            sbg_df, sugarBeetBought, sugarBeetSold))
        num_acres = m.get_constraint('num_acres')
        na_df = num_acres.get_expressions()
        max_num_cows_con = m.get_constraint('max_num_cows_def')
        mnc_df = max_num_cows_con.get_expressions()
        print(so.get_solution_table(na_df, mnc_df))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.farm_planning import test
```

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```
In [8]: test(cas_conn)
NOTE: Initialized model farm_planning.
NOTE: Added action set 'optimization'.
NOTE: Converting model farm_planning to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 143 variables (0 free, 13 fixed).
NOTE: The problem has 101 linear constraints (25 LE, 70 EQ, 5 GE, 1 range).
NOTE: The problem has 780 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 86 variables and 71 constraints.
NOTE: The LP presolver removed 551 constraint coefficients.
NOTE: The presolved problem has 57 variables, 30 constraints, and 229 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 1          1    4.195000E+02         0
          D 2         37    1.971960E+05         0
          D 2         55    1.217192E+05         0
NOTE: Optimal.
NOTE: Objective = 121719.17286.
NOTE: The Dual Simplex solve time is 0.02 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 143 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 101 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
           numCows
(0, 0)   10.000000
(0, 1)   22.800000
(0, 2)   11.584427
(0, 3)    0.000000
(0, 4)    0.000000
(0, 5)    0.000000
(1, 0)   10.000000
(1, 1)    9.500000
(1, 2)   21.660000
(1, 3)   11.005205
(1, 4)    0.000000
(1, 5)    0.000000
(2, 0)   10.000000
(2, 1)    9.500000
(2, 2)    9.025000
(2, 3)   20.577000
(2, 4)   10.454945
(2, 5)    0.000000
(3, 0)   10.000000
(3, 1)    9.800000
(3, 2)    9.310000
(3, 3)    8.844500
```

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```
(3, 4)   20.165460
(3, 5)   10.245846
(4, 0)   10.000000
(4, 1)    9.800000
(4, 2)    9.604000
(4, 3)    9.123800
(4, 4)    8.667610
(4, 5)   19.762151
(5, 0)   10.000000
(5, 1)    9.800000
(5, 2)    9.604000
(5, 3)    9.411920
(5, 4)    8.941324
(5, 5)    8.494258
(6, 0)   10.000000
(6, 1)    9.800000
(6, 2)    9.604000
(6, 3)    9.411920
(6, 4)    9.223682
(6, 5)    8.762498
(7, 0)   10.000000
(7, 1)    9.800000
(7, 2)    9.604000
(7, 3)    9.411920
(7, 4)    9.223682
(7, 5)    9.039208
(8, 0)   10.000000
(8, 1)    9.800000
(8, 2)    9.604000
(8, 3)    9.411920
(8, 4)    9.223682
(8, 5)    9.039208
(9, 0)   10.000000
(9, 1)    9.800000
(9, 2)    9.604000
(9, 3)    9.411920
(9, 4)    9.223682
(9, 5)    9.039208
(10, 0)  10.000000
(10, 1)   9.800000
(10, 2)   9.604000
(10, 3)   9.411920
(10, 4)   9.223682
(10, 5)   9.039208
(11, 0)  10.000000
(11, 1)   9.800000
(11, 2)   9.604000
(11, 3)   9.411920
(11, 4)   9.223682
(11, 5)   9.039208
(12, 0)   0.000000
(12, 1)   9.800000
(12, 2)   9.604000
(12, 3)   9.411920
(12, 4)   9.223682
(12, 5)   9.039208
   numBullocksSold  numHeifersSold  capitalOutlay  numExcessLabourHours  \
```

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```
1        53.735000       30.935000            0.0                     0.0
2        52.341850       40.757423            0.0                     0.0
3        57.435807       57.435807            0.0                     0.0
4        56.964286       56.964286            0.0                     0.0
5        50.853436       50.853436            0.0                     0.0

        revenue          cost        profit
1  41494.530000  19588.466667  21906.063333
2  41153.336497  19264.639818  21888.696679
3  45212.490308  19396.435208  25816.055100
4  45860.056078  19034.285714  26825.770363
5  42716.941438  17434.354053  25282.587385
             grainAcres  grainGrown
(group1, 1)   20.000000   22.000000
(group1, 2)   20.000000   22.000000
(group1, 3)   20.000000   22.000000
(group1, 4)   20.000000   22.000000
(group1, 5)   20.000000   22.000000
(group2, 1)    0.000000    0.000000
(group2, 2)    0.000000    0.000000
(group2, 3)    3.134152    2.820737
(group2, 4)    0.000000    0.000000
(group2, 5)    0.000000    0.000000
(group3, 1)    0.000000    0.000000
(group3, 2)    0.000000    0.000000
(group3, 3)    0.000000    0.000000
(group3, 4)    0.000000    0.000000
(group3, 5)    0.000000    0.000000
(group4, 1)    0.000000    0.000000
(group4, 2)    0.000000    0.000000
(group4, 3)    0.000000    0.000000
(group4, 4)    0.000000    0.000000
(group4, 5)    0.000000    0.000000
   grainBought  grainSold  sugarBeetAcres  sugerBeetGrown  sugarBeetBought  \
1    36.620000        0.0       60.766667       91.150000              0.0
2    35.100200        0.0       62.670049       94.005073              0.0
3    37.836507        0.0       65.100304       97.650456              0.0
4    40.142857        0.0       76.428571      114.642857              0.0
5    33.476475        0.0       87.539208      131.308812              0.0

   sugarBeetSold
1      22.760000
2      27.388173
3      24.550338
4      42.142857
5      66.586258
   num_acres  max_num_cows_def
1      200.0        130.000000
2      200.0        128.411427
3      200.0        115.433945
4      200.0        103.571429
5      200.0         92.460792
Out[8]: 121719.17286133638
```

### 4.1.9 Economic Planning

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex9_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex09.html

#### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    m = so.Model(name='economic_planning', session=cas_conn)

    industry_data = pd.DataFrame([
        ['coal', 150, 300, 60],
        ['steel', 80, 350, 60],
        ['transport', 100, 280, 30]
        ], columns=['industry', 'init_stocks', 'init_productive_capacity',
                    'demand']).set_index(['industry'])

    production_data = pd.DataFrame([
        ['coal', 0.1, 0.5, 0.4],
        ['steel', 0.1, 0.1, 0.2],
        ['transport', 0.2, 0.1, 0.2],
        ['manpower', 0.6, 0.3, 0.2],
        ], columns=['input', 'coal',
                    'steel', 'transport']).set_index(['input'])

    productive_capacity_data = pd.DataFrame([
        ['coal', 0.0, 0.7, 0.9],
        ['steel', 0.1, 0.1, 0.2],
        ['transport', 0.2, 0.1, 0.2],
        ['manpower', 0.4, 0.2, 0.1],
        ], columns=['input', 'coal',
                    'steel', 'transport']).set_index(['input'])

    manpower_capacity = 470
    num_years = 5

    YEARS = list(range(1, num_years+1))
    YEARS0 = [0] + list(YEARS)
    INDUSTRIES = industry_data.index.tolist()

    init_stocks = industry_data['init_stocks']
    init_productive_capacity = industry_data['init_productive_capacity']
    demand = industry_data['demand']

    production_coeff = so.flatten_frame(production_data)
    productive_capacity_coeff = so.flatten_frame(productive_capacity_data)
```

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```
    static_production = m.add_variables(INDUSTRIES, lb=0,
                                        name='static_production')
    m.set_objective(0, sense=so.MIN, name='Zero')
    m.add_constraints((static_production[i] == demand[i] +
                       so.quick_sum(
                           production_coeff[i, j] * static_production[j]
                           for j in INDUSTRIES) for i in INDUSTRIES),
                      name='static_con')

    m.solve()
    print(so.get_value_table(static_production))

    final_demand = so.get_value_table(
        static_production)['static_production']

    production = m.add_variables(INDUSTRIES, range(0, num_years+2), lb=0,
                                 name='production')
    stock = m.add_variables(INDUSTRIES, range(0, num_years+2), lb=0,
                            name='stock')
    extra_capacity = m.add_variables(INDUSTRIES, range(2, num_years+3), lb=0,
                                     name='extra_capacity')

    productive_capacity = so.ImplicitVar(
        (init_productive_capacity[i] +
         so.quick_sum(extra_capacity[i, y] for y in range(2, year+1))
         for i in INDUSTRIES for year in range(1, num_years+2)),
        name='productive_capacity'
    )

    for i in INDUSTRIES:
        production[i, 0].set_bounds(ub=0)
        stock[i, 0].set_bounds(lb=init_stocks[i], ub=init_stocks[i])

    total_productive_capacity = sum(productive_capacity[i, num_years]
                                    for i in INDUSTRIES)
    total_production = so.quick_sum(production[i, year] for i in INDUSTRIES
                                    for year in [4, 5])
    total_manpower = so.quick_sum(production_coeff['manpower', i] *
                                  production[i, year+1] +
                                  productive_capacity_coeff['manpower', i] *
                                  extra_capacity[i, year+2]
                                  for i in INDUSTRIES for year in YEARS)

    continuity_con = m.add_constraints((
        stock[i, year] + production[i, year] ==
        (demand[i] if year in YEARS else 0) +
        so.quick_sum(production_coeff[i, j] * production[j, year+1] +
                     productive_capacity_coeff[i, j] *
                     extra_capacity[j, year+2] for j in INDUSTRIES) +
        stock[i, year+1]
        for i in INDUSTRIES for year in YEARS0), name='continuity_con')

    manpower_con = m.add_constraints((
        so.quick_sum(production_coeff['manpower', j] * production[j, year] +
                     productive_capacity_coeff['manpower', j] *
                     extra_capacity[j, year+1]
                     for j in INDUSTRIES)
```

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```
        <= manpower_capacity for year in range(1, num_years+2)),
        name='manpower_con')

    capacity_con = m.add_constraints((production[i, year] <=
                                      productive_capacity[i, year]
                                      for i in INDUSTRIES
                                      for year in range(1, num_years+2)),
                                     name='capacity_con')

    for i in INDUSTRIES:
        production[i, num_years+1].set_bounds(lb=final_demand[i])

    for i in INDUSTRIES:
        for year in [num_years+1, num_years+2]:
            extra_capacity[i, year].set_bounds(ub=0)

    problem1 = so.Model(name='Problem1', session=cas_conn)
    problem1.include(
        production, stock, extra_capacity, continuity_con, manpower_con,
        capacity_con, productive_capacity)
    problem1.set_objective(total_productive_capacity, sense=so.MAX,
                           name='total_productive_capacity')
    problem1.solve()
    so.pd.display_dense()
    print(so.get_value_table(production, stock, extra_capacity,
                                 productive_capacity).sort_index())
    print(so.get_value_table(manpower_con.get_expressions()))

    # Problem 2

    problem2 = so.Model(name='Problem2', session=cas_conn)
    problem2.include(problem1)
    problem2.set_objective(total_production, name='total_production',
                           sense=so.MAX)
    for i in INDUSTRIES:
        for year in YEARS:
            continuity_con[i, year].set_rhs(0)
    problem2.solve()
    print(so.get_value_table(production, stock, extra_capacity,
                                 productive_capacity).sort_index())
    print(so.get_value_table(manpower_con.get_expressions()))

    # Problem 3

    problem3 = so.Model(name='Problem3', session=cas_conn)
    problem3.include(production, stock, extra_capacity, continuity_con,
                     capacity_con)
    problem3.set_objective(total_manpower, sense=so.MAX, name='total_manpower')
    for i in INDUSTRIES:
        for year in YEARS:
            continuity_con[i, year].set_rhs(demand[i])
    problem3.solve()
    print(so.get_value_table(production, stock, extra_capacity,
                                 productive_capacity).sort_index())
    print(so.get_value_table(manpower_con.get_expressions()))

    return problem3.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.economic_planning import test

In [8]: test(cas_conn)
NOTE: Initialized model economic_planning.
NOTE: Added action set 'optimization'.
NOTE: Converting model economic_planning to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 3 variables (0 free, 0 fixed).
NOTE: The problem has 3 linear constraints (0 LE, 3 EQ, 0 GE, 0 range).
NOTE: The problem has 9 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed all variables and constraints.
NOTE: Optimal.
NOTE: Objective = 0.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 3 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 3 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
           static_production
coal              166.396761
steel             105.668016
transport          92.307692
NOTE: Initialized model Problem1.
NOTE: Added action set 'optimization'.
NOTE: Converting model Problem1 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 60 variables (0 free, 12 fixed).
NOTE: The problem has 42 linear constraints (24 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 15 variables and 3 constraints.
NOTE: The LP presolver removed 37 constraint coefficients.
```

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```
NOTE: The presolved problem has 45 variables, 39 constraints, and 218 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    2.683246E+04         0
          P 2         42    2.141875E+03         0
NOTE: Optimal.
NOTE: Objective = 2141.8751967.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 60 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 42 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
             production         stock  extra_capacity  productive_capacity
coal      0    0.000000  1.500000e+02             NaN                  NaN
coal      1  260.402615  0.000000e+00             NaN           300.000000
coal      2  293.406208  0.000000e+00        0.000000           300.000000
coal      3  300.000000  0.000000e+00        0.000000           300.000000
coal      4   17.948718  1.484480e+02      189.203132           489.203132
coal      5  166.396761  0.000000e+00     1022.672065          1511.875197
coal      6  166.396761  1.421085e-14        0.000000          1511.875197
coal      7         NaN           NaN        0.000000                  NaN
steel     0    0.000000  8.000000e+01             NaN                  NaN
steel     1  135.341540  1.228110e+01             NaN           350.000000
steel     2  181.659854  0.000000e+00        0.000000           350.000000
steel     3  193.090418  0.000000e+00        0.000000           350.000000
steel     4  105.668016  0.000000e+00        0.000000           350.000000
steel     5  105.668016  0.000000e+00        0.000000           350.000000
steel     6  105.668016 -1.456613e-13        0.000000           350.000000
steel     7         NaN           NaN        0.000000                  NaN
transport 0    0.000000  1.000000e+02             NaN                  NaN
transport 1  140.722422  6.240839e+00             NaN           280.000000
transport 2  200.580168  0.000000e+00        0.000000           280.000000
transport 3  267.152497  0.000000e+00        0.000000           280.000000
transport 4   92.307692  0.000000e+00        0.000000           280.000000
transport 5   92.307692  0.000000e+00        0.000000           280.000000
transport 6   92.307692 -3.907985e-14        0.000000           280.000000
transport 7         NaN           NaN        0.000000                  NaN
   manpower_con
1    224.988515
2    270.657715
3    367.038878
4    470.000000
5    150.000000
6    150.000000
NOTE: Initialized model Problem2.
NOTE: Added action set 'optimization'.
NOTE: Converting model Problem2 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 60 variables (0 free, 12 fixed).
NOTE: The problem has 42 linear constraints (24 LE, 18 EQ, 0 GE, 0 range).
```

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```
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 15 variables and 3 constraints.
NOTE: The LP presolver removed 37 constraint coefficients.
NOTE: The presolved problem has 45 variables, 39 constraints, and 218 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    1.504360E+04         0
          P 2         46    2.618579E+03         0
NOTE: Optimal.
NOTE: Objective = 2618.5791147.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 60 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 42 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
             production       stock  extra_capacity  productive_capacity
coal      0    0.000000  150.000000             NaN                  NaN
coal      1  184.818327   31.628509             NaN           300.000000
coal      2  430.504654   16.372454    1.305047e+02           430.504654
coal      3  430.504654    0.000000    0.000000e+00           430.504654
coal      4  430.504654    0.000000   -1.207321e-12           430.504654
coal      5  430.504654    0.000000    0.000000e+00           430.504654
coal      6  166.396761  324.107893    0.000000e+00           430.504654
coal      7         NaN         NaN    0.000000e+00                  NaN
steel     0    0.000000   80.000000             NaN                  NaN
steel     1   86.729504   11.532298             NaN           350.000000
steel     2  155.337478    0.000000    0.000000e+00           350.000000
steel     3  182.867219    0.000000    0.000000e+00           350.000000
steel     4  359.402270    0.000000    9.402270e+00           359.402270
steel     5  359.402270  176.535051    0.000000e+00           359.402270
steel     6  105.668016  490.269305    0.000000e+00           359.402270
steel     7         NaN         NaN    0.000000e+00                  NaN
transport 0    0.000000  100.000000             NaN                  NaN
transport 1  141.312267    0.000000             NaN           280.000000
transport 2  198.387943    0.000000    0.000000e+00           280.000000
transport 3  225.917684    0.000000    0.000000e+00           280.000000
transport 4  519.382633    0.000000    2.393826e+02           519.382633
transport 5  519.382633  293.464949    0.000000e+00           519.382633
transport 6   92.307692  750.539890    0.000000e+00           519.382633
transport 7         NaN         NaN    0.000000e+00                  NaN
   manpower_con
1    217.374162
2    344.581624
3    384.165212
4    470.000000
5    470.000000
6    150.000000
```

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```
NOTE: Initialized model Problem3.
NOTE: Added action set 'optimization'.
NOTE: Converting model Problem3 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 60 variables (0 free, 12 fixed).
NOTE: The problem has 36 linear constraints (18 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 219 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 15 variables and 3 constraints.
NOTE: The LP presolver removed 31 constraint coefficients.
NOTE: The presolved problem has 45 variables, 33 constraints, and 188 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    1.464016E+05         0
          D 2         54    2.450706E+03         0
          P 2         56    2.450027E+03         0
NOTE: Optimal.
NOTE: Objective = 2450.0266228.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 60 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 36 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
             production       stock  extra_capacity  productive_capacity
coal      0    0.000000  150.000000             NaN                  NaN
coal      1  251.792754    0.000000             NaN           300.000000
coal      2  316.015222    0.000000       16.015222           316.015222
coal      3  319.832020    0.000000        3.816798           319.832020
coal      4  366.349753    0.000000       46.517734           366.349753
coal      5  859.359606    0.000000      493.009853           859.359606
coal      6  859.359606  460.207993        0.000000           859.359606
coal      7         NaN         NaN        0.000000                  NaN
steel     0    0.000000   80.000000             NaN                  NaN
steel     1  134.794583   11.028028             NaN           350.000000
steel     2  175.041379    0.000000        0.000000           350.000000
steel     3  224.064039    0.000000        0.000000           350.000000
steel     4  223.136289    0.000000        0.000000           350.000000
steel     5  220.043787    0.000000        0.000000           350.000000
steel     6  350.000000    0.000000        0.000000           350.000000
steel     7         NaN         NaN        0.000000                  NaN
transport 0    0.000000  100.000000             NaN                  NaN
transport 1  143.558583    4.247230             NaN           280.000000
transport 2  181.676355    0.000000        0.000000           280.000000
transport 3  280.000000    0.000000        0.000000           280.000000
transport 4  279.072249    0.000000        0.000000           280.000000
transport 5  275.979748    0.000000        0.000000           280.000000
transport 6  195.539132    0.000000        0.000000           280.000000
```

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```
transport 7         NaN         NaN         0.000000                    NaN
   manpower_con
1    226.631832
2    279.983537
3    333.725517
4    539.769130
5    636.824849
6    659.723590
Out[8]: 2450.026622821294
```

### 4.1.10 Decentralization

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex10_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex10.html

#### Model

```python
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    m = so.Model(name='decentralization', session=cas_conn)

    DEPTS = ['A', 'B', 'C', 'D', 'E']
    CITIES = ['Bristol', 'Brighton', 'London']

    benefit_data = pd.DataFrame([
        ['Bristol', 10, 15, 10, 20, 5],
        ['Brighton', 10, 20, 15, 15, 15]],
        columns=['city'] + DEPTS).set_index('city')

    comm_data = pd.DataFrame([
        ['A', 'B', 0.0],
        ['A', 'C', 1.0],
        ['A', 'D', 1.5],
        ['A', 'E', 0.0],
        ['B', 'C', 1.4],
        ['B', 'D', 1.2],
        ['B', 'E', 0.0],
        ['C', 'D', 0.0],
        ['C', 'E', 2.0],
        ['D', 'E', 0.7]], columns=['i', 'j', 'comm']).set_index(['i', 'j'])

    cost_data = pd.DataFrame([
        ['Bristol', 'Bristol', 5],
        ['Bristol', 'Brighton', 14],
        ['Bristol', 'London', 13],
```

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```
        ['Brighton', 'Brighton', 5],
        ['Brighton', 'London', 9],
        ['London', 'London', 10]], columns=['i', 'j', 'cost']).set_index(
            ['i', 'j'])

    max_num_depts = 3

    benefit = {}
    for city in CITIES:
        for dept in DEPTS:
            try:
                benefit[dept, city] = benefit_data.loc[city, dept]
            except:
                benefit[dept, city] = 0

    comm = {}
    for row in comm_data.iterrows():
        (i, j) = row[0]
        comm[i, j] = row[1]['comm']
        comm[j, i] = comm[i, j]

    cost = {}
    for row in cost_data.iterrows():
        (i, j) = row[0]
        cost[i, j] = row[1]['cost']
        cost[j, i] = cost[i, j]

    assign = m.add_variables(DEPTS, CITIES, vartype=so.BIN, name='assign')
    IJKL = [(i, j, k, l)
            for i in DEPTS for j in CITIES for k in DEPTS for l in CITIES
            if i < k]
    product = m.add_variables(IJKL, vartype=so.BIN, name='product')

    totalBenefit = so.quick_sum(benefit[i, j] * assign[i, j]
                                for i in DEPTS for j in CITIES)

    totalCost = so.quick_sum(comm[i, k] * cost[j, l] * product[i, j, k, l]
                             for (i, j, k, l) in IJKL)

    m.set_objective(totalBenefit-totalCost, name='netBenefit', sense=so.MAX)

    m.add_constraints((so.quick_sum(assign[dept, city] for city in CITIES)
                       == 1 for dept in DEPTS), name='assign_dept')

    m.add_constraints((so.quick_sum(assign[dept, city] for dept in DEPTS)
                       <= max_num_depts for city in CITIES), name='cardinality')

    product_def1 = m.add_constraints((assign[i, j] + assign[k, l] - 1
                                      <= product[i, j, k, l]
                                      for (i, j, k, l) in IJKL),
                                      name='pd1')

    product_def2 = m.add_constraints((product[i, j, k, l] <= assign[i, j]
                                       for (i, j, k, l) in IJKL),
                                      name='pd2')

    product_def3 = m.add_constraints((product[i, j, k, l] <= assign[k, l]
```

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```
                                            for (i, j, k, l) in IJKL),
                                           name='pd3')

    m.solve()
    print(m.get_problem_summary())

    m.drop_constraints(product_def1)
    m.drop_constraints(product_def2)
    m.drop_constraints(product_def3)

    m.add_constraints((
        so.quick_sum(product[i, j, k, l]
                     for j in CITIES if (i, j, k, l) in IJKL) == assign[k, l]
        for i in DEPTS for k in DEPTS for l in CITIES if i < k),
        name='pd4')

    m.add_constraints((
        so.quick_sum(product[i, j, k, l]
                     for l in CITIES if (i, j, k, l) in IJKL) == assign[i, j]
        for k in DEPTS for i in DEPTS for j in CITIES if i < k),
        name='pd5')

    m.solve()
    print(m.get_problem_summary())
    totalBenefit.set_name('totalBenefit')
    totalCost.set_name('totalCost')
    print(so.get_solution_table(totalBenefit, totalCost))
    print(so.get_solution_table(assign).unstack(level=-1))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.decentralization import test

In [8]: test(cas_conn)
NOTE: Initialized model decentralization.
NOTE: Added action set 'optimization'.
NOTE: Converting model decentralization to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 105 variables (0 free, 0 fixed).
```

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```
NOTE: The problem has 105 binary and 0 integer variables.
NOTE: The problem has 278 linear constraints (183 LE, 5 EQ, 90 GE, 0 range).
NOTE: The problem has 660 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 120 constraints.
NOTE: The MILP presolver removed 120 constraint coefficients.
NOTE: The MILP presolver added 120 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 105 variables, 158 constraints, and 540 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      2    -14.9000000    135.0000000  111.04%       0
                0        1      2    -14.9000000     67.5000000  122.07%       0
                0        1      2    -14.9000000     55.0000000  127.09%       0
                0        1      3      8.1000000     55.0000000   85.27%       0
                0        1      3      8.1000000     48.0000000   83.12%       0
                0        1      3      8.1000000     44.8375000   81.93%       0
                0        1      3      8.1000000     42.0000000   80.71%       0
                0        1      3      8.1000000     39.0666667   79.27%       0
                0        1      3      8.1000000     34.7500000   76.69%       0
                0        1      3      8.1000000     33.3692308   75.73%       0
                0        1      3      8.1000000     32.6500000   75.19%       0
                0        1      3      8.1000000     31.9066667   74.61%       0
                0        1      3      8.1000000     30.7000000   73.62%       0
                0        1      3      8.1000000     30.1600000   73.14%       0
                0        1      3      8.1000000     29.8800000   72.89%       0
                0        1      3      8.1000000     29.8000000   72.82%       0
                0        1      3      8.1000000     29.4722222   72.52%       0
                0        1      3      8.1000000     28.9117647   71.98%       0
                0        1      3      8.1000000     28.6716667   71.75%       0
                0        1      3      8.1000000     28.5000000   71.58%       0
                0        1      4     14.9000000     14.9000000    0.00%       0
NOTE: The MILP solver added 34 cuts with 185 cut coefficients at the root.
NOTE: Optimal.
NOTE: Objective = 14.9.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 105 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 278 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
Selected Rows from Table PROBLEMSUMMARY

                                Value
Label
Objective Sense          Maximization
Objective Function         netBenefit
Objective Type                 Linear

Number of Variables               105
```

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```
Bounded Above                     0
Bounded Below                     0
Bounded Below and Above         105
Free                              0
Fixed                             0
Binary                          105
Integer                           0

Number of Constraints           278
Linear LE (<=)                  183
Linear EQ (=)                     5
Linear GE (>=)                   90
Linear Range                      0

Constraint Coefficients         660
NOTE: Added action set 'optimization'.
NOTE: Converting model decentralization to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 105 variables (0 free, 0 fixed).
NOTE: The problem has 105 binary and 0 integer variables.
NOTE: The problem has 68 linear constraints (3 LE, 65 EQ, 0 GE, 0 range).
NOTE: The problem has 270 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 0 constraints.
NOTE: The MILP presolver removed 0 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 105 variables, 68 constraints, and 270 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      2    -28.1000000    135.0000000  120.81%       0
                0        1      2    -28.1000000     30.0000000  193.67%       0
                0        1      3    -16.3000000     30.0000000  154.33%       0
                0        1      3    -16.3000000     30.0000000  154.33%       0
NOTE: The MILP solver added 4 cuts with 24 cut coefficients at the root.
                2        0      4     14.9000000     14.9000000    0.00%       0
NOTE: Optimal.
NOTE: Objective = 14.9.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 105 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 68 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
Selected Rows from Table PROBLEMSUMMARY

                                Value
Label
Objective Sense           Maximization
Objective Function          netBenefit
```

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```
Objective Type                     Linear

Number of Variables                   105
Bounded Above                           0
Bounded Below                           0
Bounded Below and Above               105
Free                                    0
Fixed                                   0
Binary                                105
Integer                                 0

Number of Constraints                  68
Linear LE (<=)                          3
Linear EQ (=)                          65
Linear GE (>=)                          0
Linear Range                            0

Constraint Coefficients               270
   totalBenefit  totalCost
-          80.0       65.1
assign  (A, Bristol)     1.0
        (A, Brighton)    0.0
        (A, London)      0.0
        (B, Bristol)     0.0
        (B, Brighton)    1.0
        (B, London)      0.0
        (C, Bristol)     0.0
        (C, Brighton)    1.0
        (C, London)     -0.0
        (D, Bristol)     1.0
        (D, Brighton)    0.0
        (D, London)      0.0
        (E, Bristol)     0.0
        (E, Brighton)    1.0
        (E, London)      0.0
dtype: float64
Out[8]: 14.9
```

### 4.1.11 Optimal Wedding

#### Reference

SAS Blog: https://blogs.sas.com/content/operations/2014/11/10/do-you-have-an-uncle-louie-optimal-wedding-seat-assignments/

### Model

```
import sasoptpy as so
import math


def test(cas_conn, num_guests=20, max_table_size=3, max_tables=None):

    m = so.Model("wedding", session=cas_conn)

    # Check max. tables
    if max_tables is None:
        max_tables = math.ceil(num_guests/max_table_size)

    # Sets
    guests = range(1, num_guests+1)
    tables = range(1, max_tables+1)
    guest_pairs = [[i, j] for i in guests for j in range(i+1, num_guests+1)]

    # Variables
    x = m.add_variables(guests, tables, vartype=so.BIN, name="x")
    unhappy = m.add_variables(tables, name="unhappy", lb=0)

    # Objective
    m.set_objective(unhappy.sum('*'), sense=so.MIN, name="obj")

    # Constraints
    m.add_constraints((x.sum(g, '*') == 1 for g in guests), name="assigncon")
    m.add_constraints((x.sum('*', t) <= max_table_size for t in tables),
                      name="tablesizecon")
    m.add_constraints((unhappy[t] >= abs(g-h)*(x[g, t] + x[h, t] - 1)
                       for t in tables for [g, h] in guest_pairs),
                      name="measurecon")

    # Solve
    res = m.solve(options={
        'with': 'milp', 'decomp': {'method': 'set'}, 'presolver': 'none'})

    if res is not None:

        print(so.get_solution_table(x))

        # Print assignments
        for t in tables:
            print('Table {} : [ '.format(t), end='')
            for g in guests:
                if x[g, t].get_value() == 1:
                    print('{} '.format(g), end='')
            print(']')

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.sas_optimal_wedding import test

In [8]: test(cas_conn)
NOTE: Initialized model wedding.
NOTE: Added action set 'optimization'.
NOTE: Converting model wedding to DataFrame.
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMP6S_9JJ1V␣
↪in caslib CASUSER(casuser).
NOTE: The table TMP6S_9JJ1V has been created in caslib CASUSER(casuser) from binary␣
↪data uploaded to Cloud Analytic Services.
NOTE: The problem wedding has 147 variables (140 binary, 0 integer, 0 free, 0 fixed).
NOTE: The problem has 1357 constraints (7 LE, 20 EQ, 1330 GE, 0 range).
NOTE: The problem has 4270 constraint coefficients.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value NONE is applied.
NOTE: The MILP solver is called.
NOTE: The Decomposition algorithm is used.
NOTE: The Decomposition algorithm is executing in the distributed computing␣
↪environment in single-machine mode.
NOTE: The DECOMP method value SET is applied.
NOTE: All blocks are identical and the master model is set partitioning.
NOTE: The Decomposition algorithm is using an aggregate formulation and Ryan-Foster␣
↪branching.
NOTE: The number of block threads has been reduced to 1 threads.
NOTE: The problem has a decomposable structure with 7 blocks. The largest block␣
↪covers 14.08% of the constraints in the problem.
NOTE: The decomposition subproblems cover 147 (100%) variables and 1337 (98.53%)␣
↪constraints.
NOTE: The deterministic parallel mode is enabled.
NOTE: The Decomposition algorithm is using up to 8 threads.
         Iter         Best       Master         Best       LP        IP  CPU  Real
                     Bound    Objective      Integer      Gap       Gap Time  Time
            .       0.0000      13.0000      13.0000 1.30e+01 1.30e+01    0     0
            1       0.0000      13.0000      13.0000 1.30e+01 1.30e+01    0     0
            .       0.0000      13.0000      13.0000 1.30e+01 1.30e+01    1     2
           10       0.0000      13.0000      13.0000 1.30e+01 1.30e+01    1     2
           18       4.2500      13.0000      13.0000  205.88%  205.88%    5     6
           19       6.0000      13.0000      13.0000  116.67%  116.67%    5     7
            .       6.0000      13.0000      13.0000  116.67%  116.67%    6     7
           20       6.0000      13.0000      13.0000  116.67%  116.67%    6     7
           21       9.5000      13.0000      13.0000   36.84%   36.84%    6     7
           23      13.0000      13.0000      13.0000    0.00%    0.00%    6     8
```

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```
            Node  Active   Sols         Best          Best       Gap     CPU    Real
                                     Integer         Bound              Time    Time
               0       1      3      13.0000       13.0000     0.00%       6       8
NOTE: The Decomposition algorithm used 8 threads.
NOTE: The Decomposition algorithm time is 8.36 seconds.
NOTE: Optimal.
NOTE: Objective = 13.
           x
(1, 1)   1.0
(1, 2)   0.0
(1, 3)   0.0
(1, 4)   0.0
(1, 5)   0.0
(1, 6)   0.0
(1, 7)   0.0
(2, 1)   1.0
(2, 2)   0.0
(2, 3)   0.0
(2, 4)   0.0
(2, 5)   0.0
(2, 6)   0.0
(2, 7)   0.0
(3, 1)   1.0
(3, 2)   0.0
(3, 3)   0.0
(3, 4)   0.0
(3, 5)   0.0
(3, 6)   0.0
(3, 7)   0.0
(4, 1)   0.0
(4, 2)   1.0
(4, 3)   0.0
(4, 4)   0.0
(4, 5)   0.0
(4, 6)   0.0
(4, 7)   0.0
(5, 1)   0.0
(5, 2)   1.0
(5, 3)   0.0
(5, 4)   0.0
(5, 5)   0.0
(5, 6)   0.0
(5, 7)   0.0
(6, 1)   0.0
(6, 2)   1.0
(6, 3)   0.0
(6, 4)   0.0
(6, 5)   0.0
(6, 6)   0.0
(6, 7)   0.0
(7, 1)   0.0
(7, 2)   0.0
(7, 3)   1.0
(7, 4)   0.0
(7, 5)   0.0
(7, 6)   0.0
(7, 7)   0.0
```

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```
(8, 1)   0.0
(8, 2)   0.0
(8, 3)   1.0
(8, 4)   0.0
(8, 5)   0.0
(8, 6)   0.0
(8, 7)   0.0
(9, 1)   0.0
(9, 2)   0.0
(9, 3)   1.0
(9, 4)   0.0
(9, 5)   0.0
(9, 6)   0.0
(9, 7)   0.0
(10, 1)  0.0
(10, 2)  0.0
(10, 3)  0.0
(10, 4)  1.0
(10, 5)  0.0
(10, 6)  0.0
(10, 7)  0.0
(11, 1)  0.0
(11, 2)  0.0
(11, 3)  0.0
(11, 4)  1.0
(11, 5)  0.0
(11, 6)  0.0
(11, 7)  0.0
(12, 1)  0.0
(12, 2)  0.0
(12, 3)  0.0
(12, 4)  1.0
(12, 5)  0.0
(12, 6)  0.0
(12, 7)  0.0
(13, 1)  0.0
(13, 2)  0.0
(13, 3)  0.0
(13, 4)  0.0
(13, 5)  1.0
(13, 6)  0.0
(13, 7)  0.0
(14, 1)  0.0
(14, 2)  0.0
(14, 3)  0.0
(14, 4)  0.0
(14, 5)  1.0
(14, 6)  0.0
(14, 7)  0.0
(15, 1)  0.0
(15, 2)  0.0
(15, 3)  0.0
(15, 4)  0.0
(15, 5)  1.0
(15, 6)  0.0
(15, 7)  0.0
(16, 1)  0.0
```

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```
(16, 2)  0.0
(16, 3)  0.0
(16, 4)  0.0
(16, 5)  0.0
(16, 6)  1.0
(16, 7)  0.0
(17, 1)  0.0
(17, 2)  0.0
(17, 3)  0.0
(17, 4)  0.0
(17, 5)  0.0
(17, 6)  1.0
(17, 7)  0.0
(18, 1)  0.0
(18, 2)  0.0
(18, 3)  0.0
(18, 4)  0.0
(18, 5)  0.0
(18, 6)  1.0
(18, 7)  0.0
(19, 1)  0.0
(19, 2)  0.0
(19, 3)  0.0
(19, 4)  0.0
(19, 5)  0.0
(19, 6)  0.0
(19, 7)  1.0
(20, 1)  0.0
(20, 2)  0.0
(20, 3)  0.0
(20, 4)  0.0
(20, 5)  0.0
(20, 6)  0.0
(20, 7)  1.0
Table 1 : [ 1 2 3 ]
Table 2 : [ 4 5 6 ]
Table 3 : [ 7 8 9 ]
Table 4 : [ 10 11 12 ]
Table 5 : [ 13 14 15 ]
Table 6 : [ 16 17 18 ]
Table 7 : [ 19 20 ]
Out[8]: 13.0
```

### 4.1.12 Kidney Exchange

#### Reference

SAS Blog: https://blogs.sas.com/content/operations/2015/02/06/the-kidney-exchange-problem/

### Model

```
import sasoptpy as so
import random


def test(cas_conn, **kwargs):
    # Data generation
    n = 80
    p = 0.02

    random.seed(1)

    ARCS = {}
    for i in range(0, n):
        for j in range(0, n):
            if random.random() < p:
                ARCS[i, j] = random.random()

    max_length = 10

    # Model
    model = so.Model("kidney_exchange", session=cas_conn)

    # Sets
    NODES = set().union(*ARCS.keys())
    MATCHINGS = range(1, int(len(NODES)/2)+1)

    # Variables
    UseNode = model.add_variables(NODES, MATCHINGS, vartype=so.BIN,
                                  name="usenode")
    UseArc = model.add_variables(ARCS, MATCHINGS, vartype=so.BIN,
                                 name="usearc")
    Slack = model.add_variables(NODES, vartype=so.BIN, name="slack")

    print('Setting objective...')

    # Objective
    model.set_objective(so.quick_sum((ARCS[i, j] * UseArc[i, j, m]
                                      for [i, j] in ARCS for m in MATCHINGS)),
                        name="total_weight", sense=so.MAX)

    print('Adding constraints...')
    # Constraints
    Node_Packing = model.add_constraints((UseNode.sum(i, '*') + Slack[i] == 1
                                          for i in NODES), name="node_packing")
    Donate = model.add_constraints((UseArc.sum(i, '*', m) == UseNode[i, m]
                                    for i in NODES
                                    for m in MATCHINGS), name="donate")
    Receive = model.add_constraints((UseArc.sum('*', j, m) == UseNode[j, m]
                                     for j in NODES
                                     for m in MATCHINGS), name="receive")
    Cardinality = model.add_constraints((UseArc.sum('*', '*', m) <= max_length
                                         for m in MATCHINGS),
                                        name="cardinality")

    # Solve
```

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```
    model.solve(options={'with': 'milp', 'maxtime': 300}, **kwargs)

    # Define decomposition blocks
    for i in NODES:
        for m in MATCHINGS:
            Donate[i, m].set_block(m-1)
            Receive[i, m].set_block(m-1)
    for m in MATCHINGS:
        Cardinality[m].set_block(m-1)

    model.solve(options={
        'with': 'milp', 'maxtime': 300, 'presolver': 'basic',
        'decomp': {'method': 'user'}}, **kwargs)

    return model.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.sas_kidney_exchange import test

In [8]: test(cas_conn)
NOTE: Initialized model kidney_exchange.
Setting objective...
Adding constraints...
NOTE: Added action set 'optimization'.
NOTE: Converting model kidney_exchange to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 8133 variables (0 free, 0 fixed).
NOTE: The problem has 8133 binary and 0 integer variables.
NOTE: The problem has 5967 linear constraints (38 LE, 5929 EQ, 0 GE, 0 range).
NOTE: The problem has 24245 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The remaining solution time after problem generation and solver initialization␣
↪is 299.85 seconds.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 6193 variables and 5357 constraints.
NOTE: The MILP presolver removed 17478 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 1940 variables, 610 constraints, and 6767 constraint␣
↪coefficients.
```

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```
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 8 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      4     12.0775275   2279.8770216   99.47%       0
                0        1      4     12.0775275     18.3085704   34.03%       0
NOTE: The MILP solver's symmetry detection found 140 orbits. The largest orbit␣
↪contains 37 variables.
                0        1      4     12.0775275     18.3085704   34.03%       1
                0        1      4     12.0775275     18.3085704   34.03%       1
                0        1      4     12.0775275     18.3085704   34.03%       1
                0        1      4     12.0775275     18.3085704   34.03%       1
NOTE: The MILP solver added 4 cuts with 196 cut coefficients at the root.
               11        8      5     17.1113590     18.1252274    5.59%       1
               28        6      6     17.1113590     18.0210902    5.05%       1
               30        5      7     17.1113590     18.0210902    5.05%       1
               40        6      8     17.1113590     18.0210902    5.05%       2
               66        0      8     17.1113590     17.1113590    0.00%       2
NOTE: Optimal.
NOTE: Objective = 17.111358985.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 8133 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 5967 rows and 4␣
↪columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
NOTE: Added action set 'optimization'.
NOTE: Converting model kidney_exchange to DataFrame.
NOTE: Cloud Analytic Services made the uploaded file available as table BLOCKSTABLE␣
↪in caslib CASUSER(casuser).
NOTE: The table BLOCKSTABLE has been created in caslib CASUSER(casuser) from binary␣
↪data uploaded to Cloud Analytic Services.
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPD5NBL081␣
↪in caslib CASUSER(casuser).
NOTE: The table TMPD5NBL081 has been created in caslib CASUSER(casuser) from binary␣
↪data uploaded to Cloud Analytic Services.
NOTE: The problem kidney_exchange has 8133 variables (8133 binary, 0 integer, 0 free,␣
↪0 fixed).
NOTE: The problem has 5967 constraints (38 LE, 5929 EQ, 0 GE, 0 range).
NOTE: The problem has 24245 constraint coefficients.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value BASIC is applied.
NOTE: The MILP presolver removed 2685 variables and 1925 constraints.
NOTE: The MILP presolver removed 8005 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 5448 variables, 4042 constraints, and 16240␣
↪constraint coefficients.
NOTE: The MILP solver is called.
NOTE: The Decomposition algorithm is used.
NOTE: The Decomposition algorithm is executing in the distributed computing␣
↪environment in single-machine mode.
NOTE: The DECOMP method value USER is applied.
NOTE: All blocks are identical and the master model is set partitioning.
NOTE: The Decomposition algorithm is using an aggregate formulation and Ryan-Foster␣
↪branching.
```

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```
NOTE: The number of block threads has been reduced to 1 threads.
NOTE: The problem has a decomposable structure with 38 blocks. The largest block␣
↪covers 2.598% of the constraints in the problem.
NOTE: The decomposition subproblems cover 5396 (99.05%) variables and 3990 (98.71%)␣
↪constraints.
NOTE: The deterministic parallel mode is enabled.
NOTE: The Decomposition algorithm is using up to 8 threads.
         Iter         Best       Master         Best       LP       IP  CPU Real
                     Bound    Objective      Integer      Gap      Gap Time Time
            .     283.4155      10.5814      10.5814   96.27%   96.27%    1    1
            1     259.0121      10.5814      10.5814   95.91%   95.91%    1    1
            2     230.6758      10.5814      10.5814   95.41%   95.41%    1    1
            3     204.2627      10.5814      10.5814   94.82%   94.82%    1    2
            4     192.9770      14.7394      14.7394   92.36%   92.36%    2    2
            6     162.6582      15.6274      15.6274   90.39%   90.39%    5    6
            7     140.2584      15.6274      15.6274   88.86%   88.86%    5    6
            8     109.9454      15.6274      15.6274   85.79%   85.79%    6    7
            9      65.4530      16.1007      15.6274   75.40%   76.12%    6    7
           10      65.4530      16.1007      17.1114   75.40%   73.86%    6    7
           11      51.8662      17.1114      17.1114   67.01%   67.01%    6    7
           14      25.6849      17.1114      17.1114   33.38%   33.38%    7    8
           15      17.1114      17.1114      17.1114    0.00%    0.00%    7    9
            Node  Active   Sols         Best         Best      Gap    CPU   Real
                                     Integer        Bound            Time   Time
               0       1      9      17.1114      17.1114    0.00%      7      9
NOTE: The Decomposition algorithm used 8 threads.
NOTE: The Decomposition algorithm time is 9.43 seconds.
NOTE: Optimal.
NOTE: Objective = 17.111358985.
Out[8]: 17.11135898487
```

### 4.1.13 Multiobjective

#### Reference

https://go.documentation.sas.com/?cdcId=pgmsascdc&cdcVersion=9.4_3.4&docsetId=ormpug&docsetTarget=ormpug_lsosolver_examples07.htm&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/lsoe10.html

#### Model

```
import sasoptpy as so


def test(cas_conn, sols=False):

    m = so.Model(name='multiobjective', session=cas_conn)

    x = m.add_variables([1, 2], lb=0, ub=5, name='x')

    f1 = m.set_objective((x[1]-1)**2 + (x[1] - x[2])**2, name='f1', sense=so.MIN)
    f2 = m.append_objective((x[1]-x[2])**2 + (x[2] - 3)**2, name='f2', sense=so.MIN)
```

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```
    m.solve(verbose=True, options={'with': 'blackbox', 'obj': (f1, f2), 'logfreq': 50}
↪)

    print('f1', f1.get_value())
    print('f2', f2.get_value())

    if sols:
        return dict(solutions=cas_conn.CASTable('allsols').to_frame(),
                    x=x, f1=f1, f2=f2)
    else:
        return f1.get_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.multiobjective import test

In [8]: response = test(cas_conn, sols=True)
NOTE: Initialized model multiobjective.
NOTE: Added action set 'optimization'.
NOTE: Converting model multiobjective to OPTMODEL.
   var x {{1,2}} >= 0 <= 5;
   min f1 = (x[1] - 1) ^ (2) + (x[1] - x[2]) ^ (2);
   min f2 = (x[1] - x[2]) ^ (2) + (x[2] - 3) ^ (2);
   solve with blackbox obj (f1 f2) / logfreq=50;
   create data solution from [i]= {1.._NVAR_} var=_VAR_.name value=_VAR_ lb=_VAR_.lb␣
↪ub=_VAR_.ub rc=_VAR_.rc;
   create data dual from [j] = {1.._NCON_} con=_CON_.name value=_CON_.body dual=_CON_.
↪dual;
   create data allsols from [s]=(1.._NVAR_) name=_VAR_[s].name {j in 1.._NSOL_} <col(
↪'sol_'||j)=_VAR_[s].sol[j]>;

NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 2 variables (0 free, 0 fixed).
NOTE: The problem has 0 linear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver removed 0 variables, 0 linear constraints, and 0␣
↪nonlinear constraints.
NOTE: The black-box solver is using up to 8 threads.
NOTE: The black-box solver is using the EAGLS optimizer algorithm.
NOTE: The problem has 2 variables (0 integer, 2 continuous).
```

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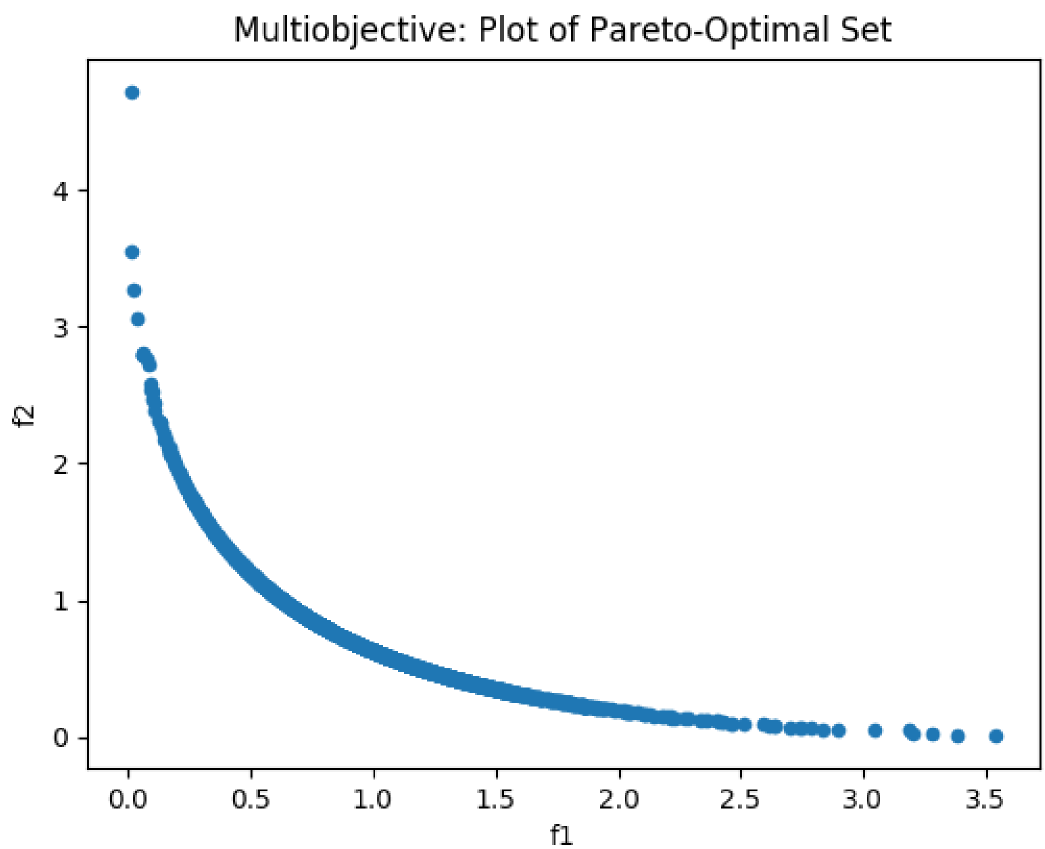
```
NOTE: The problem has 0 constraints (0 linear, 0 nonlinear).
NOTE: The problem has 2 user-defined functions.
NOTE: The deterministic parallel mode is enabled.
           Iteration     Nondom          Progress    Infeasibility     Evals      Time
                   1          4                 .                0        84         0
                  51        877         0.0000811                0      2876         0
                 101       1654         0.0000123                0      5576         1
                 151       2290    0.000003230545                0      8181         1
                 201       2874         0.0000182                0     10796         2
                 251       3422    0.000003148003                0     13447         3
                 301       3847    0.000001559509                0     16046         4
                 351       4282    0.000001159917                0     18733         5
                 401       4712    0.000002423148                0     21315         7
                 428       4932    0.000000704951                0     22734         7
NOTE: Function convergence criteria reached.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 2 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 0 rows and 4 columns.
NOTE: The output table 'ALLSOLS' in caslib 'CASUSER(casuser)' has 2 rows and 4934␣
↪columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 14 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 12 rows and 4␣
↪columns.
f1 0.01497094056129493
f2 4.721632618656377
```

```
In [9]: import matplotlib.pyplot as plt

In [10]: sols = response['solutions']

In [11]: x = response['x']

In [12]: f1 = response['f1']

In [13]: f2 = response['f2']

In [14]: tr = sols.transpose()

In [15]: scvalues = tr.iloc[2:]

In [16]: scvalues = scvalues.astype({0: float, 1: float})

In [17]: x[1].set_value(scvalues[0])

In [18]: x[2].set_value(scvalues[1])

In [19]: scvalues['f1'] = f1.get_value()

In [20]: scvalues['f2'] = f2.get_value()

In [21]: f = scvalues.plot.scatter(x='f1', y='f2')

In [22]: f.set_title('Multiobjective: Plot of Pareto-Optimal Set');

In [23]: f
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe1f8d707f0>
```




### 4.1.14 Least Squares

#### Reference

https://go.documentation.sas.com/?docsetId=ormpug&docsetTarget=ormpug_nlpsolver_gettingstarted05.htm&docsetVersion=15.1&locale=en

https://support.sas.com/documentation/onlinedoc/or/ex_code/151/nlpsg01.html

#### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn, data=None):

    # Use default data if not passed
    if data is None:
        data = pd.DataFrame([
            [4, 8, 43.71],
            [62, 5, 351.29],
```

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```
            [81, 62, 2878.91],
            [85, 75, 3591.59],
            [65, 54, 2058.71],
            [96, 84, 4487.87],
            [98, 29, 1773.52],
            [36, 33, 767.57],
            [30, 91, 1637.66],
            [3, 59, 215.28],
            [62, 57, 2067.42],
            [11, 48, 394.11],
            [66, 21, 932.84],
            [68, 24, 1069.21],
            [95, 30, 1770.78],
            [34, 14, 368.51],
            [86, 81, 3902.27],
            [37, 49, 1115.67],
            [46, 80, 2136.92],
            [87, 72, 3537.84],
        ], columns=['x1', 'x2', 'y'])

    m = so.Model(name='least_squares', session=cas_conn)

    # Regression model: L(a,b,c) = a * x1 + b * x2 + c * x1 * x2
    a = m.add_variable(name='a')
    b = m.add_variable(name='b')
    c = m.add_variable(name='c')

    x1 = data['x1']
    x2 = data['x2']
    y = data['y']

    err = m.add_implicit_variable((
        y[i] - (a * x1[i] + b * x2[i] + c * x1[i]  * x2[i]) for i in data.index
    ), name='error')
    m.set_objective(so.quick_sum(err[i]**2 for i in data.index),
                    sense=so.MIN,
                    name='total_error')
    m.solve(verbose=True, options={'with': 'nlp'})
    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.least_squares import test

In [8]: test(cas_conn)
NOTE: Initialized model least_squares.
NOTE: Added action set 'optimization'.
NOTE: Converting model least_squares to OPTMODEL.
   var a;
   var b;
   var c;
   impvar error_0 = - 4 * a - 8 * b - 32 * c + 43.71;
   impvar error_1 = - 62 * a - 5 * b - 310 * c + 351.29;
   impvar error_2 = - 81 * a - 62 * b - 5022 * c + 2878.91;
   impvar error_3 = - 85 * a - 75 * b - 6375 * c + 3591.59;
   impvar error_4 = - 65 * a - 54 * b - 3510 * c + 2058.71;
   impvar error_5 = - 96 * a - 84 * b - 8064 * c + 4487.87;
   impvar error_6 = - 98 * a - 29 * b - 2842 * c + 1773.52;
   impvar error_7 = - 36 * a - 33 * b - 1188 * c + 767.57;
   impvar error_8 = - 30 * a - 91 * b - 2730 * c + 1637.66;
   impvar error_9 = - 3 * a - 59 * b - 177 * c + 215.28;
   impvar error_10 = - 62 * a - 57 * b - 3534 * c + 2067.42;
   impvar error_11 = - 11 * a - 48 * b - 528 * c + 394.11;
   impvar error_12 = - 66 * a - 21 * b - 1386 * c + 932.84;
   impvar error_13 = - 68 * a - 24 * b - 1632 * c + 1069.21;
   impvar error_14 = - 95 * a - 30 * b - 2850 * c + 1770.78;
   impvar error_15 = - 34 * a - 14 * b - 476 * c + 368.51;
   impvar error_16 = - 86 * a - 81 * b - 6966 * c + 3902.27;
   impvar error_17 = - 37 * a - 49 * b - 1813 * c + 1115.67;
   impvar error_18 = - 46 * a - 80 * b - 3680 * c + 2136.92;
   impvar error_19 = - 87 * a - 72 * b - 6264 * c + 3537.84;
   min total_error = (- 4 * a - 8 * b - 32 * c + 43.71) ^ (2) + (- 62 * a - 5 * b -␣
↪310 * c + 351.29) ^ (2) + (- 81 * a - 62 * b - 5022 * c + 2878.91) ^ (2) + (- 85 *␣
↪a - 75 * b - 6375 * c + 3591.59) ^ (2) + (- 65 * a - 54 * b - 3510 * c + 2058.71) ^␣
↪(2) + (- 96 * a - 84 * b - 8064 * c + 4487.87) ^ (2) + (- 98 * a - 29 * b - 2842 *␣
↪c + 1773.52) ^ (2) + (- 36 * a - 33 * b - 1188 * c + 767.57) ^ (2) + (- 30 * a - 91␣
↪* b - 2730 * c + 1637.66) ^ (2) + (- 3 * a - 59 * b - 177 * c + 215.28) ^ (2) + (-␣
↪62 * a - 57 * b - 3534 * c + 2067.42) ^ (2) + (- 11 * a - 48 * b - 528 * c + 394.
↪11) ^ (2) + (- 66 * a - 21 * b - 1386 * c + 932.84) ^ (2) + (- 68 * a - 24 * b -␣
↪1632 * c + 1069.21) ^ (2) + (- 95 * a - 30 * b - 2850 * c + 1770.78) ^ (2) + (- 34␣
↪* a - 14 * b - 476 * c + 368.51) ^ (2) + (- 86 * a - 81 * b - 6966 * c + 3902.27) ^␣
↪(2) + (- 37 * a - 49 * b - 1813 * c + 1115.67) ^ (2) + (- 46 * a - 80 * b - 3680 *␣
↪c + 2136.92) ^ (2) + (- 87 * a - 72 * b - 6264 * c + 3537.84) ^ (2);
   solve with nlp / ;
   create data solution from [i]= {1.._NVAR_} var=_VAR_.name value=_VAR_ lb=_VAR_.lb␣
↪ub=_VAR_.ub rc=_VAR_.rc;
   create data dual from [j] = {1.._NCON_} con=_CON_.name value=_CON_.body dual=_CON_.
↪dual;

NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 3 variables (3 free, 0 fixed).
NOTE: The problem has 0 linear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver removed 0 variables, 0 linear constraints, and 0␣
↪nonlinear constraints.
NOTE: Using analytic derivatives for objective.
NOTE: The NLP solver is called.
NOTE: The Interior Point Direct algorithm is used.
```

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```
                        Objective                          Optimality
            Iter            Value     Infeasibility             Error
               0         95424613                 0        3.48646173
               1       7.18629678                 0   0.0000000055789
NOTE: Optimal.
NOTE: Objective = 7.1862967833.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 3 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 0 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 12 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 12 rows and 4␣
↪columns.
Out[8]: 7.186296783293
```

**Workspace Examples**

### 4.1.15 Efficiency Analysis

#### Reference

https://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex22_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex22.html

#### Model

```
import sasoptpy as so
import pandas as pd
from sasoptpy.util import iterate, concat
from sasoptpy.actions import (
    read_data, create_data, cofor_loop, for_loop, solve, if_condition, diff,
    print_item, inline_condition)


def test(cas_conn, get_tables=False):

    input_list = pd.DataFrame(
        ['staff', 'showroom', 'pop1', 'pop2', 'alpha_enq', 'beta_enq'],
        columns=['input'])
    input_data = cas_conn.upload_frame(
        data=input_list, casout={'name': 'input_data', 'replace': True})

    output_list = pd.DataFrame(
        ['alpha_sales', 'beta_sales', 'profit'], columns=['output'])
    output_data = cas_conn.upload_frame(
        data=output_list, casout={'name': 'output_data', 'replace': True})

    problem_data = pd.DataFrame([
        ['Winchester', 7, 8, 10, 12, 8.5, 4, 2, 0.6, 1.5],
        ['Andover', 6, 6, 20, 30, 9, 4.5, 2.3, 0.7, 1.6],
        ['Basingstoke', 2, 3, 40, 40, 2, 1.5, 0.8, 0.25, 0.5],
        ['Poole', 14, 9, 20, 25, 10, 6, 2.6, 0.86, 1.9],
```

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```
        ['Woking', 10, 9, 10, 10, 11, 5, 2.4, 1, 2],
        ['Newbury', 24, 15, 15, 13, 25, 19, 8, 2.6, 4.5],
        ['Portsmouth', 6, 7, 50, 40, 8.5, 3, 2.5, 0.9, 1.6],
        ['Alresford', 8, 7.5, 5, 8, 9, 4, 2.1, 0.85, 2],
        ['Salisbury', 5, 5, 10, 10, 5, 2.5, 2, 0.65, 0.9],
        ['Guildford', 8, 10, 30, 35, 9.5, 4.5, 2.05, 0.75, 1.7],
        ['Alton', 7, 8, 7, 8, 3, 2, 1.9, 0.7, 0.5],
        ['Weybridge', 5, 6.5, 9, 12, 8, 4.5, 1.8, 0.63, 1.4],
        ['Dorchester', 6, 7.5, 10, 10, 7.5, 4, 1.5, 0.45, 1.45],
        ['Bridport', 11, 8, 8, 10, 10, 6, 2.2, 0.65, 2.2],
        ['Weymouth', 4, 5, 10, 10, 7.5, 3.5, 1.8, 0.62, 1.6],
        ['Portland', 3, 3.5, 3, 2, 2, 1.5, 0.9, 0.35, 0.5],
        ['Chichester', 5, 5.5, 8, 10, 7, 3.5, 1.2, 0.45, 1.3],
        ['Petersfield', 21, 12, 6, 8, 15, 8, 6, 0.25, 2.9],
        ['Petworth', 6, 5.5, 2, 2, 8, 5, 1.5, 0.55, 1.55],
        ['Midhurst', 3, 3.6, 3, 3, 2.5, 1.5, 0.8, 0.2, 0.45],
        ['Reading', 30, 29, 120, 80, 35, 20, 7, 2.5, 8],
        ['Southampton', 25, 16, 110, 80, 27, 12, 6.5, 3.5, 5.4],
        ['Bournemouth', 19, 10, 90, 12, 25, 13, 5.5, 3.1, 4.5],
        ['Henley', 7, 6, 5, 7, 8.5, 4.5, 1.2, 0.48, 2],
        ['Maidenhead', 12, 8, 7, 10, 12, 7, 4.5, 2, 2.3],
        ['Fareham', 4, 6, 1, 1, 7.5, 3.5, 1.1, 0.48, 1.7],
        ['Romsey', 2, 2.5, 1, 1, 2.5, 1, 0.4, 0.1, 0.55],
        ['Ringwood', 2, 3.5, 2, 2, 1.9, 1.2, 0.3, 0.09, 0.4],
    ], columns=['garage_name', 'staff', 'showroom', 'pop1', 'pop2', 'alpha_enq',
                'beta_enq', 'alpha_sales', 'beta_sales', 'profit'])
    garage_data = cas_conn.upload_frame(
        data=problem_data, casout={'name': 'garage_data', 'replace': True})

    with so.Workspace(name='efficiency_analysis', session=cas_conn) as w:
        inputs = so.Set(name='INPUTS', settype=so.string)
        read_data(table=input_data, index={'target': inputs, 'key': 'input'})

        outputs = so.Set(name='OUTPUTS', settype=so.string)
        read_data(table=output_data, index={'target': outputs, 'key': 'output'})

        garages = so.Set(name='GARAGES', settype=so.number)
        garage_name = so.ParameterGroup(garages, name='garage_name', ptype=so.string)
        input = so.ParameterGroup(inputs, garages, name='input')
        output = so.ParameterGroup(outputs, garages, name='output')
        r = read_data(table=garage_data, index={'target': garages, 'key': so.N},
                      columns=[garage_name])
        with iterate(inputs, 'i') as i:
            r.append({'index': i, 'target': input[i, so.N], 'column': i})
        with iterate(outputs, 'i') as i:
            r.append({'index': i, 'target': output[i, so.N], 'column': i})

        k = so.Parameter(name='k', ptype=so.number)
        efficiency_number = so.ParameterGroup(garages, name='efficiency_number')
        weight_sol = so.ParameterGroup(garages, garages, name='weight_sol')

        weight = so.VariableGroup(garages, name='Weight', lb=0)
        inefficiency = so.Variable(name='Inefficiency', lb=0)

        obj = so.Objective(inefficiency, name='Objective', sense=so.maximize)

        input_con = so.ConstraintGroup(
```

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```
            (so.expr_sum(input[i, j] * weight[j] for j in garages) <= input[i, k]
             for i in inputs), name='input_con')
        output_con = so.ConstraintGroup(
            (so.expr_sum(output[i, j] * weight[j] for j in garages) >= output[i, k] *␣
↪inefficiency
             for i in outputs), name='output_con')

        for kk in cofor_loop(garages):
            k.set_value(kk)
            solve()
            efficiency_number[k] = 1 / inefficiency.sol
            for j in for_loop(garages):
                def if_block():
                    weight_sol[k, j] = weight[j].sol
                def else_block():
                    weight_sol[k, j] = None
                if_condition(weight[j].sol > 1e-6, if_block, else_block)

        efficient_garages = so.Set(
            name='EFFICIENT_GARAGES',
            value=[j.sym for j in garages if j.sym.under_condition(efficiency_
↪number[j] >= 1)])
        inefficient_garages = so.Set(value=diff(garages, efficient_garages), name=
↪'INEFFICIENT_GARAGES')

        p1 = print_item(garage_name, efficiency_number)
        ed = create_data(table='efficiency_data', index={'key': ['garage']}, columns=[
            garage_name, efficiency_number
        ])
        with iterate(inefficient_garages, 'inefficient_garage') as i:
            wd = create_data(table='weight_data_dense',
                             index={'key': [i], 'set': [i.get_set()]},
                             columns=[garage_name, efficiency_number])
            with iterate(efficient_garages, 'efficient_garage') as j:
                wd.append({
                    'name': concat('w', j),
                    'expression': weight_sol[i, j],
                    'index': j
                })

        filtered_set = so.InlineSet(
            lambda: ((g1, g2)
                     for g1 in inefficient_garages
                     for g2 in efficient_garages
                     if inline_condition(weight_sol[g1, g2] != None)))
        wds = create_data(table='weight_data_sparse',
                          index={'key': ['i', 'j'], 'set': [filtered_set]},
                          columns=[weight_sol])

    print(w.to_optmodel())
    w.submit()

    print('Print Table:')
    print(p1.get_response())

    print('Efficiency Data:')
    print(ed.get_response())
```

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```
    print('Weight Data (Dense):')
    print(wd.get_response())

    print('Weight Data (Sparse):')
    print(wds.get_response())

    if get_tables:
        return obj.get_value(), ed.get_response()
    else:
        return obj.get_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.server_side.efficiency_analysis import test

In [8]: test(cas_conn)
NOTE: Cloud Analytic Services made the uploaded file available as table INPUT_DATA in␣
↪caslib CASUSER(casuser).
NOTE: The table INPUT_DATA has been created in caslib CASUSER(casuser) from binary␣
↪data uploaded to Cloud Analytic Services.
NOTE: Cloud Analytic Services made the uploaded file available as table OUTPUT_DATA␣
↪in caslib CASUSER(casuser).
NOTE: The table OUTPUT_DATA has been created in caslib CASUSER(casuser) from binary␣
↪data uploaded to Cloud Analytic Services.
NOTE: Cloud Analytic Services made the uploaded file available as table GARAGE_DATA␣
↪in caslib CASUSER(casuser).
NOTE: The table GARAGE_DATA has been created in caslib CASUSER(casuser) from binary␣
↪data uploaded to Cloud Analytic Services.
proc optmodel;
   set <str> INPUTS;
   read data INPUT_DATA into INPUTS=[input] ;
   set <str> OUTPUTS;
   read data OUTPUT_DATA into OUTPUTS=[output] ;
   set GARAGES;
   str garage_name {GARAGES};
   num input {INPUTS, GARAGES};
   num output {OUTPUTS, GARAGES};
   read data GARAGE_DATA into GARAGES=[_N_] garage_name {i in INPUTS} < input[i, _N_
↪]=col(i) > {i in OUTPUTS} < output[i, _N_]=col(i) >;
   num k;
   num efficiency_number {GARAGES};
```

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```
   num weight_sol {GARAGES, GARAGES};
   var Weight {{GARAGES}} >= 0;
   var Inefficiency >= 0;
   max Objective = Inefficiency;
   con input_con {o21 in INPUTS} : input[o21, k] - (sum {j in GARAGES} (input[o21, j]␣
↪* Weight[j])) >= 0;
   con output_con {o33 in OUTPUTS} : sum {j in GARAGES} (output[o33, j] * Weight[j]) -
↪ output[o33, k] * Inefficiency >= 0;
   cofor {o46 in GARAGES} do;
      k = o46;
      solve;
      efficiency_number[k] = (1) / (Inefficiency.sol);
      for {o58 in GARAGES} do;
         if Weight[o58].sol > 1e-06 then do;
            weight_sol[k, o58] = Weight[o58].sol;
         end;
         else do;
            weight_sol[k, o58] = .;
         end;
      end;
   end;
   set EFFICIENT_GARAGES = {{o69 in GARAGES: efficiency_number[o69] >= 1}};
   set INEFFICIENT_GARAGES = GARAGES diff EFFICIENT_GARAGES;
   print garage_name efficiency_number;
   create data efficiency_data from [garage] garage_name efficiency_number;
   create data weight_data_dense from [inefficient_garage] = {{INEFFICIENT_GARAGES}}␣
↪garage_name efficiency_number {efficient_garage in EFFICIENT_GARAGES} < col('w' ||␣
↪efficient_garage)=(weight_sol[inefficient_garage, efficient_garage]) >;
   create data weight_data_sparse from [i j] = {{{o83 in INEFFICIENT_GARAGES, o85 in␣
↪EFFICIENT_GARAGES: weight_sol[o83, o85] ne .}}} weight_sol;
quit;
NOTE: Added action set 'optimization'.
NOTE: There were 6 rows read from table 'INPUT_DATA' in caslib 'CASUSER(casuser)'.
NOTE: There were 3 rows read from table 'OUTPUT_DATA' in caslib 'CASUSER(casuser)'.
NOTE: There were 28 rows read from table 'GARAGE_DATA' in caslib 'CASUSER(casuser)'.
NOTE: The COFOR statement is executing in single-machine mode.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    2.788571E+01         0
          P 2          6    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.02 seconds.
```

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```
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    6.185408E+01         0
          P 2          6    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.02 seconds.
NOTE: Problem generation will use 6 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    6.669507E+01         0
          P 2         15    1.152977E+00         0
NOTE: Optimal.
NOTE: Objective = 1.1529771581.
NOTE: The Dual Simplex solve time is 0.02 seconds.
NOTE: Problem generation will use 5 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.01 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
```

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```
         Phase Iteration        Value         Time
          D 2          1    6.771196E+01         0
          P 2          5    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    9.367804E+01         0
          P 2         18    1.191606E+00         0
NOTE: Optimal.
NOTE: Objective = 1.1916056975.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    6.282477E+01         0
          P 2          7    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
```

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```
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    2.113425E+02         0
          P 2          7    1.141723E+00         0
NOTE: Optimal.
NOTE: Objective = 1.141723356.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    8.984164E+01         0
          P 2         20    1.190229E+00         0
NOTE: Optimal.
NOTE: Objective = 1.1902294108.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    7.496160E+01         0
          P 2          7    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
```

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```
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                             Objective
         Phase Iteration        Value         Time
          D 2          1    6.137365E+01         0
          P 2          9    1.011903E+00         0
NOTE: Optimal.
NOTE: Objective = 1.0119030842.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                             Objective
         Phase Iteration        Value         Time
          D 2          1    5.430205E+01         0
          P 2         18    1.018276E+00         0
NOTE: Optimal.
NOTE: Objective = 1.0182756046.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                             Objective
         Phase Iteration        Value         Time
          D 2          1    9.121193E+01         0
          P 2         17    1.170487E+00         0
```

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```
NOTE: Optimal.
NOTE: Objective = 1.170487106.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    7.130206E+01         0
          P 2         12    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    7.942787E+01         0
          P 2         15    1.090062E+00         0
NOTE: Optimal.
NOTE: Objective = 1.0900621118.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
```

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```
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    3.333800E+01         0
          P 2          8    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    3.269636E+01         0
          P 2          5    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    1.483009E+02         0
          P 2         12    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
```

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```
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    7.522880E+01         0
          P 2          9    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    8.552410E+01         0
          P 2         14    1.160239E+00         0
NOTE: Optimal.
NOTE: Objective = 1.1602389558.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    6.743350E+01         0
          P 2         20    1.029858E+00         0
NOTE: Optimal.
NOTE: Objective = 1.0298577511.
NOTE: The Dual Simplex solve time is 0.00 seconds.
```

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```
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    1.119904E+02         0
          P 2          6    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    3.162476E+01         0
          P 2          5    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
```

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```
         Phase Iteration        Value         Time
          D 2          1    1.462372E+02         0
          P 2          9    1.205868E+00         0
NOTE: Optimal.
NOTE: Objective = 1.2058683067.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    9.913941E+01         0
          P 2         16    1.228251E+00         0
NOTE: Optimal.
NOTE: Objective = 1.2282514234.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    1.428026E+02         0
          P 2          5    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
```

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```
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    9.575369E+01         0
          P 2         16    1.213087E+00         0
NOTE: Optimal.
NOTE: Objective = 1.2130872456.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    3.928295E+01         0
          P 2          7    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: Problem generation will use 7 threads.
NOTE: The problem has 29 variables (0 free, 0 fixed).
NOTE: The problem has 9 linear constraints (0 LE, 0 EQ, 9 GE, 0 range).
NOTE: The problem has 255 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 29 variables, 9 constraints, and 255 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    4.906079E+01         0
          P 2          5    1.000000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'EFFICIENCY_DATA' in caslib 'CASUSER(casuser)' has 28 rows and␣
↪3 columns.
NOTE: The output table 'WEIGHT_DATA_DENSE' in caslib 'CASUSER(casuser)' has 17 rows␣
↪and 14 columns.
```

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```
NOTE: The output table 'WEIGHT_DATA_SPARSE' in caslib 'CASUSER(casuser)' has 43 rows␣
↪and 3 columns.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 29 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 9 rows and 4 columns.
Print Table:
    COL1  garage_name  efficiency_number
0    1.0  Bournemouth           1.000000
1    2.0       Henley           1.000000
2    3.0       Woking           0.867320
3    4.0        Alton           1.000000
4    5.0   Dorchester           0.839204
5    6.0    Alresford           1.000000
6    7.0     Ringwood           0.875869
7    8.0   Winchester           0.840174
8    9.0     Weymouth           1.000000
9   10.0     Petworth           0.988237
10  11.0      Reading           0.982052
11  12.0    Weybridge           0.854345
12  13.0   Portsmouth           1.000000
13  14.0      Andover           0.917379
14  15.0      Newbury           1.000000
15  16.0   Maidenhead           1.000000
16  17.0  Basingstoke           1.000000
17  18.0    Salisbury           1.000000
18  19.0        Poole           0.861891
19  20.0     Bridport           0.971008
20  21.0     Portland           1.000000
21  22.0  Petersfield           1.000000
22  23.0     Midhurst           0.829278
23  24.0    Guildford           0.814166
24  25.0       Romsey           1.000000
25  26.0   Chichester           0.824343
26  27.0  Southampton           1.000000
27  28.0      Fareham           1.000000
Efficiency Data:
Selected Rows from Table EFFICIENCY_DATA

    garage  garage_name  efficiency_number
0      1.0  Bournemouth           1.000000
1      2.0       Henley           1.000000
2      3.0       Woking           0.867320
3      4.0        Alton           1.000000
4      5.0   Dorchester           0.839204
5      6.0    Alresford           1.000000
6      7.0     Ringwood           0.875869
7      8.0   Winchester           0.840174
8      9.0     Weymouth           1.000000
9     10.0     Petworth           0.988237
10    11.0      Reading           0.982052
11    12.0    Weybridge           0.854345
12    13.0   Portsmouth           1.000000
13    14.0      Andover           0.917379
14    15.0      Newbury           1.000000
15    16.0   Maidenhead           1.000000
16    17.0  Basingstoke           1.000000
17    18.0    Salisbury           1.000000
```

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```
18    19.0        Poole           0.861891
19    20.0     Bridport           0.971008
20    21.0     Portland           1.000000
21    22.0  Petersfield           1.000000
22    23.0     Midhurst           0.829278
23    24.0    Guildford           0.814166
24    25.0       Romsey           1.000000
25    26.0   Chichester           0.824343
26    27.0  Southampton           1.000000
27    28.0      Fareham           1.000000
Weight Data (Dense):
Selected Rows from Table WEIGHT_DATA_DENSE

    inefficient_garage  garage_name  efficiency_number  ...       w22  w25       w27
0                  1.0  Bournemouth           1.000000  ...       NaN  NaN       NaN
1                  3.0        Woking           0.867320  ...       NaN  NaN  0.009093
2                  5.0   Dorchester           0.839204  ...       NaN  NaN       NaN
3                  7.0     Ringwood           0.875869  ...       NaN  NaN       NaN
4                  8.0   Winchester           0.840174  ...       NaN  NaN       NaN
5                 10.0     Petworth           0.988237  ...  0.015212  NaN       NaN
6                 11.0      Reading           0.982052  ...       NaN  NaN       NaN
7                 12.0    Weybridge           0.854345  ...       NaN  NaN       NaN
8                 13.0   Portsmouth           1.000000  ...       NaN  NaN       NaN
9                 14.0      Andover           0.917379  ...       NaN  NaN       NaN
10                17.0  Basingstoke           1.000000  ...       NaN  NaN       NaN
11                19.0        Poole           0.861891  ...       NaN  NaN       NaN
12                20.0     Bridport           0.971008  ...       NaN  NaN       NaN
13                23.0     Midhurst           0.829278  ...  0.043482  NaN       NaN
14                24.0    Guildford           0.814166  ...       NaN  NaN       NaN
15                26.0   Chichester           0.824343  ...       NaN  NaN       NaN
16                28.0      Fareham           1.000000  ...       NaN  NaN       NaN

[17 rows x 14 columns]
Weight Data (Sparse):
Selected Rows from Table WEIGHT_DATA_SPARSE

       i     j  weight_sol
0    5.0   2.0    0.035318
1    7.0   2.0    0.146485
2   11.0   2.0    2.862469
3   19.0   2.0    0.434419
4   20.0   2.0    0.783097
5   26.0   2.0    0.236367
6    3.0   4.0    0.021078
7    3.0   6.0    0.952525
8    5.0   6.0    0.104478
9    8.0   6.0    0.416268
10  24.0   6.0    0.622715
11  26.0   6.0    0.096820
12   5.0   9.0    0.119287
13   8.0   9.0    0.333333
14  11.0   9.0    0.544410
15  12.0   9.0    0.796562
16  14.0   9.0    0.857143
17  23.0   9.0    0.066511
18  24.0   9.0    0.191804
19  26.0   9.0    0.335428
```

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```
20  10.0  15.0    0.066345
21   3.0  16.0    0.148376
22  10.0  16.0    0.034089
23  11.0  16.0    0.137534
24  12.0  16.0    0.145236
25  14.0  16.0    0.214286
26  19.0  16.0    0.344634
27  20.0  16.0    0.194894
28  23.0  16.0    0.008940
29   8.0  18.0    0.403284
30  23.0  18.0    0.059574
31   5.0  21.0    0.751632
32   7.0  21.0    0.319728
33   8.0  21.0    0.096138
34  11.0  21.0    1.199139
35  19.0  21.0    0.757330
36  20.0  21.0    0.469693
37  23.0  21.0    0.471893
38  24.0  21.0    0.168067
39  26.0  21.0    0.165227
40  10.0  22.0    0.015212
41  23.0  22.0    0.043482
42   3.0  27.0    0.009093
Out[8]: 1.0000000000000002
```

## 4.2 Viya Examples / Abstract

### 4.2.1 Curve Fitting

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex11_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex11.html

#### Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn, sols=False):

    # Upload data to server first
    xy_raw = pd.DataFrame([
        [0.0, 1.0],
        [0.5, 0.9],
        [1.0, 0.7],
        [1.5, 1.5],
        [1.9, 2.0],
        [2.5, 2.4],
```

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```
        [3.0, 3.2],
        [3.5, 2.0],
        [4.0, 2.7],
        [4.5, 3.5],
        [5.0, 1.0],
        [5.5, 4.0],
        [6.0, 3.6],
        [6.6, 2.7],
        [7.0, 5.7],
        [7.6, 4.6],
        [8.5, 6.0],
        [9.0, 6.8],
        [10.0, 7.3]
        ], columns=['x', 'y'])
    xy_data = cas_conn.upload_frame(xy_raw, casout={'name': 'xy_data',
                                                    'replace': True})

    # Read observations
    from sasoptpy.actions import read_data
    POINTS = so.Set(name='POINTS')
    x = so.ParameterGroup(POINTS, name='x')
    y = so.ParameterGroup(POINTS, name='y')
    read_st = read_data(
        table=xy_data,
        index={'target': POINTS, 'key': so.N},
        columns=[
            {'target': x, 'column': 'x'},
            {'target': y, 'column': 'y'}
        ]
    )

    # Parameters and variables
    order = so.Parameter(name='order')
    beta = so.VariableGroup(so.exp_range(0, order), name='beta')
    estimate = so.ImplicitVar(
        (beta[0] + so.quick_sum(beta[k] * x[i] ** k
                                for k in so.exp_range(1, order))
         for i in POINTS), name='estimate')

    surplus = so.VariableGroup(POINTS, name='surplus', lb=0)
    slack = so.VariableGroup(POINTS, name='slack', lb=0)

    objective1 = so.Expression(
        so.quick_sum(surplus[i] + slack[i] for i in POINTS), name='objective1')
    abs_dev_con = so.ConstraintGroup(
        (estimate[i] - surplus[i] + slack[i] == y[i] for i in POINTS),
        name='abs_dev_con')

    minmax = so.Variable(name='minmax')
    objective2 = so.Expression(minmax + 0.0, name='objective2')
    minmax_con = so.ConstraintGroup(
        (minmax >= surplus[i] + slack[i] for i in POINTS), name='minmax_con')

    order.set_init(1)
    L1 = so.Model(name='L1', session=cas_conn)
    L1.set_objective(objective1, sense=so.MIN, name='L1obj')
    L1.include(POINTS, x, y, read_st)
```

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```
    L1.include(order, beta, estimate, surplus, slack, abs_dev_con)
    L1.add_postsolve_statement('print x y estimate surplus slack;')

    L1.solve(verbose=True)
    if sols:
        sol_data1 = L1.response['Print1.PrintTable'].sort_values('x')
        print(so.get_solution_table(beta))
        print(sol_data1.to_string())

    Linf = so.Model(name='Linf', session=cas_conn)
    Linf.include(L1, minmax, minmax_con)
    Linf.set_objective(objective2, sense=so.MIN, name='Linfobj')

    Linf.solve()
    if sols:
        sol_data2 = Linf.response['Print1.PrintTable'].sort_values('x')
        print(so.get_solution_table(beta))
        print(sol_data2.to_string())

    order.set_init(2)

    L1.solve()
    if sols:
        sol_data3 = L1.response['Print1.PrintTable'].sort_values('x')
        print(so.get_solution_table(beta))
        print(sol_data3.to_string())

    Linf.solve()
    if sols:
        sol_data4 = Linf.response['Print1.PrintTable'].sort_values('x')
        print(so.get_solution_table(beta))
        print(sol_data4.to_string())

    if sols:
        return (sol_data1, sol_data2, sol_data3, sol_data4)
    else:
        return Linf.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.server_side.curve_fitting import test
```

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```
In [8]: (s1, s2, s3, s4) = test(cas_conn, sols=True)
NOTE: Cloud Analytic Services made the uploaded file available as table XY_DATA in␣
↪caslib CASUSER(casuser).
NOTE: The table XY_DATA has been created in caslib CASUSER(casuser) from binary data␣
↪uploaded to Cloud Analytic Services.
NOTE: Initialized model L1.
NOTE: Added action set 'optimization'.
NOTE: Converting model L1 to OPTMODEL.
   set POINTS;
   num x {POINTS};
   num y {POINTS};
   read data XY_DATA into POINTS=[_N_] x y;
   num order init 1;
   var beta {{0..order}};
   impvar estimate {o8 in POINTS} = beta[0] + sum {k in 1..order} (beta[k] * (x[o8]) ^
↪ (k));
   var surplus {{POINTS}} >= 0;
   var slack {{POINTS}} >= 0;
   con abs_dev_con {o32 in POINTS} : y[o32] - estimate[o32] + surplus[o32] -␣
↪slack[o32] = 0;
   min L1obj = sum {i in POINTS} (surplus[i] + slack[i]);
   solve;
   create data solution from [i]= {1.._NVAR_} var=_VAR_.name value=_VAR_ lb=_VAR_.lb␣
↪ub=_VAR_.ub rc=_VAR_.rc;
   create data dual from [j] = {1.._NCON_} con=_CON_.name value=_CON_.body dual=_CON_.
↪dual;
   print x y estimate surplus slack;

NOTE: Submitting OPTMODEL code to CAS server.
NOTE: There were 19 rows read from table 'XY_DATA' in caslib 'CASUSER(casuser)'.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 40 variables (2 free, 0 fixed).
NOTE: The problem uses 19 implicit variables.
NOTE: The problem has 19 linear constraints (0 LE, 19 EQ, 0 GE, 0 range).
NOTE: The problem has 75 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.01 seconds.
NOTE: The LP presolver removed 38 variables and 0 constraints.
NOTE: The LP presolver removed 38 constraint coefficients.
NOTE: The LP presolver formulated the dual of the problem.
NOTE: The presolved problem has 19 variables, 2 constraints, and 37 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2           1    6.160000E+01         0
          D 2           5    1.146625E+01         0
NOTE: Optimal.
NOTE: Objective = 11.46625.
NOTE: The Dual Simplex solve time is 0.02 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 40 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 19 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
```

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```
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
      beta
0  0.58125
1  0.63750
    COL1     x    y  estimate       surplus    slack
10  11.0   0.0  1.0   0.58125  0.000000e+00  0.41875
18  19.0   0.5  0.9   0.90000  5.551115e-17  0.00000
12  13.0   1.0  0.7   1.21875  5.187500e-01  0.00000
4    5.0   1.5  1.5   1.53750  3.750000e-02  0.00000
0    1.0   1.9  2.0   1.79250  0.000000e+00  0.20750
15  16.0   2.5  2.4   2.17500  0.000000e+00  0.22500
1    2.0   3.0  3.2   2.49375  0.000000e+00  0.70625
11  12.0   3.5  2.0   2.81250  8.125000e-01  0.00000
5    6.0   4.0  2.7   3.13125  4.312500e-01  0.00000
3    4.0   4.5  3.5   3.45000  0.000000e+00  0.05000
8    9.0   5.0  1.0   3.76875  2.768750e+00  0.00000
14  15.0   5.5  4.0   4.08750  8.750000e-02  0.00000
13  14.0   6.0  3.6   4.40625  8.062500e-01  0.00000
7    8.0   6.6  2.7   4.78875  2.088750e+00  0.00000
9   10.0   7.0  5.7   5.04375  0.000000e+00  0.65625
17  18.0   7.6  4.6   5.42625  8.262500e-01  0.00000
2    3.0   8.5  6.0   6.00000  0.000000e+00  0.00000
6    7.0   9.0  6.8   6.31875  0.000000e+00  0.48125
16  17.0  10.0  7.3   6.95625  0.000000e+00  0.34375
NOTE: Initialized model Linf.
NOTE: Added action set 'optimization'.
NOTE: Converting model Linf to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: There were 19 rows read from table 'XY_DATA' in caslib 'CASUSER(casuser)'.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 41 variables (3 free, 0 fixed).
NOTE: The problem uses 19 implicit variables.
NOTE: The problem has 38 linear constraints (0 LE, 19 EQ, 19 GE, 0 range).
NOTE: The problem has 132 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 41 variables, 38 constraints, and 132 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    -1.900000E+00         0
          P 2         26     1.725000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.725.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 41 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 38 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
```

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```
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
    beta
0 -0.400
1  0.625
    COL1     x    y  estimate  surplus   slack
10  11.0   0.0  1.0   -0.4000    0.000  1.4000
18  19.0   0.5  0.9   -0.0875    0.000  0.9875
12  13.0   1.0  0.7    0.2250    0.000  0.4750
4    5.0   1.5  1.5    0.5375    0.000  0.9625
0    1.0   1.9  2.0    0.7875    0.000  1.2125
15  16.0   2.5  2.4    1.1625    0.000  1.2375
1    2.0   3.0  3.2    1.4750    0.000  1.7250
11  12.0   3.5  2.0    1.7875    0.000  0.2125
5    6.0   4.0  2.7    2.1000    0.000  0.6000
3    4.0   4.5  3.5    2.4125    0.000  1.0875
8    9.0   5.0  1.0    2.7250    1.725  0.0000
14  15.0   5.5  4.0    3.0375    0.000  0.9625
13  14.0   6.0  3.6    3.3500    0.000  0.2500
7    8.0   6.6  2.7    3.7250    1.025  0.0000
9   10.0   7.0  5.7    3.9750    0.000  1.7250
17  18.0   7.6  4.6    4.3500    0.000  0.2500
2    3.0   8.5  6.0    4.9125    0.000  1.0875
6    7.0   9.0  6.8    5.2250    0.000  1.5750
16  17.0  10.0  7.3    5.8500    0.000  1.4500
NOTE: Added action set 'optimization'.
NOTE: Converting model L1 to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: There were 19 rows read from table 'XY_DATA' in caslib 'CASUSER(casuser)'.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 41 variables (3 free, 0 fixed).
NOTE: The problem uses 19 implicit variables.
NOTE: The problem has 19 linear constraints (0 LE, 19 EQ, 0 GE, 0 range).
NOTE: The problem has 93 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 38 variables and 0 constraints.
NOTE: The LP presolver removed 38 constraint coefficients.
NOTE: The LP presolver formulated the dual of the problem.
NOTE: The presolved problem has 19 variables, 3 constraints, and 55 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    6.160000E+01         0
          D 2          5    1.045896E+01         0
NOTE: Optimal.
NOTE: Objective = 10.458964706.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 41 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 19 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
```

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```
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
       beta
0  0.982353
1  0.294510
2  0.033725
    COL1     x    y  estimate       surplus     slack
10  11.0   0.0  1.0  0.982353  0.000000e+00  0.017647
18  19.0   0.5  0.9  1.138039  2.380392e-01  0.000000
12  13.0   1.0  0.7  1.310588  6.105882e-01  0.000000
4    5.0   1.5  1.5  1.500000 -6.938894e-17  0.000000
0    1.0   1.9  2.0  1.663671  0.000000e+00  0.336329
15  16.0   2.5  2.4  1.929412  0.000000e+00  0.470588
1    2.0   3.0  3.2  2.169412  0.000000e+00  1.030588
11  12.0   3.5  2.0  2.426275  4.262745e-01  0.000000
5    6.0   4.0  2.7  2.700000 -1.110223e-16  0.000000
3    4.0   4.5  3.5  2.990588  0.000000e+00  0.509412
8    9.0   5.0  1.0  3.298039  2.298039e+00  0.000000
14  15.0   5.5  4.0  3.622353  0.000000e+00  0.377647
13  14.0   6.0  3.6  3.963529  3.635294e-01  0.000000
7    8.0   6.6  2.7  4.395200  1.695200e+00  0.000000
9   10.0   7.0  5.7  4.696471  0.000000e+00  1.003529
17  18.0   7.6  4.6  5.168612  5.686118e-01  0.000000
2    3.0   8.5  6.0  5.922353  0.000000e+00  0.077647
6    7.0   9.0  6.8  6.364706  0.000000e+00  0.435294
16  17.0  10.0  7.3  7.300000  4.440892e-16  0.000000
NOTE: Added action set 'optimization'.
NOTE: Converting model Linf to OPTMODEL.
NOTE: Submitting OPTMODEL code to CAS server.
NOTE: There were 19 rows read from table 'XY_DATA' in caslib 'CASUSER(casuser)'.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 42 variables (4 free, 0 fixed).
NOTE: The problem uses 19 implicit variables.
NOTE: The problem has 38 linear constraints (0 LE, 19 EQ, 19 GE, 0 range).
NOTE: The problem has 150 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver time is 0.00 seconds.
NOTE: The LP presolver removed 0 variables and 0 constraints.
NOTE: The LP presolver removed 0 constraint coefficients.
NOTE: The presolved problem has 42 variables, 38 constraints, and 150 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1   -1.900000E+00         0
          P 2         29    1.475000E+00         0
NOTE: Optimal.
NOTE: Objective = 1.475.
NOTE: The Dual Simplex solve time is 0.00 seconds.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 42 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 38 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 13 rows and 4␣
↪columns.
```

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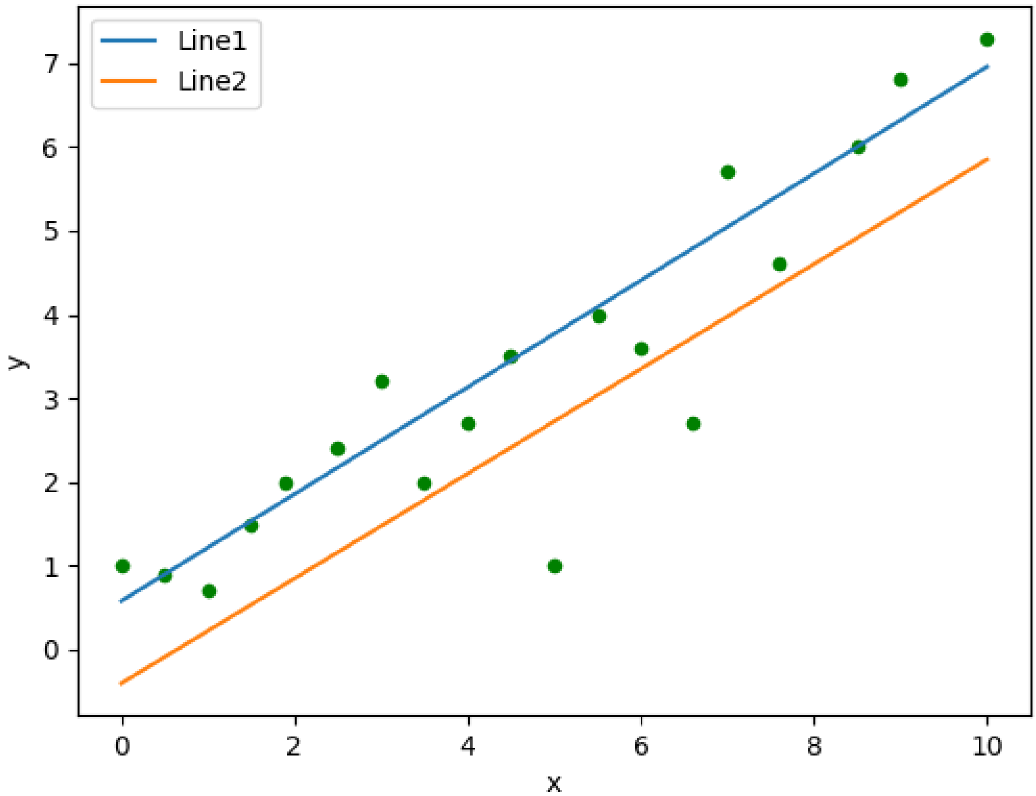
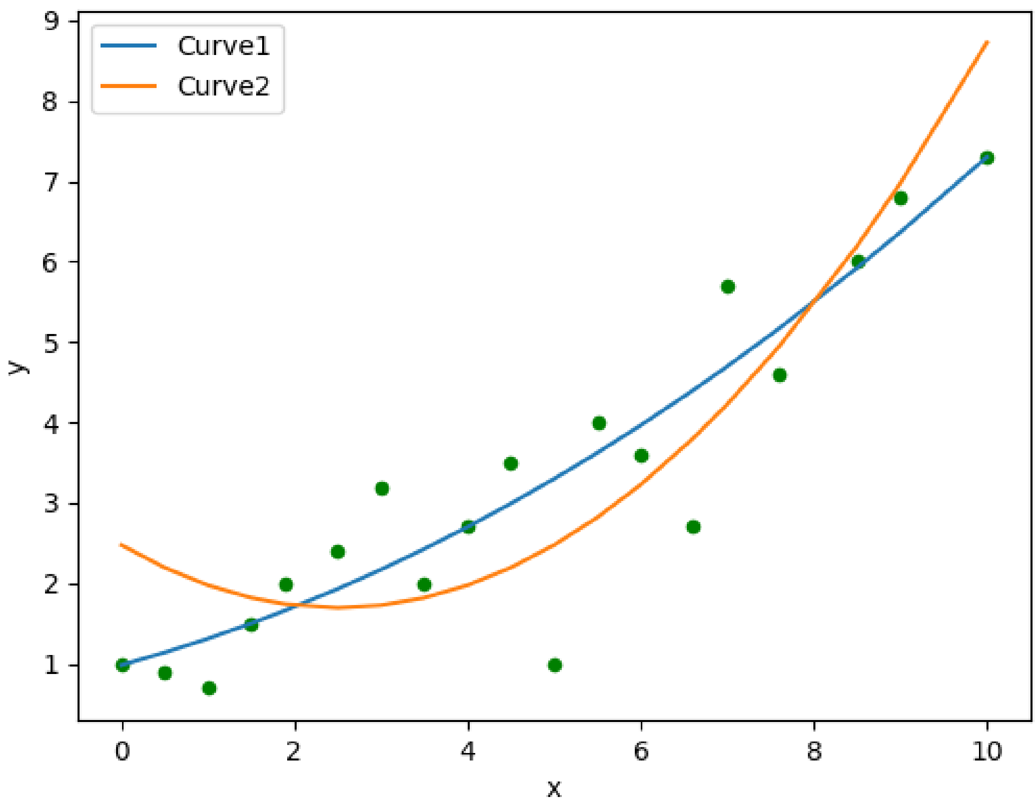
```
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 18 rows and 4␣
↪columns.
    beta
0  2.475
1 -0.625
2  0.125
    COL1     x    y  estimate   surplus     slack
10  11.0   0.0  1.0   2.47500  1.475000  0.000000
18  19.0   0.5  0.9   2.19375  1.293750  0.000000
12  13.0   1.0  0.7   1.97500  1.275000  0.000000
4    5.0   1.5  1.5   1.81875  0.318750  0.000000
0    1.0   1.9  2.0   1.73875  0.606875  0.868125
15  16.0   2.5  2.4   1.69375  0.000000  0.706250
1    2.0   3.0  3.2   1.72500  0.000000  1.475000
11  12.0   3.5  2.0   1.81875  0.000000  0.181250
5    6.0   4.0  2.7   1.97500  0.000000  0.725000
3    4.0   4.5  3.5   2.19375  0.000000  1.306250
8    9.0   5.0  1.0   2.47500  1.475000  0.000000
14  15.0   5.5  4.0   2.81875  0.000000  1.181250
13  14.0   6.0  3.6   3.22500  0.000000  0.375000
7    8.0   6.6  2.7   3.79500  1.095000  0.000000
9   10.0   7.0  5.7   4.22500  0.000000  1.475000
17  18.0   7.6  4.6   4.94500  0.345000  0.000000
2    3.0   8.5  6.0   6.19375  0.193750  0.000000
6    7.0   9.0  6.8   6.97500  0.175000  0.000000
16  17.0  10.0  7.3   8.72500  1.425000  0.000000
```

```
# Plots
In [9]: import matplotlib.pyplot as plt

In [10]: p1 = s1.plot.scatter(x='x', y='y', c='g')

In [11]: s1.plot.line(ax=p1, x='x', y='estimate', label='Line1');

In [12]: s2.plot.line(ax=p1, x='x', y='estimate', label='Line2');

In [13]: p1
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe1f9153198>

In [14]: p2 = s3.plot.scatter(x='x', y='y', c='g')

In [15]: s3.plot.line(ax=p2, x='x', y='estimate', label='Curve1');

In [16]: s4.plot.line(ax=p2, x='x', y='estimate', label='Curve2');

In [17]: p2
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe1f90965c0>
```


Line1
Line2
y
x
0
1
2
3
4
5
6
7
0
2
4
6
8
10




### 4.2.2 Nonlinear 1

#### Reference

http://go.documentation.sas.com/?docsetId=ormpug&docsetTarget=ormpug_nlpsolver_examples01.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/nlpse01.html

#### Model

```
import sasoptpy as so


def test(cas_conn):

    m = so.Model(name='nlpse01', session=cas_conn)
    x = m.add_variables(range(1, 9), lb=0.1, ub=10, name='x')

    f = so.Expression(0.4 * (x[1]/x[7]) ** 0.67 + 0.4 * (x[2]/x[8]) ** 0.67 + 10 -
↪x[1] - x[2], name='f')
    m.set_objective(f, sense=so.MIN, name='f1')
```

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```
    m.add_constraint(1 - 0.0588*x[5]*x[7] - 0.1*x[1] >= 0, name='c1')
    m.add_constraint(1 - 0.0588*x[6]*x[8] - 0.1*x[1] - 0.1*x[2] >= 0, name='c2')
    m.add_constraint(1 - 4*x[3]/x[5] - 2/(x[3]**0.71 * x[5]) - 0.0588*(x[7]/x[3]**1.
↪3) >= 0, name='c3')
    m.add_constraint(1 - 4*x[4]/x[6] - 2/(x[4]**0.71 * x[6]) - 0.0588*(x[8]/x[4]**1.
↪3) >= 0, name='c4')
    m.add_constraint(f == [0.1, 4.2], name='frange')

    x[1].set_init(6)
    x[2].set_init(3)
    x[3].set_init(0.4)
    x[4].set_init(0.2)
    x[5].set_init(6)
    x[6].set_init(6)
    x[7].set_init(1)
    x[8].set_init(0.5)

    m.solve(verbose=True, options={'with': 'nlp', 'algorithm': 'activeset'})

    print(m.get_problem_summary())
    print(m.get_solution_summary())
    if m.get_session_type() == 'CAS':
        print(m.get_solution()[['var', 'value']])

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.nonlinear_1 import test

In [8]: test(cas_conn)
NOTE: Initialized model nlpse01.
NOTE: Added action set 'optimization'.
NOTE: Converting model nlpse01 to OPTMODEL.
   var x {{1,2,3,4,5,6,7,8}} >= 0.1 <= 10;
   x[1] = 6;
   x[2] = 3;
   x[3] = 0.4;
   x[4] = 0.2;
   x[5] = 6;
```

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```
   x[6] = 6;
   x[7] = 1;
   x[8] = 0.5;
   min f1 = 0.4 * (((x[1]) / (x[7])) ^ (0.67)) + 0.4 * (((x[2]) / (x[8])) ^ (0.67)) -␣
↪x[1] - x[2] + 10.0;
   con c1 : - 0.0588 * x[5] * x[7] - 0.1 * x[1] >= -1.0;
   con c2 : - 0.0588 * x[6] * x[8] - 0.1 * x[1] - 0.1 * x[2] >= -1.0;
   con c3 : - ((4 * x[3]) / (x[5])) - ((2) / ((x[3]) ^ (0.71) * x[5])) - 0.0588 *␣
↪((x[7]) / ((x[3]) ^ (1.3))) >= -1.0;
   con c4 : - ((4 * x[4]) / (x[6])) - ((2) / ((x[4]) ^ (0.71) * x[6])) - 0.0588 *␣
↪((x[8]) / ((x[4]) ^ (1.3))) >= -1.0;
   con frange : -9.9 <= 0.4 * (((x[1]) / (x[7])) ^ (0.67)) + 0.4 * (((x[2]) / (x[8]))␣
↪^ (0.67)) - x[1] - x[2] <= -5.8;
   solve with nlp / algorithm=activeset;
   create data solution from [i]= {1.._NVAR_} var=_VAR_.name value=_VAR_ lb=_VAR_.lb␣
↪ub=_VAR_.ub rc=_VAR_.rc;
   create data dual from [j] = {1.._NCON_} con=_CON_.name value=_CON_.body dual=_CON_.
↪dual;

NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 8 variables (0 free, 0 fixed).
NOTE: The problem has 0 linear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The problem has 5 nonlinear constraints (0 LE, 0 EQ, 4 GE, 1 range).
NOTE: The OPTMODEL presolver removed 0 variables, 0 linear constraints, and 0␣
↪nonlinear constraints.
NOTE: Using analytic derivatives for objective.
NOTE: Using analytic derivatives for nonlinear constraints.
NOTE: The NLP solver is called.
NOTE: The Active Set algorithm is used.
                           Objective                          Optimality
              Iter             Value     Infeasibility             Error
                 0        3.65736570        0.41664483        0.24247905
                 1        3.65736570        0.41664483        0.24247905
                 2        3.40486061        0.10284726        0.18904638
                 3        3.51178229        0.07506389        0.18860455
                 4        4.23595983        0.03595983        0.60088809
                 5        4.16334906                 0        0.47130008
                 6        4.03168584        0.00791810        0.13742971
                 7        3.88912660        0.11248991        0.06129662
                 8        3.89579714        0.09534670        0.05994916
                 9        3.95046640        0.02649207        0.06776850
                10        3.92833580        0.03517161        0.06442935
                11        3.95179326        0.00494247        0.05837915
                12        3.94741555        0.00651989        0.05477333
                13        3.95209064        0.00058609        0.05265725
                14        3.95058104        0.00122758        0.04772557
                15        3.95055959        0.00099113        0.04613473
                16        3.95141460        0.00000381        0.04497006
                17        3.95132211   0.0000005999371        0.07584723
                18        3.95114031        0.00000941        0.04093117
                19        3.95027690        0.00011307        0.00020755
                20        3.95115797   0.0000007730235        0.00018707
                21        3.95116558                 0        0.00001366
                22        3.95116364   0.0000000153799        0.00000814
                23        3.95116355   0.0000000228326        0.00000595
                24        3.95116352   0.0000000257138        0.00000337
```

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```
                25        3.95116349   0.0000000200547        0.00000132
                26        3.95116349   0.0000000192412   0.0000002015918
NOTE: Optimal.
NOTE: Objective = 3.9511634887.
NOTE: Objective of the best feasible solution found = 3.9511579677.
NOTE: The best feasible solution found is returned.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 8 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 5 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 12 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 20 rows and 4␣
↪columns.
Selected Rows from Table PROBLEMSUMMARY

                                Value
Label
Objective Sense          Minimization
Objective Function                 f1
Objective Type              Nonlinear

Number of Variables                 8
Bounded Above                       0
Bounded Below                       0
Bounded Below and Above             8
Free                                0
Fixed                               0

Number of Constraints               5
Linear LE (<=)                      0
Linear EQ (=)                       0
Linear GE (>=)                      0
Linear Range                        0
Nonlinear LE (<=)                   0
Nonlinear EQ (=)                    0
Nonlinear GE (>=)                   4
Nonlinear Range                     1
Selected Rows from Table SOLUTIONSUMMARY

                            Value
Label
Solver                        NLP
Algorithm              Active Set
Objective Function             f1
Solution Status     Best Feasible
Objective Value      3.9511579677

Optimality Error     0.0001050714
Infeasibility        7.7302351E-7

Iterations                     26
Presolve Time                0.00
Solution Time                0.03
Selected Rows from Table SOLUTION

    var     value
0  x[1]  6.463315
```

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```
1  x[2]  2.234530
2  x[3]  0.667455
3  x[4]  0.595820
4  x[5]  5.932980
5  x[6]  5.527231
6  x[7]  1.013787
7  x[8]  0.400664
Out[8]: 3.951157967716
```

### 4.2.3 Nonlinear 2

#### Reference

http://go.documentation.sas.com/?docsetId=ormpug&docsetTarget=ormpug_nlpsolver_examples02.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/nlpse02.html

#### Model

```
import sasoptpy as so
import sasoptpy.abstract.math as sm


def test(cas_conn):

    m = so.Model(name='nlpse02', session=cas_conn)
    N = m.add_parameter(name='N', init=1000)
    x = m.add_variables(so.exp_range(1, N), name='x', init=1)
    m.set_objective(
        so.quick_sum(-4*x[i]+3 for i in so.exp_range(1, N-1)) +
        so.quick_sum((x[i]**2 + x[N]**2)**2 for i in so.exp_range(1, N-1)),
        name='f', sense=so.MIN)

    m.add_statement('print x;', after_solve=True)
    m.solve(options={'with': 'nlp'}, verbose=True)
    print(m.get_solution_summary())
    if m.get_session_type() == 'CAS':
        print(m.response['Print1.PrintTable'].head())

    # Model 2
    so.reset()
    m = so.Model(name='nlpse02_2', session=cas_conn)
    N = m.add_parameter(name='N', init=1000)
    x = m.add_variables(so.exp_range(1, N), name='x', lb=1, ub=2)
    m.set_objective(
        so.quick_sum(sm.cos(-0.5*x[i+1] - x[i]**2) for i in so.exp_range(
            1, N-1)), name='f2', sense=so.MIN)
    m.add_statement('print x;', after_solve=True)
    m.solve(verbose=True, options={'with': 'nlp', 'algorithm': 'activeset'})
    print(m.get_solution_summary())

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: hostname = os.getenv('CASHOST')

In [3]: port = os.getenv('CASPORT')

In [4]: from swat import CAS

In [5]: cas_conn = CAS(hostname, port)

In [6]: import sasoptpy
```

```
In [7]: from examples.client_side.nonlinear_2 import test

In [8]: test(cas_conn)
NOTE: Initialized model nlpse02.
NOTE: Added action set 'optimization'.
NOTE: Converting model nlpse02 to OPTMODEL.
   num N init 1000;
   var x {{1..N}} init 1;
   min f = sum {i in 1..N-1} (- 4 * x[i] + 3) + sum {i in 1..N-1} (((x[i]) ^ (2) +␣
↪(x[N]) ^ (2)) ^ (2));
   solve with nlp / ;
   create data solution from [i]= {1.._NVAR_} var=_VAR_.name value=_VAR_ lb=_VAR_.lb␣
↪ub=_VAR_.ub rc=_VAR_.rc;
   create data dual from [j] = {1.._NCON_} con=_CON_.name value=_CON_.body dual=_CON_.
↪dual;
   print x;

NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 1000 variables (1000 free, 0 fixed).
NOTE: The problem has 0 linear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver removed 0 variables, 0 linear constraints, and 0␣
↪nonlinear constraints.
NOTE: Using analytic derivatives for objective.
NOTE: Using 2 threads for nonlinear evaluation.
NOTE: The NLP solver is called.
NOTE: The Interior Point Direct algorithm is used.
                           Objective                        Optimality
              Iter             Value     Infeasibility            Error
                 0     2997.00000000                 0       2.66666667
                 1      561.93750000                 0       4.44444444
                 2       41.17478400                 0      12.76397516
                 3        0.41230550                 0      43.37933609
                 4        0.00005471                 0       0.47005128
                 5  2.2737367544E-13                 0       0.00006316
                 6                 0                 0  1.1527477269E-12
NOTE: Optimal.
NOTE: Objective = 0.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 1000 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 0 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 12 rows and 4␣
↪columns.
```

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```
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 12 rows and 4␣
↪columns.
Selected Rows from Table SOLUTIONSUMMARY

                                    Value
Label
Solver                                NLP
Algorithm           Interior Point Direct
Objective Function                      f
Solution Status                   Optimal
Objective Value                         0

Optimality Error             1.152748E-12
Infeasibility                           0

Iterations                              6
Presolve Time                        0.00
Solution Time                        0.02
   COL1    x
0   1.0  1.0
1   2.0  1.0
2   3.0  1.0
3   4.0  1.0
4   5.0  1.0
NOTE: Initialized model nlpse02_2.
NOTE: Added action set 'optimization'.
NOTE: Converting model nlpse02_2 to OPTMODEL.
   num N init 1000;
   var x {{1..N}} >= 1 <= 2;
   min f2 = sum {i in 1..N-1} (cos(- 0.5 * (x[i + 1]) - ((x[i]) ^ (2))));
   solve with nlp / algorithm=activeset;
   create data solution from [i]= {1.._NVAR_} var=_VAR_.name value=_VAR_ lb=_VAR_.lb␣
↪ub=_VAR_.ub rc=_VAR_.rc;
   create data dual from [j] = {1.._NCON_} con=_CON_.name value=_CON_.body dual=_CON_.
↪dual;
   print x;

NOTE: Submitting OPTMODEL code to CAS server.
NOTE: Problem generation will use 8 threads.
NOTE: The problem has 1000 variables (0 free, 0 fixed).
NOTE: The problem has 0 linear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver removed 0 variables, 0 linear constraints, and 0␣
↪nonlinear constraints.
NOTE: Using analytic derivatives for objective.
NOTE: Using 3 threads for nonlinear evaluation.
NOTE: The NLP solver is called.
NOTE: The Active Set algorithm is used.
NOTE: Initial point was changed to be feasible to bounds.
                           Objective                        Optimality
              Iter             Value     Infeasibility           Error
                 0       70.66646447                 0      1.24686873
                 1       70.66646439                 0      1.24686873
                 2     -996.26893548                 0      0.23815533
                 3     -998.99328004                 0      0.10718277
                 4     -998.99999439                 0      0.00379400
                 5     -999.00000000                 0      0.00000393
```

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```
                 6     -999.00000000                 0  1.7018480129E-12
NOTE: Optimal.
NOTE: Objective = -999.
NOTE: The output table 'SOLUTION' in caslib 'CASUSER(casuser)' has 1000 rows and 6␣
↪columns.
NOTE: The output table 'DUAL' in caslib 'CASUSER(casuser)' has 0 rows and 4 columns.
NOTE: The CAS table 'solutionSummary' in caslib 'CASUSER(casuser)' has 12 rows and 4␣
↪columns.
NOTE: The CAS table 'problemSummary' in caslib 'CASUSER(casuser)' has 12 rows and 4␣
↪columns.
Selected Rows from Table SOLUTIONSUMMARY

                           Value
Label
Solver                       NLP
Algorithm             Active Set
Objective Function            f2
Solution Status          Optimal
Objective Value             -999

Optimality Error    1.701848E-12
Infeasibility                  0

Iterations                     6
Presolve Time               0.00
Solution Time               0.04
Out[8]: -999.0
```

## 4.3 SAS (saspy) Examples

### 4.3.1 Decentralization (saspy)

#### Reference

http://go.documentation.sas.com/?docsetId=ormpex&docsetTarget=ormpex_ex10_toc.htm&docsetVersion=15.1&locale=en

http://support.sas.com/documentation/onlinedoc/or/ex_code/151/mpex10.html

#### Model

```python
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    m = so.Model(name='decentralization', session=cas_conn)

    DEPTS = ['A', 'B', 'C', 'D', 'E']
    CITIES = ['Bristol', 'Brighton', 'London']

```

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```
    benefit_data = pd.DataFrame([
        ['Bristol', 10, 15, 10, 20, 5],
        ['Brighton', 10, 20, 15, 15, 15]],
        columns=['city'] + DEPTS).set_index('city')

    comm_data = pd.DataFrame([
        ['A', 'B', 0.0],
        ['A', 'C', 1.0],
        ['A', 'D', 1.5],
        ['A', 'E', 0.0],
        ['B', 'C', 1.4],
        ['B', 'D', 1.2],
        ['B', 'E', 0.0],
        ['C', 'D', 0.0],
        ['C', 'E', 2.0],
        ['D', 'E', 0.7]], columns=['i', 'j', 'comm']).set_index(['i', 'j'])

    cost_data = pd.DataFrame([
        ['Bristol', 'Bristol', 5],
        ['Bristol', 'Brighton', 14],
        ['Bristol', 'London', 13],
        ['Brighton', 'Brighton', 5],
        ['Brighton', 'London', 9],
        ['London', 'London', 10]], columns=['i', 'j', 'cost']).set_index(
            ['i', 'j'])

    max_num_depts = 3

    benefit = {}
    for city in CITIES:
        for dept in DEPTS:
            try:
                benefit[dept, city] = benefit_data.loc[city, dept]
            except:
                benefit[dept, city] = 0

    comm = {}
    for row in comm_data.iterrows():
        (i, j) = row[0]
        comm[i, j] = row[1]['comm']
        comm[j, i] = comm[i, j]

    cost = {}
    for row in cost_data.iterrows():
        (i, j) = row[0]
        cost[i, j] = row[1]['cost']
        cost[j, i] = cost[i, j]

    assign = m.add_variables(DEPTS, CITIES, vartype=so.BIN, name='assign')
    IJKL = [(i, j, k, l)
            for i in DEPTS for j in CITIES for k in DEPTS for l in CITIES
            if i < k]
    product = m.add_variables(IJKL, vartype=so.BIN, name='product')

    totalBenefit = so.quick_sum(benefit[i, j] * assign[i, j]
                                for i in DEPTS for j in CITIES)
```

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```
    totalCost = so.quick_sum(comm[i, k] * cost[j, l] * product[i, j, k, l]
                             for (i, j, k, l) in IJKL)

    m.set_objective(totalBenefit-totalCost, name='netBenefit', sense=so.MAX)

    m.add_constraints((so.quick_sum(assign[dept, city] for city in CITIES)
                       == 1 for dept in DEPTS), name='assign_dept')

    m.add_constraints((so.quick_sum(assign[dept, city] for dept in DEPTS)
                       <= max_num_depts for city in CITIES), name='cardinality')

    product_def1 = m.add_constraints((assign[i, j] + assign[k, l] - 1
                                      <= product[i, j, k, l]
                                      for (i, j, k, l) in IJKL),
                                      name='pd1')

    product_def2 = m.add_constraints((product[i, j, k, l] <= assign[i, j]
                                       for (i, j, k, l) in IJKL),
                                      name='pd2')

    product_def3 = m.add_constraints((product[i, j, k, l] <= assign[k, l]
                                       for (i, j, k, l) in IJKL),
                                      name='pd3')

    m.solve()
    print(m.get_problem_summary())

    m.drop_constraints(product_def1)
    m.drop_constraints(product_def2)
    m.drop_constraints(product_def3)

    m.add_constraints((
        so.quick_sum(product[i, j, k, l]
                     for j in CITIES if (i, j, k, l) in IJKL) == assign[k, l]
        for i in DEPTS for k in DEPTS for l in CITIES if i < k),
        name='pd4')

    m.add_constraints((
        so.quick_sum(product[i, j, k, l]
                     for l in CITIES if (i, j, k, l) in IJKL) == assign[i, j]
        for k in DEPTS for i in DEPTS for j in CITIES if i < k),
        name='pd5')

    m.solve()
    print(m.get_problem_summary())
    totalBenefit.set_name('totalBenefit')
    totalCost.set_name('totalCost')
    print(so.get_solution_table(totalBenefit, totalCost))
    print(so.get_solution_table(assign).unstack(level=-1))

    return m.get_objective_value()
```

### Output

```
In [1]: import os

In [2]: import saspy

In [3]: config_file = os.path.abspath('../tests/examples/saspy_config.py')

In [4]: sas_conn = saspy.SASsession(cfgfile=config_file)
Using SAS Config named: sshsas
SAS Connection established. Subprocess id is 8720


In [5]: import sasoptpy
```

```
In [6]: from examples.client_side.decentralization import test

In [7]: test(sas_conn)
NOTE: Initialized model decentralization.
NOTE: Converting model decentralization to OPTMODEL.
NOTE: Submitting OPTMODEL code to SAS instance.

NOTE: Writing HTML5(SASPY_INTERNAL) Body file: STDOUT
NOTE: Problem generation will use 4 threads.
NOTE: The problem has 105 variables (0 free, 0 fixed).
NOTE: The problem has 105 binary and 0 integer variables.
NOTE: The problem has 278 linear constraints (183 LE, 5 EQ, 90 GE, 0 range).
NOTE: The problem has 660 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 120 constraints.
NOTE: The MILP presolver removed 120 constraint coefficients.
NOTE: The MILP presolver added 120 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 105 variables, 158 constraints, and 540 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
NOTE: The Branch and Cut algorithm is using up to 4 threads.
          Node   Active   Sols    BestInteger      BestBound      Gap    Time
             0        1      2    -14.9000000    135.0000000  111.04%       0
             0        1      2    -14.9000000     67.5000000  122.07%       0
             0        1      2    -14.9000000     52.0000000  128.65%       0
             0        1      3      8.1000000     52.0000000   84.42%       0
             0        1      3      8.1000000     50.0000000   83.80%       0
             0        1      3      8.1000000     48.2500000   83.21%       0
             0        1      3      8.1000000     40.0000000   79.75%       0
             0        1      3      8.1000000     39.2500000   79.36%       0
             0        1      3      8.1000000     34.2000000   76.32%       0
             0        1      3      8.1000000     33.6187500   75.91%       0
             0        1      3      8.1000000     33.0761905   75.51%       0
             0        1      3      8.1000000     32.6521739   75.19%       0
             0        1      3      8.1000000     32.0142857   74.70%       0
             0        1      3      8.1000000     31.8222222   74.55%       0
             0        1      3      8.1000000     31.3333333   74.15%       0
```

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```
             0        1      3      8.1000000     30.0000000   73.00%       0
             0        1      3      8.1000000     28.5000000   71.58%       0
             0        1      4     14.9000000     14.9000000    0.00%       0
NOTE: The MILP solver added 28 cuts with 146 cut coefficients at the root.
NOTE: Optimal.
NOTE: Objective = 14.9.
NOTE: The data set WORK.PROB_SUMMARY has 20 observations and 3 variables.
NOTE: The data set WORK.SOL_SUMMARY has 18 observations and 3 variables.
NOTE: The data set WORK.SOLUTION has 105 observations and 6 variables.
NOTE: The data set WORK.DUAL has 278 observations and 4 variables.
NOTE: PROCEDURE OPTMODEL used (Total process time):
      real time           0.18 seconds
      cpu time            0.15 seconds


                                Value
Label
Objective Sense          Maximization
Objective Function         netBenefit
Objective Type                 Linear

Number of Variables               105
Bounded Above                       0
Bounded Below                       0
Bounded Below and Above           105
Free                                0
Fixed                               0
Binary                            105
Integer                             0

Number of Constraints             278
Linear LE (<=)                    183
Linear EQ (=)                       5
Linear GE (>=)                     90
Linear Range                        0

Constraint Coefficients           660
NOTE: Converting model decentralization to OPTMODEL.
NOTE: Submitting OPTMODEL code to SAS instance.

NOTE: Writing HTML5(SASPY_INTERNAL) Body file: STDOUT
NOTE: Problem generation will use 4 threads.
NOTE: The problem has 105 variables (0 free, 0 fixed).
NOTE: The problem has 105 binary and 0 integer variables.
NOTE: The problem has 68 linear constraints (3 LE, 65 EQ, 0 GE, 0 range).
NOTE: The problem has 270 linear constraint coefficients.
NOTE: The problem has 0 nonlinear constraints (0 LE, 0 EQ, 0 GE, 0 range).
NOTE: The OPTMODEL presolver is disabled for linear problems.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 0 variables and 0 constraints.
NOTE: The MILP presolver removed 0 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 105 variables, 68 constraints, and 270 constraint␣
↪coefficients.
NOTE: The MILP solver is called.
NOTE: The parallel Branch and Cut algorithm is used.
```

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```
NOTE: The Branch and Cut algorithm is using up to 4 threads.
          Node   Active   Sols    BestInteger      BestBound      Gap    Time
             0        1      2    -28.1000000    135.0000000  120.81%       0
             0        1      2    -28.1000000     30.0000000  193.67%       0
             0        1      3    -16.3000000     30.0000000  154.33%       0
             0        1      4     14.9000000     14.9000000    0.00%       0
NOTE: Optimal.
NOTE: Objective = 14.9.
NOTE: The data set WORK.PROB_SUMMARY has 20 observations and 3 variables.
NOTE: The data set WORK.SOL_SUMMARY has 18 observations and 3 variables.
NOTE: The data set WORK.SOLUTION has 105 observations and 6 variables.
NOTE: The data set WORK.DUAL has 68 observations and 4 variables.
NOTE: PROCEDURE OPTMODEL used (Total process time):
      real time           0.10 seconds
      cpu time            0.09 seconds


                                Value
Label
Objective Sense          Maximization
Objective Function         netBenefit
Objective Type                 Linear

Number of Variables               105
Bounded Above                       0
Bounded Below                       0
Bounded Below and Above           105
Free                                0
Fixed                               0
Binary                            105
Integer                             0

Number of Constraints              68
Linear LE (<=)                      3
Linear EQ (=)                      65
Linear GE (>=)                      0
Linear Range                        0

Constraint Coefficients           270
   totalBenefit  totalCost
-          80.0       65.1
assign  (A, Bristol)     1.0
        (A, Brighton)    0.0
        (A, London)      0.0
        (B, Bristol)     0.0
        (B, Brighton)    1.0
        (B, London)      0.0
        (C, Bristol)     0.0
        (C, Brighton)    1.0
        (C, London)      0.0
        (D, Bristol)     1.0
        (D, Brighton)    0.0
        (D, London)      0.0
        (E, Bristol)     0.0
        (E, Brighton)    1.0
        (E, London)      0.0
dtype: float64
```

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```
Out[7]: 14.9
```

CHAPTER

FIVE

# API REFERENCE

## 5.1 Core

### 5.1.1 Model

#### Constructor

| | |
|---|---|
| *Model*(**kwargs) | Creates an optimization model |

#### sasoptpy.Model

**class Model** (***kwargs*)

Bases: object

Creates an optimization model

**Parameters**

**name** [string] Name of the model

**session** [swat.cas.connection.CAS or saspy.SASsession, optional] CAS or SAS Session object

#### Examples

```
>>> from swat import CAS
>>> import sasoptpy as so
>>> s = CAS('cas.server.address', port=12345)
>>> m = so.Model(name='my_model', session=s)
NOTE: Initialized model my_model
```

```
>>> mip = so.Model(name='mip')
NOTE: Initialized model mip
```

### Components

| | |
|---|---|
| *Model.get_name*(self) | Returns model name |
| *Model.set_session*(self, session) | Sets the session of model (SAS Viya via swat or SAS 9.4 via saspy) |
| *Model.get_session*(self) | Returns the session of the model |
| *Model.get_session_type*(self) | Tests if the model session is defined and still active |
| *Model.set_objective*(self, expression, name) | Sets the objective function for the model |
| *Model.append_objective*(self, expression, name) | Appends a new objective to the model |
| *Model.get_objective*(self) | Returns the objective function as an *Expression* object |
| *Model.get_all_objectives*(self) | Returns a list of objectives in the model |
| *Model.add_variable*(self, name[, vartype, …]) | Adds a new variable to the model |
| *Model.add_variables*(self, *argv[, name, …]) | Adds a group of variables to the model |
| *Model.add_implicit_variable*(self[, argv, name]) | Adds an implicit variable to the model |
| *Model.get_variable*(self, name) | Returns the reference to a variable in the model |
| *Model.get_variables*(self) | Returns a list of variables |
| *Model.get_grouped_variables*(self) | Get an ordered dictionary of variables, grouped based on creation |
| *Model.get_implicit_variables*(self) | Returns a list of implicit variables |
| *Model.get_variable_coef*(self, var) | Returns the objective value coefficient of a variable |
| *Model.drop_variable*(self, variable) | Drops a variable from the model |
| *Model.drop_variables*(self, variables) | Drops a variable group from the model |
| *Model.add_constraint*(self, c, name) | Adds a single constraint to the model |
| *Model.add_constraints*(self, argv[, name]) | Adds a set of constraints to the model |
| *Model.get_constraint*(self, name) | Returns the reference to a constraint in the model |
| *Model.get_constraints*(self) | Returns a list of constraints in the model |
| *Model.get_grouped_constraints*(self) | Get an ordered dictionary of constraints, grouped based on creation |
| *Model.drop_constraint*(self, constraint) | Drops a constraint from the model |
| *Model.drop_constraints*(self, constraints) | Drops a constraint group from the model |
| *Model.add_set*(self, name[, init, value, settype]) | Adds a set to the model |
| *Model.add_parameter*(self, *argv[, name, …]) | Adds a parameter to the model |
| *Model.add_statement*(self, statement[, …]) | Adds a PROC OPTMODEL statement to the model |
| *Model.get_sets*(self) | Returns a list of `Set` objects in the model |
| *Model.get_parameters*(self) | Returns a list of `Parameter` objects in the model |
| *Model.get_statements*(self) | Returns a list of all abstract statements inside the model. |
| *Model.include*(self, *argv) | Adds existing variables and constraints to a model |

### sasoptpy.Model.get_name

`Model.get_name(self)`
Returns model name

### sasoptpy.Model.set_session

`Model.set_session(self, session)`
Sets the session of model (SAS Viya via swat or SAS 9.4 via saspy)

**Parameters**

**session** [`swat.cas.connection.CAS` or `saspy.SASsession`] CAS or SAS Session object

#### Notes

- Session of a model can be set at initialization. See *`Model`*.

### sasoptpy.Model.get_session

`Model.get_session(self)`
Returns the session of the model

**Returns**

**session** [`swat.cas.connection.CAS` or `saspy.SASsession`] Session of the model, or None

### sasoptpy.Model.get_session_type

`Model.get_session_type(self)`
Tests if the model session is defined and still active

**Returns**

**session** [string] 'CAS' for CAS sessions, 'SAS' for SAS sessions, None otherwise

### sasoptpy.Model.set_objective

`Model.set_objective(self, expression, name, sense=None)`
Sets the objective function for the model

**Parameters**

**expression** [Expression] The objective function as an Expression

**name** [string] Name of the objective value

**sense** [string, optional] Objective value direction, 'MIN' or 'MAX'

**Returns**

**objective** [Expression] Objective function as an *`Expression`* object

**See also:**

*Model.append_objective()*

### Notes

- Default objective sense is minimization (MIN)
- This method replaces the existing objective of the model. When working with multiple objectives, use `Model.append_objective()` method.

### Examples

```
>>> profit = so.Expression(5 * sales - 2 * material, name='profit')
>>> m.set_objective(profit, so.MAX)
>>> print(m.get_objective())
 -  2.0 * material  +  5.0 * sales
```

```
>>> m.set_objective(4 * x - 5 * y, name='obj')
>>> print(repr(m.get_objective()))
sasoptpy.Expression(exp =  4.0 * x  -  5.0 * y , name='obj')
```

```
>>> f1 = m.set_objective(2 * x + y, sense=so.MIN, name='f1')
>>> f2 = m.append_objective( (x - y) ** 2, sense=so.MIN, name='f2')
>>> print(m.to_optmodel(options={'with': 'blackbox', 'obj': (f1, f2)}))
proc optmodel;
var x;
var y;
min f1 = 2 * x + y;
min f2 = (x - y) ^ (2);
solve with blackbox obj (f1 f2);
print _var_.name _var_.lb _var_.ub _var_ _var_.rc;
print _con_.name _con_.body _con_.dual;
quit;
```

## sasoptpy.Model.append_objective

`Model.append_objective`(*self*, *expression*, *name*, *sense=None*)

Appends a new objective to the model

**Parameters**

**expression** [Expression] The objective function as an Expression

**name** [string] Name of the objective value

**sense** [string, optional] Objective value direction, 'MIN' or 'MAX'

**Returns**

**objective** [Expression] Objective function as an `Expression` object

**See also:**

*Model.set_objective()*

### Notes

- Default objective sense is minimization (MIN)

### Examples

```
>>> f1 = m.set_objective(2 * x + y, sense=so.MIN, name='f1')
>>> f2 = m.append_objective( (x - y) ** 2, sense=so.MIN, name='f2')
>>> print(m.to_optmodel(options={'with': 'blackbox', 'obj': (f1, f2)}))
proc optmodel;
var x;
var y;
min f1 = 2 * x + y;
min f2 = (x - y) ^ (2);
solve with blackbox obj (f1 f2);
print _var_.name _var_.lb _var_.ub _var_ _var_.rc;
print _con_.name _con_.body _con_.dual;
quit;
```

## sasoptpy.Model.get_objective

`Model.`**`get_objective`**(*self*)

Returns the objective function as an *`Expression`* object

**Returns**

**objective** [Expression] Objective function

### Examples

```
>>> m.set_objective(4 * x - 5 * y, name='obj')
>>> print(repr(m.get_objective()))
sasoptpy.Expression(exp =  4.0 * x  -  5.0 * y , name='obj')
```

## sasoptpy.Model.get_all_objectives

`Model.`**`get_all_objectives`**(*self*)

Returns a list of objectives in the model

**Returns**

**all_objectives** [list] A list of *`Objective`* objects

### Examples

```
>>> m = so.Model(name='test_set_get_objective')
>>> x = m.add_variable(name='x')
>>> obj1 = m.set_objective(2 * x, sense=so.MIN, name='obj1')
>>> obj2 = m.set_objective(5 * x, sense=so.MIN, name='obj2') # Overrides obj1
>>> obj3 = m.append_objective(10 * x, sense=so.MIN, name='obj3')
>>> assertEqual(m.get_all_objectives(), [obj2, obj3])
True
```

## sasoptpy.Model.add_variable

`Model.add_variable`(*self*, *name*, *vartype=None*, *lb=None*, *ub=None*, *init=None*)

Adds a new variable to the model

New variables can be created via this method or existing variables can be added to the model.

**Parameters**

**name** [string, optional] Name of the variable to be created

**vartype** [string, optional] Type of the variable, either 'BIN', 'INT' or 'CONT'

**lb** [float, optional] Lower bound of the variable

**ub** [float, optional] Upper bound of the variable

**init** [float, optional] Initial value of the variable

**Returns**

**var** [Variable] Variable that is added to the model

**See also:**

*Variable*, *Model.include()*

### Notes

- If argument *var* is not None, then all other arguments are ignored.
- A generic variable name is generated if name argument is None.

### Examples

Adding a variable on the fly

```
>>> m = so.Model(name='demo')
>>> x = m.add_variable(name='x', vartype=so.INT, ub=10, init=2)
>>> print(repr(x))
NOTE: Initialized model demo
sasoptpy.Variable(name='x', lb=0, ub=10, init=2, vartype='INT')
```

Adding an existing variable to a model

```
>>> y = so.Variable(name='y', vartype=so.BIN)
>>> m = so.Model(name='demo')
>>> m.include(y)
```

### sasoptpy.Model.add_variables

`Model.add_variables`(*self*, **argv*, *name=None*, *vartype=None*, *lb=None*, *ub=None*, *init=None*)

Adds a group of variables to the model

**Parameters**

**argv** [list, dict, `pandas.Index`] Loop index for variable group

**name** [string, optional] Name of the variables

**vartype** [string, optional] Type of variables, *BIN*, *INT*, or *CONT*

**lb** [list, dict, `pandas.Series`] Lower bounds of variables

**ub** [list, dict, `pandas.Series`] Upper bounds of variables

**init** [list, dict, `pandas.Series`] Initial values of variables

**See also:**

`VariableGroup`, `Model.include()`

#### Notes

If *vg* argument is passed, all other arguments are ignored.

#### Examples

```
>>> production = m.add_variables(PERIODS, vartype=so.INT,
                                 name='production', lb=min_production)
>>> print(production)
>>> print(repr(production))
Variable Group (production) [
  [Period1: production['Period1',]]
  [Period2: production['Period2',]]
  [Period3: production['Period3',]]
]
sasoptpy.VariableGroup(['Period1', 'Period2', 'Period3'],
name='production')
```

### sasoptpy.Model.add_implicit_variable

`Model.add_implicit_variable`(*self*, *argv=None*, *name=None*)

Adds an implicit variable to the model

**Parameters**

**argv** [Generator-type object] Generator object where each item is an entry

**name** [string, optional] Name of the implicit variable

### Notes

- Based on whether generated by a regular expression or an abstract one, implicit variables may appear in generated OPTMODEL codes.

### Examples

```
>>> x = m.add_variables(range(5), name='x')
>>> y = m.add_implicit_variable((
>>>     x[i] + 2 * x[i+1] for i in range(4)), name='y')
>>> print(y[2])
x[2] + 2 * x[3]
```

```
>>> I = m.add_set(name='I')
>>> z = m.add_implicit_variable((x[i] * 2 + 2 for i in I), name='z')
>>> print(z._defn())
impvar z {i_1 in I} = 2 * x[i_1] + 2;
```

## sasoptpy.Model.get_variable

`Model.get_variable(self, name)`
Returns the reference to a variable in the model

**Parameters**

**name** [string] Name or key of the variable requested

**Returns**

**variable** [Variable] Reference to the variable

### Examples

```
>>> m.add_variable(name='x', vartype=so.INT, lb=3, ub=5)
>>> var1 = m.get_variable('x')
>>> print(repr(var1))
sasoptpy.Variable(name='x', lb=3, ub=5, vartype='INT')
```

## sasoptpy.Model.get_variables

`Model.get_variables(self)`
Returns a list of variables

**Returns**

**variables** [list] List of variables in the model

### Examples

```
>>> x = m.add_variables(2, name='x')
>>> y = m.add_variable(name='y')
>>> print(m.get_variables())
[sasoptpy.Variable(name='x_0',  vartype='CONT'),
 sasoptpy.Variable(name='x_1',  vartype='CONT'),
 sasoptpy.Variable(name='y',  vartype='CONT')]
```

## sasoptpy.Model.get_grouped_variables

`Model.get_grouped_variables(self)`

Get an ordered dictionary of variables, grouped based on creation

**Returns**

**grouped_vars** [OrderedDict] Dictionary of variables and variable groups in the model

**See also:**

*Model.get_variables()*, *Model.get_grouped_constraints()*

### Examples

```
>>> m1 = so.Model(name='test_copy_model_1')
>>> x = m1.add_variable(name='x')
>>> y = m1.add_variables(2, name='y')
>>> vars = OrderedDict([('x', x), ('y', y)])
>>> self.assertEqual(m1.get_grouped_variables(), vars)
True
```

## sasoptpy.Model.get_implicit_variables

`Model.get_implicit_variables(self)`

Returns a list of implicit variables

**Returns**

**implicit_variables** [list] List of implicit variables in the model

### Examples

```
>>> m = so.Model(name='test_add_impvar')
>>> x = m.add_variables(5, name='x')
>>> y = m.add_implicit_variable((i * x[i] + x[i] ** 2 for i in range(5)),
                                name='y')
>>> assertEqual([y], m.get_implicit_variables())
True
```

### sasoptpy.Model.get_variable_coef

Model.**get_variable_coef**(*self*, *var*)

Returns the objective value coefficient of a variable

**Parameters**

**var** [Variable or string] Variable whose objective value is requested or its name

**Returns**

**coef** [float] Objective value coefficient of the given variable

#### Examples

```
>>> x = m.add_variable(name='x')
>>> y = m.add_variable(name='y')
>>> m.set_objective(4 * x - 5 * y, name='obj', sense=so.MAX)
>>> print(m.get_variable_coef(x))
4.0
>>> print(m.get_variable_coef('y'))
-5.0
```

### sasoptpy.Model.drop_variable

Model.**drop_variable**(*self*, *variable*)

Drops a variable from the model

**Parameters**

**variable** [Variable] The variable to be dropped from the model

**See also:**

*Model.drop_variables()*

*Model.drop_constraint()*

*Model.drop_constraints()*

#### Examples

```
>>> x = m.add_variable(name='x')
>>> y = m.add_variable(name='y')
>>> print(m.get_variable('x'))
 x
>>> m.drop_variable(x)
>>> print(m.get_variable('x'))
None
```

### sasoptpy.Model.drop_variables

`Model.drop_variables(self, variables)`

Drops a variable group from the model

**Parameters**

**variables** [VariableGroup] The variable group to be dropped from the model

**See also:**

*Model.drop_variable()*

*Model.drop_constraint()*

*Model.drop_constraints()*

#### Examples

```
>>> x = m.add_variables(3, name='x')
>>> print(m.get_variables())
[sasoptpy.Variable(name='x_0',  vartype='CONT'),
 sasoptpy.Variable(name='x_1',  vartype='CONT')]
>>> m.drop_variables(x)
>>> print(m.get_variables())
[]
```

### sasoptpy.Model.add_constraint

`Model.add_constraint(self, c, name)`

Adds a single constraint to the model

**Parameters**

**c** [Constraint] Constraint to be added to the model

**name** [string, optional] Name of the constraint

**Returns**

**c** [Constraint] Reference to the constraint

**See also:**

*Constraint*, *Model.include()*

#### Examples

```
>>> x = m.add_variable(name='x', vartype=so.INT, lb=0, ub=5)
>>> y = m.add_variables(3, name='y', vartype=so.CONT, lb=0, ub=10)
>>> c1 = m.add_constraint(x + y[0] >= 3, name='c1')
>>> print(c1)
 x  +  y[0]  >=  3
```

```
>>> c2 = m.add_constraint(x - y[2] == [4, 10], name='c2')
>>> print(c2)
 -  y[2]  +  x  =  [4, 10]
```

### sasoptpy.Model.add_constraints

`Model.add_constraints(self, argv, name=None)`
Adds a set of constraints to the model

**Parameters**

**argv** [Generator-type object] List of constraints as a Generator-type object

**name** [string, optional] Name for the constraint group and individual constraint prefix

**Returns**

**cg** [ConstraintGroup] Reference to the ConstraintGroup

**See also:**

*ConstraintGroup*, *Model.include()*

#### Examples

```
>>> x = m.add_variable(name='x', vartype=so.INT, lb=0, ub=5)
>>> y = m.add_variables(3, name='y', vartype=so.CONT, lb=0, ub=10)
>>> c = m.add_constraints((x + 2 * y[i] >= 2 for i in [0, 1, 2]),
                          name='c')
>>> print(c)
Constraint Group (c) [
  [0:  2.0 * y[0]  +  x  >=  2]
  [1:  2.0 * y[1]  +  x  >=  2]
  [2:  2.0 * y[2]  +  x  >=  2]
]
```

```
>>> t = m.add_variables(3, 4, name='t')
>>> ct = m.add_constraints((t[i, j] <= x for i in range(3)
                           for j in range(4)), name='ct')
>>> print(ct)
Constraint Group (ct) [
  [(0, 0):  -  x  +  t[0, 0]  <=  0]
  [(0, 1):  t[0, 1]  -  x  <=  0]
  [(0, 2):  -  x  +  t[0, 2]  <=  0]
  [(0, 3):  t[0, 3]  -  x  <=  0]
  [(1, 0):  t[1, 0]  -  x  <=  0]
  [(1, 1):  t[1, 1]  -  x  <=  0]
  [(1, 2):  -  x  +  t[1, 2]  <=  0]
  [(1, 3):  -  x  +  t[1, 3]  <=  0]
  [(2, 0):  -  x  +  t[2, 0]  <=  0]
  [(2, 1):  t[2, 1]  -  x  <=  0]
  [(2, 2):  t[2, 2]  -  x  <=  0]
  [(2, 3):  t[2, 3]  -  x  <=  0]
]
```

### sasoptpy.Model.get_constraint

Model.**get_constraint**(*self*, *name*)

Returns the reference to a constraint in the model

**Parameters**

**name** [string] Name of the constraint requested

**Returns**

**constraint** [Constraint] Reference to the constraint

#### Examples

```
>>> m.add_constraint(2 * x + y <= 15, name='c1')
>>> print(m.get_constraint('c1'))
2.0 * x  +  y  <=  15
```

### sasoptpy.Model.get_constraints

Model.**get_constraints**(*self*)

Returns a list of constraints in the model

**Returns**

**constraints** [list] A list of Constraint objects

#### Examples

```
>>> m.add_constraint(x[0] + y <= 15, name='c1')
>>> m.add_constraints((2 * x[i] - y >= 1 for i in [0, 1]), name='c2')
>>> print(m.get_constraints())
[sasoptpy.Constraint( x[0]  +  y  <=  15, name='c1'),
 sasoptpy.Constraint( 2.0 * x[0]  -  y  >=  1, name='c2_0'),
 sasoptpy.Constraint( 2.0 * x[1]  -  y  >=  1, name='c2_1')]
```

### sasoptpy.Model.get_grouped_constraints

Model.**get_grouped_constraints**(*self*)

Get an ordered dictionary of constraints, grouped based on creation

**Returns**

**grouped_cons** [OrderedDict] Dictionary of constraints and constraint groups in the model

**See also:**

*Model.get_constraints()*, *Model.get_grouped_variables()*

### Examples

```
>>> m1 = so.Model(name='test_copy_model_1')
>>> x = m1.add_variable(name='x')
>>> y = m1.add_variables(2, name='y')
>>> c1 = m1.add_constraint(x + y[0] >= 2, name='c1')
>>> c2 = m1.add_constraints((x - y[i] <= 10 for i in range(2)), name='c2')
>>> cons = OrderedDict([('c1', c1), ('c2', c2)])
>>> self.assertEqual(m1.get_grouped_constraints(), cons)
True
```

## sasoptpy.Model.drop_constraint

Model.**drop_constraint**(*self*, *constraint*)

Drops a constraint from the model

**Parameters**

**constraint** [Constraint] The constraint to be dropped from the model

**See also:**

*Model.drop_constraints()*

*Model.drop_variable()*

*Model.drop_variables()*

### Examples

```
>>> c1 = m.add_constraint(2 * x + y <= 15, name='c1')
>>> print(m.get_constraint('c1'))
2 * x  +  y  <=  15
>>> m.drop_constraint(c1)
>>> print(m.get_constraint('c1'))
None
```

## sasoptpy.Model.drop_constraints

Model.**drop_constraints**(*self*, *constraints*)

Drops a constraint group from the model

**Parameters**

**constraints** [ConstraintGroup] The constraint group to be dropped from the model

**See also:**

*Model.drop_constraints()*

*Model.drop_variable()*

*Model.drop_variables()*

### Examples

```
>>> c1 = m.add_constraints((x[i] + y <= 15 for i in [0, 1]), name='c1')
>>> print(m.get_constraints())
[sasoptpy.Constraint( x[0]  +  y  <=  15, name='c1_0'),
 sasoptpy.Constraint( x[1]  +  y  <=  15, name='c1_1')]
>>> m.drop_constraints(c1)
>>> print(m.get_constraints())
[]
```

## sasoptpy.Model.add_set

Model.**add_set**(*self*, *name*, *init=None*, *value=None*, *settype=None*)

Adds a set to the model

**Parameters**

**name** [string, optional] Name of the set

**init** [Set, optional] Initial value of the set

**value** [list, float, optional] Exact value of the set

**settype** [list, optional] Types of the set, a list consists of 'num' and 'str' values

### Examples

```
>>> I = m.add_set(name='I')
>>> print(I._defn())
set I;
```

```
>>> J = m.add_set(name='J', settype=['str'])
>>> print(J._defn())
set <str> J;
```

```
>>> N = m.add_parameter(name='N', init=4)
>>> K = m.add_set(name='K', init=so.exp_range(1, N))
>>> print(K._defn())
set K = 1..N;
```

## sasoptpy.Model.add_parameter

Model.**add_parameter**(*self*, **argv*, *name=None*, *init=None*, *value=None*, *p_type=None*)

Adds a parameter to the model

**Parameters**

**argv** [Set, optional] Key set of the parameter

**name** [string, optional] Name of the parameter

**init** [float or expression, optional] Initial value of the parameter

**p_type** [string, optional] Type of the parameter, 'num' for floats or 'str' for strings

### Examples

```
>>> I = m.add_set(name='I')
>>> a = m.add_parameter(I, name='a', init=5)
>>> print(a._defn())
num a {I} init 5 ;
```

## sasoptpy.Model.add_statement

`Model.add_statement(self, statement, after_solve=None)`

Adds a PROC OPTMODEL statement to the model

**Parameters**

**statement** [Expression or string] Statement object

### Notes

- If the statement string includes 'print', then it is automatically placed after solve.
- The first parameter, *statement* could be a Statement object when internally used.

### Examples

```
>>> I = m.add_set(name='I')
>>> x = m.add_variables(I, name='x', vartype=so.INT)
>>> a = m.add_parameter(I, name='a')
>>> c = m.add_constraints((x[i] <= 2 * a[i] for i in I), name='c')
>>> m.add_statement('print x;', after_solve=True)
>>> print(m.to_optmodel())
proc optmodel;
min m_obj = 0;
set I;
var x {I} integer >= 0;
num a {I};
con c {i_1 in I} : x[i_1] - 2.0 * a[i_1] <= 0;
solve;
print _var_.name _var_.lb _var_.ub _var_ _var_.rc;
print _con_.name _con_.body _con_.dual;
print x;
quit;
```

## sasoptpy.Model.get_sets

`Model.get_sets(self)`

Returns a list of `Set` objects in the model

### sasoptpy.Model.get_parameters

`Model.get_parameters(self)`

Returns a list of `Parameter` objects in the model

### sasoptpy.Model.get_statements

`Model.get_statements(self)`

Returns a list of all abstract statements inside the model.

### sasoptpy.Model.include

`Model.include(self, *argv)`

Adds existing variables and constraints to a model

**Parameters**

**argv :** Objects to be included in the model

#### Notes

- Valid argument types:
  - `Model`
  - `Variable`
  - `Constraint`
  - `VariableGroup`
  - `ConstraintGroup`
  - `Objective`
  - `Set`
  - `Parameter`
  - `ParameterGroup`
  - `Statement` and all subclasses
  - `ImplicitVar`
- Including a model causes all variables and constraints inside the original model to be included.

#### Examples

Adding an existing variable

```
>>> x = so.Variable(name='x', vartype=so.CONT)
>>> m.include(x)
```

Adding an existing constraint

```
>>> c1 = so.Constraint(x + y <= 5, name='c1')
>>> m.include(c1)
```

Adding an existing set of variables

```
>>> z = so.VariableGroup(3, 5, name='z', ub=10)
>>> m.include(z)
```

Adding an existing set of constraints

```
>>> c2 = so.ConstraintGroup((x + 2 * z[i, j] >= 2 for i in range(3)
                             for j in range(5)), name='c2')
>>> m.include(c2)
```

Adding an existing model (including all of its elements)

```
>>> new_model = so.Model(name='new_model')
>>> new_model.include(m)
```

### Solver calls

| | |
|---|---|
| `Model.solve`(self, **kwargs) | Solves the model by calling CAS or SAS optimization solvers |
| `Model.tune_parameters`(self, **kwargs) | Uses model tuner to find ideal parameters for given model |
| `Model.get_solution`(self[, vtype, solution, . . . ]) | Returns the solution details associated with the primal or dual solution |
| `Model.get_variable_value`(self, var) | Returns the value of a variable. |
| `Model.get_objective_value`(self) | Returns the optimal objective value, if it exists |
| `Model.get_solution_summary`(self) | Returns the solution summary table to the user |
| `Model.get_problem_summary`(self) | Returns the problem summary table to the user |
| `Model.get_tuner_results`(self) | Returns the tuner responses for the model |
| `Model.print_solution`(self) | Prints the current values of the variables |
| `Model.clear_solution`(self) | Clears the cached solution of the model |

#### sasoptpy.Model.solve

`Model.solve`(*self*, ***kwargs*)

Solves the model by calling CAS or SAS optimization solvers

**Parameters**

**options** [dict, optional] A dictionary solver options

**submit** [boolean, optional] Switch for calling the solver instantly

**name** [string, optional] Name of the table name

**frame** [boolean, optional] Switch for uploading problem as a MPS DataFrame format

**drop** [boolean, optional] Switch for dropping the MPS table after solve (only CAS)

**replace** [boolean, optional] Switch for replacing an existing MPS table (only CAS and MPS)

**primalin** [boolean, optional] Switch for using initial values (only MILP)

**verbose** [boolean, optional (experimental)] Switch for printing generated OPTMODEL code

**Returns**

**solution** [pandas.DataFrame] Solution of the optimization model

**See also:**

**Model.solve_on_cas(),Model.solve_on_mva()**

### Notes

- This method is essentially a wrapper for two other methods.
- Some of the options listed under `options` argument may not be passed based on which CAS Action is being used.
- The `option` argument should be a dictionary, where keys are option names. For example, `m.solve(options={'maxtime': 600})` limits the solution time to 600 seconds.
- See *Solver Options* for a list of solver options.

### Examples

```
>>> m.solve()
NOTE: Initialized model food_manufacture_1
NOTE: Converting model food_manufacture_1 to DataFrame
NOTE: Added action set 'optimization'.
...
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: The Dual Simplex solve time is 0.01 seconds.
```

```
>>> m.solve(options={'maxtime': 600})
```

```
>>> m.solve(options={'algorithm': 'ipm'})
```

## sasoptpy.Model.tune_parameters

`Model.`**tune_parameters**(*self*, ***kwargs*)

Uses model tuner to find ideal parameters for given model

**Parameters**

**kwargs :** Keyword arguments as defined in the optimization.tuner action Acceptable values are:

- milpParameters : Parameters for the solveMilp action, such as *maxTime*, *heuristics*, *feasTol*
- tunerParameters : Parameters for tuner itself, such as *maxConfigs*, *printLevel*, *logFreq*
- tuningParameters : List of parameters to be tuned, such as *cutStrategy*, *presolver*, *restarts*

**Returns**

**tunerResults** [swat.dataframe.SASDataFrame] Results of tuner as a table

**See also:**

*Model.get_tuner_results()*

### Notes

- See SAS Optimization documentation for a full list of tunable parameters: https://go.documentation.sas.com/?docsetId=casactmopt&docsetTarget=cas-optimization-tuner.htm&docsetVersion=8.5&locale=en#PYTHON.cas-optimization-tuner-tunerparameters
- See full documentation at: https://go.documentation.sas.com/?docsetId=casactmopt&docsetTarget=casactmopt_optimization_details35.htm&docsetVersion=8.5&locale=en

### Examples

```
>>> m = so.Model(name='model1')
>>> ...
>>> results = m.tune_parameters(tunerParameters={'maxConfigs': 10})
NOTE: Initialized model knapsack_with_tuner.
NOTE: Added action set 'optimization'.
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table KNAPSACK_
↪WITH_TUNER in caslib CASUSER(casuser).
NOTE: The table KNAPSACK_WITH_TUNER has been created in caslib CASUSER(casuser)␣
↪from binary data uploaded to Cloud Analytic Services.
NOTE: Start to tune the MILP
         SolveCalls  Configurations    BestTime        Time
                  1               1        0.21        0.26
                  2               2        0.19        0.50
                  3               3        0.19        0.72
                  4               4        0.19        0.95
                  5               5        0.19        1.17
                  6               6        0.19        1.56
                  7               7        0.18        1.76
                  8               8        0.17        1.96
                  9               9        0.17        2.16
                 10              10        0.17        2.35
NOTE: Configuration limit reached.
NOTE: The tuning time is 2.35 seconds.
>>> print(results)
   Configuration conflictSearch  ... Sum of Run Times Percentage Successful
0            0.0      automatic  ...             0.20                 100.0
1            1.0           none  ...             0.17                 100.0
2            2.0           none  ...             0.17                 100.0
3            3.0       moderate  ...             0.17                 100.0
4            4.0           none  ...             0.18                 100.0
5            5.0           none  ...             0.18                 100.0
6            6.0     aggressive  ...             0.18                 100.0
7            7.0       moderate  ...             0.18                 100.0
8            8.0     aggressive  ...             0.19                 100.0
9            9.0      automatic  ...             0.36                 100.0
```

```
>>> results = m.tune_parameters(
      milpParameters={'maxtime': 10},
      tunerParameters={'maxConfigs': 20, 'logfreq': 5},
      tuningParameters=[
         {'option': 'presolver', 'initial': 'none', 'values': ['basic',
↪'aggressive', 'none']},
         {'option': 'cutStrategy'},
         {'option': 'strongIter', 'initial': -1, 'values': [-1, 100, 1000]}
```

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```
       ])
NOTE: Added action set 'optimization'.
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table KNAPSACK_
↪WITH_TUNER in caslib CASUSER(casuser).
NOTE: The table KNAPSACK_WITH_TUNER has been created in caslib CASUSER(casuser)␣
↪from binary data uploaded to Cloud Analytic Services.
NOTE: Start to tune the MILP
         SolveCalls  Configurations    BestTime        Time
                  5               5        0.17        1.01
                 10              10        0.17        2.00
                 15              15        0.17        2.98
                 20              20        0.17        3.95
NOTE: Configuration limit reached.
NOTE: The tuning time is 3.95 seconds.
>>> print(results)
    Configuration conflictSearch  ... Sum of Run Times Percentage Successful
0             0.0      automatic  ...             0.17                 100.0
1             1.0           none  ...             0.16                 100.0
2             2.0           none  ...             0.16                 100.0
3             3.0           none  ...             0.16                 100.0
4             4.0           none  ...             0.16                 100.0
5             5.0           none  ...             0.17                 100.0
6             6.0           none  ...             0.17                 100.0
7             7.0           none  ...             0.17                 100.0
8             8.0           none  ...             0.17                 100.0
9             9.0           none  ...             0.17                 100.0
10           10.0           none  ...             0.17                 100.0
11           11.0     aggressive  ...             0.17                 100.0
12           12.0           none  ...             0.17                 100.0
13           13.0     aggressive  ...             0.17                 100.0
14           14.0      automatic  ...             0.17                 100.0
15           15.0           none  ...             0.17                 100.0
16           16.0           none  ...             0.17                 100.0
17           17.0       moderate  ...             0.17                 100.0
18           18.0       moderate  ...             0.17                 100.0
19           19.0           none  ...             0.17                 100.0
```

### sasoptpy.Model.get_solution

`Model.get_solution` (*self*, *vtype='Primal'*, *solution=None*, *pivot=False*)

Returns the solution details associated with the primal or dual solution

**Parameters**

**vtype** [string, optional] 'Primal' or 'Dual'

**solution** [integer, optional] Solution number to be returned (for MILP)

**pivot** [boolean, optional] Switch for returning multiple solutions in columns as a pivot table

**Returns**

**solution** [`pandas.DataFrame`] Primal or dual solution table returned from the CAS Action

### Notes

- If *Model.solve()* method is used with `frame=True` option, MILP solver returns multiple solutions. You can obtain different results using `solution` parameter.

### Examples

```
>>> m.solve()
>>> print(m.get_solution('Primal'))
             var   lb             ub  value  solution
0       x[clock]  0.0  1.797693e+308    0.0       1.0
1          x[pc]  0.0  1.797693e+308    5.0       1.0
2   x[headphone]  0.0  1.797693e+308    2.0       1.0
3         x[mug]  0.0  1.797693e+308    0.0       1.0
4        x[book]  0.0  1.797693e+308    0.0       1.0
5         x[pen]  0.0  1.797693e+308    1.0       1.0
6       x[clock]  0.0  1.797693e+308    0.0       2.0
7          x[pc]  0.0  1.797693e+308    5.0       2.0
8   x[headphone]  0.0  1.797693e+308    2.0       2.0
9         x[mug]  0.0  1.797693e+308    0.0       2.0
10       x[book]  0.0  1.797693e+308    0.0       2.0
11        x[pen]  0.0  1.797693e+308    0.0       2.0
12      x[clock]  0.0  1.797693e+308    1.0       3.0
13         x[pc]  0.0  1.797693e+308    4.0       3.0
...
```

```
>>> print(m.get_solution('Primal', solution=2))
             var   lb             ub  value  solution
6       x[clock]  0.0  1.797693e+308    0.0       2.0
7          x[pc]  0.0  1.797693e+308    5.0       2.0
8   x[headphone]  0.0  1.797693e+308    2.0       2.0
9         x[mug]  0.0  1.797693e+308    0.0       2.0
10       x[book]  0.0  1.797693e+308    0.0       2.0
11        x[pen]  0.0  1.797693e+308    0.0       2.0
```

```
>>> print(m.get_solution(pivot=True))
solution      1.0  2.0  3.0  4.0  5.0
var
x[book]       0.0  0.0  0.0  1.0  0.0
x[clock]      0.0  0.0  1.0  1.0  0.0
x[headphone]  2.0  2.0  1.0  1.0  0.0
x[mug]        0.0  0.0  0.0  1.0  0.0
x[pc]         5.0  5.0  4.0  1.0  0.0
x[pen]        1.0  0.0  0.0  1.0  0.0
```

```
>>> print(m.get_solution('Dual'))
                       con  value  solution
0               weight_con   20.0       1.0
1          limit_con[clock]   0.0       1.0
2             limit_con[pc]   5.0       1.0
3      limit_con[headphone]   2.0       1.0
4            limit_con[mug]   0.0       1.0
5           limit_con[book]   0.0       1.0
6            limit_con[pen]   1.0       1.0
7               weight_con   19.0       2.0
```

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```
8       limit_con[clock]    0.0       2.0
9          limit_con[pc]    5.0       2.0
10  limit_con[headphone]    2.0       2.0
11         limit_con[mug]    0.0       2.0
12        limit_con[book]    0.0       2.0
13         limit_con[pen]    0.0       2.0
...
```

```
>>> print(m.get_solution('dual', pivot=True))
solution               1.0   2.0   3.0   4.0  5.0
con
limit_con[book]        0.0   0.0   0.0   1.0  0.0
limit_con[clock]       0.0   0.0   1.0   1.0  0.0
limit_con[headphone]   2.0   2.0   1.0   1.0  0.0
limit_con[mug]         0.0   0.0   0.0   1.0  0.0
limit_con[pc]          5.0   5.0   4.0   1.0  0.0
limit_con[pen]         1.0   0.0   0.0   1.0  0.0
weight_con            20.0  19.0  20.0  19.0  0.0
```

### sasoptpy.Model.get_variable_value

`Model.`**`get_variable_value`**(*self*, *var*)

Returns the value of a variable.

**Parameters**

**var** [Variable or string] Variable reference

#### Notes

- It is possible to get a variable's value by using the `Variable.get_value()` method, if the variable is not abstract.
- This method is a wrapper around `Variable.get_value()` and an overlook function for model components

### sasoptpy.Model.get_objective_value

`Model.`**`get_objective_value`**(*self*)

Returns the optimal objective value, if it exists

**Returns**

**objective_value** [float] Objective value at current solution

### Notes

- This method should be used for getting the objective value after solve. Using `m.get_objective().get_value()` actually evaluates the expression using optimal variable values. This may not be available for nonlinear expressions.

### Examples

```
>>> m.solve()
>>> print(m.get_objective_value())
42.0
```

## sasoptpy.Model.get_solution_summary

`Model.get_solution_summary`(*self*)

Returns the solution summary table to the user

**Returns**

**ss** [`swat.dataframe.SASDataFrame`] Solution summary obtained after solve

### Examples

```
>>> m.solve()
>>> soln = m.get_solution_summary()
>>> print(type(soln))
<class 'swat.dataframe.SASDataFrame'>
```

```
>>> print(soln)
Solution Summary
                               Value
Label
Solver                            LP
Algorithm               Dual Simplex
Objective Function               obj
Solution Status              Optimal
Objective Value                   10
Primal Infeasibility               0
Dual Infeasibility                 0
Bound Infeasibility                0
Iterations                         2
Presolve Time                   0.00
Solution Time                   0.01
```

```
>>> print(soln.index)
Index(['Solver', 'Algorithm', 'Objective Function', 'Solution Status',
       'Objective Value', '', 'Primal Infeasibility',
       'Dual Infeasibility', 'Bound Infeasibility', '', 'Iterations',
       'Presolve Time', 'Solution Time'],
      dtype='object', name='Label')
```

```
>>> print(soln.loc['Solution Status', 'Value'])
Optimal
```

### sasoptpy.Model.get_problem_summary

`Model.get_problem_summary(self)`

Returns the problem summary table to the user

**Returns**

**ps** [`swat.dataframe.SASDataFrame`] Problem summary obtained after `Model.solve()`

#### Examples

```
>>> m.solve()
>>> ps = m.get_problem_summary()
>>> print(type(ps))
<class 'swat.dataframe.SASDataFrame'>
```

```
>>> print(ps)
Problem Summary
                                Value
Label
Problem Name                   model1
Objective Sense          Maximization
Objective Function                obj
RHS                               RHS
Number of Variables                 2
Bounded Above                       0
Bounded Below                       2
Bounded Above and Below             0
Free                                0
Fixed                               0
Number of Constraints               2
LE (<=)                             1
EQ (=)                              0
GE (>=)                             1
Range                               0
Constraint Coefficients             4
```

```
>>> print(ps.index)
Index(['Problem Name', 'Objective Sense', 'Objective Function', 'RHS',
'', 'Number of Variables', 'Bounded Above', 'Bounded Below',
'Bounded Above and Below', 'Free', 'Fixed', '',
'Number of Constraints', 'LE (<=)', 'EQ (=)', 'GE (>=)', 'Range', '',
'Constraint Coefficients'],
dtype='object', name='Label')
```

```
>>> print(ps.loc['Number of Variables'])
Value               2
Name: Number of Variables, dtype: object
```

```
>>> print(ps.loc['Constraint Coefficients', 'Value'])
4
```

### sasoptpy.Model.get_tuner_results

Model.**get_tuner_results**(*self*)
Returns the tuner responses for the model

**Returns**

**tunerResults** [dict] Returns tuner results as a dictionary. Its members are - Performance Information - Tuner Information - Tuner Summary - Tuner Results

**See also:**

*Model.tune_parameters()*

#### Examples

```
>>> m.tune_parameters(tunerParameters={'maxConfigs': 10})
>>> results = m.get_tuner_reults()
```

### sasoptpy.Model.print_solution

Model.**print_solution**(*self*)
Prints the current values of the variables

**See also:**

*Model.get_solution()*

#### Notes

- This function may not work for abstract variables and nonlinear models.

#### Examples

```
>>> m.solve()
>>> m.print_solution()
x: 2.0
y: 0.0
```

### sasoptpy.Model.clear_solution

Model.**clear_solution**(*self*)
Clears the cached solution of the model

#### Notes

- This method only cleans model's own parameters, not its components'

### Export

| | |
|---|---|
| *Model.to_mps*(self, **kwargs) | |
| *Model.to_optmodel*(self, **kwargs) | |

#### sasoptpy.Model.to_mps

Model.**to_mps**(*self*, ***kwargs*)

#### sasoptpy.Model.to_optmodel

Model.**to_optmodel**(*self*, ***kwargs*)

### Internal functions

| | |
|---|---|
| *Model._is_linear*(self) | Checks if the model can be written as a linear model (in MPS format) |

#### sasoptpy.Model._is_linear

Model.**_is_linear**(*self*)

Checks if the model can be written as a linear model (in MPS format)

**Returns**

**is_linear** [boolean] True if model does not have any nonlinear components or abstract operations, False otherwise

### Deprecated

Deprecated since version 1.0.0.

The following method(s) are deprecated and will be removed in future minor updates.

| |
|---|
| *Model.to_frame*(self, **kwargs) |

#### sasoptpy.Model.to_frame

`Model.to_frame(self, **kwargs)`

### 5.1.2 Expression

#### Constructor

| | |
|---|---|
| *Expression*([exp, name]) | Creates a mathematical expression to represent model components |
| *Auxiliary*(base[, prefix, suffix, operator, . . . ]) | Represents an auxiliary expression, often as a symbolic attribute |
| *Symbol*(name) | Represents a symbolic string, to be evaluated on server-side |

#### sasoptpy.Expression

**class Expression**(*exp=None*, *name=None*)

Bases: `object`

Creates a mathematical expression to represent model components

**Parameters**

**exp** [Expression, optional] An existing expression where arguments are being passed

**name** [string, optional] A local name for the expression

**temp** [boolean, optional] A boolean shows whether expression is temporary or permanent

#### Notes

- Two other classes (*Variable* and *Constraint*) are subclasses of this class.
- Expressions are created automatically after linear math operations with variables.
- An expression object can be called when defining constraints and other expressions.

#### Examples

```
>>> x = so.Variable(name='x')
>>> y = so.VariableGroup(3, name='y')
>>> e = so.Expression(exp=x + 3 * y[0] - 5 * y[1], name='exp1')
>>> print(e)
 -  5.0 * y[1]  +  3.0 * y[0]  +  x
>>> print(repr(e))
sasoptpy.Expression(exp =  -  5.0 * y[1]  +  3.0 * y[0]  +  x ,
                    name='exp1')
```

```
>>> sales = so.Variable(name='sales')
>>> material = so.Variable(name='material')
>>> profit = 5 * sales - 3 * material
```

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```
>>> print(profit)
 5.0 * sales  -  3.0 * material
>>> print(repr(profit))
sasoptpy.Expression(exp =  5.0 * sales  -  3.0 * material , name=None)
```

```
>>> import sasoptpy.abstract.math as sm
>>> f = sm.sin(x) + sm.min(y[1],1) ** 2
>>> print(type(f))
<class 'sasoptpy.core.Expression'>
>>> print(f)
sin(x) + (min(y[1] , 1)) ** (2)
```

### sasoptpy.Auxiliary

**class Auxiliary**(*base*, *prefix=None*, *suffix=None*, *operator=None*, *value=None*)

Bases: `sasoptpy.core.expression.Expression`

Represents an auxiliary expression, often as a symbolic attribute

**Parameters**

**base** [*Expression*] Original owner of the auxiliary value

**prefix** [string, optional] Prefix of the expression

**suffix** [string, optional] Suffix of the expression

**operator** [string, optional] Wrapping operator

**value** [float, optional] Initial value of the symbolic object

#### Notes

- Auxiliary objects are for internal use

### sasoptpy.Symbol

**class Symbol**(*name*)

Bases: `sasoptpy.core.expression.Expression`

Represents a symbolic string, to be evaluated on server-side

**Parameters**

**name** [string] String to be symbolized

#### Notes

- Symbol objects can be used for values that does not translate to a value on client-side, but have meaning on execution. For example, *_N_* is a SAS symbol, which can be used in OPTMODEL strings.

### General methods

| | |
|---|---|
| *Expression.set_name*(self[, name]) | Sets the name of the expression |
| *Expression.set_permanent*(self) | Converts a temporary expression into a permanent one |
| *Expression.set_temporary*(self) | Converts expression into temporary to enable in-place operations |
| *Expression.get_name*(self) | Returns the name of the expression |
| *Expression.get_value*(self) | Calculates and returns the value of the linear expression |
| *Expression.get_dual*(self) | Returns the dual value if exists |

### sasoptpy.Expression.set_name

Expression.**set_name**(*self*, *name=None*)

Sets the name of the expression

**Parameters**

**name** [string] Name of the expression

**Returns**

**name** [string] Name of the expression after resolving conflicts

#### Examples

```
>>> x = so.Variable(name='x')
>>> e = x**2 + 2*x + 1
>>> e.set_name('expansion')
```

### sasoptpy.Expression.set_permanent

Expression.**set_permanent**(*self*)

Converts a temporary expression into a permanent one

**Parameters**

**name** [string, optional] Name of the expression

**Returns**

**name** [string] Name of the expression in the namespace

### sasoptpy.Expression.set_temporary

Expression.**set_temporary**(*self*)

Converts expression into temporary to enable in-place operations

### sasoptpy.Expression.get_name

Expression.**get_name**(*self*)

Returns the name of the expression

**Returns**

**name** [string] Name of the expression

#### Examples

```
>>> m = so.Model()
>>> var1 = m.add_variables(name='x')
>>> print(var1.get_name())
x
```

### sasoptpy.Expression.get_value

Expression.**get_value**(*self*)

Calculates and returns the value of the linear expression

**Returns**

**v** [float] Value of the expression

#### Examples

```
>>> sales = so.Variable(name='sales', init=10)
>>> material = so.Variable(name='material', init=3)
>>> profit = so.Expression(5 * sales - 3 * material)
>>> print(profit.get_value())
41
```

### sasoptpy.Expression.get_dual

Expression.**get_dual**(*self*)

Returns the dual value if exists

**Returns**

**dual** [float] Dual value of the variable

## Operations

| | |
|---|---|
| `Expression.add`(self, other[, sign]) | Combines two expressions and produces a new one |
| `Expression.copy`(self[, name]) | Returns a copy of the `Expression` object |
| `Expression.mult`(self, other) | Multiplies the `Expression` with a scalar value |
| `Expression.get_member`(self, key) | Returns the requested member using the key |
| `Expression.get_member_dict`(self) | Returns an ordered dictionary of elements |
| `Expression.get_member_value`(self, key) | Returns coefficient of requested member |
| `Expression.get_constant`(self) | Returns the constant term in the expression |
| `Expression.set_member`(self, key, ref, val[, op]) | Adds a new member or changes an existing member |
| `Expression.set_member_value`(self, key, value) | Changes the coefficient of the requested member |
| `Expression.add_to_member_value`(self, key, value) | Adds given value to the coefficient of the requested member |
| `Expression.mult_member_value`(self, key, value) | Multiplies coefficient of the requested member with given value |
| `Expression.copy_member`(self, key, exp) | Copies member of another expression |
| `Expression.delete_member`(self, key) | Deletes the requested member from the core dictionary |

### sasoptpy.Expression.add

`Expression.`**add**(*self*, *other*, *sign=1*)

Combines two expressions and produces a new one

**Parameters**

**other** [float or Expression] Second expression or constant value to be added

**sign** [int, optional] Sign of the addition, 1 or -1

**Returns**

**r** [Expression] Reference to the outcome of the operation

#### Notes

- Adding an expression is equivalent to calling this method: (x-y)+(3*x-2*y) and (x-y).add(3*x-2*y) result the same.

### sasoptpy.Expression.copy

`Expression.`**copy**(*self*, *name=None*)

Returns a copy of the `Expression` object

**Parameters**

**name** [string, optional] Name for the copy

**Returns**

**r** [Expression] Copy of the object

### Examples

```
>>> x = so.Variable(name='x')
>>> y = so.VariableGroup(1, name='y')
>>> e = so.Expression(7 * x - y[0], name='e')
>>> print(repr(e))
sasoptpy.Expression(exp =  -  y[0]  +  7.0 * x , name='e')
>>> f = e.copy(name='f')
>>> print(repr(f))
sasoptpy.Expression(exp =  -  y[0]  +  7.0 * x , name='f')
```

## sasoptpy.Expression.mult

`Expression.mult(self, other)`

Multiplies the `Expression` with a scalar value

**Parameters**

**other** [Expression or int] Second expression to be multiplied

**Returns**

**r** [Expression] A new `Expression` that represents the multiplication

### Notes

- This method is mainly for internal use.
- Multiplying an expression is equivalent to calling this method: 3*(x-y) and (x-y).mult(3) are interchangeable.

## sasoptpy.Expression.get_member

`Expression.get_member(self, key)`

Returns the requested member using the key

**Parameters**

**key** [string] Identifier of the member, name for single objects

**Returns**

**member** [dict] A dictionary of coefficient, operator, and reference of member

## sasoptpy.Expression.get_member_dict

`Expression.get_member_dict(self)`

Returns an ordered dictionary of elements

### sasoptpy.Expression.get_member_value

`Expression.get_member_value(self, key)`
Returns coefficient of requested member

**Parameters**

**key** [string] Identifier of the member

**Returns**

**value** [float] Coefficient value of the requested member

### sasoptpy.Expression.get_constant

`Expression.get_constant(self)`
Returns the constant term in the expression

#### Examples

```
>>> x = so.Variable(name='x')
>>> e = 2 * x + 5
>>> print(e.get_constant())
5
```

### sasoptpy.Expression.set_member

`Expression.set_member(self, key, ref, val, op=None)`
Adds a new member or changes an existing member

**Parameters**

**key** [string] Identifier of the member

**ref** [Object] A reference to the new member

**val** [float] Initial coefficient of the element

**op** [string, optional] Operator, if member consists of multiple children

### sasoptpy.Expression.set_member_value

`Expression.set_member_value(self, key, value)`
Changes the coefficient of the requested member

**Parameters**

**key** [string] Identifier of the member

**value** [float] New coefficient value of the member

### sasoptpy.Expression.add_to_member_value

`Expression.`**`add_to_member_value`**(*self*, *key*, *value*)

Adds given value to the coefficient of the requested member

**Parameters**

**key** [string] Identifier of the member

**value** [float] Value to be added

### sasoptpy.Expression.mult_member_value

`Expression.`**`mult_member_value`**(*self*, *key*, *value*)

Multiplies coefficient of the requested member with given value

**Parameters**

**key** [string] Identifier of the member

**value** [float] Value to be multiplied with

### sasoptpy.Expression.copy_member

`Expression.`**`copy_member`**(*self*, *key*, *exp*)

Copies member of another expression

**Parameters**

**key** [string] Identifier of the member

**exp** [`Expression`] Other expression to be copied from

### sasoptpy.Expression.delete_member

`Expression.`**`delete_member`**(*self*, *key*)

Deletes the requested member from the core dictionary

### Class methods

| |
|---|
| `Expression.to_expression`(obj) |

### sasoptpy.Expression.to_expression

**classmethod** Expression.**to_expression**(*obj*)

### Private Methods

| | |
|---|---|
| *Expression._expr*(self) | Generates the OPTMODEL compatible string representation of the object. |
| *Expression._is_linear*(self) | Checks if the expression is composed of linear components |
| *Expression._relational*(self, other, direction_) | Creates a logical relation between *Expression* objects |
| *Expression.__repr__*(self) | Returns a string representation of the object. |
| *Expression.__str__*(self) | Generates a representation string that is Python compatible |

### sasoptpy.Expression._expr

Expression.**_expr**(*self*)

Generates the OPTMODEL compatible string representation of the object.

#### Examples

```
>>> x = so.Variable(name='x')
>>> y = so.Variable(name='y')
>>> f = x + y ** 2
>>> print(f)
x + (y) ** (2)
>>> print(f._expr())
x + (y) ^ (2)
```

### sasoptpy.Expression._is_linear

Expression.**_is_linear**(*self*)

Checks if the expression is composed of linear components

**Returns**

**is_linear** [boolean] True if the expression is linear, False otherwise

### Examples

```
>>> x = so.Variable()
>>> e = x*x
>>> print(e.is_linear())
False
```

```
>>> f = x*x + x*x - 2*x*x + 5
>>> print(f.is_linear())
True
```

## sasoptpy.Expression._relational

Expression.**_relational**(*self*, *other*, *direction_*)

Creates a logical relation between `Expression` objects

**Parameters**

**other** [Expression] Expression on the other side of the relation wrt self

**direction_** [string] Direction of the logical relation, either 'E', 'L', or 'G'

**Returns**

**generated_constraint** [Constraint] Constraint generated as a result of linear relation

## sasoptpy.Expression.__repr__

Expression.**__repr__**(*self*)

Returns a string representation of the object.

### Examples

```
>>> x = so.Variable(name='x')
>>> y = so.Variable(name='y')
>>> f = x + y ** 2
>>> print(repr(f))
sasoptpy.Expression(exp = x + (y) ** (2), name=None)
```

## sasoptpy.Expression.__str__

Expression.**__str__**(*self*)

Generates a representation string that is Python compatible

#### Examples

```
>>> f = x + y ** 2
>>> print(str(f))
x + (y) ** (2)
```

### 5.1.3 Variable

#### Constructor

| | |
|---|---|
| *Objective*(**kwargs) | Objective represents expressions with sense and used as target value in optimization |

#### sasoptpy.Objective

**class Objective**(***kwargs*)

Bases: `sasoptpy.core.expression.Expression`

Objective represents expressions with sense and used as target value in optimization

**Parameters**

**exp** [*Expression*] Objective as an expression

**name** [string] Unique name of the expression

**sense** [string, optional] Direction of the objective, sasoptpy.MIN (default) or sasoptpy.MAX

#### Examples

```
>>> m = so.Model(name='test_objective')
>>> x = m.add_variable(name='x')
>>> obj = m.set_objective(2 * x - x ** 3, sense=so.MIN, name='new_obj')
>>> str(m.get_objective())
2 * x - (x) ** (3)
>>> type(obj)
sasoptpy.Objective
```

#### Methods

| | |
|---|---|
| *Objective.set_sense*(self, sense) | Sets the objective sense (direction) |
| *Objective.get_sense*(self) | Returns the objective sense (direction) |

#### sasoptpy.Objective.set_sense

Objective.**set_sense**(*self*, *sense*)

Sets the objective sense (direction)

**Parameters**

**sense** [string] sasoptpy.MIN or sasoptpy.MAX

#### sasoptpy.Objective.get_sense

Objective.**get_sense**(*self*)

Returns the objective sense (direction)

### 5.1.4 Variable

#### Constructor

| | |
|---|---|
| *Variable*(**kwargs) | Creates an optimization variable to be used inside models |

#### sasoptpy.Variable

**class Variable**(***kwargs*)

Bases: `sasoptpy.core.expression.Expression`

Creates an optimization variable to be used inside models

**Parameters**

**name** [string] Name of the variable

**vartype** [string, optional] Type of the variable, default is continuous

**lb** [float, optional] Lower bound of the variable, default is -inf

**ub** [float, optional] Upper bound of the variable, default is inf

**init** [float, optional] Initial value of the variable

**abstract** [boolean, optional] Indicator of whether the variable is abstract or not

**shadow** [boolean, optional] Indicator of whether the variable is shadow or not Used for internal purposes

**See also:**

*sasoptpy.Model.add_variable()*

### Examples

```
>>> x = so.Variable(name='x', lb=0, ub=20, vartype=so.CONT)
>>> print(repr(x))
sasoptpy.Variable(name='x', lb=0, ub=20, vartype='CONT')
```

```
>>> y = so.Variable(name='y', init=1, vartype=so.INT)
>>> print(repr(y))
sasoptpy.Variable(name='y', lb=0, ub=inf, init=1, vartype='INT')
```

**Attributes**

*lb* Lower bound of the variable

*ub* Upper bound of the variable

## Attributes

| | |
|---|---|
| `Variable.lb` | Lower bound of the variable |
| `Variable.ub` | Upper bound of the variable |

### sasoptpy.Variable.lb

**property** `Variable.lb`
Lower bound of the variable

### sasoptpy.Variable.ub

**property** `Variable.ub`
Upper bound of the variable

## Methods

| | |
|---|---|
| `Variable.set_bounds`(self, *[, lb, ub]) | Changes bounds on a variable |
| `Variable.set_init`(self[, init]) | Changes initial value of a variable |
| `Variable.get_type`(self) | Returns the type of variable, valid values are: |
| `Variable.get_attributes`(self) | Returns an OrderedDict of main attributes |

### sasoptpy.Variable.set_bounds

`Variable.`**`set_bounds`**(*self*, *, *lb=None*, *ub=None*)
Changes bounds on a variable

**Parameters**

**lb** [float or `Expression`] Lower bound of the variable

**ub** [float or `Expression`] Upper bound of the variable

### Examples

```
>>> x = so.Variable(name='x', lb=0, ub=20)
>>> print(repr(x))
sasoptpy.Variable(name='x', lb=0, ub=20, vartype='CONT')
>>> x.set_bounds(lb=5, ub=15)
>>> print(repr(x))
sasoptpy.Variable(name='x', lb=5, ub=15, vartype='CONT')
```

## sasoptpy.Variable.set_init

`Variable.`**`set_init`**(*self*, *init=None*)

Changes initial value of a variable

**Parameters**

**init** [float or None] Initial value of the variable

### Examples

```
>>> x = so.Variable(name='x')
>>> x.set_init(5)
```

```
>>> y = so.Variable(name='y', init=3)
>>> y.set_init()
```

## sasoptpy.Variable.get_type

`Variable.`**`get_type`**(*self*)

Returns the type of variable, valid values are:

- sasoptpy.CONT
- sasoptpy.INT
- sasoptpy.BIN

## sasoptpy.Variable.get_attributes

`Variable.`**`get_attributes`**(*self*)

Returns an OrderedDict of main attributes

**Returns**

**attributes** [dict] OrderedDict consists of *init*, *lb*, and *ub* attributes

#### Inherited Methods

| | |
|---|---|
| `Variable.copy`(self[, name]) | Returns a copy of the `Expression` object |
| `Variable.get_dual`(self) | Returns the dual value if exists |
| `Variable.get_name`(self) | Returns the name of the expression |
| `Variable.get_value`(self) | Returns value of a variable |

### sasoptpy.Variable.copy

`Variable.copy(self, name=None)`

Returns a copy of the `Expression` object

**Parameters**

**name** [string, optional] Name for the copy

**Returns**

**r** [Expression] Copy of the object

#### Examples

```
>>> x = so.Variable(name='x')
>>> y = so.VariableGroup(1, name='y')
>>> e = so.Expression(7 * x - y[0], name='e')
>>> print(repr(e))
sasoptpy.Expression(exp =  -  y[0]  +  7.0 * x , name='e')
>>> f = e.copy(name='f')
>>> print(repr(f))
sasoptpy.Expression(exp =  -  y[0]  +  7.0 * x , name='f')
```

### sasoptpy.Variable.get_dual

`Variable.get_dual(self)`

Returns the dual value if exists

**Returns**

**dual** [float] Dual value of the variable

### sasoptpy.Variable.get_name

`Variable.get_name(self)`

Returns the name of the expression

**Returns**

**name** [string] Name of the expression

#### Examples

```
>>> m = so.Model()
>>> var1 = m.add_variables(name='x')
>>> print(var1.get_name())
x
```

### sasoptpy.Variable.get_value

`Variable.get_value(self)`
Returns value of a variable

## 5.1.5 Variable Group

### Constructor

| | |
|---|---|
| `VariableGroup`(**kwargs) | Creates a group of `Variable` objects |

### sasoptpy.VariableGroup

**class VariableGroup**(***kwargs*)
Bases: `sasoptpy.core.group.Group`

Creates a group of `Variable` objects

**Parameters**

**argv** [list, dict, int, `pandas.Index`] Loop index for variable group

**name** [string, optional] Name (prefix) of the variables

**vartype** [string, optional] Type of variables, *BIN*, *INT*, or *CONT*

**lb** [list, dict, `pandas.Series`, optional] Lower bounds of variables

**ub** [list, dict, `pandas.Series`, optional] Upper bounds of variables

**init** [float, optional] Initial values of variables

**See also:**

`sasoptpy.Model.add_variables()`

`sasoptpy.Model.include()`

### Notes

- When working with a single model, use the *sasoptpy.Model.add_variables()* method.
- If a variable group object is created, it can be added to a model using the *sasoptpy.Model.include()* method.
- An individual variable inside the group can be accessed using indices.

```
>>> z = so.VariableGroup(2, ['a', 'b', 'c'], name='z', lb=0, ub=10)
>>> print(repr(z[0, 'a']))
sasoptpy.Variable(name='z_0_a', lb=0, ub=10, vartype='CONT')
```

### Examples

```
>>> PERIODS = ['Period1', 'Period2', 'Period3']
>>> production = so.VariableGroup(PERIODS, vartype=so.INT,
                                  name='production', lb=10)
>>> print(production)
Variable Group (production) [
  [Period1: production['Period1']]
  [Period2: production['Period2']]
  [Period3: production['Period3']]
]
```

```
>>> x = so.VariableGroup(4, vartype=so.BIN, name='x')
>>> print(x)
Variable Group (x) [
  [0: x[0]]
  [1: x[1]]
  [2: x[2]]
  [3: x[3]]
]
```

```
>>> z = so.VariableGroup(2, ['a', 'b', 'c'], name='z')
>>> print(z)
Variable Group (z) [
  [(0, 'a'): z[0, 'a']]
  [(0, 'b'): z[0, 'b']]
  [(0, 'c'): z[0, 'c']]
  [(1, 'a'): z[1, 'a']]
  [(1, 'b'): z[1, 'b']]
  [(1, 'c'): z[1, 'c']]
]
>>> print(repr(z))
sasoptpy.VariableGroup([0, 1], ['a', 'b', 'c'], name='z')
```

### Methods

| | |
|---|---|
| `VariableGroup.get_name`(self) | Returns the name of the variable group |
| `VariableGroup.get_attributes`(self) | Returns an OrderedDict of main attributes |
| `VariableGroup.get_type`(self) | Returns the type of variable, valid values are: |
| `VariableGroup.get_members`(self) | Returns a dictionary of members |
| `VariableGroup.set_bounds`(self[, lb, ub, members]) | Sets / updates bounds for the given variable |
| `VariableGroup.set_init`(self, init) | Sets / updates initial value for the given variable |
| `VariableGroup.mult`(self, vector) | Quick multiplication method for the variable groups |
| `VariableGroup.sum`(self, *argv) | Quick sum method for the variable groups |

#### sasoptpy.VariableGroup.get_name

`VariableGroup.`**`get_name`**(*self*)

Returns the name of the variable group

**Returns**

**name** [string] Name of the variable group

### Examples

```
>>> m = so.Model(name='m')
>>> var1 = m.add_variables(4, name='x')
>>> print(var1.get_name())
x
```

#### sasoptpy.VariableGroup.get_attributes

`VariableGroup.`**`get_attributes`**(*self*)

Returns an OrderedDict of main attributes

**Returns**

**attributes** [dict] OrderedDict consists of *init*, *lb*, and *ub* attributes

#### sasoptpy.VariableGroup.get_type

`VariableGroup.`**`get_type`**(*self*)

Returns the type of variable, valid values are:

- sasoptpy.CONT
- sasoptpy.INT
- sasoptpy.BIN

### sasoptpy.VariableGroup.get_members

VariableGroup.**get_members**(*self*)
Returns a dictionary of members

### sasoptpy.VariableGroup.set_bounds

VariableGroup.**set_bounds**(*self*, *lb=None*, *ub=None*, *members=True*)
Sets / updates bounds for the given variable

**Parameters**

**lb** [float, `pandas.Series`, optional] Lower bound

**ub** [float, `pandas.Series`, optional] Upper bound

#### Examples

```
>>> z = so.VariableGroup(2, ['a', 'b', 'c'], name='z', lb=0, ub=10)
>>> print(repr(z[0, 'a']))
sasoptpy.Variable(name='z_0_a', lb=0, ub=10, vartype='CONT')
>>> z.set_bounds(lb=3, ub=5)
>>> print(repr(z[0, 'a']))
sasoptpy.Variable(name='z_0_a', lb=3, ub=5, vartype='CONT')
```

```
>>> u = so.VariableGroup(['a', 'b', 'c', 'd'], name='u')
>>> lb_vals = pd.Series([1, 4, 0, -1], index=['a', 'b', 'c', 'd'])
>>> u.set_bounds(lb=lb_vals)
>>> print(repr(u['b']))
sasoptpy.Variable(name='u_b', lb=4, ub=inf, vartype='CONT')
```

### sasoptpy.VariableGroup.set_init

VariableGroup.**set_init**(*self*, *init*)
Sets / updates initial value for the given variable

**Parameters**

**init** [float, list, dict, `pandas.Series`] Initial value of the variables

#### Examples

```
>>> m = so.Model(name='m')
>>> y = m.add_variables(3, name='y')
>>> print(y._defn())
var y {{0,1,2}};
>>> y.set_init(5)
>>> print(y._defn())
var y {{0,1,2}} init 5;
```

### sasoptpy.VariableGroup.mult

`VariableGroup.mult(self, vector)`

Quick multiplication method for the variable groups

**Parameters**

**vector** [list, dictionary, `pandas.Series`, or `pandas.DataFrame`] Vector to be multiplied with the variable group

**Returns**

**r** [Expression] An expression that is the product of the variable group with the given vector

#### Examples

Multiplying with a list

```
>>> x = so.VariableGroup(4, vartype=so.BIN, name='x')
>>> e1 = x.mult([1, 5, 6, 10])
>>> print(e1)
 10.0 * x[3]  +  6.0 * x[2]  +  x[0]  +  5.0 * x[1]
```

Multiplying with a dictionary

```
>>> y = so.VariableGroup([0, 1], ['a', 'b'], name='y', lb=0, ub=10)
>>> dvals = {(0, 'a'): 1, (0, 'b'): 2, (1, 'a'): -1, (1, 'b'): 5}
>>> e2 = y.mult(dvals)
>>> print(e2)
 2.0 * y[0, 'b']  -  y[1, 'a']  +  y[0, 'a']  +  5.0 * y[1, 'b']
```

Multiplying with a pandas.Series object

```
>>> u = so.VariableGroup(['a', 'b', 'c', 'd'], name='u')
>>> ps = pd.Series([0.1, 1.5, -0.2, 0.3], index=['a', 'b', 'c', 'd'])
>>> e3 = u.mult(ps)
>>> print(e3)
 1.5 * u['b']  +  0.1 * u['a']  -  0.2 * u['c']  +  0.3 * u['d']
```

Multiplying with a pandas.DataFrame object

```
>>> data = np.random.rand(3, 3)
>>> df = pd.DataFrame(data, columns=['a', 'b', 'c'])
>>> print(df)
NOTE: Initialized model model1
          a         b         c
0  0.966524  0.237081  0.944630
1  0.821356  0.074753  0.345596
2  0.065229  0.037212  0.136644
>>> y = m.add_variables(3, ['a', 'b', 'c'], name='y')
>>> e = y.mult(df)
>>> print(e)
0.9665237354418064 * y[0, 'a']  +  0.23708064143289442 * y[0, 'b']  +
0.944629500537536 * y[0, 'c']  +  0.8213562592159828 * y[1, 'a']  +
0.07475256894157478 * y[1, 'b']  +  0.3455957019116668 * y[1, 'c']  +
0.06522945752546017 * y[2, 'a']  +  0.03721153533250843 * y[2, 'b']  +
0.13664422498043194 * y[2, 'c']
```

### sasoptpy.VariableGroup.sum

VariableGroup.**sum**(*self*, **argv*)

Quick sum method for the variable groups

**Parameters**

**argv** [Arguments] List of indices for the sum

**Returns**

**r** [Expression] Expression that represents the sum of all variables in the group

#### Examples

```
>>> z = so.VariableGroup(2, ['a', 'b', 'c'], name='z', lb=0, ub=10)
>>> e1 = z.sum('*', '*')
>>> print(e1)
z[1, 'c']  +  z[1, 'a']  +  z[1, 'b']  +  z[0, 'a']  +  z[0, 'b']  +
z[0, 'c']
>>> e2 = z.sum('*', 'a')
>>> print(e2)
 z[1, 'a']  +  z[0, 'a']
>>> e3 = z.sum('*', ['a', 'b'])
>>> print(e3)
 z[1, 'a']  +  z[0, 'b']  +  z[1, 'b']  +  z[0, 'a']
```

## 5.1.6 Constraint

### Constructor

| | |
|---|---|
| *Constraint*(**kwargs) | Creates a linear or quadratic constraint for optimization models |

### sasoptpy.Constraint

**class Constraint**(***kwargs*)

Bases: sasoptpy.core.expression.Expression

Creates a linear or quadratic constraint for optimization models

Constraints should be created by adding logical relations to *Expression* objects.

**Parameters**

**exp** [Expression] A logical expression that forms the constraint

**direction** [string] Direction of the logical expression, 'E' (=), 'L' (<=) or 'G' (>=)

**name** [string, optional] Name of the constraint object

**crange** [float, optional] Range for ranged constraints

**See also:**

*sasoptpy.Model.add_constraint()*

### Notes

- A constraint can be generated in multiple ways:
  1. Using the `sasoptpy.Model.add_constraint()` method

     ```
     >>> m = so.Model(name='m')
     >>> c1 = m.add_constraint(3 * x - 5 * y <= 10, name='c1')
     >>> print(repr(c1))
     sasoptpy.Constraint( - 5.0 * y + 3.0 * x <= 10, name='c1')
     ```

  2. Using the constructor

     ```
     >>> c1 = sasoptpy.Constraint(3 * x - 5 * y <= 10, name='c1')
     >>> print(repr(c1))
     sasoptpy.Constraint( - 5.0 * y + 3.0 * x <= 10, name='c1')
     ```

- The same constraint can be included into other models using the `Model.include()` method.

### Examples

```
>>> x = so.Variable(name='x')
>>> y = so.Variable(name='y')
>>> c1 = so.Constraint( 3 * x - 5 * y <= 10, name='c1')
>>> print(repr(c1))
sasoptpy.Constraint( - 5.0 * y + 3.0 * x <= 10, name='c1')
```

```
>>> c2 = so.Constraint( - x + 2 * y - 5, direction='L', name='c2')
sasoptpy.Constraint( - x + 2.0 * y <= 5, name='c2')
```

## Methods

| | |
|---|---|
| `Constraint.get_value`(self[, rhs]) | Returns the current value of the constraint |
| `Constraint.set_block`(self, block_number) | Sets the decomposition block number for a constraint |
| `Constraint.set_direction`(self, direction) | Changes the direction of a constraint |
| `Constraint.set_rhs`(self, value) | Changes the RHS of a constraint |
| `Constraint.update_var_coef`(self, var, value) | Updates the coefficient of a variable inside the constraint |

### sasoptpy.Constraint.get_value

`Constraint.`**`get_value`**(*self*, *rhs=False*)

Returns the current value of the constraint

**Parameters**

**rhs** [boolean, optional] Whether constant values (RHS) will be included in the value or not. Default is false

#### Examples

```
>>> x = so.Variable(name='x', init=2)
>>> c = so.Constraint(x ** 2 + 2 * x <= 15, name='c')
>>> print(c.get_value())
8
>>> print(c.get_value(rhs=True))
-7
```

### sasoptpy.Constraint.set_block

`Constraint.`**`set_block`**(*self*, *block_number*)

Sets the decomposition block number for a constraint

**Parameters**

**block_number** [int] Block number of the constraint

#### Examples

```
>>> c1 = m.add_constraints((x + 2 * y[i] <= 5 for i in NODES),
                           name='c1')
>>> for i in NODES:
      c1[i].set_block(i)
```

### sasoptpy.Constraint.set_direction

`Constraint.`**`set_direction`**(*self*, *direction*)

Changes the direction of a constraint

**Parameters**

**direction** [string] Direction of the constraint, 'E', 'L', or 'G' for equal to, less than or equal to, and greater than or equal to, respectively

#### Examples

```
>>> c1 = so.Constraint(exp=3 * x - 5 * y <= 10, name='c1')
>>> print(repr(c1))
sasoptpy.Constraint( 3.0 * x  -  5.0 * y  <=  10, name='c1')
>>> c1.set_direction('G')
>>> print(repr(c1))
sasoptpy.Constraint( 3.0 * x  -  5.0 * y  >=  10, name='c1')
```

### sasoptpy.Constraint.set_rhs

`Constraint.`**`set_rhs`**`(`*self*, *value*`)`

Changes the RHS of a constraint

**Parameters**

**value** [float] New RHS value for the constraint

#### Examples

```
>>> x = m.add_variable(name='x')
>>> y = m.add_variable(name='y')
>>> c = m.add_constraint(x + 3*y <= 10, name='con_1')
>>> print(c)
x  +  3.0 * y  <=  10
>>> c.set_rhs(5)
>>> print(c)
x  +  3.0 * y  <=  5
```

### sasoptpy.Constraint.update_var_coef

`Constraint.`**`update_var_coef`**`(`*self*, *var*, *value*`)`

Updates the coefficient of a variable inside the constraint

**Parameters**

**var** [Variable] Variable to be updated

**value** [float] Coefficient of the variable in the constraint

**See also:**

**`sasoptpy.Model.set_coef()`**

#### Examples

```
>>> c1 = so.Constraint(exp=3 * x - 5 * y <= 10, name='c1')
>>> print(repr(c1))
sasoptpy.Constraint( -  5.0 * y  +  3.0 * x  <=  10, name='c1')
>>> c1.update_var_coef(x, -1)
>>> print(repr(c1))
sasoptpy.Constraint( -  5.0 * y  -  x  <=  10, name='c1')
```

### 5.1.7 Constraint Group

#### Constructor

| | |
|---|---|
| `ConstraintGroup`(**kwargs) | Creates a group of `Constraint` objects |

#### sasoptpy.ConstraintGroup

**class ConstraintGroup**(***kwargs*)

Bases: `sasoptpy.core.group.Group`

Creates a group of `Constraint` objects

**Parameters**

**argv** [Generator-type object] A Python generator that includes `Expression` objects

**name** [string, optional] Name (prefix) of the constraints

**See also:**

***sasoptpy.Model.add_constraints()***

***sasoptpy.Model.include()***

##### Notes

Use `sasoptpy.Model.add_constraints()` when working with a single model.

##### Examples

```
>>> var_ind = ['a', 'b', 'c', 'd']
>>> u = so.VariableGroup(var_ind, name='u')
>>> t = so.Variable(name='t')
>>> cg = so.ConstraintGroup((u[i] + 2 * t <= 5 for i in var_ind), name='cg')
>>> print(cg)
Constraint Group (cg) [
  [a:  2.0 * t  +  u['a']  <=  5]
  [b:  u['b']  +  2.0 * t  <=  5]
  [c:  2.0 * t  +  u['c']  <=  5]
  [d:  2.0 * t  +  u['d']  <=  5]
]
```

```
>>> z = so.VariableGroup(2, ['a', 'b', 'c'], name='z', lb=0, ub=10)
>>> cg2 = so.ConstraintGroup((2 * z[i, j] + 3 * z[i-1, j] >= 2 for i in
                              [1] for j in ['a', 'b', 'c']), name='cg2')
>>> print(cg2)
Constraint Group (cg2) [
  [(1, 'a'):  3.0 * z[0, 'a']  +  2.0 * z[1, 'a']  >=  2]
  [(1, 'b'):  2.0 * z[1, 'b']  +  3.0 * z[0, 'b']  >=  2]
  [(1, 'c'):  2.0 * z[1, 'c']  +  3.0 * z[0, 'c']  >=  2]
]
```

### Methods

| | |
|---|---|
| *ConstraintGroup.get_name*(self) | Returns the name of the constraint group |
| *ConstraintGroup.get_all_keys*(self) | Returns a list of all keys (indices) in the group |
| *ConstraintGroup.get_expressions*(self[, rhs]) | Returns constraints as a list of expressions |
| *ConstraintGroup.get_members*(self) | Returns a dictionary of members |

#### sasoptpy.ConstraintGroup.get_name

ConstraintGroup.**get_name**(*self*)

Returns the name of the constraint group

**Returns**

**name** [string] Name of the constraint group

### Examples

```
>>> m = so.Model(name='m')
>>> x = m.add_variable(name='x')
>>> indices = ['a', 'b', 'c']
>>> y = m.add_variables(indices, name='y')
>>> c1 = m.add_constraints((x + y[i] <= 4 for i in indices),
                            name='con1')
>>> print(c1.get_name())
con1
```

#### sasoptpy.ConstraintGroup.get_all_keys

ConstraintGroup.**get_all_keys**(*self*)

Returns a list of all keys (indices) in the group

#### sasoptpy.ConstraintGroup.get_expressions

ConstraintGroup.**get_expressions**(*self*, *rhs=False*)

Returns constraints as a list of expressions

**Parameters**

**rhs** [boolean, optional] Whether to pass the constant part (rhs) of the constraint or not

**Returns**

**df** [pandas.DataFrame] Returns a DataFrame consisting of constraints as expressions

### Examples

```
>>> m = so.Model(name='m')
>>> var_ind = ['a', 'b', 'c', 'd']
>>> u = m.add_variables(var_ind, name='u')
>>> t = m.add_variable(name='t')
>>> cg = so.ConstraintGroup((u[i] + 2 * t <= 5 for i in var_ind),
                            name='cg')
>>> ce = cg.get_expressions()
>>> print(ce)
             cg
a  u[a] + 2 * t
b  u[b] + 2 * t
c  u[c] + 2 * t
d  u[d] + 2 * t
>>> ce_rhs = cg.get_expressions(rhs=True)
>>> print(ce_rhs)
                 cg
a  u[a] + 2 * t - 5
b  u[b] + 2 * t - 5
c  u[c] + 2 * t - 5
d  u[d] + 2 * t - 5
```

### sasoptpy.ConstraintGroup.get_members

ConstraintGroup.**get_members**(*self*)
Returns a dictionary of members

## 5.1.8 Workspace

### Constructor

| | |
|---|---|
| *Workspace*(name[, session]) | Workspace represents an OPTMODEL block that allows multiple solves |

### sasoptpy.Workspace

**class Workspace**(*name*, *session=None*)
Bases: object

Workspace represents an OPTMODEL block that allows multiple solves

**Parameters**

**name** [string] Name of the workspace

**session** [saspy.SASsession or swat.cas.connection.CAS, optional] Session to be submitted

### Methods

| | |
|---|---|
| `Workspace.get_elements`(self) | Returns a list of elements in the Workspace |
| `Workspace.set_active_model`(self, model) | Marks given model as active, to be used in solve statements |
| `Workspace.append`(self, element) | Appends a new element (operation or statement) to the Workspace |
| `Workspace.submit`(self, **kwargs) | Submits the Workspace as an OPTMODEL block and returns solutions |
| `Workspace.parse_solve_responses`(self) | Grabs the solutions to all solve statements |
| `Workspace.parse_print_responses`(self) | Grabs responses to all print statements |
| `Workspace.get_variable`(self, name) | Obtains the value of a given variable name |
| `Workspace.set_variable_value`(self, name, value) | Sets variable value |
| `Workspace.to_optmodel`(self) | Returns equivalent OPTMODEL code of given workspace |

#### sasoptpy.Workspace.get_elements

`Workspace.`**`get_elements`**(*self*)

Returns a list of elements in the Workspace

#### sasoptpy.Workspace.set_active_model

`Workspace.`**`set_active_model`**(*self*, *model*)

Marks given model as active, to be used in solve statements

**Parameters**

**model** [`Model`] Model to be activated

#### sasoptpy.Workspace.append

`Workspace.`**`append`**(*self*, *element*)

Appends a new element (operation or statement) to the Workspace

**Parameters**

**element** [`sasoptpy.abstract.Statement`] Any statement that can be appended

#### sasoptpy.Workspace.submit

`Workspace.`**`submit`**(*self*, ***kwargs*)

Submits the Workspace as an OPTMODEL block and returns solutions

#### sasoptpy.Workspace.parse_solve_responses

`Workspace.parse_solve_responses`(*self*)
Grabs the solutions to all solve statements

#### sasoptpy.Workspace.parse_print_responses

`Workspace.parse_print_responses`(*self*)
Grabs responses to all print statements

#### sasoptpy.Workspace.get_variable

`Workspace.get_variable`(*self*, *name*)
Obtains the value of a given variable name

**Parameters**

**name** [string] Name of the variable

#### sasoptpy.Workspace.set_variable_value

`Workspace.set_variable_value`(*self*, *name*, *value*)
Sets variable value

**Parameters**

**name** [string] Name of the variable

**value** [float] New value of the variable

#### sasoptpy.Workspace.to_optmodel

`Workspace.to_optmodel`(*self*)
Returns equivalent OPTMODEL code of given workspace

**Returns**

**optmodel** [string] Generated OPTMODEL code of the workspace object

## 5.2 Abstract

### 5.2.1 Abstract

#### Main classes

| | |
|---|---|
| *Parameter*(**kwargs) | |
| *ParameterGroup*(**kwargs) | |
| *Set*(**kwargs) | Creates an index set to be represented inside PROC OPTMODEL |

Continued on next page

Table 26 – continued from previous page

| | |
|---|---|
| *SetIterator*(initset[, name, datatype]) | Creates an iterator object for a given Set |
| *SetIteratorGroup*(initset[, datatype, names]) | |
| *Statement*() | |

### sasoptpy.abstract.Parameter

**class Parameter**(***kwargs*)

Bases: `sasoptpy.core.expression.Expression`

### sasoptpy.abstract.ParameterGroup

**class ParameterGroup**(***kwargs*)

Bases: `object`

### sasoptpy.abstract.Set

**class Set**(***kwargs*)

Bases: `object`

Creates an index set to be represented inside PROC OPTMODEL

**Parameters**

**name** [string] Name of the parameter

**init** [Expression, optional] Initial value expression of the parameter

**settype** [list, optional] List of types for the set, consisting of 'num' and 'str' values

#### Examples

```
>>> I = so.Set('I')
>>> print(I._defn())
set I;
```

```
>>> J = so.Set('J', settype=['num', 'str'])
>>> print(J._defn())
set <num, str> J;
```

```
>>> N = so.Parameter(name='N', init=5)
>>> K = so.Set('K', init=so.exp_range(1,N))
>>> print(K._defn())
set K = 1..N;
```

### sasoptpy.abstract.SetIterator

**class SetIterator**(*initset*, *name=None*, *datatype=None*)
Bases: `sasoptpy.core.expression.Expression`

Creates an iterator object for a given Set

**Parameters**

**initset** [Set] Set to be iterated on

**name** [string, optional] Name of the iterator

**datatype** [string, optional] Type of the iterator

#### Notes

- SetIterator objects are automatically created when looping over a `Set`.
- This class is mainly intended for internal use.
- The `group` parameter consists of following keys
  - **order** : int Order of the parameter inside the group
  - **outof** : int Total number of indices inside the group
  - **id** : int ID number assigned to group by Python

### sasoptpy.abstract.SetIteratorGroup

**class SetIteratorGroup**(*initset*, *datatype=None*, *names=None*)
Bases: `collections.OrderedDict`, `sasoptpy.core.expression.Expression`

### sasoptpy.abstract.Statement

**class Statement**
Bases: `abc.ABC`

### Statements

| | |
|---|---|
| `Assignment`(identifier, expression[, keyword]) | |
| `CoForLoopStatement`(*args) | |
| `CreateDataStatement`(table, index[, columns]) | |
| `DropStatement`(**kwargs) | |
| `ForLoopStatement`(*args) | |
| `IfElseStatement`(logic_expression, if_statement) | |
| `LiteralStatement`(**kwargs) | |
| `ObjectiveStatement`(expression, **kwargs) | |
| `ReadDataStatement`(table, index[, columns]) | |
| `SolveStatement`(*args, **kwargs) | |
| `FixStatement`(*elements) | |
| `UnfixStatement`(*elements) | |

Continued on next page

Table 27 – continued from previous page

| |
|---|
| PrintStatement(*args) |

### sasoptpy.abstract.statement.Assignment

**class Assignment** (*identifier*, *expression*, *keyword=None*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__** (*self*, *identifier*, *expression*, *keyword=None*)

Initialize self. See help(type(self)) for accurate signature.

#### Methods

| | |
|---|---|
| __init__(self, identifier, expression[, keyword]) | Initialize self. |
| append(self, *args, **kwargs) | |
| fix_value(obj, value) | |
| get_response(self) | |
| is_internal(self) | |
| set_bounds(var, **kwargs) | |
| set_internal(self, value) | |
| set_response(self, response) | |
| set_value(obj, value) | |

### sasoptpy.abstract.statement.CoForLoopStatement

**class CoForLoopStatement** (**args*)

Bases: `sasoptpy.abstract.statement.for_loop.ForLoopStatement`

**__init__** (*self*, **args*)

Initialize self. See help(type(self)) for accurate signature.

#### Methods

| | |
|---|---|
| __init__(self, *args) | Initialize self. |
| append(self, element) | |
| cofor_loop(*args) | |
| for_loop(*args) | |
| get_response(self) | |
| is_internal(self) | |
| set_internal(self, value) | |
| set_response(self, response) | |

### sasoptpy.abstract.statement.CreateDataStatement

**class CreateDataStatement**(*table*, *index*, *columns=None*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__**(*self*, *table*, *index*, *columns=None*)

Initialize self. See help(type(self)) for accurate signature.

#### Methods

| | |
|---|---|
| `__init__`(self, table, index[, columns]) | Initialize self. |
| `append`(self, element, **kwargs) | |
| `create_data`(*args, **kwargs) | |
| `get_column_str`(c) | |
| `get_columns_expr`(self) | |
| `get_index_expr`(self) | |
| `get_response`(self) | |
| `get_table_expr`(self) | |
| `get_table_name`(self) | |
| `is_internal`(self) | |
| `set_internal`(self, value) | |
| `set_response`(self, response) | |

### sasoptpy.abstract.statement.DropStatement

**class DropStatement**(***kwargs*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__**(**args*, ***kwargs*)

#### Methods

| |
|---|
| `__init__`(*args, **kwargs) |
| `append`(self, element) |
| `drop_constraint`(*constraints) |
| `get_response`(self) |
| `is_internal`(self) |
| `model_drop_constraint`(_, c) |
| `set_internal`(self, value) |
| `set_response`(self, response) |

### sasoptpy.abstract.statement.ForLoopStatement

**class ForLoopStatement**(**args*)
Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__**(*self*, **args*)
Initialize self. See help(type(self)) for accurate signature.

#### Methods

| | |
|---|---|
| *__init__*(self, *args) | Initialize self. |
| append(self, element) | |
| for_loop(*args) | |
| get_response(self) | |
| is_internal(self) | |
| set_internal(self, value) | |
| set_response(self, response) | |

### sasoptpy.abstract.statement.IfElseStatement

**class IfElseStatement**(*logic_expression*, *if_statement*, *else_statement=None*)
Bases: `sasoptpy.abstract.statement.if_else.NestedConditions`

**__init__**(*self*, *logic_expression*, *if_statement*, *else_statement=None*)
Initialize self. See help(type(self)) for accurate signature.

#### Methods

| | |
|---|---|
| *__init__*(self, logic_expression, if_statement) | Initialize self. |
| append(self, element) | |
| get_response(self) | |
| if_condition(logic_expression, if_statement) | |
| is_internal(self) | |
| set_internal(self, value) | |
| set_response(self, response) | |

### sasoptpy.abstract.statement.LiteralStatement

**class LiteralStatement**(***kwargs*)
Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__**(**args*, ***kwargs*)

### Methods

| | |
|---|---|
| `__init__`(*args, **kwargs) | |
| `append`(self, literal) | |
| `diff`(*args) | |
| `expand`() | |
| `get_response`(self) | |
| `is_internal`(self) | |
| `set_internal`(self, value) | |
| `set_response`(self, response) | |
| `substring`(main_string, first_pos, last_pos) | |
| `union`(*args) | |
| `use_problem`(problem) | |

## sasoptpy.abstract.statement.ObjectiveStatement

**class ObjectiveStatement**(*expression*, ***kwargs*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**`__init__`**(*self*, *expression*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### Methods

| | |
|---|---|
| `__init__`(self, expression, **kwargs) | Initialize self. |
| `append`(self) | |
| `get_response`(self) | |
| `is_internal`(self) | |
| `set_internal`(self, value) | |
| `set_objective`(expression, name, sense) | |
| `set_response`(self, response) | |

## sasoptpy.abstract.statement.ReadDataStatement

**class ReadDataStatement**(*table*, *index*, *columns=None*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**`__init__`**(*self*, *table*, *index*, *columns=None*)

Initialize self. See help(type(self)) for accurate signature.

### Methods

| | |
|---|---|
| `__init__`(self, table, index[, columns]) | Initialize self. |
| `append`(self, element, **kwargs) | |
| `flatten_column`(col) | |
| `get_column_str`(c) | |
| `get_columns_expr`(self) | |
| `get_index_expr`(self) | |
| `get_response`(self) | |
| `get_table_expr`(self) | |
| `get_target_expr`(target) | |
| `is_internal`(self) | |
| `read_data`(*args, **kwargs) | |
| `set_internal`(self, value) | |
| `set_response`(self, response) | |

## sasoptpy.abstract.statement.SolveStatement

**class SolveStatement**(**args, **kwargs*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__**(*self, *args, **kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### Methods

| | |
|---|---|
| `__init__`(self, *args, **kwargs) | Initialize self. |
| `append`(self, element) | |
| `get_problem_summary`(self) | |
| `get_response`(self) | |
| `get_solution_summary`(self) | |
| `is_internal`(self) | |
| `set_internal`(self, value) | |
| `set_response`(self, problem_summary, . . . ) | |
| `solve`(*args, **kwargs) | |
| `solve_model`(model, **kwargs) | |

## sasoptpy.abstract.statement.FixStatement

**class FixStatement**(**elements*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__**(*self, *elements*)

Initialize self. See help(type(self)) for accurate signature.

#### Methods

| | |
|---|---|
| `__init__`(self, *elements) | Initialize self. |
| `append`(self, element) | |
| `fix`(*items) | |
| `get_response`(self) | |
| `is_internal`(self) | |
| `set_internal`(self, value) | |
| `set_response`(self, response) | |

### sasoptpy.abstract.statement.UnfixStatement

**class UnfixStatement**(**elements*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__**(*self*, **elements*)

Initialize self. See help(type(self)) for accurate signature.

#### Methods

| | |
|---|---|
| `__init__`(self, *elements) | Initialize self. |
| `append`(self, element) | |
| `get_response`(self) | |
| `is_internal`(self) | |
| `set_internal`(self, value) | |
| `set_response`(self, response) | |
| `unfix`(*items) | |

### sasoptpy.abstract.statement.PrintStatement

**class PrintStatement**(**args*)

Bases: `sasoptpy.abstract.statement.statement_base.Statement`

**__init__**(*self*, **args*)

Initialize self. See help(type(self)) for accurate signature.

#### Methods

| | |
|---|---|
| `__init__`(self, *args) | Initialize self. |
| `allow_print_names`(self) | |
| `append`(self, arg) | |
| `get_response`(self) | |
| `is_internal`(self) | |
| `print_item`(*args) | |
| `put_item`(*args[, names]) | |
| `set_internal`(self, value) | |
| `set_print_type`(self, print_type) | |

Continued on next page

Table 40 – continued from previous page

| | |
|---|---|
| set_response(self, response) | |

# 5.3 Interface

## 5.3.1 Interface

### CAS (Viya)

| | |
|---|---|
| *CASMediator*(caller, cas_session) | Handles the connection between sasoptpy and SAS Viya (CAS) server |

### sasoptpy.interface.CASMediator

**class CASMediator**(*caller*, *cas_session*)

Bases: `sasoptpy.interface.solver.mediator.Mediator`

Handles the connection between sasoptpy and SAS Viya (CAS) server

**Parameters**

**caller** [`Model` or `Workspace`] Model or workspace that mediator belongs to

**cas_session** [`swat.cas.connection.CAS`] CAS connection

#### Notes

- CAS Mediator is used by `Model` and `Workspace` objects internally.

### Model

| | |
|---|---|
| *CASMediator.solve*(self, **kwargs) | Solve action for `Model` objects |
| *CASMediator.tune*(self, **kwargs) | Checks if CAS session has optimizaiton.tuner capability and calls `tune_problem()` |
| *CASMediator.tune_problem*(self, **kwargs) | Calls optimization.tuner CAS action to find out ideal configuration |
| *CASMediator.solve_with_mps*(self, **kwargs) | Submits the problem in MPS (DataFrame) format, supported by old versions |
| *CASMediator.solve_with_optmodel*(self, **kwargs) | Submits the problem in OPTMODEL format |
| *CASMediator.parse_cas_solution*(self) | Performs post-solve operations |
| *CASMediator.parse_cas_table*(self, table) | Converts requested `swat.cas.table.CASTable` objects to `swat.dataframe.SASDataFrame` |
| *CASMediator.set_variable_values*(self, solution) | Performs post-solve assignment of variable values |
| *CASMediator.set_constraint_values*(self, solution) | Performs post-solve assignment of constraint values |
| *CASMediator.set_model_objective_value*(self) | Performs post-solve assignment of objective values |

Continued on next page

Table 42 – continued from previous page

| | |
|---|---|
| `CASMediator.set_variable_init_values`(self) | Performs post-solve assignment of variable initial values |
| `CASMediator.upload_user_blocks`(self) | Uploads user-defined decomposition blocks to the CAS server |
| `CASMediator.upload_model`(self[, name, ...]) | Converts internal model to MPS table and upload to CAS session |

### sasoptpy.interface.CASMediator.solve

`CASMediator.solve(self, **kwargs)`
Solve action for `Model` objects

### sasoptpy.interface.CASMediator.tune

`CASMediator.tune(self, **kwargs)`
Checks if CAS session has optimizaiton.tuner capability and calls `tune_problem()`

### sasoptpy.interface.CASMediator.tune_problem

`CASMediator.tune_problem(self, **kwargs)`
Calls optimization.tuner CAS action to find out ideal configuration

### sasoptpy.interface.CASMediator.solve_with_mps

`CASMediator.solve_with_mps(self, **kwargs)`
Submits the problem in MPS (DataFrame) format, supported by old versions

**Parameters**

**kwargs** [dict] Keyword arguments for solver settings and options

**Returns**

**primal_solution** [`swat.dataframe.SASDataFrame`] Solution of the model or None

### sasoptpy.interface.CASMediator.solve_with_optmodel

`CASMediator.solve_with_optmodel(self, **kwargs)`
Submits the problem in OPTMODEL format

**Parameters**

**kwargs** [dict] Keyword arguments for solver settings and options

**Returns**

**primal_solution** [`swat.dataframe.SASDataFrame`] Solution of the model or None

### sasoptpy.interface.CASMediator.parse_cas_solution

`CASMediator.parse_cas_solution(self)`
Performs post-solve operations

**Returns**

**solution** [`swat.dataframe.SASDataFrame`] Solution of the problem

### sasoptpy.interface.CASMediator.parse_cas_table

`CASMediator.parse_cas_table(self, table)`
Converts requested `swat.cas.table.CASTable` objects to `swat.dataframe.SASDataFrame`

### sasoptpy.interface.CASMediator.set_variable_values

`CASMediator.set_variable_values(self, solution)`
Performs post-solve assignment of variable values

**Parameters**

**solution** [class:*swat.dataframe.SASDataFrame*] Primal solution of the problem

### sasoptpy.interface.CASMediator.set_constraint_values

`CASMediator.set_constraint_values(self, solution)`
Performs post-solve assignment of constraint values

**Parameters**

**solution** [class:*swat.dataframe.SASDataFrame*] Primal solution of the problem

### sasoptpy.interface.CASMediator.set_model_objective_value

`CASMediator.set_model_objective_value(self)`
Performs post-solve assignment of objective values

**Parameters**

**solution** [class:*swat.dataframe.SASDataFrame*] Primal solution of the problem

### sasoptpy.interface.CASMediator.set_variable_init_values

`CASMediator.set_variable_init_values(self)`
Performs post-solve assignment of variable initial values

**Parameters**

**solution** [class:*swat.dataframe.SASDataFrame*] Primal solution of the problem

### sasoptpy.interface.CASMediator.upload_user_blocks

CASMediator.**upload_user_blocks**(*self*)

Uploads user-defined decomposition blocks to the CAS server

**Returns**

**name** [string] CAS table name of the user-defined decomposition blocks

#### Examples

```
>>> userblocks = m.upload_user_blocks()
>>> m.solve(milp={'decomp': {'blocks': userblocks}})
```

### sasoptpy.interface.CASMediator.upload_model

CASMediator.**upload_model**(*self*, *name=None*, *replace=True*, *constant=False*, *verbose=False*)

Converts internal model to MPS table and upload to CAS session

**Parameters**

**name** [string, optional] Desired name of the MPS table on the server

**replace** [boolean, optional] Option to replace the existing MPS table

**Returns**

**frame** [swat.cas.table.CASTable] Reference to the uploaded CAS Table

#### Notes

- This method returns None if the model session is not valid.
- Name of the table is randomly assigned if name argument is None or not given.
- This method should not be used if `Model.solve()` is going to be used. `Model.solve()` calls this method internally.

## Workspace

| | |
|---|---|
| *CASMediator.submit*(self, **kwargs) | Submit action for custom input and `Workspace` objects |
| *CASMediator.submit_optmodel_code*(self, ...) | Converts caller into OPTMODEL code and submits using optimization.runOptmodel action |
| *CASMediator.parse_cas_workspace_response*(self) | Parses results of workspace submission |
| *CASMediator.set_workspace_variable_values*(...) | Performs post-solve assignment of `Workspace` variable values |

#### sasoptpy.interface.CASMediator.submit

CASMediator.**submit**(*self*, ***kwargs*)
Submit action for custom input and `Workspace` objects

#### sasoptpy.interface.CASMediator.submit_optmodel_code

CASMediator.**submit_optmodel_code**(*self*, ***kwargs*)
Converts caller into OPTMODEL code and submits using optimization.runOptmodel action

**Parameters**

**kwargs :** Solver settings and options

#### sasoptpy.interface.CASMediator.parse_cas_workspace_response

CASMediator.**parse_cas_workspace_response**(*self*)
Parses results of workspace submission

#### sasoptpy.interface.CASMediator.set_workspace_variable_values

CASMediator.**set_workspace_variable_values**(*self*, *solution*)
Performs post-solve assignment of `Workspace` variable values

### SAS

| | |
|---|---|
| *SASMediator*(caller, sas_session) | Handles the connection between sasoptpy and SAS instance |

#### sasoptpy.interface.SASMediator

**class SASMediator**(*caller*, *sas_session*)
Bases: `sasoptpy.interface.solver.mediator.Mediator`

Handles the connection between sasoptpy and SAS instance

**Parameters**

**caller** [`Model` or `Workspace`] Model or workspace that mediator belongs to

**sas_session** [`saspy.SASsession`] SAS session object

### Notes

- SAS Mediator is used by `Model` and `Workspace` objects internally.

## Model

| | |
|---|---|
| *SASMediator.solve*(self, **kwargs) | Solve action for `Model` objects |
| *SASMediator.solve_with_mps*(self, **kwargs) | Submits the problem in MPS (DataFrame) format, supported by old versions |
| *SASMediator.solve_with_optmodel*(self, **kwargs) | Submits the problem in OPTMODEL format |
| *SASMediator.parse_sas_mps_solution*(self) | Parses MPS solution after *solve* and returns solution |
| *SASMediator.parse_sas_solution*(self) | Performs post-solve operations |
| *SASMediator.parse_sas_table*(self, table_name) | Converts requested table name into `pandas.DataFrame` |
| *SASMediator.convert_to_original*(self, table) | Converts variable names to their original format if a placeholder gets used |
| *SASMediator.perform_postsolve_operations*(self) | Performs post-solve operations for proper output display |

### sasoptpy.interface.SASMediator.solve

`SASMediator.solve(self, **kwargs)`

Solve action for `Model` objects

### sasoptpy.interface.SASMediator.solve_with_mps

`SASMediator.solve_with_mps(self, **kwargs)`

Submits the problem in MPS (DataFrame) format, supported by old versions

**Parameters**

**kwargs** [dict] Keyword arguments for solver settings and options

**Returns**

**primal_solution** [`pandas.DataFrame`] Solution of the model or None

### sasoptpy.interface.SASMediator.solve_with_optmodel

`SASMediator.solve_with_optmodel(self, **kwargs)`

Submits the problem in OPTMODEL format

**Parameters**

**kwargs** [dict] Keyword arguments for solver settings and options

**Returns**

**primal_solution** [`pandas.DataFrame`] Solution of the model or None

### sasoptpy.interface.SASMediator.parse_sas_mps_solution

`SASMediator.parse_sas_mps_solution(self)`

Parses MPS solution after *solve* and returns solution

### sasoptpy.interface.SASMediator.parse_sas_solution

`SASMediator.parse_sas_solution(self)`

Performs post-solve operations

**Returns**

**solution** [`pandas.DataFrame`] Solution of the problem

### sasoptpy.interface.SASMediator.parse_sas_table

`SASMediator.parse_sas_table(self, table_name)`

Converts requested table name into `pandas.DataFrame`

### sasoptpy.interface.SASMediator.convert_to_original

`SASMediator.convert_to_original(self, table)`

Converts variable names to their original format if a placeholder gets used

### sasoptpy.interface.SASMediator.perform_postsolve_operations

`SASMediator.perform_postsolve_operations(self)`

Performs post-solve operations for proper output display

### Workspace

| | |
|---|---|
| `SASMediator.submit`(self, **kwargs) | Submit action for custom input and `Workspace` objects |
| `SASMediator.submit_optmodel_code`(self, ...) | Submits given `Workspace` object in OPTMODEL format |
| `SASMediator.parse_sas_workspace_response`(self) | Parses results of workspace submission |
| `SASMediator.set_workspace_variable_values`(...) | Performs post-solve assignment of `Workspace` variable values |

#### sasoptpy.interface.SASMediator.submit

`SASMediator.submit(self, **kwargs)`
Submit action for custom input and `Workspace` objects

#### sasoptpy.interface.SASMediator.submit_optmodel_code

`SASMediator.submit_optmodel_code(self, **kwargs)`
Submits given `Workspace` object in OPTMODEL format

**Parameters**

**kwargs :** Solver settings and options

#### sasoptpy.interface.SASMediator.parse_sas_workspace_response

`SASMediator.parse_sas_workspace_response(self)`
Parses results of workspace submission

#### sasoptpy.interface.SASMediator.set_workspace_variable_values

`SASMediator.set_workspace_variable_values(self, solution)`
Performs post-solve assignment of `Workspace` variable values

## 5.4 Functions

### 5.4.1 Functions

#### Utility Functions

| | |
|---|---|
| *dict_to_frame*(dictobj[, cols]) | Converts dictionaries to DataFrame objects for pretty printing |
| *exp_range*(start, stop[, step]) | Creates a set within given range |
| *flatten_frame*(df[, swap]) | Converts a `pandas.DataFrame` object into `pandas.Series` |
| *get_solution_table*(*argv[, key, rhs]) | |
| *quick_sum*(argv) | |
| *reset*() | Resets package configs and internal counters |

### sasoptpy.dict_to_frame

**dict_to_frame** (*dictobj*, *cols=None*)

Converts dictionaries to DataFrame objects for pretty printing

**Parameters**

**dictobj** [dict] Dictionary to be converted

**cols** [list, optional] Column names

**Returns**

**frobj** [DataFrame] DataFrame representation of the dictionary

#### Examples

```
>>> d = {'coal': {'period1': 1, 'period2': 5, 'period3': 7},
>>>      'steel': {'period1': 8, 'period2': 4, 'period3': 3},
>>>      'copper': {'period1': 5, 'period2': 7, 'period3': 9}}
>>> df = so.dict_to_frame(d)
>>> print(df)
        period1  period2  period3
coal          1        5        7
copper        5        7        9
steel         8        4        3
```

### sasoptpy.exp_range

**exp_range** (*start*, *stop*, *step=1*)

Creates a set within given range

**Parameters**

**start** [Expression] First value of the range

**stop** [Expression] Last value of the range

**step** [Expression, optional] Step size of the range

**Returns**

**exset** [Set] Set that represents the range

#### Examples

```
>>> N = so.Parameter(name='N')
>>> p = so.exp_range(1, N)
>>> print(p._defn())
set 1..N;
```

### sasoptpy.flatten_frame

**flatten_frame** (*df*, *swap=False*)

Converts a `pandas.DataFrame` object into `pandas.Series`

**Parameters**

**df** [`pandas.DataFrame`] DataFrame to be flattened

**swap** [boolean, optional] Option to use columns as first index

**Returns**

**new_frame** [`pandas.DataFrame`] A new DataFrame where indices consist of index and columns names as tuples

#### Examples

```
>>> price = pd.DataFrame([
>>>     [1, 5, 7],
>>>     [8, 4, 3],
>>>     [5, 7, 9]], columns=['period1', 'period2', 'period3']).\
>>>     set_index([['coal', 'steel', 'copper']])
>>> print('Price data: \n{}'.format(price))
>>> price_f = so.flatten_frame(price)
>>> print('Price data: \n{}'.format(price_f))
Price data:
        period1  period2  period3
coal          1        5        7
steel         8        4        3
copper        5        7        9
Price data:
(coal, period1)       1
(coal, period2)       5
(coal, period3)       7
(steel, period1)      8
(steel, period2)      4
(steel, period3)      3
(copper, period1)     5
(copper, period2)     7
(copper, period3)     9
dtype: int64
```

### sasoptpy.get_solution_table

**get_solution_table** (**argv*, *key=None*, *rhs=False*)

### sasoptpy.quick_sum

**quick_sum**(*argv*)

### sasoptpy.reset

**reset**()

Resets package configs and internal counters

### Abstract Actions

| | |
|---|---|
| *actions.read_data*(table, index, columns) | Reads data tables inside Set and Parameter objects |
| *actions.create_data*(table, index, columns) | Creates data tables from variables, parameters and expressions |
| *actions.solve*([options, primalin]) | Solves the active optimization problem and generates results |
| *actions.for_loop*(*args) | Creates a for-loop container that is to be executed on server-side |
| *actions.cofor_loop*(*args) | Creates a cofor-loop that is to be executed on server-side concurrently |
| *actions.if_condition*(logic_expression, . . . ) | Creates an if-else block |
| *actions.switch_conditions*(**args) | Creates several if-else blocks using given arguments |
| *actions.set_value*(left, right) | Creates an assignment statement |
| *actions.fix*(*args) | Fixes values of variables to given values |
| *actions.unfix*(*args) | Unfixes values of variables |
| *actions.set_objective*(expression, name, sense) | Sets objective function |
| *actions.print_item*(*args) | Prints given argument list on server-side |
| *actions.put_item*(*args[, names]) | Prints given item values to output log |
| *actions.expand*() | Prints expanded problem to output |
| *actions.drop*(*args) | Drops given constraints or constraint groups from model |
| *actions.restore*(*args) | Restores dropped constraint and constraint groups |
| *actions.union*(*args) | Aggregates given sets and set expressions |
| *actions.diff*(left, right) | Gets the difference between set and set expressions |
| *actions.substring*(main_string, first_pos, . . . ) | Gets the substring of given positions |
| *actions.use_problem*(problem) | Changes the currently active problem |

### sasoptpy.actions.read_data

**read_data**(*table*, *index*, *columns*)

Reads data tables inside Set and Parameter objects

**Parameters**

**table** [string or `swat.cas.table.CASTable`] Table object or name to be read, case insensitive

**index** [dict] Index properties of the table

Has two main members:

- **target** [*sasoptpy.abstract.Set*] Target Set object to be read into
- **key** [string, list or None] Column name that will be read from.

  For multiple indices it should be a list of string or *sasoptpy.abstract.SetIterator* objects

For a given Set *YEAR* and column name *year_no*, the index dictionary should be written as:

```
>>> {'target': YEAR, 'key': 'year_no'}
```

If index is simply the row number, use *'key': so.N* which is equivalent to special *_N_* character at SAS language.

**columns** [list] A list of dictionaries, each holding column properties.

Columns are printed in given order. Each column should be represented as a dictionary with following fields:

- **target** [*sasoptpy.abstract.ParameterGroup*] Target parameter object to be read into
- **column** [string] Column name to be read from
- **index** [`sasoptpy.SetIterator`, optional] Sub-index for specific column, needed for complex operations

If the name of the *sasoptpy.abstract.Parameter* object is same as the column name, calling

```
>>> p = so.Parameter(name='price')
>>> read_data(..., columns=[{'target': p}])
```

is enough. For reading a different column name, *column* field should be given:

```
>>> {'target': p, 'column': 'price_usd'}
```

When working with Parameter Group objects, sometimes a secondary loop is needed. This is achieved by using *index* field, along with `sasoptpy.abstract.statement.ReadDataStatement.append()` method.

**Returns**

**r** [*sasoptpy.abstract.statement.ReadDataStatement*] Read data statement object, that includes all properties

Additional columns can be added using `sasoptpy.abstract.statement.ReadDataStatement.append()` function.

**See also:**

***tests.abstract.statement.test_read_data.TestReadData***

### Examples

Reading a regular set

```
>>> with Workspace('test_workspace') as ws:
>>>     ITEMS = Set(name='ITEMS')
>>>     value = ParameterGroup(ITEMS, name='value', init=0)
>>>     get = VariableGroup(ITEMS, name='get', vartype=so.INT, lb=0)
>>>     read_data(
...         table="values",
...         index={'target': ITEMS, 'key': None},
...         columns=[{'target': value}])
>>> print(so.to_optmodel(w))
proc optmodel;
    set ITEMS;
    num value {ITEMS} init 0;
    var get {{ITEMS}} integer >= 0;
    read data values into ITEMS value;
quit;
```

Reading with row index

```
>>> with so.Workspace('test_read_data_n') as ws:
>>>     ASSETS = so.Set(name='ASSETS')
>>>     ret = so.ParameterGroup(ASSETS, name='return', ptype=so.NUM)
>>>     read_data(
...         table='means',
...         index={'target': ASSETS, 'key': so.N},
...         columns=[{'target': ret}]
...     )
>>> print(so.to_optmodel(w))
proc optmodel;
    set ASSETS;
    num return {ASSETS};
    read data means into ASSETS=[_N_] return;
quit;
```

Reading with no index set and subindex

```
>>> with so.Workspace('test_read_data_no_index_expression') as ws:
>>>     ASSETS = so.Set(name='ASSETS')
>>>     cov = so.ParameterGroup(ASSETS, ASSETS, name='cov', init=0)
>>>     with iterate(ASSETS, 'asset1') as asset1, iterate(ASSETS, 'asset2') as␣
↪asset2:
>>>         read_data(
...             table='covdata',
...             index={'key': [asset1, asset2]},
...             columns=[
...                 {'target': cov},
...                 {'target': cov[asset2, asset1],
...                 'column': 'cov'}])
>>> print(so.to_optmodel(w))
proc optmodel;
    set ASSETS;
    num cov {ASSETS, ASSETS} init 0;
    read data covdata into [asset1 asset2] cov cov[asset2, asset1]=cov;
quit;
```

Reading a column with multiple indices

```
>>> with so.Workspace(name='test_read_data_idx_col') as ws:
>>>     dow = so.Set(name='DOW', value=so.exp_range(1, 6))
>>>     locs = so.Set(name='LOCS', settype=so.STR)
>>>     demand = so.ParameterGroup(locs, dow, name='demand')
>>>     with iterate(locs, name='loc') as loc:
>>>         r = read_data(
...             table='dmnd',
...             index={'target': locs, 'key': loc}
...         )
>>>         with iterate(dow, name='d') as d:
>>>             r.append({
...                 'index': d,
...                 'target': demand[loc, d],
...                 'column': concat('day', d)
...             })
>>> optmodel_code = so.to_optmodel(ws)
proc optmodel;
    set DOW = 1..5;
    set <str> LOCS;
    num demand {LOCS, DOW};
    read data dmnd into LOCS=[loc] {d in DOW} < demand[loc, d]=col('day' || d) >;
quit;
```

### sasoptpy.actions.create_data

**create_data** (*table*, *index*, *columns*)

Creates data tables from variables, parameters and expressions

**Parameters**

**table** [string] Name of the table to be created

**index** [dict] Table index properties

This dictionary can be empty if no index is needed. It can have following fields:

- **key** [list] List of index keys. Keys can be string or *sasoptpy.abstract.SetIterator* objects
- **set** [list] List of sets, that is being assigned to keys

**columns** [list] List of columns. Columns can be *sasoptpy.abstract.Parameter*, *sasoptpy.abstract.ParameterGroup* objects or dictionaries. If given as a dictionary, each can have following keys:

- **name** [string] Name of the column in output table
- **expression** [sasoptpy.core.Expression] Any expression
- **index** [list or *sasoptpy.abstract.SetIterator*] Index for internal loops

The *index* field can be used when a subindex is needed. When given as a list, members should be *sasoptpy.abstract.SetIterator* objects. See examples for more details.

**See also:**

*tests.abstract.statement.test_create_data.TestCreateData*

### Examples

Regular column

```
>>> with so.Workspace('w') as w:
>>>     m = so.Parameter(name='m', value=7)
>>>     n = so.Parameter(name='n', value=5)
>>>     create_data(table='example', index={}, columns=[m, n])
>>> print(so.to_optmodel(w))
proc optmodel;
    num m = 7;
    num n = 5;
    create data example from m n;
quit;
```

Column with name

```
>>> with so.Workspace('w') as w:
>>>     m = so.Parameter(name='m', value=7)
>>>     n = so.Parameter(name='n', value=5)
>>>     create_data(table='example', index={}, columns=[
...         {'name': 'ratio', 'expression': m/n}
...     ])
>>> print(so.to_optmodel(w))
proc optmodel;
    num m = 7;
    num n = 5;
    create data example from ratio=((m) / (n));
quit;
```

Column name with concat

```
>>> from sasoptpy.util import concat
>>> with so.Workspace('w') as w:
>>>     m = so.Parameter(name='m', value=7)
>>>     n = so.Parameter(name='n', value=5)
>>>     create_data(table='example', index={}, columns=[
...         {'name': concat('s', n), 'expression': m+n}
...     ])
>>> print(so.to_optmodel(w))
proc optmodel;
    num m = 7;
    num n = 5;
    create data example from col('s' || n)=(m + n);
quit;
```

Table with index

```
>>> with so.Workspace('w') as w:
>>>     m = so.ParameterGroup(
>>>         so.exp_range(1, 6), so.exp_range(1, 4), name='m', init=0)
>>>     m[1, 1] = 1
>>>     m[4, 1] = 1
>>>     S = so.Set(name='ISET', value=[i**2 for i in range(1, 3)])
>>>     create_data(
...         table='example',
...         index={'key': ['i', 'j'], 'set': [S, [1, 2]]},
...         columns=[m]
```

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```
...     )
>>> print(so.to_optmodel(w))
proc optmodel;
    num m {1..5, 1..3} init 0;
    m[1, 1] = 1;
    m[4, 1] = 1;
    set ISET = {1,4};
    create data example from [i j] = {{ISET,{1,2}}} m;
quit;
```

Index over Python range

```
>>> with so.Workspace('w') as w:
>>>     s = so.Set(name='S', value=so.exp_range(1, 6))
>>>     x = so.VariableGroup(s, name='x')
>>>     x[1] = 1
>>>     create_data(table='example',
...         index={'key': ['i'], 'set': so.exp_range(1, 4)}, columns=[x])
>>> print(so.to_optmodel(w))
proc optmodel;
    set S = 1..5;
    var x {{S}};
    x[1] = 1;
    create data example from [i] = {1..3} x;
quit;
```

Append column with index

```
>>> from sasoptpy.util import iterate, concat
>>> with so.Workspace('w', session=session) as w:
>>>     alph = so.Set(name='alph', settype=so.string, value=['a', 'b', 'c'])
>>>     x = so.VariableGroup([1, 2, 3], alph, name='x', init=2)
>>>     with iterate(so.exp_range(1, 4), name='i') as i:
>>>         c = create_data(
...             table='example',
...             index={'key': [i], 'set': [i.get_set()]})
>>>         with iterate(alph, name='j') as j:
>>>             c.append(
...                 {'name': concat('x', j),
...                  'expression': x[i, j],
...                  'index': j})
>>> print(so.to_optmodel(w))
proc optmodel;
    set <str> alph = {'a','b','c'};
    var x {{1,2,3}, {alph}} init 2;
    create data example from [i] = {{1..3}} {j in alph} < col('x' || j)=(x[i, j])
↪>;
quit;
```

Multiple column indices

```
>>> from sasoptpy.util import concat, iterate
>>> with so.Workspace('w') as w:
>>>     S = so.Set(name='S', value=[1, 2, 3])
>>>     T = so.Set(name='T', value=[1, 3, 5])
>>>     x = so.VariableGroup(S, T, name='x', init=1)
>>>     with iterate(S, name='i') as i, iterate(T, name='j') as j:
```

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```
>>>         create_data(
...             table='out',
...             index={},
...             columns=[
...                 {'name': concat('x', concat(i, j)), 'expression': x[i, j],
...                  'index': [i, j]}])
>>> print(so.to_optmodel(w))
proc optmodel;
    set S = {1,2,3};
    set T = {1,3,5};
    var x {{S}, {T}} init 1;
    create data out from {i in S, j in T} < col('x' || i || j)=(x[i, j]) >;
quit;
```

### sasoptpy.actions.solve

**solve**(*options=None*, *primalin=False*)

Solves the active optimization problem and generates results

**Parameters**

**options** [dict, optional] Solver options

This dictionary can have several fields.

- **with** [string] Name of the solver, see possible values under Notes.

See *Solver Options* for a list of solver options. All fields in options (except *with*) is passed directly to the solver.

**primalin** [bool, optional] Switch for using existing variable values as an initial point in MILP solver

**Returns**

**ss** [`sasoptpy.abstract.statement.SolveStatement`] Solve statement object.

Contents of the response can be grabbed using *get_response* function.

#### Notes

Possible solver names for *with* parameter:

- *lp* : Linear programming
- *milp* : Mixed integer linear programming
- *nlp* : General nonlinear programming
- *qp* : Quadratic programming
- *blackbox* : Black-box optimization

SAS Optimization also has Constraint Programming (clp) and Network Solver (network) but they are not currently supported.

### Examples

Regular solve

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x', lb=1, ub=10)
>>>     o = so.Objective(2*x, sense=so.maximize, name='obj')
>>>     s = solve()
>>>     p = print_item(x)
>>> print(so.to_optmodel(w))
proc optmodel;
    var x >= 1 <= 10;
    max obj = 2 * x;
    solve;
    print x;
quit;
```

Option alternatives

```
>>> with so.Workspace('w') as w:
>>>     # Problem declaration, etc..
>>>     solve()
>>>     solve(options={'with': 'milp'})
>>>     solve(options={'with': 'milp'}, primalin=True)
>>>     solve(options={'with': 'milp', 'presolver': None, 'feastol': 1e-6,
>>>                    'logfreq': 2, 'maxsols': 3, 'scale': 'automatic',
>>>                    'restarts': None, 'cutmir': 'aggressive'})
>>> print(so.to_optmodel(w))
proc optmodel;
    solve;
    solve with milp;
    solve with milp / primalin;
    solve with milp / presolver=None feastol=1e-06 logfreq=2 maxsols=3␣
↪scale=automatic restarts=None cutmir=aggressive;
quit;
```

## sasoptpy.actions.for_loop

**for_loop**(**args*)

Creates a for-loop container that is to be executed on server-side

**Parameters**

**args** [`sasoptpy.abstract.Set` objects] Any number of Set objects can be given

**Returns**

**set_iterator** [`sasoptpy.abstract.SetIterator`, `sasoptpy.abstract.SetIteratorGroup`] Set iterators to be used inside for-loop

**See also:**

`sasoptpy.actions.cofor_loop()`

### Notes

For tasks that can be run concurrently, consider using *sasoptpy.actions.cofor_loop()*

### Examples

Regular for loop

```
>>> with so.Workspace('w') as w:
>>>     r = so.exp_range(1, 11)
>>>     x = so.VariableGroup(r, name='x')
>>>     for i in for_loop(r):
>>>         x[i] = 1
>>> print(so.to_optmodel(w))
proc optmodel;
    var x {{1,2,3,4,5,6,7,8,9,10}};
    for {o13 in 1..10} do;
        x[o13] = 1;
    end;
quit;
```

Nested for loops

```
>>> from sasoptpy.actions import put_item
>>> with so.Workspace('w') as w:
>>>     for i in for_loop(range(1, 3)):
>>>         for j in for_loop(['a', 'b']):
>>>             put_item(i, j)
>>> print(so.to_optmodel(w))
proc optmodel;
    for {o2 in 1..2} do;
        for {o5 in {'a','b'}} do;
            put o2 o5;
        end;
    end;
quit;
```

Multiple set for-loops

```
>>> with so.Workspace('w') as w:
>>>     r = so.Set(name='R', value=range(1, 11))
>>>     c = so.Set(name='C', value=range(1, 6))
>>>     a = so.ParameterGroup(r, c, name='A', ptype=so.number)
>>>     for (i, j) in for_loop(r, c):
>>>         a[i, j] = 1
>>> print(so.to_optmodel(w))
proc optmodel;
    set R = 1..10;
    set C = 1..5;
    num A {R, C};
    for {o5 in R, o7 in C} do;
        A[o5, o7] = 1;
    end;
quit;
```

### sasoptpy.actions.cofor_loop

**cofor_loop**(**args*)

Creates a cofor-loop that is to be executed on server-side concurrently

**Parameters**

**args** [`sasoptpy.abstract.Set` objects] Any number of Set objects can be given

**Returns**

**set_iterator** [`sasoptpy.abstract.SetIterator`, `sasoptpy.abstract.SetIteratorGroup`] Set iterators to be used inside cofor-loop

**See also:**

`sasoptpy.actions.for_loop()`

#### Notes

A cofor-loop runs its content concurrently. For tasks that depend on each other, consider using `sasoptpy.actions.for_loop()`

#### Examples

```
>>> with so.Workspace('w') as w:
>>>     x = so.VariableGroup(6, name='x', lb=0)
>>>     so.Objective(
>>>         so.expr_sum(x[i] for i in range(6)), name='z', sense=so.MIN)
>>>     a1 = so.Constraint(x[1] + x[2] + x[3] <= 4, name='a1')
>>>     for i in cofor_loop(so.exp_range(3, 6)):
>>>         fix(x[1], i)
>>>         solve()
>>>         put_item(i, x[1], so.Symbol('_solution_status_'), names=True)
>>> print(so.to_optmodel(w))
proc optmodel;
    var x {{0,1,2,3,4,5}} >= 0;
    min z = x[0] + x[1] + x[2] + x[3] + x[4] + x[5];
    con a1 : x[1] + x[2] + x[3] <= 4;
    cofor {o13 in 3..5} do;
        fix x[1]=o13;
        solve;
        put o13= x[1]= _solution_status_=;
    end;
quit;
```

### sasoptpy.actions.if_condition

**if_condition** (*logic_expression*, *if_statement*, *else_statement=None*)

Creates an if-else block

**Parameters**

**logic_expression** [`sasoptpy.Constraint` or `sasoptpy.abstract.Condition`] Logical condition for the True case

For the condition, it is possible to combine constraints, such as

```
>>> a = so.Parameter(value=5)
>>> if_condition((a < 3) | (a > 6), func1, func2)
```

Constraints should be combined using bitwise operators (& for *and*, | for *or*).

**if_statement** [function or `IfElseStatement`] Python function or if-else statement to be called if the condition is True

**else_statement** [function or `IfElseStatement`, optional] Python function or if-else statement to be called if the condition is False

#### Examples

Regular condition

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x')
>>>     x.set_value(0.5)
>>>     def func1():
>>>         x.set_value(1)
>>>     def func2():
>>>         x.set_value(0)
>>>     if_condition(x > 1e-6, func1, func2)
>>> print(so.to_optmodel(w))
proc optmodel;
    var x;
    x = 0.5;
    if x > 1e-06 then do;
        x = 1;
    end;
    else do;
        x = 0;
    end;
quit;
```

Combined conditions

```
>>> with so.Workspace('w') as w:
>>>     p = so.Parameter(name='p')
>>>     def case1():
>>>         p.set_value(10)
>>>     def case2():
>>>         p.set_value(20)
>>>     r = so.Parameter(name='r', value=10)
>>>     if_condition((r < 5) | (r > 10), case1, case2)
>>> print(so.to_optmodel(w))
```

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```
proc optmodel;
    num p;
    num r = 10;
    if (r < 5) or (r > 10) then do;
        p = 10;
    end;
    else do;
        p = 20;
    end;
quit;
```

### sasoptpy.actions.switch_conditions

**switch_conditions**(***args*)

Creates several if-else blocks using given arguments

**Parameters**

**args :** Several arguments can be passed to the function

If an argument is a Constraint or Condition (combined Constraints) the following callable argument is used as a case

#### Examples

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x')
>>>     p = so.Parameter(name='p')
>>>     x.set_value(2.5)
>>>     def func1():
>>>         p.set_value(1)
>>>     def func2():
>>>         p.set_value(2)
>>>     def func3():
>>>         p.set_value(3)
>>>     def func4():
>>>         p.set_value(0)
>>>     switch_conditions(x < 1, func1, x < 2, func2, x < 3, func3, func4)
>>> print(to.optmodel(w))
proc optmodel;
    var x;
    num p;
    x = 2.5;
    if x < 1 then do;
        p = 1;
    end;
    else if x < 2 then do;
        p = 2;
    end;
    else if x < 3 then do;
        p = 3;
    end;
    else do;
        p = 0;
```

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```
    end;
quit;
```

### sasoptpy.actions.set_value

**set_value** (*left*, *right*)

Creates an assignment statement

**Parameters**

**left** [*sasoptpy.Expression*] Any expression (variable or parameter)

**right** [*sasoptpy.Expression* or float] Right-hand-side expression

#### Examples

```
>>> with so.Workspace('ex_9_1_matirx_sqrt', session=None) as w:
>>>     so.LiteralStatement('call streaminit(1);')
>>>     n = so.Parameter(name='n', value=5)
>>>     rn = so.Set(name='RN', value=so.exp_range(1, n))
>>>     A = so.ParameterGroup(rn, rn, name='A', value="10-20*rand('UNIFORM')")
>>>     P = so.ParameterGroup(rn, rn, name='P')
>>>     for i in for_loop(rn):
>>>         for j in for_loop(so.exp_range(i, n)):
>>>             set_value(P[i, j], so.expr_sum(A[i, k] * A[j, k] for k in rn))
>>> print(so.to_optmodel(w))
proc optmodel;
    call streaminit(1);
    num n = 5;
    set RN = 1..n;
    num A {RN, RN} = 10-20*rand('UNIFORM');
    num P {RN, RN};
    for {o7 in RN} do;
        for {o10 in o7..n} do;
            P[o7, o10] = sum {k in RN} (A[o7, k] * A[o10, k]);
        end;
    end;
quit;
```

### sasoptpy.actions.fix

**fix** (**args*)

Fixes values of variables to given values

**Parameters**

**args** [*sasoptpy.Variable*, float, *sasoptpy.Expression*, tuple] Set of arguments to be fixed

Arguments get paired (if not given in tuples) to allow several fix operations

**See also:**

*sasoptpy.actions.unfix()*

*tests.abstract.statement.test_fix_unfix.TestFix*

### Examples

Regular fix statement

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x')
>>>     fix(x, 1)
>>>     solve()
>>>     unfix(x)
>>> print(so.to_optmodel(w))
proc optmodel;
    var x;
    fix x=1;
    solve;
    unfix x;
quit;
```

Multiple fix-unfix

```
>>> with so.Workspace('w') as w:
>>>     x = so.VariableGroup(4, name='x')
>>>     for i in cofor_loop(range(4)):
>>>         fix((x[0], i), (x[1], 1))
>>>         solve()
>>>         unfix(x[0], (x[1], 2))
>>> print(so.to_optmodel(w))
proc optmodel;
    var x {{0,1,2,3}};
    cofor {o7 in 0..3} do;
        fix x[0]=o7 x[1]=1;
        solve;
        unfix x[0] x[1]=2;
    end;
quit;
```

## sasoptpy.actions.unfix

**unfix**(**args*)

Unfixes values of variables

**Parameters**

**args** [*sasoptpy.Variable* objects] Set of arguments to be unfixed

**See also:**

*sasoptpy.actions.fix()*

*tests.abstract.statement.test_fix_unfix.TestFix*

### Examples

Regular unfix statement

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x')
>>>     fix(x, 1)
>>>     solve()
>>>     unfix(x)
>>> print(so.to_optmodel(w))
proc optmodel;
    var x;
    fix x=1;
    solve;
    unfix x;
quit;
```

Multiple fix-unfix

```
>>> with so.Workspace('w') as w:
>>>     x = so.VariableGroup(4, name='x')
>>>     for i in cofor_loop(range(4)):
>>>         fix((x[0], i), (x[1], 1))
>>>         solve()
>>>         unfix(x[0], (x[1], 2))
>>> print(so.to_optmodel(w))
proc optmodel;
    var x {{0,1,2,3}};
    cofor {o7 in 0..3} do;
        fix x[0]=o7 x[1]=1;
        solve;
        unfix x[0] x[1]=2;
    end;
quit;
```

## sasoptpy.actions.set_objective

**set_objective**(*expression*, *name*, *sense*)

Sets objective function

**Parameters**

**expression** [*sasoptpy.Expression*] Objective function

**name** [string] Name of the objective function

**sense** [string] Direction of the objective function, *so.MAX* or *so.MIN*

### Examples

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x', lb=1)
>>>     set_objective(x ** 3, name='xcube', sense=so.minimize)
>>>     solve()
>>> print(so.to_optmodel(w))
proc optmodel;
    var x >= 1;
    MIN xcube = (x) ^ (3);
    solve;
quit;
```

## sasoptpy.actions.print_item

**print_item**(**args*)

Prints given argument list on server-side

**Parameters**

**args** [*sasoptpy.Variable*, *sasoptpy.Expression*] Arbitrary number of arguments to be printed

These values are printed on server-side, but can be grabbed after execution

**Returns**

**ps** [*sasoptpy.abstract.statement.PrintStatement*] Print statement object.

Contents of the response can be grabbed using *get_response* function.

### Examples

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x', lb=1, ub=10)
>>>     o = so.Objective(2*x, sense=so.maximize, name='obj')
>>>     s = solve()
>>>     p = print_item(x)
>>> print(so.to_optmodel(w))
proc optmodel;
    var x >= 1 <= 10;
    max obj = 2 * x;
    solve;
    print x;
quit;
>>> print(p.get_response())
     x
0  10.0
```

### sasoptpy.actions.put_item

**put_item**(**args*, *names=None*)

Prints given item values to output log

**Parameters**

**args** [*sasoptpy.Expression*, string] Arbitrary elements to be put into log

Variables, variable groups, expressions can be printed to log

**names** [bool, optional] Whether name of the arguments be printed in the log

#### Examples

Regular operation

```
>>> with so.Workspace('w') as w:
>>>     for i in for_loop(range(1, 3)):
>>>         for j in for_loop(['a', 'b']):
>>>             put_item(i, j)
>>> print(so.to_optmodel(w))
proc optmodel;
    for {o2 in 1..2} do;
        for {o5 in {'a','b'}} do;
            put o2 o5;
        end;
    end;
quit;
```

Print with names

```
>>> with so.Workspace('w') as w:
>>>     x = so.VariableGroup(6, name='x', lb=0)
>>>     so.Objective(
>>>         so.expr_sum(x[i] for i in range(6)), name='z', sense=so.MIN)
>>>     a1 = so.Constraint(x[1] + x[2] + x[3] <= 4, name='a1')
>>>     for i in cofor_loop(so.exp_range(3, 6)):
>>>         fix(x[1], i)
>>>         solve()
>>>         put_item(i, x[1], so.Symbol('_solution_status_'), names=True)
proc optmodel;
    var x {{0,1,2,3,4,5}} >= 0;
    min z = x[0] + x[1] + x[2] + x[3] + x[4] + x[5];
    con a1 : x[1] + x[2] + x[3] <= 4;
    cofor {o13 in 3..5} do;
        fix x[1]=o13;
        solve;
        put o13= x[1]= _solution_status_=;
    end;
quit;
```

### sasoptpy.actions.expand

**expand**()

Prints expanded problem to output

#### Examples

```
>>> with so.Workspace(name='w') as w:
>>>     x = so.VariableGroup(3, name='x')
>>>     self.assertEqual(x[0].sym.get_conditions_str(), '')
>>>     # solve
>>>     x[0].set_value(1)
>>>     x[1].set_value(5)
>>>     x[2].set_value(0)
>>>     c = so.ConstraintGroup(None, name='c')
>>>     with iterate([0, 1, 2], 's') as i:
>>>         with condition(x[i].sym > 0):
>>>             c[i] = x[i] >= 1
>>>     set_objective(x[0], name='obj', sense=so.MIN)
>>>     expand()
>>>     solve()
>>> print(so.to_optmodel(w))
proc optmodel;
    var x {{0,1,2}};
    x[0] = 1;
    x[1] = 5;
    x[2] = 0;
    con c {s in {0,1,2}: x[s].sol > 0} : x[s] >= 1;
    MIN obj = x[0];
    expand;
    solve;
quit;
```

### sasoptpy.actions.drop

**drop**(**args*)

Drops given constraints or constraint groups from model

**Parameters**

**args** [*sasoptpy.Constraint*, *sasoptpy.ConstraintGroup*] Constraints to be dropped

**See also:**

*sasoptpy.actions.restore()*

### Examples

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x', lb=1)
>>>     y = so.Variable(name='y', lb=0)
>>>     c = so.Constraint(sm.sqrt(x) >= 5, name='c')
>>>     o = so.Objective(x + y, sense=so.MIN, name='obj')
>>>     s = solve()
>>>     drop(c)
>>>     o2 = so.Objective(x, sense=so.MIN, name='obj2')
>>>     s2 = solve()
>>> print(so.to_optmodel(w))
proc optmodel;
    var x >= 1;
    var y >= 0;
    con c : sqrt(x) >= 5;
    min obj = x + y;
    solve;
    drop c;
    min obj2 = x;
    solve;
quit;
```

## sasoptpy.actions.restore

**restore** (**args*)

Restores dropped constraint and constraint groups

**Parameters**

**args** [*sasoptpy.Constraint*, *sasoptpy.ConstraintGroup*] Constraints to be restored

**See also:**

*sasoptpy.actions.drop()*

### Examples

```
>>> with so.Workspace('w') as w:
>>>     x = so.Variable(name='x', lb=-1)
>>>     set_objective(x**3, name='xcube', sense=so.minimize)
>>>     c = so.Constraint(x >= 1, name='xbound')
>>>     solve()
>>>     drop(c)
>>>     solve()
>>>     restore(c)
>>>     solve()
>>> print(so.to_optmodel(w))
proc optmodel;
    var x >= -1;
    MIN xcube = (x) ^ (3);
    con xbound : x >= 1;
    solve;
    drop xbound;
```

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```
    solve;
    restore xbound;
    solve;
quit;
```

### sasoptpy.actions.union

**union** (**args*)

Aggregates given sets and set expressions

**Parameters**

**args** [*sasoptpy.abstract.Set* and `sasoptpy.abstract.InlineSet`] Objects to be aggregated

#### Examples

```
>>> from sasoptpy.actions import union, put_item
>>> with so.Workspace('w') as w:
>>>     n = so.Parameter(name='n', value=11)
>>>     S = so.Set(name='S', value=so.exp_range(1, n))
>>>     T = so.Set(name='T', value=so.exp_range(n+1, 20))
>>>     U = so.Set(name='U', value=union(S, T))
>>>     put_item(U, names=True)
>>> print(so.to_optmodel(w))
proc optmodel;
    num n = 11;
    set S = 1..n;
    set T = n+1..20;
    set U = S union T;
    put U=;
quit;
```

### sasoptpy.actions.diff

**diff** (*left*, *right*)

Gets the difference between set and set expressions

**Parameters**

**left** [*sasoptpy.abstract.Set*] Left operand

**right** [*sasoptpy.abstract.Set*] Right operand

### Examples

```
>>> from sasoptpy.actions import diff, put_item
>>> with so.Workspace('w') as w:
>>>     S = so.Set(name='S', value=so.exp_range(1, 20))
>>>     T = so.Set(name='T', value=so.exp_range(1, 15))
>>>     U = so.Set(name='U', value=diff(S, T))
>>>     put_item(U, names=True)
>>> print(so.to_optmodel(w))
proc optmodel;
    set S = 1..19;
    set T = 1..14;
    set U = S diff T;
    put U=;
quit;
```

## sasoptpy.actions.substring

**substring**(*main_string*, *first_pos*, *last_pos*)

Gets the substring of given positions

**Parameters**

**main_string** [*sasoptpy.abstract.Parameter* or string] Main string

**first_pos** [integer] First position of the substring, starting from 1

**last_pos** [integer] Last position of the substring

### Examples

```
>>> with so.Workspace('w') as w:
>>>     p = so.Parameter(name='p', value='random_string', ptype=so.STR)
>>>     r = so.Parameter(name='r', value=substring(p, 1, 6), ptype=so.STR)
>>>     put_item(r)
>>> print(so.to_optmodel(w))
proc optmodel;
    str p = 'random_string';
    str r = substr(p, 1, 6);
    put r;
quit;
```

## sasoptpy.actions.use_problem

**use_problem**(*problem*)

Changes the currently active problem

**Parameters**

**problem** [*sasoptpy.Model*] Model to be activated

### Examples

```
>>> from sasoptpy.actions import use_problem
>>> with so.Workspace('w') as w:
>>>     m = so.Model(name='m')
>>>     m2 = so.Model(name='m2')
>>>     use_problem(m)
>>>     x = so.Variable(name='x')
>>>     use_problem(m2)
>>>     m.solve()
>>>     m2.solve()
>>> print(so.to_optmodel(w))
proc optmodel;
    problem m;
    problem m2;
    use problem m;
    var x;
    use problem m2;
    use problem m;
    solve;
    use problem m2;
    solve;
quit;
```

## Math Functions

| | |
|---|---|
| math.math_func(exp, op, *args) | Function wrapper for math functions |
| math.abs(exp) | Absolute value function |
| math.log(exp) | Natural logarithm function |
| math.log2(exp) | Logarithm function to the base 2 |
| math.log10(exp) | Logarithm function to the base 10 |
| math.exp(exp) | Exponential function |
| math.sqrt(exp) | Square root function |
| math.mod(exp, divisor) | Modulo function |
| math.int(exp) | Integer value function |
| math.sign(exp) | Sign value function |
| math.max(exp, *args) | Largest value function |
| math.min(exp, *args) | Smallest value function |
| math.sin(exp) | Sine function |
| math.cos(exp) | Cosine function |
| math.tan(exp) | Tangent function |

### sasoptpy.math.math_func

**math_func**(*exp*, *op*, **args*)

Function wrapper for math functions

**Parameters**

**exp** [Expression] Expression where the math func will be applied

**op** [string] String representation of the math function

**args** [float, optional] Additional arguments

### sasoptpy.math.abs

**abs** (*exp*)
Absolute value function

### sasoptpy.math.log

**log** (*exp*)
Natural logarithm function

### sasoptpy.math.log2

**log2** (*exp*)
Logarithm function to the base 2

### sasoptpy.math.log10

**log10** (*exp*)
Logarithm function to the base 10

### sasoptpy.math.exp

**exp** (*exp*)
Exponential function

### sasoptpy.math.sqrt

**sqrt** (*exp*)
Square root function

### sasoptpy.math.mod

**mod** (*exp*, *divisor*)
Modulo function

**Parameters**

**exp** [Expression] Dividend

**divisor** [Expression] Divisor

#### sasoptpy.math.int

**int** (*exp*)
  Integer value function

#### sasoptpy.math.sign

**sign** (*exp*)
  Sign value function

#### sasoptpy.math.max

**max** (*exp*, **args*)
  Largest value function

#### sasoptpy.math.min

**min** (*exp*, **args*)
  Smallest value function

#### sasoptpy.math.sin

**sin** (*exp*)
  Sine function

#### sasoptpy.math.cos

**cos** (*exp*)
  Cosine function

#### sasoptpy.math.tan

**tan** (*exp*)
  Tangent function

## 5.5 Tests

### 5.5.1 Unit Tests

#### Core

| |
|---|
| *test_expression.TestExpression*([methodName]) |
| *test_objective.TestObjective*([methodName]) |

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Table 50 – continued from previous page

| | |
|---|---|
| `test_model.TestModel`([methodName]) | |
| `test_variable.TestVariable`([methodName]) | |
| `test_variable_group.TestVariableGroup`([…]) | |
| `test_constraint.TestConstraint`([methodName]) | |
| `test_constraint_group.TestConstraintGroup`([…]) | |
| `test_util.TestUtil`([methodName]) | |

### tests.core.test_expression.TestExpression

**class TestExpression**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.core.test_objective.TestObjective

**class TestObjective**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.core.test_model.TestModel

**class TestModel**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.core.test_variable.TestVariable

**class TestVariable**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.core.test_variable_group.TestVariableGroup

**class TestVariableGroup**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.core.test_constraint.TestConstraint

**class TestConstraint**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.core.test_constraint_group.TestConstraintGroup

**class TestConstraintGroup**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.core.test_util.TestUtil

**class TestUtil**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

## Abstract

| | |
|---|---|
| *test_math.TestAbstractMath*([methodName]) | |
| *test_set.TestSet*([methodName]) | |
| *test_set_iterator.TestSetIterator*([methodName]) | |
| *test_parameter.TestParameter*([methodName]) | |
| *test_implicit_variable.TestImplicitVariable*([...]) | |
| *test_condition.TestCondition*([methodName]) | |
| *statement.test_assignment.TestAssignment*([...]) | |
| *statement.test_cofor_loop.TestCoforLoop*([...]) | |
| *statement.test_create_data.TestCreateData*([...]) | |
| *statement.test_drop_restore.TestDropRestore*([...]) | |
| *statement.test_fix_unfix.TestFix*([methodName]) | |
| *statement.test_for_loop.TestForLoop*([methodName]) | |
| *statement.test_literal.TestLiteral*([methodName]) | |
| *statement.test_read_data.TestReadData*([...]) | |
| *statement.test_solve.TestSolve*([methodName]) | |

### tests.abstract.test_math.TestAbstractMath

**class TestAbstractMath**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.test_set.TestSet

**class TestSet**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.test_set_iterator.TestSetIterator

**class TestSetIterator**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.test_parameter.TestParameter

**class TestParameter**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.test_implicit_variable.TestImplicitVariable

**class TestImplicitVariable**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.test_condition.TestCondition

**class TestCondition**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_assignment.TestAssignment

**class TestAssignment**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_cofor_loop.TestCoforLoop

**class TestCoforLoop**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_create_data.TestCreateData

**class TestCreateData**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_drop_restore.TestDropRestore

**class TestDropRestore**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_fix_unfix.TestFix

**class TestFix**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_for_loop.TestForLoop

**class TestForLoop**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_literal.TestLiteral

**class TestLiteral**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_read_data.TestReadData

**class TestReadData**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### tests.abstract.statement.test_solve.TestSolve

**class TestSolve**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### Interface

| |
|---|
| `test_cas_interface.TestCASInterface`([methodName]) |
| `test_sas_interface.TestSASInterface`([methodName]) |

#### tests.interface.test_cas_interface.TestCASInterface

**class TestCASInterface**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

#### tests.interface.test_sas_interface.TestSASInterface

**class TestSASInterface**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

### Session

| | |
|---|---|
| *test_workspace.TestWorkspace*([methodName]) | |

#### tests.session.test_workspace.TestWorkspace

**class TestWorkspace**(*methodName='runTest'*)
Bases: `unittest.case.TestCase`

CHAPTER

SIX

# VERSION HISTORY

This page outlines changes from each release.

## 6.1 v0.2.1 (February 26, 2019)

### 6.1.1 New Features

- Support for evaluating nonlinear expressions is added, see `Expression.get_value()` and `utils._evaluate()`
- Support for multiple objectives is added for LSO solver, see `Model.set_objective()` and *Multiobjective* example
- Support for spaces inside variable indices is added
- Experimental RESTful API is added

### 6.1.2 Changes

- Dictionaries inside components are replaced with ordered dictionaries to preserve deterministic behavior
- Math operators are added into the keys of linear coefficient dictionaries
- Some iterators are rewritten by using the *yield* keyword for performance
- *key_name* and *col_names* parameters are added into `read_table()`

### 6.1.3 Bug Fixes

- Fixed: Using a single variable as an objective is producing incorrect input
- Fixed: `Expression.get_value()` fails to evaluate expressions with operators
- Fixed: `Expression.add()` overrides operators in some instances
- Fixed: Expressions with same components but different operators get summed incorrectly
- Fixed: New version of Viya complains about `pandas.DataFrame` column types
- Syntax fixes for **PEP 8** compliance

### 6.1.4 Notes

- A Jupyter notebook example of the Diet Problem is added
- A new example is added to show usage of experiment RESTful API
- Unit tests are added for development repository
- CD/CI integration is added for the development repository on Gitlab
- Generated models can be checked by using the hash values inside tests.responses

## 6.2 v0.2.0 (July 30, 2018)

### 6.2.1 New Features

- Support for the new *runOptmodel* CAS action is added
- Nonlinear optimization model building support is added for both SAS 9.4 and SAS Viya solvers
- Abstract model building support is added when by using SAS Viya solvers
- New object types, `Set`, `SetIterator`, `Parameter`, `ParameterValue`, `ImplicitVar`, `ExpressionDict`, and `Statement` are added for abstract model building
- `Model.to_optmodel()` method is added for exporting model objects into PROC OPTMODEL codes as a string
- Wrapper functions `read_table()` and `read_data()` are added to read CASTable and DataFrame objects into the models
- Math function wrappers are added
- `_expr` and `_defn` methods are added to all object types for producing OPTMODEL expression and definitions
- Multiple solutions are now being returned when by using *solveMilp* action and can be retrieved by using `Model.get_solution()` method
- `Model.get_variable_value()` is added to get solution values of abstract variables

### 6.2.2 Changes

- Variable and constraint naming schemes are replaced with OPTMODEL equivalent versions
- Variables and constraints now preserve the order they are inserted to the problem
- `Model.to_frame()` method is updated to reflect changes to VG and CG orderings
- Two solve methods, `Model.solve_on_cas()` and `Model.solve_on_viya()` are merged into `Model.solve()`
- `Model.solve()` method checks the available CAS actions and uses *runOptmodel* whenever possible
- As part of the merging process, `lp` and `milp` arguments are replaced with `options` argument in `Model.solve()` and `Model.to_optmodel()`
- An optional argument `frame` is added to `Model.solve()` for forcing to use MPS mode and *solveLp-solveMilp* actions
- Minor changes are applied to `__str__` and `__repr__` methods
- Creation indices for objects are being kept by using the return of the `register_name()` function

- Objective constant values are now being passed by using new CAS action arguments when posssible
- A linearity check is added for models
- Test folder is added to the repository

### 6.2.3 Bug Fixes

- Nondeterministic behavior when generating MPS files is fixed.

### 6.2.4 Notes

- Abstract and nonlinear models can be solved on Viya only if *runOptmodel* action is available on the CAS server.
- Three new examples are added which demonstrate abstract model building.
- Some minor changes are applied to the existing examples.

## 6.3 v0.1.2 (April 24, 2018)

### 6.3.1 New Features

- As an experimental feature, *sasoptpy* supports *saspy* connections now
- `Model.solve_local()` method is added for solving optimization problems by using SAS 9.4 installations
- *`Model.drop_variable()`*, *`Model.drop_variables()`*, *`Model.drop_constraint()`*, *`Model.drop_constraints()`* methods are added
- *`Model.get_constraint()`* and *`Model.get_constraints()`* methods are added to grab *`Constraint`* objects in a model
- *`Model.get_variables()`* method is added
- `_dual` attribute is added to the *`Expression`* objects
- *`Variable.get_dual()`* and `Constraint.get_dual()` methods are added
- *`Expression.set_name()`* method is added

### 6.3.2 Changes

- Session argument accepts `saspy.SASsession` objects
- *`VariableGroup.mult()`* method now supports `pandas.DataFrame`
- Type check for the *`Model.set_session()`* is removed to support new session types
- Problem and solution summaries are not being printed by default anymore, see *`Model.get_problem_summary()`* and *`Model.get_solution_summary()`*
- The default behavior of dropping the table after each solve is changed, but can be controlled with the `drop` argument of the *`Model.solve()`* method

### 6.3.3 Bug Fixes

- Fixed: Variables do not appear in MPS files if they are not used in the model
- Fixed: `Model.solve()` primalin argument does not pass into options

### 6.3.4 Notes

- A .gitignore file is added to the repository.
- A new example is added: Decentralization.
- Both *CAS/Viya* and *SAS* versions of the new example are available.
- There is a known issue with the nondeterministic behavior when creating MPS tables. This will be fixed with a hotfix after the release.
- A new option (no-ex) is added to makedocs script for skipping examples when building docs.

## 6.4 v0.1.1 (February 26, 2018)

### 6.4.1 New Features

- Initial value argument 'init' is added for `Variable` objects
- `Variable.set_init()` method is added for variables
- Initial value option 'primalin' is added to `Model.solve()` method
- Table name argument 'name', table drop option 'drop' and replace option 'replace' are added to `Model.solve()` method
- Decomposition block implementation is rewritten, block numbers does not need to be consecutive and ordered `Model.upload_user_blocks()`
- `VariableGroup.get_name()` and `ConstraintGroup.get_name()` methods are added
- `Model.test_session()` method is added for checking if session is defined for models
- `quick_sum()` function is added for faster summation of `Expression` objects

### 6.4.2 Changes

- methods.py is renamed to utils.py

### 6.4.3 Bug Fixes

- Fixed: Crash in VG and CG when a key not in the list is called
- Fixed: get_value of pandas is depreceated
- Fixed: Variables can be set as temporary expressions
- Fixed: Ordering in `get_solution_table()` is incorrect for multiple entries

## 6.5 v0.1.0 (December 22, 2017)

- Initial release

# PYTHON MODULE INDEX

## S

# INDEX

## Symbols



## A



## C



## D



## E



## F

## G



## I



## L



## M



## O



## P

## Q



## R



## S



## T

## U



## V



## W