sasoptpy Documentation

Release 0.1.1

SAS Institute Inc.

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sasoptpy is a Python package providing a modeling interface for SAS Viya Optimization solvers. It provides a quick way for users to deploy optimization models and solve them using CAS Action.

sasoptpy currently can handle linear optimization and mixed integer linear optimization problems. Users can benefit from native Python structures like dictionaries, tuples, and list to define an optimization problem. **sasoptpy** uses Pandas structures extensively.

Underlying methods for communication to SAS Viya are provided by the SAS-SWAT Package.

sasoptpy is merely 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.

CHAPTER

ONE

WHAT'S NEW

This page outlines changes from each release.

1.1 v0.1.1 (February 26, 2018)

1.1.1 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

1.1.2 Changes

- methods.py is renamed to utils.py

1.1.3 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

1.2 v0.1.0 (December 22, 2017)

- Initial release

CHAPTER

TWO

INSTALLATION

2.1 Python version support and dependencies

sasoptpy is developed and tested for Python version 3.5+.

It depends on the following packages:

- Pandas
- SAS-SWAT
- Numpy

Note: You need to download SAS-SWAT from the online repository before using **sasoptpy**.

2.2 Getting SAS-SWAT

SAS-SWAT should be available to use solver actions.

Releases are listed at https://github.com/sassoftware/python-swat/releases. After downloading the platform-specific release file, it can be installed using pip:

```
pip install python-swat-X.X.X-platform.tar.gz
```

2.3 Getting sasoptpy

Latest release of **sasoptpy** can be obtained from the online repository. 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
```

2.4 Step-by-step installation

1. **Installing pandas and numpy**

   First, download and install numpy and pandas using pip:

   ```
   pip install numpy
   pip install pandas
   ```

2. **Installing the SAS-SWAT package**

   First, check the SAS-SWAT release page to find the latest release of the SAS-SWAT package for your environment.

   Then install it using

   ```
   pip install python-swat-X.X.X.platform.tar.gz
   ```

   As an example, run

   ```
   wget https://github.com/sassoftware/python-swat/releases/download/v1.2.1/python-
   ↪swat-1.2.1-linux64.tar.gz
   pip install python-swat-1.2.1-linux64.tar.gz
   ```

   to install the version 1.2.1 of the SAS-SWAT package for 64-bit Linux environments.

3. **Installing sasoptpy**

   Finally you can install *sasoptpy* by downloading the latest archive file and install via pip.

   ```
   wget *url-to-sasoptpy.tar.gz*
   pip install sasoptpy.tar.gz
   ```

   Latest release file is available at Github releases page.

CHAPTER

THREE

GETTING STARTED

Solving an optimization problem via **sasoptpy** starts with having a running CAS Server. It is possible to model a problem without a server but solving a problem requires access to SAS Viya Optimization solvers.

3.1 Connecting to a CAS server

sasoptpy uses the CAS connection provided by the SAS-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 cases. See SAS-SWAT Documentation.

3.2 Initializing a model

After having an active CAS session, now an empty model can be defined 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.

3.3 Processing input data

The easiest way to work with **sasoptpy** is to define problem inputs as Pandas DataFrames. Objective and cost coefficients, and lower and upper bounds can be defined 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'])
   ...:
```

```
In [7]: price_per_product = 10

In [8]: capacity_cost = 10
```

Set PERIODS and other fields demand, min_production can be extracted as follows

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

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

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

Notice that PERIODS is a list, where both demand and min_production are Pandas Series objects.

3.4 Adding variables

Model objects have two different methods for adding variables.

- The first one is *Model.add_variable()* which 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 can be added to the model as m.add_variable(production_cap).

- The second one is *Model.add_variables()* where a set of variables can be added to the model.

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

  When passed as a set of variables, individual variables can be obtained by using individual keys, such as production['Period1']. To create multi-dimensional variables, simply list all the keys as multivar = m.add_variables(KEYS1, KEYS2, KEYS3, name='multivar').

3.5 Creating expressions

Expression objects keep linear 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
```

The first thing to notice is the use of the *VariableGroup.sum()* function over a variable group. This function returns the sum of variables inside the group as an *Expression* object. Its multiplication with a scalar profit_per_product gives the final expression.

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

3.6 Setting an objective function

Objective functions can be written in terms of linear expressions. In this problem, the objective is to maximize the profit, so *Model.set_objective()* function is used as follows:

```
In [16]: m.set_objective(totalRevenue-totalCost, sense=so.MAX, name='totalProfit')
Out[16]: sasoptpy.Expression(exp =  10.0 * production['Period2']  -  10.0 *␣
↪production_cap  +  10.0 * production['Period1']  +  10.0 * production['Period3'] ,␣
↪name='obj_1')
```

Notice that you can define the same objective 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.

3.7 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 functions to add constraints. The first one is *Model.add_constraint()* where a single constraint can be inserted into 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_cap  +  production['Period3']  <= ␣
↪0,  -  production_cap  +  production['Period1']  <=  0,  production['Period2']  - ␣
↪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['Period3']  <=  25,  production[
↪'Period1']  <=  30,  production['Period2']  <=  15, ], 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.

3.8 Solving a problem

Defined problems can be simply sent to CAS Servers by calling the *Model.solve()* function.

See the solution output to the problem.

```
In [19]: m.solve()
NOTE: Converting model my_first_model to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPX28FLEXD␣
↪in caslib CASUSERHDFS(casuser).
```

```
NOTE: The table TMPX28FLEXD has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem my_first_model has 4 variables (0 binary, 4 integer, 0 free, 0␣
↪fixed).
NOTE: The problem has 6 constraints (6 LE, 0 EQ, 0 GE, 0 range).
NOTE: The problem has 9 constraint coefficients.
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: Cloud Analytic Services dropped table TMPX28FLEXD from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                  Value
Label
Problem Name             my_first_model
Objective Sense            Maximization
Objective Function                obj_1
RHS                                 RHS

Number of Variables                   4
Bounded Above                         0
Bounded Below                         4
Bounded Above and Below               0
Free                                  0
Fixed                                 0
Binary                                0
Integer                               4

Number of Constraints                 6
LE (<=)                               6
EQ (=)                                0
GE (>=)                               0
Range                                 0

Constraint Coefficients               9
Solution Summary

                                Value
Label
Solver                           MILP
Algorithm              Branch and Cut
Objective Function              obj_1
Solution Status               Optimal
Objective Value                   400

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

Best Bound                        400
Nodes                               0
Iterations                          0
```

```
Presolve Time                         0.01
Solution Time                         0.01
Out[19]:
Selected Rows from Table PRIMAL

  _OBJ_ID_ _RHS_ID_               _VAR_ _TYPE_  _OBJCOEF_  _LBOUND_  \
0    obj_1      RHS      production_cap      I      -10.0       0.0
1    obj_1      RHS  production_Period1      I       10.0       5.0
2    obj_1      RHS  production_Period2      I       10.0       5.0
3    obj_1      RHS  production_Period3      I       10.0       0.0

         _UBOUND_  _VALUE_
0  1.797693e+308     25.0
1  1.797693e+308     25.0
2  1.797693e+308     15.0
3  1.797693e+308     25.0
```

As you can see, at the end of the solve operation, the CAS Server returns and prints both Problem Summary and Solution Summary tables. These tables can be later accessed using `m.get_problem_summary()` and `m.get_solution_summary`.

The *`Model.solve()`* function returns either the primal solution to the problem or `None` to catch any unexpected result.

3.9 Printing solutions

Solutions provided by the solver can be obtained using *`sasoptpy.get_solution_table()`* function. It is strongly suggested to group only variables and expressions that share the same keys.

```
In [20]: print(so.get_solution_table(demand, production))
         demand  production
1
Period1      30        25.0
Period2      15        15.0
Period3      25        25.0
```

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

3.10 Next steps

You can browse *Examples* to see various uses of aformentioned functionality.

If you have a good understanding of the flow, then check *API Reference* to access API details.

CHAPTER

FOUR

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.

4.1 Indices

Functions like *`Model.add_variables()`* can utilize native Python object types like list and range as variable and constraint indices. `pandas.Index` can be used as index as well.

4.1.1 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']]
  [Spring: production['Spring']]
  [Summer: production['Summer']]
  [Winter: production['Winter']]
]
```

```
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 accesible using the index keys. Accepted types are dict and pandas.Series.

4.1.2 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', ub=1,  vartype='BIN')
```

4.1.3 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')
```

4.2 Operations

Lists and `pandas.Series` objects can be used for mathematical operations like *`VariableGroup.mult()`*.

```
In [19]: sd = [3, 5, 6]

In [20]: z = m.add_variables(3, name='z')
```

```
In [21]: print(z)
Variable Group (z) [
  [0: z[0]]
  [1: z[1]]
  [2: z[2]]
]
```

```
In [22]: print(repr(z))
sasoptpy.VariableGroup([0, 1, 2], name='z')
```

```
In [23]: e1 = z.mult(sd)

In [24]: print(e1)
 3.0 * z[0]  +  5.0 * z[1]  +  6.0 * z[2]
```

```
In [25]: ps = pd.Series(sd)

In [26]: e2 = z.mult(ps)

In [27]: print(e2)
 3.0 * z[0]  +  5.0 * z[1]  +  6.0 * z[2]
```

CHAPTER

FIVE

SESSIONS AND MODELS

5.1 CAS Sessions

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

A sample CAS Session can be created using the following commands.

```
>>> 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))
```

5.2 Models

5.2.1 Creating a model

An empty model can be created using the *Model* constructor:

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

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

5.2.2 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 []
  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 []
  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 []
  Variables (2): [
    x
    y
  ]
  Constraints (1): [
     2.0 * y  +  x  <=  10
  ]
]
```

5.2.3 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()* function:

```
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 []
  Variables (2): [
    x
    y
  ]
  Constraints (0): [
  ]
```

```
]

In [12]: new_model.include(c1)

In [13]: print(new_model)
Model: [
  Name: new_model
  Objective: MIN []
  Variables (2): [
    x
    y
  ]
  Constraints (1): [
     2.0 * y  +  x  <=  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 []
  Variables (3): [
    x
    y
    z
  ]
  Constraints (1): [
     2.0 * y  +  x  <=  10
  ]
]
```

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

5.2.4 Copying a model

An exact copy of the existing model can be obtained by including the *Model* object itself.

```
In [17]: copy_model = so.Model(name='copy_model')
NOTE: Initialized model copy_model

In [18]: copy_model.include(m)

In [19]: print(copy_model)
Model: [
  Name: copy_model
  Objective: MIN []
  Variables (2): [
    x
    y
  ]
  Constraints (1): [
     2.0 * y  +  x  <=  10
```

```
  ]
]
```

Note that all variables and constraints are included by reference.

5.2.5 Solving a model

A model is solved using the *Model.solve()* function. This function converts Python definitions into an MPS file and uploads to a CAS server for the optimization action. The type of the optimization problem (Linear Optimization or Mixed Integer Linear Optimization) is determined based on variable types.

```
>>> 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.
NOTE: Data length = 189 rows
NOTE: Conversion to MPS =   0.0010 secs
NOTE: Upload to CAS time =  0.0710 secs
NOTE: Solution parse time = 0.1900 secs
NOTE: Server solve time =   0.1560 secs
```

5.2.6 Solve options

All options listed for the CAS solveLp and solveMilp actions can be used through *Model.solve()* function. LP options can passed to *Model.solve()* using `lp` argument, while MILP options can be passed using `milp` argument:

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

See http://go.documentation.sas.com/?cdcId=vdmmlcdc&cdcVersion=8.11&docsetId=casactmopt&docsetTarget=casactmopt_solvelp_syntax.htm&locale=en for a list of LP options.

See http://go.documentation.sas.com/?cdcId=vdmmlcdc&cdcVersion=8.11&docsetId=casactmopt&docsetTarget=casactmopt_solvemilp_syntax.htm&locale=en for a list of MILP options.

5.2.7 Getting solutions

After the solve is completed, all variable and constraint values are parsed automatically. A summary of the problem can be accessed using the *Model.get_problem_summary()* function, and a summary of the solution can be accesed using the *Model.get_solution_summary()* function.

To print values of any object, *get_solution_table()* can be used:

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

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

CHAPTER

SIX

MODEL COMPONENTS

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

6.1 Expressions

`Expression` objects represent linear expressions in **sasoptpy**.

6.1.1 Creating expressions

An `Expression` can be created as follows:

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

In [2]: print(repr(profit))
sasoptpy.Expression(exp =  5.0 * sales  -  3.0 * material , name='profit')
```

6.1.2 Operations

Getting the current value

After the solve is completed, the current value of an expression can be obtained using the `Expression.get_value()` function:

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

Addition

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

```
In [3]: tax = 0.5

In [4]: profit_after_tax = profit - tax
```

```
In [5]: print(repr(profit_after_tax))
sasoptpy.Expression(exp =  5.0 * sales  -  0.5  -  3.0 * material , name=None)
```

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

```
In [6]: profit_after_tax = profit.add(tax, sign=-1)
```

```
In [7]: print(profit_after_tax)
 5.0 * sales  -  0.5  -  3.0 * material
```

```
In [8]: print(repr(profit_after_tax))
sasoptpy.Expression(exp =  5.0 * sales  -  0.5  -  3.0 * material , name=None)
```

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

Multiplication

You can only multiply a number with an existing *Expression* object:

```
In [9]: investment = profit.mult(0.2)

In [10]: print(investment)
 sales  -  0.6000000000000001 * material
```

6.1.3 Copying an expression

An *Expression* can be copied using *Expression.copy()*.

```
In [11]: copy_profit = profit.copy(name='copy_profit')

In [12]: print(repr(copy_profit))
sasoptpy.Expression(exp =  5.0 * sales  -  3.0 * material , name='copy_profit')
```

6.1.4 Temporary expressions

An *Expression* object can be defined as temporary, which enables faster `Expression.sum()` and *Expression.mult()* operations.

```
In [13]: new_profit = so.Expression(10 * sales - 2 * material, temp=True)

In [14]: print(repr(new_profit))
sasoptpy.Expression(exp =  10.0 * sales  -  2.0 * material , name=None)
```

The expression can be modified inside a function:

```
In [15]: new_profit + 5
Out[15]: sasoptpy.Expression(exp =  10.0 * sales  +  5  -  2.0 * material , name=None)
```

```
In [16]: print(repr(new_profit))
sasoptpy.Expression(exp =  10.0 * sales  +  5  -  2.0 * material , name=None)
```

As you can see, the value of `new_profit` is changed due to an in-place addition. To prevent the change, such expressions can be converted to permanent expressions using the *Expression.set_permanent()* function or constructor:

```
In [17]: new_profit = so.Expression(10 * sales - 2 * material, temp=True)

In [18]: new_profit.set_permanent()
Out[18]: 'expr_1'
```

```
In [19]: tmp = new_profit + 5

In [20]: print(repr(new_profit))
sasoptpy.Expression(exp =  10.0 * sales  -  2.0 * material , name='expr_1')
```

6.2 Objective Functions

6.2.1 Setting and getting an objective function

Any valid *Expression* can be used as the objective function of a model. An existing expression can be used as an objective function using the *Model.set_objective()* function. The objective function of a model can be obtained using the *Model.get_objective()* function.

```
>>> 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
```

6.2.2 Getting the value

After a solve, the objective value can be checked using the `Expression.get_objective_value()` function.

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

6.3 Variables

6.3.1 Creating variables

Variables can be created either separately 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)
```

and

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

are equivalent.

Creating a variable inside a model

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

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

6.3.2 Arguments

There are three types of variables: continuous variables, integer variables, and binary variables. Continuous variables are the default type and can be created using the `vartype=so.CONT` argument. Integer variables and binary variables can be created 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. If the given name already exists in the namespace, then a different generic name can be used for the variable. The *reset_globals()* function can be used to reset sasoptpy namespace when needed.

6.3.3 Changing bounds

The function *Variable.set_bounds()* can change 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')
```

6.3.4 Working with a set of variables

A set of variables can be added using single or multiple indices. Valid index sets include list, dict, and `pandas.Index` objects. See *Handling Data* for more 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')
```

6.4 Constraints

6.4.1 Creating constraints

Similar to *Variable* objects, *Constraint* objects can be created inside or outside optimization models.

Creating a constraint outside a model

```
>>> c1 = sasoptpy.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')
```

6.4.2 Modifying variable coefficients

The coefficient of a variable inside a constraint can be updated using the *Constraint.update_var_coef()* function:

```
>>> 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')
```

6.4.3 Working with a set of constraints

A set of constraints can be added using single or multiple indices. Valid index sets include list, dict, and `pandas.Index` objects. See *Handling Data* for more about allowed index types.

Creating a set of variables 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 variables 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]
  [(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]
]
```

CHAPTER

SEVEN

API REFERENCE

7.1 Classes

`Model`(name[, session])	Creates an optimization model
`Expression`([exp, name, temp])	Creates a linear expression to represent model components
`Variable`(name[, vartype, lb, ub, init])	Creates an optimization variable to be used inside models
`VariableGroup`(*argv, name[, vartype, lb, . . .])	Creates a group of `Variable` objects
`Constraint`(exp[, direction, name, crange])	Creates a linear or quadratic constraint for optimization models
`ConstraintGroup`(argv, name)	Creates a group of `Constraint` objects

7.1.1 sasoptpy.Model

class sasoptpy.**Model**(*name*, *session=None*)

Creates an optimization model

Parameters **name** : string

Name of the model

session : `swat.cas.connection.CAS` object, optional

CAS 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
```

Methods

add_constraint(c[, name])	Adds a single constraint to the model
add_constraints(argv[, cg, name])	Adds a set of constraints to the model
add_variable([var, vartype, name, lb, ub, init])	Adds a new variable to the model
add_variables(*argv[, vg, name, vartype, . . .])	Adds a group of variables to the model
get_objective()	Returns the objective function as an *Expression* object
get_objective_value()	Returns the optimal objective value, if it exists
get_problem_summary()	Returns the problem summary table to the user
get_solution([vtype])	Returns the solution details associated with the primal or dual
get_solution_summary()	Returns the solution summary table to the user
get_variable(name)	Returns the reference to a variable in the model
get_variable_coef(var)	Returns the objective value coefficient of a variable
include(*argv)	Adds existing variables and constraints to a model
print_solution()	Prints the current values of the variables
set_coef(var, con, value)	Updates the coefficient of a variable inside constraints
set_objective(expression, sense[, name])	Sets the objective function for the model
set_session(session)	Sets the CAS session for model
solve([milp, lp, name, drop, replace, primalin])	Solves the model by calling CAS optimization solvers
test_session()	
to_frame()	Converts the Python model into a DataFrame object in MPS format
upload_model([name, replace])	
upload_user_blocks()	Uploads user-defined decomposition blocks to the CAS server

sasoptpy.Model.add_constraint

`Model.`**`add_constraint`**(*c*, *name=None*)

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 *Constraint* object

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**(*argv*, *cg=None*, *name=None*)
Adds a set of constraints to the model

Parameters **argv** : Generator type objects

List of constraints as a Generator-type object

cg : *ConstraintGroup* object, optional

An existing list of constraints if an existing group is being added

name : string, optional

Name for the constraint group and individual constraint prefix

Returns *ConstraintGroup* object

A group object for all constraints aded

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.add_variable

Model.**add_variable**(*var=None*, *vartype='CONT'*, *name=None*, *lb=0*, *ub=inf*, *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 **var** : `Variable` object, optional

Existing variable to be added to the problem

vartype : string, optional

Type of the variable, either 'BIN', 'INT' or 'CONT'

name : string, optional

Name of the variable to be created

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 `Variable` object

Variable that is added to the model

See also:

`sasoptpy.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.add_variable(var=y)
```

sasoptpy.Model.add_variables

`Model.`**`add_variables`**(**argv*, *vg=None*, *name=None*, *vartype='CONT'*, *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

vg : *VariableGroup* object, optional

An existing object if it is being added to the model

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

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.get_objective

`Model.get_objective()`

Returns the objective function as an *Expression* object

Returns **:class:'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_objective_value

`Model.`**`get_objective_value`**`()`

Returns the optimal objective value, if it exists

Returns float : Objective value at current solution

Examples

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

sasoptpy.Model.get_problem_summary

`Model.`**`get_problem_summary`**`()`

Returns the problem summary table to the user

Returns `swat.dataframe.SASDataFrame` object

Problem summary obtained after *`sasoptpy.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_solution

Model.**get_solution**(*vtype='Primal'*)

Returns the solution details associated with the primal or dual solution

Parameters **vtype** : string, optional

'Primal' or 'Dual'

Returns `pandas.DataFrame` object

Primal or dual solution table returned from the CAS Action

Examples

```
>>> m.solve()
>>> print(m.get_solution('Primal'))
      _OBJ_ID_ _RHS_ID_                _VAR_ _TYPE_  _OBJCOEF_  _LBOUND_
0  totalProfit      RHS      production_cap      I      -10.0       0.0
1  totalProfit      RHS  production_Period1      I       10.0       5.0
2  totalProfit      RHS  production_Period2      I       10.0       5.0
3  totalProfit      RHS  production_Period3      I       10.0       0.0
     _UBOUND_  _VALUE_
1.797693e+308     25.0
1.797693e+308     25.0
1.797693e+308     15.0
1.797693e+308     25.0
```

```
>>> print(m.get_solution('Dual'))
      _OBJ_ID_ _RHS_ID_       _ROW_ _TYPE_  _RHS_  _L_RHS_  _U_RHS_
0  totalProfit      RHS  capacity_0      L    0.0      NaN      NaN
1  totalProfit      RHS  capacity_1      L    0.0      NaN      NaN
2  totalProfit      RHS  capacity_2      L    0.0      NaN      NaN
3  totalProfit      RHS    demand_0      L   30.0      NaN      NaN
4  totalProfit      RHS    demand_1      L   15.0      NaN      NaN
```

```
5  totalProfit       RHS     demand_2       L    25.0       NaN       NaN
_ACTIVITY_
       0.0
     -10.0
       0.0
      25.0
      15.0
      25.0
```

sasoptpy.Model.get_solution_summary

Model.**get_solution_summary**()

Returns the solution summary table to the user

Returns `swat.dataframe.SASDataFrame` object

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_variable

`Model.get_variable(name)`

Returns the reference to a variable in the model

Parameters **name** : string

Name or key of the variable requested

Returns `Variable` object

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_variable_coef

`Model.get_variable_coef(var)`

Returns the objective value coefficient of a variable

Parameters **var** : `Variable` object or string

Variable whose objective value is requested or its name

Returns 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.include

`Model.include(*argv)`

Adds existing variables and constraints to a model

Parameters **argv** : `Model`, `Variable`, `Constraint`,

`VariableGroup`, `ConstraintGroup` Objects to be included in the model

Notes

- This method is essentially a wrapper for two methods, `sasoptpy.Model.add_variable()` and `sasoptpy.Model.add_constraint()`.
- 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 its elements)

```
>>> new_model = so.Model(name='new_model')
>>> new_model.include(m)
```

sasoptpy.Model.print_solution

`Model.`**`print_solution`**`()`

Prints the current values of the variables

See also:

`sasoptpy.Model.get_solution()`

Examples

```
>>> m.solve()
>>> m.print_solution()
x: 2.0
y: 0.0
```

sasoptpy.Model.set_coef

`Model.set_coef(var, con, value)`

Updates the coefficient of a variable inside constraints

Parameters **var** : `Variable` object

Variable whose coefficient will be updated

con : `Constraint` object

Constraint where the coefficient will be updated

value : float

The new value for the coefficient of the variable

See also:

`sasoptpy.Constraint.update_var_coef()`

Notes

Variable coefficient inside the constraint is replaced in-place.

Examples

```
>>> c1 = m.add_constraint(x + y >= 1, name='c1')
>>> print(c1)
y  +  x  >=  1
>>> m.set_coef(x, c1, 3)
>>> print(c1)
y  +  3.0 * x  >=  1
```

sasoptpy.Model.set_objective

`Model.set_objective(expression, sense, name=None)`

Sets the objective function for the model

Parameters **expression** : `Expression` object

The objective function as an Expression

sense : string

Objective value direction, 'MIN' or 'MAX'

name : string, optional

Name of the objective value

Returns `Expression`

Objective function as an `Expression` object

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')
```

sasoptpy.Model.set_session

`Model.set_session(session)`

Sets the CAS session for model

Parameters **session** : `swat.cas.connection.CAS`

CAS Session

sasoptpy.Model.solve

`Model.solve(milp={}, lp={}, name=None, drop=True, replace=True, primalin=False)`

Solves the model by calling CAS optimization solvers

Parameters **milp** : dict, optional

A dictionary of MILP options for the solveMilp CAS Action

lp : dict, optional

A dictionary of LP options for the solveLp CAS Action

name : string, optional

Name of the table name on CAS Server

drop : boolean, optional

Switch for dropping the MPS table on CAS Server after solve

replace : boolean, optional

Switch for replacing an existing MPS table on CAS Server

primalin : boolean, optional

Switch for using initial values (for MIP only)

Returns `pandas.DataFrame` object

Solution of the optimization model

Notes

- This method takes two optional arguments (milp and lp).
- These arguments pass options to the solveLp and solveMilp CAS actions.

- Both milp and lp should be defined as dictionaries, where keys are option names. For example, `m.solve(milp={'maxtime': 600})` limits solution time to 600 seconds.
- See http://go.documentation.sas.com/?cdcId=vdmmlcdc&cdcVersion=8.11&docsetId=casactmopt&docsetTarget=casactmopt_solvelp_syntax.htm&locale=en for a list of LP options.
- See http://go.documentation.sas.com/?cdcId=vdmmlcdc&cdcVersion=8.11&docsetId=casactmopt&docsetTarget=casactmopt_solvemilp_syntax.htm&locale=en for a list of MILP 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.
NOTE: Data length = 419 rows
NOTE: Conversion to MPS =   0.0010 secs
NOTE: Upload to CAS time =  0.1420 secs
NOTE: Solution parse time = 0.2500 secs
NOTE: Server solve time =   0.1168 secs
```

```
>>> m.solve(milp={'maxtime': 600})
```

```
>>> m.solve(lp={'algorithm': 'ipm'})
```

sasoptpy.Model.test_session

`Model.test_session()`

sasoptpy.Model.to_frame

`Model.to_frame()`

Converts the Python model into a DataFrame object in MPS format

Returns `pandas.DataFrame` object

Problem in strict MPS format

Notes

- This method is called inside *`sasoptpy.Model.solve()`*.

Examples

```
>>> df = m.to_frame()
>>> print(df)
     Field1 Field2  Field3 Field4 Field5 Field6 _id_
```

```
0       NAME          model1      0           0    1
1       ROWS                                       2
2        MAX     obj                               3
3          L      c1                               4
4    COLUMNS                                       5
5                  x      obj     4                6
6                  x       c1     3                7
7                  y      obj    -5                8
8                  y       c1     1                9
9        RHS                                      10
10               RHS       c1     6               11
11    RANGES                                      12
12    BOUNDS                                      13
13    ENDATA                      0           0   14
```

sasoptpy.Model.upload_model

`Model.`**`upload_model`**`(`*name=None*, *replace=True*`)`

sasoptpy.Model.upload_user_blocks

`Model.`**`upload_user_blocks`**`()`

Uploads user-defined decomposition blocks to the CAS server

Returns string

CAS table name of the user-defined decomposition blocks

Examples

```
>>> userblocks = m.upload_user_blocks()
>>> m.solve(milp={'decomp': {'blocks': userblocks}})
```

7.1.2 sasoptpy.Expression

class `sasoptpy.`**`Expression`**`(`*exp=None*, *name=None*, *temp=False*`)`

Creates a linear expression to represent model components

Parameters **exp** : *`Expression`* object, 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
>>> print(profit)
 5.0 * sales  -  3.0 * material
>>> print(repr(profit))
sasoptpy.Expression(exp =  5.0 * sales  -  3.0 * material , name=None)
```

Methods

add(other[, sign])	Combines two expressions and produces a new one
copy([name])	Returns a copy of the *Expression* object
get_name()	Returns the name of the expression
get_value()	Returns the value of the expression after variable values are changed
mult(other)	Multiplies the *Expression* with a scalar value
set_permanent([name])	Converts a temporary expression into a permanent one

sasoptpy.Expression.add

Expression.**add**(*other*, *sign=1*)

Combines two expressions and produces a new one

Parameters **other** : float or *Expression* object

Second expression or constant value to be added

sign : int, optional

Sign of the addition, 1 or -1

in_place : boolean, optional

Whether the addition will be performed in place or not

Returns *Expression* object

Notes

- This method is mainly for internal use.
- Adding an expression is equivalent to calling this method: (x-y)+(3*x-2*y) and (x-y).add(3*x-2*y) are interchangeable.

sasoptpy.Expression.copy

Expression.**copy**(*name=None*)

Returns a copy of the *Expression* object

Parameters name : string, optional

Name for the copy

Returns *Expression* object

Copy of the object

Examples

```
>>> 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.get_name

Expression.**get_name**()

Returns the name of the expression

Returns string

Name of the expression

Examples

```
>>> var1 = m.add_variables(name='x')
>>> print(var1.get_name())
x
```

sasoptpy.Expression.get_value

Expression.**get_value**()

Returns the value of the expression after variable values are changed

Returns float

Value of the expression

Examples

```
>>> profit = so.Expression(5 * sales - 3 * material)
>>> m.solve()
>>> print(profit.get_value())
41.0
```

sasoptpy.Expression.mult

Expression.**mult**(*other*)
Multiplies the *Expression* with a scalar value

Parameters **other** : *Expression* or int

Second expression to be multiplied

Returns *Expression* object

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.set_permanent

Expression.**set_permanent**(*name=None*)
Converts a temporary expression into a permanent one

Parameters **name** : string, optional

Name of the expression

Returns string

Name of the expression in the namespace

7.1.3 sasoptpy.Variable

class sasoptpy.**Variable**(*name*, *vartype='CONT'*, *lb=0*, *ub=inf*, *init=None*)
Creates an optimization variable to be used inside models

Parameters **name** : string

Name of the variable

vartype : string, optional

Type of the variable

lb : float, optional

Lower bound of the variable

ub : float, optional

Upper bound of the variable

init : float, optional

Initial value of the variable

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')
```

Methods

add(other[, sign])	Combines two expressions and produces a new one
copy([name])	Returns a copy of the *Expression* object
get_name()	Returns the name of the expression
get_value()	Returns the value of the expression after variable values are changed
mult(other)	Multiplies the *Expression* with a scalar value
set_bounds([lb, ub])	Changes bounds on a variable
set_init([init])	Changes initial value of a variable
set_permanent([name])	Converts a temporary expression into a permanent one

sasoptpy.Variable.add

Variable.**add**(*other*, *sign=1*)

Combines two expressions and produces a new one

Parameters other : float or *Expression* object

Second expression or constant value to be added

sign : int, optional

Sign of the addition, 1 or -1

in_place : boolean, optional

Whether the addition will be performed in place or not

Returns *Expression* object

Notes

- This method is mainly for internal use.

- Adding an expression is equivalent to calling this method: (x-y)+(3*x-2*y) and (x-y).add(3*x-2*y) are interchangeable.

sasoptpy.Variable.copy

`Variable.copy(name=None)`

Returns a copy of the *Expression* object

Parameters name : string, optional

Name for the copy

Returns *Expression* object

Copy of the object

Examples

```
>>> 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_name

`Variable.get_name()`

Returns the name of the expression

Returns string

Name of the expression

Examples

```
>>> var1 = m.add_variables(name='x')
>>> print(var1.get_name())
x
```

sasoptpy.Variable.get_value

`Variable.get_value()`

Returns the value of the expression after variable values are changed

Returns float

Value of the expression

Examples

```
>>> profit = so.Expression(5 * sales - 3 * material)
>>> m.solve()
>>> print(profit.get_value())
41.0
```

sasoptpy.Variable.mult

`Variable.mult(other)`

Multiplies the `Expression` with a scalar value

Parameters **other** : `Expression` or int

Second expression to be multiplied

Returns `Expression` object

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.Variable.set_bounds

`Variable.set_bounds(lb=None, ub=None)`

Changes bounds on a variable

Parameters **lb** : float

Lower bound of the variable

ub : float

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(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.set_permanent

`Variable.`**`set_permanent`**(*name=None*)

Converts a temporary expression into a permanent one

Parameters **name** : string, optional

Name of the expression

Returns string

Name of the expression in the namespace

7.1.4 sasoptpy.VariableGroup

`class` `sasoptpy.`**`VariableGroup`**(**argv*, *name*, *vartype='CONT'*, *lb=0*, *ub=inf*, *init=None*)

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

get_name()	Returns the name of the variable group
mult(vector)	Quick multiplication method for the variable groups
set_bounds([lb, ub])	Sets / updates bounds for the given variable

Continued on next page

Table 7.5 – continued from previous page

sum(*argv)	Quick sum method for the variable groups

sasoptpy.VariableGroup.get_name

`VariableGroup.get_name()`

Returns the name of the variable group

Returns string

Name of the variable group

Examples

```
>>> var1 = m.add_variables(4, name='x')
>>> print(var1.get_name())
x
```

sasoptpy.VariableGroup.mult

`VariableGroup.mult(vector)`

Quick multiplication method for the variable groups

Parameters **vector** : list, dictionary, or `pandas.Series` object

Vector to be multiplied with the variable group

Returns *Expression* object

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']
```

sasoptpy.VariableGroup.set_bounds

`VariableGroup.set_bounds(lb=None, ub=None)`
Sets / updates bounds for the given variable

Parameters **lb** : Lower bound, optional

ub : Upper bound, optional

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.sum

`VariableGroup.sum(*argv)`
Quick sum method for the variable groups

Parameters **argv** : Arguments

List of indices for the sum

Returns *Expression* object

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']
```

7.1.5 sasoptpy.Constraint

class sasoptpy.**Constraint**(*exp*, *direction=None*, *name=None*, *crange=0*)

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

range : 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

```
>>> 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

```
>>> 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

add(other[, sign])	Combines two expressions and produces a new one
copy([name])	Returns a copy of the Expression object
get_name()	Returns the name of the expression
get_value([rhs])	Returns the current value of the constraint
mult(other)	Multiplies the Expression with a scalar value
set_block(block_number)	Sets the decomposition block number for a constraint
set_direction(direction)	Changes the direction of a constraint
set_permanent([name])	Converts a temporary expression into a permanent one
set_rhs(value)	Changes the RHS of a constraint
update_var_coef(var, value)	Updates the coefficient of a variable inside the constraint

sasoptpy.Constraint.add

`Constraint.add(other, sign=1)`

Combines two expressions and produces a new one

Parameters **other** : float or `Expression` object

Second expression or constant value to be added

sign : int, optional

Sign of the addition, 1 or -1

in_place : boolean, optional

Whether the addition will be performed in place or not

Returns `Expression` object

Notes

- This method is mainly for internal use.
- Adding an expression is equivalent to calling this method: (x-y)+(3*x-2*y) and (x-y).add(3*x-2*y) are interchangeable.

sasoptpy.Constraint.copy

`Constraint.copy(name=None)`

Returns a copy of the `Expression` object

Parameters **name** : string, optional

Name for the copy

Returns `Expression` object

Copy of the object

Examples

```
>>> 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.Constraint.get_name

`Constraint.get_name()`

Returns the name of the expression

Returns string

Name of the expression

Examples

```
>>> var1 = m.add_variables(name='x')
>>> print(var1.get_name())
x
```

sasoptpy.Constraint.get_value

`Constraint.get_value(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

```
>>> m.solve()
>>> print(c1.get_value())
6.0
>>> print(c1.get_value(rhs=True))
0.0
```

sasoptpy.Constraint.mult

`Constraint.mult(other)`

Multiplies the `Expression` with a scalar value

Parameters other : `Expression` or int

Second expression to be multiplied

Returns `Expression` object

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.Constraint.set_block

`Constraint.set_block(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(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_permanent

`Constraint.set_permanent(name=None)`

Converts a temporary expression into a permanent one

Parameters **name** : string, optional

Name of the expression

Returns string

Name of the expression in the namespace

sasoptpy.Constraint.set_rhs

`Constraint.set_rhs(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(var, value)`
Updates the coefficient of a variable inside the constraint

Parameters **var** : *Variable* object

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')
```

7.1.6 sasoptpy.ConstraintGroup

class `sasoptpy.ConstraintGroup(argv, name)`
Creates a group of *Constraint* objects

Parameters **argv** : GeneratorType object

A Python generator that includes `sasoptpy.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

`get_expressions`([rhs])	Returns constraints as a list of expressions
`get_name`()	Returns the name of the constraint group

sasoptpy.ConstraintGroup.get_expressions

`ConstraintGroup.`**`get_expressions`**`(`*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 `pandas.DataFrame`

Returns a DataFrame consisting of constraints as expressions

Examples

```
>>> cg = so.ConstraintGroup((u[i] + 2 * t <= 5 for i in var_ind),
                             name='cg')
>>> ce = cg.get_expressions()
>>> print(ce)
                     cg
c   u['c']  +  2.0 * t
b   u['b']  +  2.0 * t
d   u['d']  +  2.0 * t
a   u['a']  +  2.0 * t
>>> ce_rhs = cg.get_expressions(rhs=True)
>>> print(ce_rhs)
                              cg
b      u['b']  -  5  +  2.0 * t
c   -  5  +  u['c']  +  2.0 * t
d   -  5  +  u['d']  +  2.0 * t
a   -  5  +  2.0 * t  +  u['a']
```

sasoptpy.ConstraintGroup.get_name

`ConstraintGroup.get_name()`

Returns the name of the constraint group

Returns string

Name of the constraint group

Examples

```
>>> c1 = m.add_constraints((x + y[i] <= 4 for i in indices),
                            name='con1')
>>> print(c1.get_name())
con1
```

7.2 Functions

check_name(name[, ctype])	Checks if a name is in valid and returns a random string if not
dict_to_frame(dictobj[, cols])	Converts dictionaries to DataFrame objects for pretty printing
extract_list_value(tuplist, listname)	Extracts values inside various object types
flatten_frame(df)	Converts a `pandas.DataFrame` object into a `pandas.Series`
get_counter(ctrtype)	Returns and increments the list counter for naming
get_namespace()	Prints details of components registered to the global name dictionary

Continued on next page

Table 7.8 – continued from previous page

get_obj_by_name(name)	Returns the reference to an object by using the unique name
get_solution_table(*argv[, sort, rhs])	Returns the requested variable names as a DataFrame table
list_length(listobj)	Returns the length of an object if it is a list, tuple or dict
print_model_mps(model)	Prints the MPS representation of the model
quick_sum(argv)	Quick summation function for Expression objects
read_frame(df[, cols])	Reads each column in pandas.DataFrame into a list of pandas.Series objects
register_name(name, obj)	Adds the name of a component into the global reference list
reset_globals()	Deletes the references inside the global dictionary and restarts counters
tuple_pack(obj)	Converts a given object to a tuple object
tuple_unpack(tp)	Grabs the first element in a tuple, if a tuple is given as argument

7.2.1 sasoptpy.check_name

sasoptpy.**check_name**(*name*, *ctype=None*)

Checks if a name is in valid and returns a random string if not

Parameters **name** : str

Name to be checked if unique

Returns **str** : The given name if valid, a random string otherwise

7.2.2 sasoptpy.dict_to_frame

sasoptpy.**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 DataFrame object

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
```

7.2.3 sasoptpy.extract_list_value

`sasoptpy.extract_list_value(tuplist, listname)`

Extracts values inside various object types

Parameters **tuplist** : tuple

Key combination to be extracted

listname : dict or list or int or float or DataFrame or Series object

List where the value will be extracted

Returns object

Corresponding value inside listname

7.2.4 sasoptpy.flatten_frame

`sasoptpy.flatten_frame(df)`

Converts a `pandas.DataFrame` object into a `pandas.Series` object where indices are tuples of row and column indices

Parameters **df** : `pandas.DataFrame` object

Returns `pandas.DataFrame` object

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
```

7.2.5 sasoptpy.get_counter

sasoptpy.**get_counter**(*ctrtype*)

Returns and increments the list counter for naming

Parameters ctrtype : string

Type of the counter, 'obj', 'var', 'con' or 'expr'

Returns int

Current value of the counter

7.2.6 sasoptpy.get_namespace

sasoptpy.**get_namespace**()

Prints details of components registered to the global name dictionary

The list includes models, variables, constraints and expressions

7.2.7 sasoptpy.get_obj_by_name

sasoptpy.**get_obj_by_name**(*name*)

Returns the reference to an object by using the unique name

Returns object

Reference to the object that has the name

See also:

reset_globals()

Notes

If there is a conflict in the namespace, you might not get the object you request. Clear the namespace using *reset_globals()* when needed.

Examples

```
>>> m.add_variable(name='var_x', lb=0)
>>> m.add_variables(2, name='var_y', vartype=so.INT)
>>> x = so.get_obj_by_name('var_x')
>>> y = so.get_obj_by_name('var_y')
>>> print(x)
>>> print(y)
>>> m.add_constraint(x + y[0] <= 3, name='con_1')
>>> c1 = so.get_obj_by_name('con_1')
>>> print(c1)
var_x
Variable Group var_y
[(0,): Variable [ var_y_0 | INT ]]
[(1,): Variable [ var_y_1 | INT ]]
var_x  +  var_y_0  <=  3
```

7.2.8 sasoptpy.get_solution_table

sasoptpy.**get_solution_table**(**argv*, *sort=True*, *rhs=False*)

Returns the requested variable names as a DataFrame table

Parameters sort : bool, optional

Sort option for the indices

Returns pandas.DataFrame

DataFrame object that holds keys and values

7.2.9 sasoptpy.list_length

sasoptpy.**list_length**(*listobj*)

Returns the length of an object if it is a list, tuple or dict

Parameters listobj : Python object

Returns int

Length of the list, tuple or dict, otherwise 1

7.2.10 sasoptpy.print_model_mps

sasoptpy.**print_model_mps**(*model*)

Prints the MPS representation of the model

Parameters model : *Model* object

See also:

sasoptpy.Model.to_frame()

Examples

```
>>> m = so.Model(name='print_example', session=s)
>>> x = m.add_variable(lb=1, name='x')
>>> y = m.add_variables(2, name='y', ub=3, vartype=so.INT)
>>> m.add_constraint(x + y.sum('*') <= 9, name='c1')
>>> m.add_constraints((x + y[i] >= 2 for i in [0, 1]), name='c2')
>>> m.set_objective(x+3*y[0], sense=so.MAX, name='obj')
>>> so.print_model_mps(m)
NOTE: Initialized model print_example
     Field1     Field2          Field3 Field4     Field5 Field6 _id_
0      NAME            print_example      0                  0     1
1      ROWS                                                        2
2       MAX        obj                                             3
3         L         c1                                             4
4         G       c2_0                                             5
5         G       c2_1                                             6
6   COLUMNS                                                        7
7                    x             obj      1                      8
8                    x              c1      1                      9
9                    x            c2_0      1                     10
10                   x            c2_1      1                     11
```

```
11          MARK0000       'MARKER'          'INTORG'          12
12               y_0            obj       3                    13
13               y_0             c1       1                    14
14               y_0           c2_0       1                    15
15               y_1             c1       1                    16
16               y_1           c2_1       1                    17
17          MARK0001       'MARKER'          'INTEND'          18
18      RHS                                                    19
19               RHS             c1       9                    20
20               RHS           c2_0       2                    21
21               RHS           c2_1       2                    22
22   RANGES                                                    23
23   BOUNDS                                                    24
24        LO     BND              x       1                    25
25        UP     BND            y_0       3                    26
26        LO     BND            y_0       0                    27
27        UP     BND            y_1       3                    28
28        LO     BND            y_1       0                    29
29   ENDATA                               0                0   30
```

7.2.11 sasoptpy.quick_sum

sasoptpy.**quick_sum**(*argv*)

Quick summation function for `Expression` objects

Returns `Expression` object

Sum of given arguments

Notes

This function is faster for expressions compared to Python's native sum() function.

Examples

```
>>> x = so.VariableGroup(10000, name='x')
>>> y = so.quick_sum(2*x[i] for i in range(10000))
```

7.2.12 sasoptpy.read_frame

sasoptpy.**read_frame**(*df*, *cols=None*)

Reads each column in `pandas.DataFrame` into a list of `pandas.Series` objects

Parameters **df** : `pandas.DataFrame` object

DataFrame to be read

cols : list of strings, optional

Column names to be read. By default, it reads all columns

Returns list

List of `pandas.Series` objects

Examples

```
>>> price = pd.DataFrame([
>>>     [1, 5, 7],
>>>     [8, 4, 3],
>>>     [5, 7, 9]], columns=['period1', 'period2', 'period3']).\
>>>     set_index([['coal', 'steel', 'copper']])
>>> [period2, period3] = so.read_frame(price, ['period2', 'period3'])
>>> print(period2)
coal      5
steel     4
copper    7
Name: period2, dtype: int64
```

7.2.13 sasoptpy.register_name

sasoptpy.**register_name**(*name*, *obj*)

Adds the name of a component into the global reference list

7.2.14 sasoptpy.reset_globals

sasoptpy.**reset_globals**()

Deletes the references inside the global dictionary and restarts counters

See also:

get_namespace()

Examples

```
>>> import sasoptpy as so
>>> m = so.Model(name='my_model')
>>> print(so.get_namespace())
Global namespace:
    Model
            0 my_model <class 'sasoptpy.model.Model'>, sasoptpy.Model(name='my_
↪model', session=None)
    VariableGroup
    ConstraintGroup
    Expression
    Variable
    Constraint
>>> so.reset_globals()
>>> print(so.get_namespace())
Global namespace:
    Model
    VariableGroup
    ConstraintGroup
    Expression
    Variable
    Constraint
```

7.2.15 sasoptpy.tuple_pack

sasoptpy.**tuple_pack**(*obj*)

Converts a given object to a tuple object

If the object is a tuple, the function returns itself, otherwise creates a single dimensional tuple.

Parameters **obj** : Object

Object that is converted to tuple

Returns tuple

Corresponding tuple to the object.

7.2.16 sasoptpy.tuple_unpack

sasoptpy.**tuple_unpack**(*tp*)

Grabs the first element in a tuple, if a tuple is given as argument

Parameters **tp** : tuple

Returns object

The first object inside the tuple.

CHAPTER

EIGHT

EXAMPLES

Examples are provided from SAS/OR documentation.

8.1 Food Manufacture 1

8.1.1 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)
    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

    # 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 = [use.sum('*', p) for p in PERIODS]
```

```
    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-1] for p in PERIODS)
    rawcost = so.quick_sum(cost.at[p-1, o] * 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-1] 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-1] for p in PERIODS),
                      name='hardness_lb')
    res = m.solve()

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

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

    return m.get_objective_value()
```

8.1.2 Output

```
In [1]: from examples.food_manufacture_1 import test

In [2]: test(cas_conn)
NOTE: Initialized model food_manufacture_1
NOTE: Converting model food_manufacture_1 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMP14OHCS9Q␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMP14OHCS9Q has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem food_manufacture_1 has 95 variables (0 free, 10 fixed).
```

```
NOTE: The problem has 54 constraints (18 LE, 30 EQ, 6 GE, 0 range).
NOTE: The problem has 210 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 10 variables and 0 constraints.
NOTE: The LP presolver removed 10 constraint coefficients.
NOTE: The presolved problem has 85 variables, 54 constraints, and 200 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    1.019986E+06         0
          D 2         54    1.253907E+05         0
          P 2         71    1.078426E+05         0
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMP14OHCS9Q from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                      Value
Label
Problem Name                food_manufacture_1
Objective Sense                   Maximization
Objective Function                      profit
RHS                                        RHS

Number of Variables                         95
Bounded Above                                0
Bounded Below                               60
Bounded Above and Below                     25
Free                                         0
Fixed                                       10

Number of Constraints                       54
LE (<=)                                     18
EQ (=)                                      30
GE (>=)                                      6
Range                                        0

Constraint Coefficients                    210
Solution Summary

                               Value
Label
Solver                            LP
Algorithm               Dual Simplex
Objective Function            profit
Solution Status              Optimal
Objective Value         107842.59259

Primal Infeasibility    4.289902E-13
Dual Infeasibility                 0
Bound Infeasibility                0

Iterations                        71
Presolve Time                   0.00
```

```
Solution Time                      0.01
NOTE: Converting model food_manufacture_1 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMP1ASTJEPD␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMP1ASTJEPD has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem food_manufacture_1 has 95 variables (0 free, 10 fixed).
NOTE: The problem has 54 constraints (18 LE, 30 EQ, 6 GE, 0 range).
NOTE: The problem has 210 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 10 variables and 0 constraints.
NOTE: The LP presolver removed 10 constraint coefficients.
NOTE: The presolved problem has 85 variables, 54 constraints, and 200 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Primal Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          P 1          1    2.310290E+03         0
          P 2         47    4.276988E+04         0
          P 2         56    8.634295E+04         0
          D 2         70    1.078426E+05         0
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: The Primal Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMP1ASTJEPD from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                      Value
Label
Problem Name              food_manufacture_1
Objective Sense                 Maximization
Objective Function                    profit
RHS                                      RHS

Number of Variables                       95
Bounded Above                              0
Bounded Below                             60
Bounded Above and Below                   25
Free                                       0
Fixed                                     10

Number of Constraints                     54
LE (<=)                                   18
EQ (=)                                    30
GE (>=)                                    6
Range                                      0

Constraint Coefficients                  210
Solution Summary

                               Value
Label
Solver                            LP
Algorithm             Primal Simplex
```

```
Objective Function            profit
Solution Status              Optimal
Objective Value         107842.59259

Primal Infeasibility    9.947598E-14
Dual Infeasibility      3.552714E-15
Bound Infeasibility                0

Iterations                        70
Presolve Time                   0.00
Solution Time                   0.01
NOTE: Converting model food_manufacture_1 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPXVI0J9T1␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPXVI0J9T1 has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem food_manufacture_1 has 95 variables (0 free, 10 fixed).
NOTE: The problem has 54 constraints (18 LE, 30 EQ, 6 GE, 0 range).
NOTE: The problem has 210 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 10 variables and 0 constraints.
NOTE: The LP presolver removed 10 constraint coefficients.
NOTE: The presolved problem has 85 variables, 54 constraints, and 200 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 32 threads.
                                           Primal        Bound         Dual
         Iter  Complement Duality Gap      Infeas       Infeas       Infeas    Time
            0  4.2997E+03  1.5010E+01  4.2157E-02  1.4325E-01  4.2366E-01      0
            1  2.7239E+03  4.0077E+00  1.7368E-03  5.9018E-03  2.5867E-01      0
            2  8.0938E+02  7.4301E-01  8.4899E-04  2.8850E-03  6.5283E-02      0
            3  3.8789E+02  3.7949E-01  3.2532E-04  1.1055E-03  8.4918E-03      0
            4  4.1836E+01  3.8559E-02  3.6316E-05  1.2341E-04  6.4884E-04      0
            5  1.2878E+00  1.1373E-03  5.0477E-07  1.7153E-06  2.5783E-05      0
            6  1.2953E-02  1.1443E-05  5.1201E-09  1.7399E-08  2.5813E-07      0
            7  0.0000E+00  7.9506E-08  3.0784E-07  8.9734E-10  9.0537E-07      0
NOTE: The Interior Point solve time is 0.00 seconds.
NOTE: The CROSSOVER option is enabled.
NOTE: The crossover basis contains 11 primal and 3 dual superbasic variables.
                              Objective
         Phase Iteration        Value         Time
          P C          1    1.056115E+03         0
          D C         13    1.753674E+02         0
          D 2         16    1.078426E+05         0
          D 2         17    1.078426E+05         0
NOTE: The Crossover time is 0.01 seconds.
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: Cloud Analytic Services dropped table TMPXVI0J9T1 from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                      Value
Label
```

```
Problem Name                 food_manufacture_1
Objective Sense                    Maximization
Objective Function                       profit
RHS                                         RHS

Number of Variables                          95
Bounded Above                                 0
Bounded Below                                60
Bounded Above and Below                      25
Free                                          0
Fixed                                        10

Number of Constraints                        54
LE (<=)                                      18
EQ (=)                                       30
GE (>=)                                       6
Range                                         0

Constraint Coefficients                     210
Solution Summary

                               Value
Label
Solver                            LP
Algorithm             Interior Point
Objective Function            profit
Solution Status              Optimal
Objective Value         107842.59259

Primal Infeasibility     4.52971E-14
Dual Infeasibility      1.776357E-14
Bound Infeasibility                0
Complementarity                    0
Duality Gap                        0

Iterations                         7
Iterations2                       17
Presolve Time                   0.00
Solution Time                   0.02
NOTE: Converting model food_manufacture_1 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPRP3BDIU5␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPRP3BDIU5 has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem food_manufacture_1 has 95 variables (0 free, 10 fixed).
NOTE: The problem has 54 constraints (18 LE, 30 EQ, 6 GE, 0 range).
NOTE: The problem has 210 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 10 variables and 0 constraints.
NOTE: The LP presolver removed 10 constraint coefficients.
NOTE: The presolved problem has 85 variables, 54 constraints, and 200 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Network Simplex algorithm is used.
NOTE: The network has 24 rows (44.44%), 51 columns (60.00%), and 1 component.
NOTE: The network extraction and setup time is 0.00 seconds.
```

```
                        Primal          Primal            Dual
         Iteration      Objective   Infeasibility   Infeasibility     Time
                 1   -1.250000E+04   5.000000E+02   4.076000E+03     0.00
                39    5.125000E+04   0.000000E+00   0.000000E+00     0.00
NOTE: The Network Simplex solve time is 0.00 seconds.
NOTE: The total Network Simplex solve time is 0.00 seconds.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    4.090791E+05         0
          P 2         42    1.078426E+05         0
NOTE: Optimal.
NOTE: Objective = 107842.59259.
NOTE: The Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMPRP3BDIU5 from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                      Value
Label
Problem Name              food_manufacture_1
Objective Sense                 Maximization
Objective Function                    profit
RHS                                      RHS

Number of Variables                       95
Bounded Above                              0
Bounded Below                             60
Bounded Above and Below                   25
Free                                       0
Fixed                                     10

Number of Constraints                     54
LE (<=)                                   18
EQ (=)                                    30
GE (>=)                                    6
Range                                      0

Constraint Coefficients                  210
Solution Summary

                                Value
Label
Solver                             LP
Algorithm             Network Simplex
Objective Function             profit
Solution Status               Optimal
Objective Value          107842.59259

Primal Infeasibility     3.410605E-13
Dual Infeasibility       2.842171E-14
Bound Infeasibility       8.21565E-14

Iterations                         39
Iterations2                        42
Presolve Time                    0.00
Solution Time                    0.01
            buy           use          store
```

```
1    2
oil1 0        -            -  5.000000e+02
oil1 1        0            0  5.000000e+02
oil1 2        0            0  5.000000e+02
oil1 3        0            0  5.000000e+02
oil1 4        0            0  5.000000e+02
oil1 5        0            0  5.000000e+02
oil1 6        0            0  5.000000e+02
oil2 0        -            -  5.000000e+02
oil2 1        0            0  5.000000e+02
oil2 2      250            0  7.500000e+02
oil2 3        0          250  5.000000e+02
oil2 4        0          250  2.500000e+02
oil2 5        0          250  0.000000e+00
oil2 6      750          250  5.000000e+02
oil3 0        -            -  5.000000e+02
oil3 1        0          250  2.500000e+02
oil3 2        0          250  0.000000e+00
oil3 3        0            0 -8.215650e-14
oil3 4        0 -8.21565e-14  0.000000e+00
oil3 5      500            0  5.000000e+02
oil3 6        0            0  5.000000e+02
veg1 0        -            -  5.000000e+02
veg1 1        0      85.1852  4.148148e+02
veg1 2        0      85.1852  3.296296e+02
veg1 3        0      159.259  1.703704e+02
veg1 4        0      11.1111  1.592593e+02
veg1 5        0      159.259  0.000000e+00
veg1 6  659.259      159.259  5.000000e+02
veg2 0        -            -  5.000000e+02
veg2 1        0      114.815  3.851852e+02
veg2 2        0      114.815  2.703704e+02
veg2 3        0      40.7407  2.296296e+02
veg2 4        0      188.889  4.074074e+01
veg2 5        0      40.7407  0.000000e+00
veg2 6  540.741      40.7407  5.000000e+02
Out[2]: 107842.59259259261
```

8.2 Food Manufacture 2

8.2.1 Model

```python
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)
    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 = [use.sum('*', p) for p in PERIODS]
    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-1] for p in PERIODS)
    rawcost = so.quick_sum(cost.at[p-1, o] * 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-1] 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-1] 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()
```

8.2.2 Output

```
In [1]: from examples.food_manufacture_2 import test

In [2]: test(cas_conn)
NOTE: Initialized model food_manufacture_2
NOTE: Converting model food_manufacture_2 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPEU5XZABE␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPEU5XZABE has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem food_manufacture_2 has 125 variables (30 binary, 0 integer, 0 free,␣
↪10 fixed).
NOTE: The problem has 132 constraints (66 LE, 30 EQ, 36 GE, 0 range).
NOTE: The problem has 384 constraint coefficients.
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 32 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      4  77764.2857143         343250   77.34%       0
                0        1      4  77764.2857143         107333   27.55%       0
                0        1      4  77764.2857143         106191   26.77%       0
                0        1      4  77764.2857143         105907   26.57%       0
                0        1      4  77764.2857143         104924   25.89%       0
                0        1      4  77764.2857143         104751   25.76%       0
                0        1      4  77764.2857143         104461   25.56%       0
```

```
              0        1      4  77764.2857143        104350   25.48%       0
              0        1      4  77764.2857143        104173   25.35%       0
              0        1      4  77764.2857143        104066   25.27%       0
              0        1      4  77764.2857143        103777   25.07%       0
              0        1      4  77764.2857143        103697   25.01%       0
              0        1      4  77764.2857143        103654   24.98%       0
              0        1      4  77764.2857143        103578   24.92%       0
              0        1      4  77764.2857143        103455   24.83%       0
              0        1      4  77764.2857143        103424   24.81%       0
              0        1      4  77764.2857143        103407   24.80%       0
              0        1      5  87368.5185185        103407   15.51%       0
NOTE: The MILP solver added 29 cuts with 144 cut coefficients at the root.
             35       23      6  87791.6666667        102113   14.03%       0
             36       23      7  99908.3333333        102113    2.16%       0
             41       27      8  99908.3333333        102113    2.16%       0
             76       31      9         100192        101638    1.42%       0
            116       41     10         100214        101434    1.20%       1
            210       19     11         100279        101074    0.79%       1
            254        0     11         100279        100279    0.00%       1
NOTE: Optimal.
NOTE: Objective = 100278.7037.
NOTE: Cloud Analytic Services dropped table TMPEU5XZABE from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                      Value
Label
Problem Name             food_manufacture_2
Objective Sense                Maximization
Objective Function                   profit
RHS                                     RHS

Number of Variables                     125
Bounded Above                             0
Bounded Below                            30
Bounded Above and Below                  85
Free                                      0
Fixed                                    10
Binary                                   30
Integer                                   0

Number of Constraints                   132
LE (<=)                                  66
EQ (=)                                   30
GE (>=)                                  36
Range                                     0

Constraint Coefficients                 384
Solution Summary

                                Value
Label
Solver                           MILP
Algorithm              Branch and Cut
Objective Function             profit
Solution Status               Optimal
Objective Value           100278.7037
```

```
Relative Gap                      0
Absolute Gap                      0
Primal Infeasibility    7.338079E-13
Bound Infeasibility     8.636037E-13
Integer Infeasibility   6.489791E-15

Best Bound               100278.7037
Nodes                            255
Iterations                      3823

Presolve Time                   0.02
Solution Time                   1.83
                buy          use       store      is_used
1    2
oil1 0            -            -  500.000000            -
oil1 1            0            0  500.000000            0
oil1 2            0            0  500.000000            0
oil1 3            0            0  500.000000            0
oil1 4 -5.68434e-14 -6.82121e-14  500.000000            0
oil1 5            0            0  500.000000            0
oil1 6            0            0  500.000000            0
oil2 0            -            -  500.000000            -
oil2 1            0            0  500.000000            0
oil2 2            0           40  460.000000            1
oil2 3 -5.68434e-14  5.05275e-14  460.000000            0
oil2 4  1.13687e-13          230  230.000000            1
oil2 5            0          230    0.000000            1
oil2 6          730          230  500.000000            1
oil3 0            -            -  500.000000            -
oil3 1            0          250  250.000000            1
oil3 2 -2.84217e-14          210   40.000000            1
oil3 3          770          250  560.000000            1
oil3 4            0           20  540.000000            1
oil3 5            0           20  520.000000            1
oil3 6            0           20  500.000000            1
veg1 0            -            -  500.000000            -
veg1 1            0      85.1852  414.814815            1
veg1 2            0            0  414.814815            0
veg1 3            0      85.1852  329.629630            1
veg1 4            0          155  174.629630            1
veg1 5  2.84217e-14          155   19.629630            1
veg1 6       480.37 -8.63604e-13  500.000000 -6.48979e-15
veg2 0            -            -  500.000000            -
veg2 1            0      114.815  385.185185            1
veg2 2            0          200  185.185185            1
veg2 3            0      114.815   70.370370            1
veg2 4            0            0   70.370370            0
veg2 5            0            0   70.370370            0
veg2 6       629.63          200  500.000000            1
Out[2]: 100278.70370370374
```

8.3 Factory Planning 1

8.3.1 Model

```
import sasoptpy as so
import pandas as pd


def test(cas_conn):

    m = so.Model(name='factory_planning_1', 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']).set_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)\
                    .set_index([[i for i in 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']

    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))

    print(m.get_solution('Primal'))
    print(m.get_solution('Dual'))

    return m.get_objective_value()
```

8.3.2 Output

```
In [1]: from examples.factory_planning_1 import test

In [2]: test(cas_conn)
NOTE: Initialized model factory_planning_1
NOTE: Converting model factory_planning_1 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPMZM_NMFM␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPMZM_NMFM has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
```

```
NOTE: Added action set 'optimization'.
NOTE: The problem factory_planning_1 has 126 variables (0 free, 6 fixed).
NOTE: The problem has 72 constraints (30 LE, 42 EQ, 0 GE, 0 range).
NOTE: The problem has 281 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 24 variables and 21 constraints.
NOTE: The LP presolver removed 83 constraint coefficients.
NOTE: The presolved problem has 102 variables, 51 constraints, and 198 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    9.501963E+04         0
          P 2         34    9.371518E+04         0
NOTE: Optimal.
NOTE: Objective = 93715.178571.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMPMZM_NMFM from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                      Value
Label
Problem Name                 factory_planning_1
Objective Sense                    Maximization
Objective Function                 total_profit
RHS                                         RHS

Number of Variables                         126
Bounded Above                                 0
Bounded Below                                42
Bounded Above and Below                      78
Free                                          0
Fixed                                         6

Number of Constraints                        72
LE (<=)                                      30
EQ (=)                                       42
GE (>=)                                       0
Range                                         0

Constraint Coefficients                     281
Solution Summary

                               Value
Label
Solver                            LP
Algorithm               Dual Simplex
Objective Function      total_profit
Solution Status              Optimal
Objective Value         93715.178571

Primal Infeasibility               0
Dual Infeasibility                 0
Bound Infeasibility                0

Iterations                        34
```

```
Presolve Time                    0.00
Solution Time                    0.01
                make          sell  store
1      2
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
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
Selected Rows from Table PRIMAL

         _OBJ_ID_ _RHS_ID_          _VAR_ _TYPE_  _OBJCOEF_  _LBOUND_  \
0    total_profit      RHS   make_prod1_1      N        0.0       0.0
1    total_profit      RHS   make_prod1_2      N        0.0       0.0
2    total_profit      RHS   make_prod1_3      N        0.0       0.0
3    total_profit      RHS   make_prod1_4      N        0.0       0.0
4    total_profit      RHS   make_prod1_5      N        0.0       0.0
5    total_profit      RHS   make_prod1_6      N        0.0       0.0
6    total_profit      RHS   make_prod2_1      N        0.0       0.0
7    total_profit      RHS   make_prod2_2      N        0.0       0.0
8    total_profit      RHS   make_prod2_3      N        0.0       0.0
```

```
9    total_profit      RHS   make_prod2_4      N       0.0       0.0
10   total_profit      RHS   make_prod2_5      N       0.0       0.0
11   total_profit      RHS   make_prod2_6      N       0.0       0.0
12   total_profit      RHS   make_prod3_1      N       0.0       0.0
13   total_profit      RHS   make_prod3_2      N       0.0       0.0
14   total_profit      RHS   make_prod3_3      N       0.0       0.0
15   total_profit      RHS   make_prod3_4      N       0.0       0.0
16   total_profit      RHS   make_prod3_5      N       0.0       0.0
17   total_profit      RHS   make_prod3_6      N       0.0       0.0
18   total_profit      RHS   make_prod4_1      N       0.0       0.0
19   total_profit      RHS   make_prod4_2      N       0.0       0.0
20   total_profit      RHS   make_prod4_3      N       0.0       0.0
21   total_profit      RHS   make_prod4_4      N       0.0       0.0
22   total_profit      RHS   make_prod4_5      N       0.0       0.0
23   total_profit      RHS   make_prod4_6      N       0.0       0.0
24   total_profit      RHS   make_prod5_1      N       0.0       0.0
25   total_profit      RHS   make_prod5_2      N       0.0       0.0
26   total_profit      RHS   make_prod5_3      N       0.0       0.0
27   total_profit      RHS   make_prod5_4      N       0.0       0.0
28   total_profit      RHS   make_prod5_5      N       0.0       0.0
29   total_profit      RHS   make_prod5_6      N       0.0       0.0
..            ...      ...            ...    ...       ...       ...
96   total_profit      RHS  store_prod3_1      D      -0.5       0.0
97   total_profit      RHS  store_prod3_2      D      -0.5       0.0
98   total_profit      RHS  store_prod3_3      D      -0.5       0.0
99   total_profit      RHS  store_prod3_4      D      -0.5       0.0
100  total_profit      RHS  store_prod3_5      D      -0.5       0.0
101  total_profit      RHS  store_prod3_6      D      -0.5      50.0
102  total_profit      RHS  store_prod4_1      D      -0.5       0.0
103  total_profit      RHS  store_prod4_2      D      -0.5       0.0
104  total_profit      RHS  store_prod4_3      D      -0.5       0.0
105  total_profit      RHS  store_prod4_4      D      -0.5       0.0
106  total_profit      RHS  store_prod4_5      D      -0.5       0.0
107  total_profit      RHS  store_prod4_6      D      -0.5      50.0
108  total_profit      RHS  store_prod5_1      D      -0.5       0.0
109  total_profit      RHS  store_prod5_2      D      -0.5       0.0
110  total_profit      RHS  store_prod5_3      D      -0.5       0.0
111  total_profit      RHS  store_prod5_4      D      -0.5       0.0
112  total_profit      RHS  store_prod5_5      D      -0.5       0.0
113  total_profit      RHS  store_prod5_6      D      -0.5      50.0
114  total_profit      RHS  store_prod6_1      D      -0.5       0.0
115  total_profit      RHS  store_prod6_2      D      -0.5       0.0
116  total_profit      RHS  store_prod6_3      D      -0.5       0.0
117  total_profit      RHS  store_prod6_4      D      -0.5       0.0
118  total_profit      RHS  store_prod6_5      D      -0.5       0.0
119  total_profit      RHS  store_prod6_6      D      -0.5      50.0
120  total_profit      RHS  store_prod7_1      D      -0.5       0.0
121  total_profit      RHS  store_prod7_2      D      -0.5       0.0
122  total_profit      RHS  store_prod7_3      D      -0.5       0.0
123  total_profit      RHS  store_prod7_4      D      -0.5       0.0
124  total_profit      RHS  store_prod7_5      D      -0.5       0.0
125  total_profit      RHS  store_prod7_6      D      -0.5      50.0

          _UBOUND_      _VALUE_ _STATUS_   _R_COST_
0    1.797693e+308   500.000000        B  -0.000000
1    1.797693e+308   700.000000        B  -0.000000
2    1.797693e+308     0.000000        B  -0.000000
3    1.797693e+308   200.000000        B  -0.000000
```

```
4    1.797693e+308     0.000000        L  -0.000000
5    1.797693e+308   550.000000        B  -0.000000
6    1.797693e+308   888.571429        B  -0.000000
7    1.797693e+308   600.000000        B  -0.000000
8    1.797693e+308     0.000000        L  -0.000000
9    1.797693e+308   300.000000        B  -0.000000
10   1.797693e+308   100.000000        B  -0.000000
11   1.797693e+308   550.000000        B  -0.000000
12   1.797693e+308   382.500000        B  -0.000000
13   1.797693e+308   117.500000        B  -0.000000
14   1.797693e+308     0.000000        L  -0.000000
15   1.797693e+308   400.000000        B  -0.000000
16   1.797693e+308   600.000000        B  -0.000000
17   1.797693e+308     0.000000        B  -0.000000
18   1.797693e+308   300.000000        B  -0.000000
19   1.797693e+308     0.000000        L  -0.000000
20   1.797693e+308     0.000000        L -14.500000
21   1.797693e+308   500.000000        B  -0.000000
22   1.797693e+308   100.000000        B  -0.000000
23   1.797693e+308   350.000000        B  -0.000000
24   1.797693e+308   800.000000        B  -0.000000
25   1.797693e+308   500.000000        B  -0.000000
26   1.797693e+308     0.000000        L  -9.000000
27   1.797693e+308   200.000000        B  -0.000000
28   1.797693e+308  1100.000000        B  -0.000000
29   1.797693e+308     0.000000        L -29.000000
..             ...          ...      ...         ...
96    1.000000e+02    82.500000        B  -0.000000
97    1.000000e+02     0.000000        L  -1.000000
98    1.000000e+02     0.000000        L  -0.500000
99    1.000000e+02     0.000000        L  -0.500000
100   1.000000e+02   100.000000        U   7.500000
101   5.100000e+01    50.000000        L  -8.500000
102   1.000000e+02     0.000000        L  -0.500000
103   1.000000e+02     0.000000        L  -1.000000
104   1.000000e+02    -0.000000        B  -0.000000
105   1.000000e+02     0.000000        L  -0.500000
106   1.000000e+02     0.000000        L  -0.500000
107   5.100000e+01    50.000000        L  -0.500000
108   1.000000e+02     0.000000        L  -3.071429
109   1.000000e+02   100.000000        U  10.500000
110   1.000000e+02     0.000000        L -11.500000
111   1.000000e+02     0.000000        L  -0.500000
112   1.000000e+02   100.000000        U  10.500000
113   5.100000e+01    50.000000        L -11.500000
114   1.000000e+02     0.000000        L  -2.214286
115   1.000000e+02     0.000000        L  -0.500000
116   1.000000e+02     0.000000        L  -0.500000
117   1.000000e+02     0.000000        L  -0.500000
118   1.000000e+02     0.000000        L  -0.500000
119   5.100000e+01    50.000000        L  -0.500000
120   1.000000e+02     0.000000        L  -4.410714
121   1.000000e+02   100.000000        U   2.125000
122   1.000000e+02     0.000000        L  -3.500000
123   1.000000e+02     0.000000        L  -0.500000
124   1.000000e+02   100.000000        U   2.500000
125   5.100000e+01    50.000000        L  -3.500000
```

```
[126 rows x 10 columns]
Selected Rows from Table DUAL

       _OBJ_ID_ _RHS_ID_             _ROW_ _TYPE_   _RHS_  _L_RHS_  _U_RHS_  \
0   total_profit      RHS  machine_hours_13      L   384.0      NaN      NaN
1   total_profit      RHS  machine_hours_19      L   384.0      NaN      NaN
2   total_profit      RHS   machine_hours_1      L  1536.0      NaN      NaN
3   total_profit      RHS   machine_hours_9      L   384.0      NaN      NaN
4   total_profit      RHS  machine_hours_29      L     0.0      NaN      NaN
5   total_profit      RHS  machine_hours_16      L  1152.0      NaN      NaN
6   total_profit      RHS  machine_hours_11      L   768.0      NaN      NaN
7   total_profit      RHS  machine_hours_27      L   384.0      NaN      NaN
8   total_profit      RHS   machine_hours_5      L  1536.0      NaN      NaN
9   total_profit      RHS   machine_hours_3      L  1536.0      NaN      NaN
10  total_profit      RHS  machine_hours_12      L  1152.0      NaN      NaN
11  total_profit      RHS   machine_hours_7      L   768.0      NaN      NaN
12  total_profit      RHS  machine_hours_22      L   384.0      NaN      NaN
13  total_profit      RHS  machine_hours_14      L  1152.0      NaN      NaN
14  total_profit      RHS  machine_hours_26      L   384.0      NaN      NaN
15  total_profit      RHS  machine_hours_20      L     0.0      NaN      NaN
16  total_profit      RHS  machine_hours_10      L   384.0      NaN      NaN
17  total_profit      RHS  machine_hours_24      L   384.0      NaN      NaN
18  total_profit      RHS  machine_hours_18      L   384.0      NaN      NaN
19  total_profit      RHS   machine_hours_2      L  1536.0      NaN      NaN
20  total_profit      RHS   machine_hours_0      L  1152.0      NaN      NaN
21  total_profit      RHS  machine_hours_15      L  1152.0      NaN      NaN
22  total_profit      RHS   machine_hours_6      L   768.0      NaN      NaN
23  total_profit      RHS  machine_hours_28      L   384.0      NaN      NaN
24  total_profit      RHS  machine_hours_17      L   768.0      NaN      NaN
25  total_profit      RHS   machine_hours_8      L   768.0      NaN      NaN
26  total_profit      RHS  machine_hours_23      L   384.0      NaN      NaN
27  total_profit      RHS   machine_hours_4      L  1152.0      NaN      NaN
28  total_profit      RHS  machine_hours_25      L   384.0      NaN      NaN
29  total_profit      RHS  machine_hours_21      L   384.0      NaN      NaN
..           ...      ...               ...    ...     ...      ...      ...
42  total_profit      RHS   flow_balance_28      E     0.0      NaN      NaN
43  total_profit      RHS    flow_balance_0      E     0.0      NaN      NaN
44  total_profit      RHS   flow_balance_14      E     0.0      NaN      NaN
45  total_profit      RHS   flow_balance_40      E     0.0      NaN      NaN
46  total_profit      RHS   flow_balance_25      E     0.0      NaN      NaN
47  total_profit      RHS    flow_balance_8      E     0.0      NaN      NaN
48  total_profit      RHS   flow_balance_16      E     0.0      NaN      NaN
49  total_profit      RHS   flow_balance_38      E     0.0      NaN      NaN
50  total_profit      RHS   flow_balance_22      E     0.0      NaN      NaN
51  total_profit      RHS    flow_balance_6      E     0.0      NaN      NaN
52  total_profit      RHS    flow_balance_5      E     0.0      NaN      NaN
53  total_profit      RHS   flow_balance_20      E     0.0      NaN      NaN
54  total_profit      RHS   flow_balance_30      E     0.0      NaN      NaN
55  total_profit      RHS   flow_balance_33      E     0.0      NaN      NaN
56  total_profit      RHS    flow_balance_3      E     0.0      NaN      NaN
57  total_profit      RHS   flow_balance_18      E     0.0      NaN      NaN
58  total_profit      RHS   flow_balance_29      E     0.0      NaN      NaN
59  total_profit      RHS   flow_balance_10      E     0.0      NaN      NaN
60  total_profit      RHS   flow_balance_37      E     0.0      NaN      NaN
61  total_profit      RHS    flow_balance_1      E     0.0      NaN      NaN
62  total_profit      RHS   flow_balance_39      E     0.0      NaN      NaN
63  total_profit      RHS   flow_balance_35      E     0.0      NaN      NaN
64  total_profit      RHS    flow_balance_7      E     0.0      NaN      NaN
```

```
65  total_profit      RHS   flow_balance_13      E     0.0      NaN      NaN
66  total_profit      RHS   flow_balance_41      E     0.0      NaN      NaN
67  total_profit      RHS   flow_balance_23      E     0.0      NaN      NaN
68  total_profit      RHS   flow_balance_31      E     0.0      NaN      NaN
69  total_profit      RHS   flow_balance_32      E     0.0      NaN      NaN
70  total_profit      RHS   flow_balance_15      E     0.0      NaN      NaN
71  total_profit      RHS   flow_balance_21      E     0.0      NaN      NaN

       _VALUE_ _STATUS_   _ACTIVITY_
0     0.625000        L   384.000000
1     0.000000        B   123.000000
2     0.000000        B  1105.000000
3     0.000000        B   230.000000
4   800.000000        L     0.000000
5     0.000000        B   540.000000
6     0.000000        B   600.000000
7     0.000000        B    19.000000
8     0.000000        B   770.000000
9     0.000000        B   420.000000
10   -0.000000        B   406.000000
11    0.000000        B   370.000000
12    0.000000        B   128.000000
13   -0.000000        B     0.000000
14   -0.000000        B     0.000000
15  200.000000        L     0.000000
16    0.000000        B   230.000000
17   -0.000000        B    43.825000
18   -0.000000        B   152.657143
19   -0.000000        B    80.000000
20    8.571429        L  1152.000000
21    0.000000        B   420.000000
22   -0.000000        B   437.714286
23   -0.000000        B    66.000000
24   -0.000000        B   110.000000
25   -0.000000        B   240.000000
26    0.000000        B    68.500000
27    0.000000        B   510.000000
28   -0.000000        B    38.675000
29    0.000000        B    82.000000
..         ...      ...          ...
42    0.000000        L     0.000000
43   -4.285714        U     0.000000
44    0.000000        B     0.000000
45    0.000000        L     0.000000
46    0.000000        L     0.000000
47   -6.000000        U     0.000000
48    0.000000        L     0.000000
49   -3.000000        U     0.000000
50    0.000000        L     0.000000
51   -6.000000        U     0.000000
52    0.000000        L     0.000000
53    0.500000        L     0.000000
54   -1.714286        U     0.000000
55    0.000000        B     0.000000
56    0.000000        L     0.000000
57    0.000000        U     0.000000
58  -11.000000        U     0.000000
59    0.000000        L     0.000000
```

```
60   -0.375000        U     0.000000
61   -0.125000        U     0.000000
62    0.000000        L     0.000000
63    0.000000        L     0.000000
64    0.000000        L     0.000000
65   -0.500000        U     0.000000
66   -3.000000        U     0.000000
67    0.000000        L     0.000000
68    0.000000        L     0.000000
69    0.000000        L     0.000000
70    0.000000        L     0.000000
71    0.000000        L     0.000000

[72 rows x 10 columns]
Out[2]: 93715.17857142858
```

8.4 Factory Planning 2

8.4.1 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']).set_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)\
                    .set_index([[i for i in range(1, 7)]])
    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'])
    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']

    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')

    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')
    m.add_constraints((so.quick_sum(numMachinesDown[mc, t] for t in PERIODS) ==
                       num_machines_needing_maintenance.at[mc]
                       for mc in MACHINE_TYPES), name='maintenance')
    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] - numMachinesDown[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))
        print(so.get_solution_table(numMachinesDown))

    return m.get_objective_value()
```

8.4.2 Output

```
In [1]: from examples.factory_planning_2 import test

In [2]: test(cas_conn)
NOTE: Initialized model factory_planning_2
NOTE: Converting model factory_planning_2 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMP5NPG9XM9␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMP5NPG9XM9 has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem factory_planning_2 has 156 variables (0 binary, 30 integer, 0 free,␣
↪6 fixed).
NOTE: The problem has 77 constraints (30 LE, 47 EQ, 0 GE, 0 range).
NOTE: The problem has 341 constraint coefficients.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 20 variables and 15 constraints.
NOTE: The MILP presolver removed 56 constraint coefficients.
NOTE: The MILP presolver modified 16 constraint coefficients.
NOTE: The presolved problem has 136 variables, 62 constraints, and 285 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 32 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      3  92404.5000000         116455   20.65%       0
                0        1      3  92404.5000000         116455   20.65%       0
                0        1      3  92404.5000000         116163   20.45%       0
                0        1      3  92404.5000000         115267   19.83%       0
                0        1      3  92404.5000000         114008   18.95%       0
                0        1      3  92404.5000000         113245   18.40%       0
                0        1      3  92404.5000000         112321   17.73%       0
                0        1      3  92404.5000000         110999   16.75%       0
                0        1      3  92404.5000000         110638   16.48%       0
                0        1      3  92404.5000000         109952   15.96%       0
                0        1      3  92404.5000000         109726   15.79%       0
                0        1      3  92404.5000000         109660   15.74%       0
                0        1      3  92404.5000000         109549   15.65%       0
                0        1      3  92404.5000000         108896   15.14%       0
                0        1      3  92404.5000000         108869   15.12%       0
                0        1      3  92404.5000000         108855   15.11%       0
                0        1      4         108855         108855    0.00%       0
NOTE: The MILP solver added 35 cuts with 107 cut coefficients at the root.
NOTE: Optimal within relative gap.
```

```
NOTE: Objective = 108855.00533.
NOTE: Cloud Analytic Services dropped table TMP5NPG9XM9 from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                    Value
Label
Problem Name             factory_planning_2
Objective Sense                Maximization
Objective Function             total_profit
RHS                                     RHS

Number of Variables                     156
Bounded Above                             0
Bounded Below                            72
Bounded Above and Below                  78
Free                                      0
Fixed                                     6
Binary                                    0
Integer                                  30

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

Constraint Coefficients                 341
Solution Summary

                                           Value
Label
Solver                                      MILP
Algorithm                         Branch and Cut
Objective Function                  total_profit
Solution Status       Optimal within Relative Gap
Objective Value                     108855.00533

Relative Gap                        4.4954049E-6
Absolute Gap                        0.4893495272
Primal Infeasibility                 1.98952E-13
Bound Infeasibility                 1.136868E-13
Integer Infeasibility               2.0848118E-6

Best Bound                          108855.49468
Nodes                                          1
Iterations                                   301

Presolve Time                               0.02
Solution Time                               1.15
                 make         sell       store
1     2
prod1 1  5.000000e+02   500.000000    0.000000
prod1 2  6.000000e+02   600.000000    0.000000
prod1 3  3.999984e+02   300.000000   99.998430
prod1 4  1.754937e-03   100.000185    0.000000
prod1 5  0.000000e+00     0.000000    0.000000
prod1 6  5.499993e+02   499.999298   50.000000
```

```
prod2 1  1.000000e+03  1000.000000    0.000000
prod2 2  5.000000e+02   500.000000    0.000000
prod2 3  6.999998e+02   600.000000   99.999815
prod2 4  1.385476e-03   100.000369    0.000831
prod2 5  9.999917e+01   100.000000    0.000000
prod2 6  5.500000e+02   500.000000   50.000000
prod3 1  3.000000e+02   300.000000    0.000000
prod3 2  2.000000e+02   200.000000    0.000000
prod3 3  9.999982e+01     0.000000   99.999815
prod3 4  7.389206e-04   100.000554    0.000000
prod3 5  5.000000e+02   500.000000    0.000000
prod3 6  1.500000e+02   100.000000   50.000000
prod4 1  3.000000e+02   300.000000    0.000000
prod4 2  0.000000e+00     0.000000    0.000000
prod4 3  1.000000e+02     0.000000  100.000000
prod4 4  9.236508e-04   100.000924    0.000000
prod4 5  1.000000e+02   100.000000    0.000000
prod4 6  3.499996e+02   299.999604   50.000000
prod5 1  8.000007e+02   800.000000    0.000739
prod5 2  3.999993e+02   400.000000    0.000000
prod5 3  6.000000e+02   500.000000  100.000000
prod5 4  1.847302e-04   100.000185    0.000000
prod5 5  1.000000e+03  1000.000000    0.000000
prod5 6  1.150000e+03  1100.000000   50.000000
prod6 1  2.000000e+02   200.000000    0.000000
prod6 2  3.000000e+02   300.000000    0.000000
prod6 3  4.000000e+02   400.000000    0.000000
prod6 4  0.000000e+00     0.000000    0.000000
prod6 5  3.000000e+02   300.000000    0.000000
prod6 6  5.500000e+02   500.000000   50.000000
prod7 1  1.000002e+02   100.000000    0.000185
prod7 2  1.499997e+02   149.999871    0.000000
prod7 3  2.000000e+02   100.000000  100.000000
prod7 4  1.421085e-13   100.000000    0.000000
prod7 5  0.000000e+00     0.000000    0.000000
prod7 6  1.100000e+02    60.000000   50.000000
           numMachinesDown
1       2
borer   1     0.000000e+00
borer   2    -1.209843e-16
borer   3     0.000000e+00
borer   4     9.999982e-01
borer   5     0.000000e+00
borer   6     1.847302e-06
grinder 1     0.000000e+00
grinder 2     0.000000e+00
grinder 3     0.000000e+00
grinder 4     2.000000e+00
grinder 5     0.000000e+00
grinder 6     0.000000e+00
hdrill  1     1.000000e+00
hdrill  2     0.000000e+00
hdrill  3     0.000000e+00
hdrill  4     0.000000e+00
hdrill  5     1.000000e+00
hdrill  6     1.000000e+00
planer  1     0.000000e+00
planer  2     1.847302e-06
```

```
planer  3      0.000000e+00
planer  4      9.999982e-01
planer  5      0.000000e+00
planer  6      0.000000e+00
vdrill  1      0.000000e+00
vdrill  2      2.084812e-06
vdrill  3      0.000000e+00
vdrill  4      1.999998e+00
vdrill  5      0.000000e+00
vdrill  6      0.000000e+00
Out[2]: 108855.00532550657
```

8.5 Manpower Planning

8.5.1 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],
        [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.values
```

```
PERIODS0 = demand_data.index.values
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)
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.get_value())
        print(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')
    res = m.solve()
    if res is not None:
        print(redundancy.get_value())
        print(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()
```

8.5.2 Output

```
In [1]: from examples.manpower_planning import test

In [2]: test(cas_conn)
NOTE: Initialized model manpower_planning
NOTE: Converting model manpower_planning to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMP5ELZG0L0␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMP5ELZG0L0 has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem manpower_planning has 63 variables (0 free, 3 fixed).
NOTE: The problem has 24 constraints (6 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 108 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 21 variables and 9 constraints.
```

```
NOTE: The LP presolver removed 21 constraint coefficients.
NOTE: The presolved problem has 42 variables, 15 constraints, and 87 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    5.223600E+02         0
          P 2         13    8.417969E+02         0
NOTE: Optimal.
NOTE: Objective = 841.796875.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMP5ELZG0L0 from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                     Value
Label
Problem Name             manpower_planning
Objective Sense               Minimization
Objective Function          redundancy_obj
RHS                                    RHS

Number of Variables                     63
Bounded Above                            0
Bounded Below                           39
Bounded Above and Below                 21
Free                                     0
Fixed                                    3

Number of Constraints                   24
LE (<=)                                  6
EQ (=)                                  18
GE (>=)                                  0
Range                                    0

Constraint Coefficients                108
Solution Summary

                               Value
Label
Solver                            LP
Algorithm               Dual Simplex
Objective Function    redundancy_obj
Solution Status              Optimal
Objective Value           841.796875

Primal Infeasibility    1.421085E-14
Dual Infeasibility                 0
Bound Infeasibility                0

Iterations                        13
Presolve Time                   0.00
Solution Time                   0.01
841.796875
1462047.6973684211
               numWorkers numRecruits numRedundant numShortTime numExcess
1           2
```

```
semiskilled 0  1500.00000          -            -            -         -
semiskilled 1  1442.96875          0            0           50   17.9687
semiskilled 2  2000.00000    682.198            0            0         0
semiskilled 3  2500.00000    645.724            0            0         0
skilled     0  1000.00000          -            -            -         -
skilled     1  1025.00000          0            0           50         0
skilled     2  1525.00000        500            0           50         0
skilled     3  2000.00000        500            0            0         0
unskilled   0  2000.00000          -            -            -         -
unskilled   1  1157.03125          0      442.969           50   132.031
unskilled   2   675.00000          0      166.328           50       150
unskilled   3   175.00000          0        232.5           50       150
                           numRetrain
1           2           3
semiskilled skilled     1  256.250000
semiskilled skilled     2  106.578947
semiskilled skilled     3  106.578947
unskilled   semiskilled 1  200.000000
unskilled   semiskilled 2  200.000000
unskilled   semiskilled 3  200.000000
                           numDowngrade
1           2           3
semiskilled unskilled   1        0.0000
semiskilled unskilled   2        0.0000
semiskilled unskilled   3        0.0000
skilled     semiskilled 1      168.4375
skilled     semiskilled 2        0.0000
skilled     semiskilled 3        0.0000
skilled     unskilled   1        0.0000
skilled     unskilled   2        0.0000
skilled     unskilled   3        0.0000
NOTE: Converting model manpower_planning to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPDDA_M__V␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPDDA_M__V has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem manpower_planning has 63 variables (0 free, 3 fixed).
NOTE: The problem has 24 constraints (6 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 108 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 30 variables and 11 constraints.
NOTE: The LP presolver removed 39 constraint coefficients.
NOTE: The presolved problem has 33 variables, 13 constraints, and 69 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    2.143730E+05         0
          D 2          8    4.986773E+05         0
NOTE: Optimal.
NOTE: Objective = 498677.28532.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMPDDA_M__V from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary
```

```
                                  Value
Label
Problem Name             manpower_planning
Objective Sense               Minimization
Objective Function                cost_obj
RHS                                    RHS

Number of Variables                     63
Bounded Above                            0
Bounded Below                           39
Bounded Above and Below                 21
Free                                     0
Fixed                                    3

Number of Constraints                   24
LE (<=)                                  6
EQ (=)                                  18
GE (>=)                                  0
Range                                    0

Constraint Coefficients                108
Solution Summary

                            Value
Label
Solver                         LP
Algorithm            Dual Simplex
Objective Function       cost_obj
Solution Status           Optimal
Objective Value      498677.28532

Primal Infeasibility 2.842171E-14
Dual Infeasibility              0
Bound Infeasibility             0

Iterations                      8
Presolve Time                0.00
Solution Time                0.01
1423.7188365650968
498677.2853185596
              numWorkers numRecruits numRedundant numShortTime numExcess
1           2
semiskilled 0      1500.0           -            -            -         -
semiskilled 1      1400.0           0            0            0         0
semiskilled 2      2000.0         800            0            0         0
semiskilled 3      2500.0         800            0            0         0
skilled     0      1000.0           -            -            -         -
skilled     1      1000.0     55.5556            0            0         0
skilled     2      1500.0         500            0            0         0
skilled     3      2000.0         500            0            0         0
unskilled   0      2000.0           -            -            -         -
unskilled   1      1000.0           0        812.5            0         0
unskilled   2       500.0           0      257.618            0         0
unskilled   3         0.0           0      353.601            0         0
                            numRetrain
1           2           3
semiskilled skilled     1    0.000000
```

```
semiskilled skilled     2  105.263158
semiskilled skilled     3  131.578947
unskilled   semiskilled 1    0.000000
unskilled   semiskilled 2  142.382271
unskilled   semiskilled 3   96.398892
                           numDowngrade
1           2           3
semiskilled unskilled   1          25.0
semiskilled unskilled   2           0.0
semiskilled unskilled   3           0.0
skilled     semiskilled 1           0.0
skilled     semiskilled 2           0.0
skilled     semiskilled 3           0.0
skilled     unskilled   1           0.0
skilled     unskilled   2           0.0
skilled     unskilled   3           0.0
Out[2]: 498677.2853185596
```

8.6 Refinery Optimization

8.6.1 Model

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


def test(cas_conn):

    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],
        ['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')
    NODES = np.unique([i for j in ARCS for i in j])

    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')
    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')

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')

print(m.to_frame())

res = m.solve()
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()
```

8.6.2 Output

```
In [1]: from examples.refinery_optimization import test

In [2]: test(cas_conn)
NOTE: Initialized model refinery_optimization
NOTE: Converting model refinery_optimization to DataFrame
     Field1                                Field2                  Field3  \
0      NAME                                              refinery_optimization
1      ROWS
2       MAX                           totalProfit
3         E                        flow_balance_5
4         E                       flow_balance_13
5         E                       flow_balance_17
6         E                        flow_balance_2
7         E                        flow_balance_9
8         E                        flow_balance_0
9         E                       flow_balance_11
10        E                       flow_balance_10
11        E                       flow_balance_14
12        E                        flow_balance_8
13        E                        flow_balance_6
14        E                        flow_balance_7
15        E                       flow_balance_16
16        E                       flow_balance_12
17        E                        flow_balance_1
18        E                        flow_balance_3
19        E                        flow_balance_4
20        E                       flow_balance_15
21        E                        distillation_0
22        E                        distillation_1
23        E                       distillation_10
24        E                        distillation_2
25        E                        distillation_3
26        E                        distillation_6
27        E                        distillation_7
28        E                        distillation_8
29        E                        distillation_4
..      ...                                   ...                     ...
130          flow_reformed_gasoline_regular_petrol         flow_balance_16
131                        flow_regular_petrol_sink             totalProfit
132                        flow_regular_petrol_sink         flow_balance_16
133                          flow_residuum_fuel_oil      blending_fuel_oil_3
```

```
134                         flow_residuum_fuel_oil          flow_balance_4
135                         flow_residuum_fuel_oil         flow_balance_17
136                         flow_residuum_jet_fuel       blending_jet_fuel
137                         flow_residuum_jet_fuel          flow_balance_8
138                         flow_residuum_lube_oil         flow_balance_17
139                             flow_source_crude1          flow_balance_2
140                             flow_source_crude2          flow_balance_3
141                         crudesDistilled_crude1          distillation_5
142                         crudesDistilled_crude1          distillation_2
143                         crudesDistilled_crude1          distillation_3
144                         crudesDistilled_crude1          distillation_4
145                         crudesDistilled_crude2         distillation_10
146                         crudesDistilled_crude2          distillation_8
147                         crudesDistilled_crude2          distillation_6
148                         crudesDistilled_crude2         distillation_11
149                   oilCracked_heavy_oil_cracked              cracking_3
150                   oilCracked_light_oil_cracked              cracking_1
151     RHS
152                                            RHS          crude_total_ub
153                                            RHS          cracked_oil_ub
154  RANGES
155                                            rng          lube_oil_range
156  BOUNDS
157      UP                                    BND  crudesDistilled_crude1
158      UP                                    BND  crudesDistilled_crude2
159  ENDATA

    Field4               Field5 Field6 _id_
0        0                    0     1
1                                   2
2                                   3
3                                   4
4                                   5
5                                   6
6                                   7
7                                   8
8                                   9
9                                  10
10                                 11
11                                 12
12                                 13
13                                 14
14                                 15
15                                 16
16                                 17
17                                 18
18                                 19
19                                 20
20                                 21
21                                 22
22                                 23
23                                 24
24                                 25
25                                 26
26                                 27
27                                 28
28                                 29
29                                 30
```

```
..     ...                  ...    ...  ...
130     -1                              131
131      6       premium_ratio   -0.4  132
132      1                              133
133     17  blending_fuel_oil_1     -3  134
134     -1  blending_fuel_oil_0    -10  135
135      1  blending_fuel_oil_2     -4  136
136  -0.95      flow_balance_17      1  137
137     -1                              138
138      1      flow_balance_12   -0.5  139
139     -6                              140
140     -6                              141
141     -1       distillation_1     -1  142
142     -1       crude_total_ub      1  143
143     -1       distillation_0     -1  144
144     -1                              145
145     -1       distillation_9     -1  146
146     -1       crude_total_ub      1  147
147     -1       distillation_7     -1  148
148     -1                              149
149     -1           cracking_2     -1  150
150     -1           cracking_0     -1  151
151                                     152
152  45000           naphtba_ub  10000  153
153   8000       lube_oil_range    500  154
154                                     155
155    500                              156
156                                     157
157  20000                              158
158  30000                              159
159      0                           0  160

[160 rows x 7 columns]
NOTE: Converting model refinery_optimization to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPO0PYZUL5␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPO0PYZUL5 has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem refinery_optimization has 51 variables (0 free, 0 fixed).
NOTE: The problem has 46 constraints (4 LE, 38 EQ, 3 GE, 1 range).
NOTE: The problem has 158 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
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    7.181778E+05         0
          P 2         22    2.113651E+05         0
NOTE: Optimal.
NOTE: Objective = 211365.13477.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMPO0PYZUL5 from caslib␣
↪CASUSERHDFS(casuser).
```

```
Problem Summary

                                        Value
Label
Problem Name             refinery_optimization
Objective Sense                   Maximization
Objective Function                 totalProfit
RHS                                        RHS

Number of Variables                         51
Bounded Above                                0
Bounded Below                               49
Bounded Above and Below                      2
Free                                         0
Fixed                                        0

Number of Constraints                       46
LE (<=)                                      4
EQ (=)                                      38
GE (>=)                                      3
Range                                        1

Constraint Coefficients                    158
Solution Summary

                              Value
Label
Solver                           LP
Algorithm              Dual Simplex
Objective Function      totalProfit
Solution Status             Optimal
Objective Value        211365.13477

Primal Infeasibility   7.275958E-12
Dual Infeasibility     1.776357E-15
Bound Infeasibility               0

Iterations                       22
Presolve Time                  0.00
Solution Time                  0.01
        crudesDistilled
1
crude1          15000.0
crude2          30000.0
                   oilCracked
1
heavy_oil_cracked      3800.0
light_oil_cracked      4200.0
                                             flow
1                 2
cracked_gasoline  premium_petrol         0.000000
cracked_gasoline  regular_petrol      1936.000000
cracked_oil       fuel_oil               0.000000
cracked_oil       jet_fuel            5706.000000
crude1            heavy_naphtha      15000.000000
crude1            heavy_oil          15000.000000
crude1            light_naphtha      15000.000000
crude1            light_oil          15000.000000
```

```
crude1             medium_naphtha     15000.000000
crude1             residuum           15000.000000
crude2             heavy_naphtha      30000.000000
crude2             heavy_oil          30000.000000
crude2             light_naphtha      30000.000000
crude2             light_oil          30000.000000
crude2             medium_naphtha     30000.000000
crude2             residuum           30000.000000
fuel_oil           sink                   0.000000
heavy_naphtha      premium_petrol      1677.804016
heavy_naphtha      reformed_gasoline   5406.861844
heavy_naphtha      regular_petrol      1315.334140
heavy_oil          fuel_oil               0.000000
heavy_oil          heavy_oil_cracked   3800.000000
heavy_oil          jet_fuel            4900.000000
heavy_oil_cracked cracked_gasoline    3800.000000
heavy_oil_cracked cracked_oil         3800.000000
jet_fuel           sink               15156.000000
light_naphtha      premium_petrol      2706.887007
light_naphtha      reformed_gasoline      0.000000
light_naphtha      regular_petrol      3293.112993
light_oil          fuel_oil               0.000000
light_oil          jet_fuel               0.000000
light_oil          light_oil_cracked   4200.000000
light_oil_cracked cracked_gasoline    4200.000000
light_oil_cracked cracked_oil         4200.000000
lube_oil           sink                 500.000000
medium_naphtha     premium_petrol         0.000000
medium_naphtha     reformed_gasoline      0.000000
medium_naphtha     regular_petrol     10500.000000
premium_petrol     sink                6817.778853
reformed_gasoline premium_petrol      2433.087830
reformed_gasoline regular_petrol         0.000000
regular_petrol     sink               17044.447133
residuum           fuel_oil               0.000000
residuum           jet_fuel            4550.000000
residuum           lube_oil            1000.000000
source             crude1             15000.000000
source             crude2             30000.000000
                octane_sol  octane_lb
1
premium_petrol        94.0         94
regular_petrol        84.0         84
             vapour_pressure
1
cracked_oil             1.50
heavy_oil               0.60
light_oil               1.00
residuum                0.05
Vapour_pressure_sol: 0.7737
             coefficient  num_fuel_oil_ratio_sol
1
cracked_oil            4                     NaN
heavy_oil              3                     NaN
light_oil             10                     NaN
residuum               1                     NaN
Out[2]: 211365.134768933
```

8.7 Mining Optimization

8.7.1 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']

    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()
```

8.7.2 Output

```
In [1]: from examples.mining_optimization import test

In [2]: test(cas_conn)
NOTE: Initialized model mining_optimization
NOTE: Converting model mining_optimization to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPWDD_285H␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPWDD_285H has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem mining_optimization has 60 variables (40 binary, 0 integer, 0 free,␣
↪0 fixed).
NOTE: The problem has 66 constraints (61 LE, 5 EQ, 0 GE, 0 range).
NOTE: The problem has 151 constraint coefficients.
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 11 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 32 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      5     95.6438817    364.3638322   73.75%       0
                0        1      5     95.6438817    157.7308887   39.36%       0
                0        1      5     95.6438817    153.3061673   37.61%       0
                0        1      5     95.6438817    149.6494350   36.09%       0
```

```
                0        1      5     95.6438817    148.9399006   35.78%       0
                0        1      5     95.6438817    146.9093764   34.90%       0
                0        1      6    146.8619786    146.8619786    0.00%       0
                0        0      6    146.8619786    146.8619786    0.00%       0
NOTE: The MILP solver added 8 cuts with 36 cut coefficients at the root.
NOTE: Optimal.
NOTE: Objective = 146.86197857.
NOTE: Cloud Analytic Services dropped table TMPWDD_285H from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                       Value
Label
Problem Name              mining_optimization
Objective Sense                  Maximization
Objective Function                totalProfit
RHS                                       RHS

Number of Variables                        60
Bounded Above                               0
Bounded Below                               0
Bounded Above and Below                    60
Free                                        0
Fixed                                       0
Binary                                     40
Integer                                     0

Number of Constraints                      66
LE (<=)                                    61
EQ (=)                                      5
GE (>=)                                     0
Range                                       0

Constraint Coefficients                   151
Solution Summary

                                Value
Label
Solver                           MILP
Algorithm              Branch and Cut
Objective Function        totalProfit
Solution Status               Optimal
Objective Value          146.86197857

Relative Gap                        0
Absolute Gap                        0
Primal Infeasibility     4.440892E-15
Bound Infeasibility      2.442491E-15
Integer Infeasibility    1.5384592E-6

Best Bound               146.86197857
Nodes                               1
Iterations                         76

Presolve Time                    0.02
Solution Time                    0.98
           isOpen  isWorked   extract
1     2
```

```
mine1 1  1.000000  1.000000  2.000000
mine1 2  1.000000  0.000000  0.000000
mine1 3  1.000000  1.000000  1.950000
mine1 4  1.000000  1.000000  0.125000
mine1 5  1.000000  1.000000  2.000000
mine2 1  1.000000  0.000000  0.000000
mine2 2  1.000000  1.000000  2.500000
mine2 3  1.000000  0.000000  0.000000
mine2 4  1.000000  1.000000  2.500000
mine2 5  0.999998  0.999998  2.166667
mine3 1  1.000000  1.000000  1.300000
mine3 2  1.000000  1.000000  1.300000
mine3 3  1.000000  1.000000  1.300000
mine3 4  1.000000  0.000000  0.000000
mine3 5  1.000000  1.000000  1.300000
mine4 1  1.000000  1.000000  2.450000
mine4 2  1.000000  1.000000  2.200000
mine4 3  1.000000  0.000000  0.000000
mine4 4  1.000000  1.000000  3.000000
mine4 5  0.000000  0.000000  0.000000
   extracted_per_year  quality_sol  quality_required
1
1            5.750000          0.9               0.9
2            6.000000          0.8               0.8
3            3.250000          1.2               1.2
4            5.625000          0.6               0.6
5            5.466667          1.0               1.0
Out[2]: 146.8619785673816
```

8.8 Farm Planning

8.8.1 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,
                 '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

    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)
            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) +
        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:
        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 = so.get_obj_by_name('num_acres')
        na_df = num_acres.get_expressions()
        max_num_cows_con = so.get_obj_by_name('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()
```

8.8.2 Output

```
In [1]: from examples.farm_planning import test

In [2]: test(cas_conn)
NOTE: Initialized model farm_planning
NOTE: Converting model farm_planning to DataFrame
WARNING: The objective function contains a constant term. An auxiliary variable is␣
↪added.
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPVMHV1NEB␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPVMHV1NEB has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
```

```
NOTE: Added action set 'optimization'.
NOTE: The problem farm_planning has 143 variables (0 free, 13 fixed).
NOTE: The problem has 101 constraints (25 LE, 70 EQ, 5 GE, 1 range).
NOTE: The problem has 780 constraint coefficients.
NOTE: The following columns have no constraint coefficients:
         obj_constant
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 84 variables and 69 constraints.
NOTE: The LP presolver removed 533 constraint coefficients.
NOTE: The presolved problem has 59 variables, 32 constraints, and 247 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    1.744078E+05         0
          D 2         55    1.217192E+05         0
NOTE: Optimal.
NOTE: Objective = 121719.17286.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMPVMHV1NEB from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                        Value
Label
Problem Name                    farm_planning
Objective Sense                  Maximization
Objective Function        totalProfit_constant
RHS                                       RHS

Number of Variables                       143
Bounded Above                               0
Bounded Below                             110
Bounded Above and Below                    20
Free                                        0
Fixed                                      13

Number of Constraints                     101
LE (<=)                                    25
EQ (=)                                     70
GE (>=)                                     5
Range                                       1

Constraint Coefficients                   780
Solution Summary

                                     Value
Label
Solver                                  LP
Algorithm                     Dual Simplex
Objective Function    totalProfit_constant
Solution Status                    Optimal
Objective Value               121719.17286

Primary Infeasibility          1.818989E-12
Dual Infeasibility                       0
```

```
Bound Infeasibility                          0

Iterations                                  55
Presolve Time                             0.00
Solution Time                             0.01
        numCows
1  2
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
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
...          ...
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

[78 rows x 1 columns]
   numBullocksSold  numHeifersSold  capitalOutlay  numExcessLabourHours  \
1
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
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
1      2
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
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
1      22.760000
2      27.388173
3      24.550338
4      42.142857
5      66.586258
   num_acres  max_num_cows_def
1
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[2]: 121719.1728613383
```

8.9 Economic Planning

8.9.1 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, init_productive_capacity, demand] = so.read_frame(
    industry_data)
# INPUTS = production_data.index.tolist()
production_coeff = so.flatten_frame(production_data)
productive_capacity_coeff = so.flatten_frame(productive_capacity_data)

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_solution_table(static_production))

final_demand = so.get_solution_table(
    static_production)['static_production']
# Alternative way
# final_demand = {}
# for i in INDUSTRIES:
#     final_demand[i] = static_production.get_value()

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(1, num_years+3), lb=0,
                                 name='extra_capacity')
productive_capacity = {}
for i in INDUSTRIES:
    for year in range(1, num_years+2):
        productive_capacity[i, year] = init_productive_capacity[i] +\
            so.quick_sum(extra_capacity[i, y] for y in range(2, year+1))
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)
        <= 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)
    problem1.set_objective(total_productive_capacity, sense=so.MAX,
                           name='total_productive_capacity')
    problem1.solve()
    productive_capacity_fr = so.dict_to_frame(productive_capacity,
                                              cols=['productive_capacity'])
    print(so.get_solution_table(production, stock, extra_capacity,
                                productive_capacity_fr))
    print(so.get_solution_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_solution_table(production, stock, extra_capacity,
                                productive_capacity))
    print(so.get_solution_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_solution_table(production, stock, extra_capacity,
                                productive_capacity))
    print(so.get_solution_table(manpower_con.get_expressions()))

    return problem3.get_objective_value()
```

8.9.2 Output

```
In [1]: from examples.economic_planning import test

In [2]: test(cas_conn)
NOTE: Initialized model economic_planning
NOTE: Converting model economic_planning to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMP153XBVSR␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMP153XBVSR has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem economic_planning has 3 variables (0 free, 0 fixed).
NOTE: The problem has 3 constraints (0 LE, 3 EQ, 0 GE, 0 range).
NOTE: The problem has 9 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed all variables and constraints.
NOTE: Optimal.
NOTE: Objective = 0.
NOTE: Cloud Analytic Services dropped table TMP153XBVSR from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                     Value
Label
Problem Name                 economic_planning
Objective Sense                   Minimization
Objective Function                        Zero
RHS                                        RHS

Number of Variables                          3
Bounded Above                                0
Bounded Below                                3
Bounded Above and Below                      0
Free                                         0
Fixed                                        0

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

Constraint Coefficients                      9
Solution Summary

                               Value
Label
```

```
Solver                                  LP
Algorithm                     Dual Simplex
Objective Function                    Zero
Solution Status                    Optimal
Objective Value                          0

Primal Infeasibility          1.421085E-14
Dual Infeasibility                       0
Bound Infeasibility                      0

Iterations                               0
Presolve Time                         0.00
Solution Time                         0.00
           static_production
1
coal              166.396761
steel             105.668016
transport          92.307692
NOTE: Initialized model Problem1
NOTE: Converting model Problem1 to DataFrame
WARNING: The objective function contains a constant term. An auxiliary variable is␣
↪added.
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPQRAFKYFB␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPQRAFKYFB has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem Problem1 has 61 variables (0 free, 13 fixed).
NOTE: The problem has 42 constraints (24 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 255 constraint coefficients.
NOTE: The following columns have no constraint coefficients:
         obj_constant
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 19 variables and 7 constraints.
NOTE: The LP presolver removed 64 constraint coefficients.
NOTE: The presolved problem has 42 variables, 35 constraints, and 191 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    1.360782E+04         0
          P 2         38    2.141875E+03         0
NOTE: Optimal.
NOTE: Objective = 2141.8751967.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMPQRAFKYFB from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                                      Value
Label
Problem Name                                       Problem1
Objective Sense                                Maximization
Objective Function       total_productive_capacity_constant
RHS                                                     RHS
```

```
Number of Variables                                        61
Bounded Above                                               0
Bounded Below                                              48
Bounded Above and Below                                     0
Free                                                        0
Fixed                                                      13

Number of Constraints                                      42
LE (<=)                                                    24
EQ (=)                                                     18
GE (>=)                                                     0
Range                                                       0

Constraint Coefficients                                   255
Solution Summary

                                                    Value
Label
Solver                                                 LP
Algorithm                                    Dual Simplex
Objective Function    total_productive_capacity_constant
Solution Status                                   Optimal
Objective Value                              2141.8751967

Primal Infeasibility                         5.115908E-13
Dual Infeasibility                                      0
Bound Infeasibility                          1.421085E-14

Iterations                                             38
Presolve Time                                        0.00
Solution Time                                        0.01
            production        stock extra_capacity productive_capacity
1         2
coal      0          0          150              -                   -
coal      1    260.403            0              0                 300
coal      2    293.406            0              0                 300
coal      3        300            0              0                 300
coal      4    17.9487      148.448        189.203             489.203
coal      5    166.397            0        1022.67             1511.88
coal      6    166.397 -1.42109e-14              0             1511.88
coal      7          -            -              0                   -
steel     0          0           80              -                   -
steel     1    135.342      12.2811              0                 350
steel     2     181.66            0              0                 350
steel     3     193.09            0              0                 350
steel     4    105.668            0              0                 350
steel     5    105.668            0              0                 350
steel     6    105.668            0              0                 350
steel     7          -            -              0                   -
transport 0          0          100              -                   -
transport 1    140.722      6.24084              0                 280
transport 2     200.58            0              0                 280
transport 3    267.152            0              0                 280
transport 4    92.3077            0              0                 280
transport 5    92.3077            0              0                 280
transport 6    92.3077  1.42109e-14              0                 280
transport 7          -            -              0                   -
   manpower_con
```

```
1
1    224.988515
2    270.657715
3    367.038878
4    470.000000
5    150.000000
6    150.000000
NOTE: Initialized model Problem2
NOTE: Converting model Problem2 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPPULFAZ5N␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPPULFAZ5N has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem Problem2 has 60 variables (0 free, 12 fixed).
NOTE: The problem has 42 constraints (24 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 255 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
NOTE: The LP presolver removed 18 variables and 7 constraints.
NOTE: The LP presolver removed 64 constraint coefficients.
NOTE: The presolved problem has 42 variables, 35 constraints, and 191 constraint␣
↪coefficients.
NOTE: The LP solver is called.
NOTE: The Dual Simplex algorithm is used.
                              Objective
         Phase Iteration        Value         Time
          D 2          1    9.413902E+03         0
          P 2         40    2.618579E+03         0
NOTE: Optimal.
NOTE: Objective = 2618.5791147.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMPPULFAZ5N from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                    Value
Label
Problem Name                     Problem2
Objective Sense              Maximization
Objective Function       total_production
RHS                                   RHS

Number of Variables                    60
Bounded Above                           0
Bounded Below                          48
Bounded Above and Below                 0
Free                                    0
Fixed                                  12

Number of Constraints                  42
LE (<=)                                24
EQ (=)                                 18
GE (>=)                                 0
Range                                   0

Constraint Coefficients               255
Solution Summary
```

```
                                Value
Label
Solver                             LP
Algorithm                Dual Simplex
Objective Function   total_production
Solution Status               Optimal
Objective Value          2618.5791147

Primal Infeasibility     1.755041E-12
Dual Infeasibility                  0
Bound Infeasibility                 0

Iterations                         40
Presolve Time                    0.00
Solution Time                    0.01
            production    stock extra_capacity     dict
1         2
coal      0          0      150              -        -
coal      1        300  20.1103              0      300
coal      2    315.323  131.554         15.323  315.323
coal      3    430.505        0        115.182  430.505
coal      4    430.505        0              0  430.505
coal      5    430.505        0              0  430.505
coal      6    166.397  324.108              0  430.505
coal      7          -        -              0        -
steel     0          0       80              -        -
steel     1    86.7295  11.5323              0      350
steel     2    155.337        0              0      350
steel     3    182.867        0              0      350
steel     4    359.402        0        9.40227  359.402
steel     5    359.402  176.535              0  359.402
steel     6    105.668  490.269              0  359.402
steel     7          -        -              0        -
transport 0          0      100              -        -
transport 1    141.312        0              0      280
transport 2    198.388        0              0      280
transport 3    225.918        0              0      280
transport 4    519.383        0        239.383  519.383
transport 5    519.383  293.465              0  519.383
transport 6    92.3077   750.54              0  519.383
transport 7          -        -              0        -
   manpower_con
1
1    240.410497
2    321.545290
3    384.165212
4    470.000000
5    470.000000
6    150.000000
NOTE: Initialized model Problem3
NOTE: Converting model Problem3 to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMP4_NQHTZM␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMP4_NQHTZM has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
```

```
NOTE: The problem Problem3 has 60 variables (0 free, 12 fixed).
NOTE: The problem has 36 constraints (18 LE, 18 EQ, 0 GE, 0 range).
NOTE: The problem has 219 constraint coefficients.
NOTE: The LP presolver value AUTOMATIC is applied.
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    4.013232E+04         0
          P 2         49    2.450027E+03         0
NOTE: Optimal.
NOTE: Objective = 2450.0266228.
NOTE: The Dual Simplex solve time is 0.01 seconds.
NOTE: Cloud Analytic Services dropped table TMP4_NQHTZM from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                  Value
Label
Problem Name                   Problem3
Objective Sense            Maximization
Objective Function       total_manpower
RHS                                 RHS

Number of Variables                  60
Bounded Above                         0
Bounded Below                        48
Bounded Above and Below               0
Free                                  0
Fixed                                12

Number of Constraints                36
LE (<=)                              18
EQ (=)                               18
GE (>=)                               0
Range                                 0

Constraint Coefficients             219
Solution Summary

                               Value
Label
Solver                            LP
Algorithm               Dual Simplex
Objective Function    total_manpower
Solution Status              Optimal
Objective Value         2450.0266228

Primal Infeasibility    2.195577E-12
Dual Infeasibility                 0
Bound Infeasibility                0

Iterations                        49
Presolve Time                   0.00
```

```
Solution Time                    0.01
            production    stock extra_capacity     dict
1          2
coal       0         0      150              -        -
coal       1   251.793        0              0      300
coal       2   316.015        0        16.0152  316.015
coal       3   319.832        0         3.8168  319.832
coal       4    366.35        0        46.5177   366.35
coal       5    859.36        0         493.01   859.36
coal       6    859.36  460.208              0   859.36
coal       7         -        -              0        -
steel      0         0       80              -        -
steel      1   134.795   11.028              0      350
steel      2   175.041        0              0      350
steel      3   224.064        0              0      350
steel      4   223.136        0              0      350
steel      5   220.044        0              0      350
steel      6       350        0              0      350
steel      7         -        -              0        -
transport 0         0      100              -        -
transport 1   143.559  4.24723              0      280
transport 2   181.676        0              0      280
transport 3       280        0              0      280
transport 4   279.072        0              0      280
transport 5    275.98        0              0      280
transport 6   195.539        0              0      280
transport 7         -        -              0        -
   manpower_con
1
1    226.631832
2    279.983537
3    333.725517
4    539.769130
5    636.824849
6    659.723590
Out[2]: 2450.0266228212977
```

8.10 Optimal Wedding

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

8.10.1 Model

```
import sasoptpy as so
import math


def test(cas_conn, num_guests=10, 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)
```

```python
    # 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(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()
```

8.10.2 Output

```
In [1]: from examples.sas_optimal_wedding import test

In [2]: test(cas_conn)
NOTE: Initialized model wedding
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 TMPLDIFT87Y␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPLDIFT87Y has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
NOTE: The problem wedding has 44 variables (40 binary, 0 integer, 0 free, 0 fixed).
NOTE: The problem has 194 constraints (4 LE, 10 EQ, 180 GE, 0 range).
NOTE: The problem has 620 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: The number of block threads has been reduced to 4 threads.
NOTE: The problem has a decomposable structure with 4 blocks. The largest block␣
↪covers 23.71% of the constraints in the problem.
NOTE: The decomposition subproblems cover 44 (100%) variables and 184 (94.85%)␣
↪constraints.
NOTE: The deterministic parallel mode is enabled.
NOTE: The Decomposition algorithm is using up to 32 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
            7       0.0000       6.0000       6.0000 6.00e+00 6.00e+00    3    5
            .       0.0000       6.0000       6.0000 6.00e+00 6.00e+00    6    9
           10       0.0000       6.0000       6.0000 6.00e+00 6.00e+00    6   10
           16       2.0000       6.0000       6.0000  200.00%  200.00%   13   15
           17       6.0000       6.0000       6.0000    0.00%    0.00%   14   16
            Node  Active   Sols         Best         Best       Gap     CPU    Real
                                     Integer        Bound              Time    Time
               0       0      5       6.0000       6.0000    0.00%      14      16
NOTE: The Decomposition algorithm used 32 threads.
NOTE: The Decomposition algorithm time is 16.75 seconds.
NOTE: Optimal.
NOTE: Objective = 6.
NOTE: Cloud Analytic Services dropped table TMPLDIFT87Y from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                Value
Label
Problem Name                  wedding
Objective Sense          Minimization
Objective Function                obj
RHS                               RHS

Number of Variables                44
Bounded Above                       0
Bounded Below                       4
Bounded Above and Below            40
Free                                0
Fixed                               0
Binary                             40
Integer                             0

Number of Constraints             194
LE (<=)                             4
EQ (=)                             10
GE (>=)                           180
Range                               0

Constraint Coefficients           620
Solution Summary

                                Value
Label
```

```
Solver                             MILP
Algorithm                 Decomposition
Objective Function                  obj
Solution Status                 Optimal
Objective Value                       6

Relative Gap                          0
Absolute Gap                          0
Primal Infeasibility       1.065814E-14
Bound Infeasibility                   0
Integer Infeasibility      1.065814E-14

Best Bound                            6
Nodes                                 1
Iterations                           17

Presolve Time                      0.01
Solution Time                     16.76
                 x
1  2
1  1  0.000000e+00
1  2  1.000000e+00
1  3  0.000000e+00
1  4  0.000000e+00
2  1  0.000000e+00
2  2  1.000000e+00
2  3  0.000000e+00
2  4  0.000000e+00
3  1  0.000000e+00
3  2  0.000000e+00
3  3  0.000000e+00
3  4  1.000000e+00
4  1  0.000000e+00
4  2  0.000000e+00
4  3  1.065814e-14
4  4  1.000000e+00
5  1  1.000000e+00
5  2  0.000000e+00
5  3  0.000000e+00
5  4  0.000000e+00
6  1  1.000000e+00
6  2  0.000000e+00
6  3  0.000000e+00
6  4  0.000000e+00
7  1  1.000000e+00
7  2  0.000000e+00
7  3  0.000000e+00
7  4  0.000000e+00
8  1  0.000000e+00
8  2  0.000000e+00
8  3  1.000000e+00
8  4  0.000000e+00
9  1  0.000000e+00
9  2  0.000000e+00
9  3  1.000000e+00
9  4  0.000000e+00
10 1  0.000000e+00
10 2  0.000000e+00
```

```
10 3  1.000000e+00
10 4  0.000000e+00
Table 1 : [ 5 6 7 ]
Table 2 : [ 1 2 ]
Table 3 : [ 8 9 10 ]
Table 4 : [ 3 4 ]
Out[2]: 6.000000000000005
```

8.11 Kidney Exchange

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

8.11.1 Model

```
import sasoptpy as so
import random


def test(cas_conn):
    # 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
    model.solve(milp={'maxtime': 300})

    # 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(milp={'maxtime': 300, 'presolver': 'basic',
                      'decomp': {'method': 'user'}})

    return model.get_objective_value()
```

8.11.2 Output

```
In [1]: from examples.sas_kidney_exchange import test

In [2]: test(cas_conn)
NOTE: Initialized model kidney_exchange
Setting objective...
Adding constraints...
NOTE: Converting model kidney_exchange to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPVPYAYCO1␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPVPYAYCO1 has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
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 remaining solution time after solver initialization is 299.89 seconds.
NOTE: The initial MILP heuristics are applied.
NOTE: The MILP presolver value AUTOMATIC is applied.
NOTE: The MILP presolver removed 6212 variables and 5352 constraints.
NOTE: The MILP presolver removed 17534 constraint coefficients.
NOTE: The MILP presolver modified 0 constraint coefficients.
NOTE: The presolved problem has 1921 variables, 615 constraints, and 6711 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 32 threads.
             Node   Active   Sols    BestInteger      BestBound      Gap    Time
                0        1      3      3.5275019     18.3085704   80.73%       3
NOTE: The MILP solver's symmetry detection found 778 orbits. The largest orbit␣
↪contains 15 variables.
                0        1      4      3.5936462     18.3085704   80.37%       3
NOTE: The MILP solver added 1 cuts with 31 cut coefficients at the root.
                2        2      5     17.1113590     18.3085704    6.54%       4
               23        3      6     17.1113590     18.3085704    6.54%       5
               24        2      6     17.1113590     18.3085704    6.54%       5
               58        4      7     17.1113590     18.0278830    5.08%       5
               69        2      8     17.1113590     18.0125221    5.00%       6
               74        0      8     17.1113590     17.1113590    0.00%       6
NOTE: Optimal.
NOTE: Objective = 17.111358985.
NOTE: Cloud Analytic Services dropped table TMPVPYAYCO1 from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                   Value
Label
Problem Name             kidney_exchange
Objective Sense             Maximization
Objective Function          total_weight
RHS                                  RHS

Number of Variables                 8133
Bounded Above                          0
Bounded Below                          0
Bounded Above and Below             8133
Free                                   0
Fixed                                  0
Binary                              8133
Integer                                0

Number of Constraints               5967
LE (<=)                               38
EQ (=)                              5929
GE (>=)                                0
Range                                  0

Constraint Coefficients            24245
Solution Summary

                                Value
Label
Solver                           MILP
Algorithm              Branch and Cut
Objective Function       total_weight
Solution Status               Optimal
Objective Value          17.111358985

Relative Gap                        0
Absolute Gap                        0
Primal Infeasibility     9.325873E-15
Bound Infeasibility      6.661338E-16
```

```
Integer Infeasibility    9.325873E-15

Best Bound               17.111358985
Nodes                              75
Iterations                       8909

Presolve Time                    2.68
Solution Time                    7.03
NOTE: Cloud Analytic Services made the uploaded file available as table BLOCKSTABLE␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table BLOCKSTABLE has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Converting model kidney_exchange to DataFrame
NOTE: Uploading the problem DataFrame to the server.
NOTE: Cloud Analytic Services made the uploaded file available as table TMPS7CCLMBF␣
↪in caslib CASUSERHDFS(casuser).
NOTE: The table TMPS7CCLMBF has been created in caslib CASUSERHDFS(casuser) from␣
↪binary data uploaded to Cloud Analytic Services.
NOTE: Added action set 'optimization'.
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 remaining solution time after solver initialization is 299.87 seconds.
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: 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 32 threads.
         Iter         Best       Master         Best       LP        IP  CPU Real
                     Bound    Objective      Integer      Gap       Gap Time Time
            .     283.4155      10.6475      10.6475   96.24%    96.24%    3    3
            1     283.4155      10.6475      10.6475   96.24%    96.24%    5    6
            2     226.1977      10.6475      10.6475   95.29%    95.29%    8    8
            3     209.4256      10.6475      10.6475   94.92%    94.92%   10   10
            4     148.3711      14.8383      14.8383   90.00%    90.00%   14   13
            7     100.1095      17.1114      17.1114   82.91%    82.91%   20   19
            8      80.4083      17.1114      17.1114   78.72%    78.72%   22   21
            9      53.9515      17.1114      17.1114   68.28%    68.28%   25   24
            .      53.9515      17.1114      17.1114   68.28%    68.28%   26   25
           10      25.4548      17.1114      17.1114   32.78%    32.78%   28   28
           12      17.1114      17.1114      17.1114    0.00%     0.00%   52   33
            Node  Active    Sols         Best         Best      Gap     CPU    Real
                                      Integer        Bound             Time    Time
               0       0       8      17.1114      17.1114    0.00%      52      33
```

```
NOTE: The Decomposition algorithm used 32 threads.
NOTE: The Decomposition algorithm time is 33.80 seconds.
NOTE: Optimal.
NOTE: Objective = 17.111358985.
NOTE: Cloud Analytic Services dropped table TMPS7CCLMBF from caslib␣
↪CASUSERHDFS(casuser).
NOTE: Cloud Analytic Services dropped table BLOCKSTABLE from caslib␣
↪CASUSERHDFS(casuser).
Problem Summary

                                   Value
Label
Problem Name                 kidney_exchange
Objective Sense                 Maximization
Objective Function              total_weight
RHS                                      RHS

Number of Variables                     8133
Bounded Above                              0
Bounded Below                              0
Bounded Above and Below                 8133
Free                                       0
Fixed                                      0
Binary                                  8133
Integer                                    0

Number of Constraints                   5967
LE (<=)                                   38
EQ (=)                                  5929
GE (>=)                                    0
Range                                      0

Constraint Coefficients                24245
Solution Summary

                                Value
Label
Solver                           MILP
Algorithm               Decomposition
Objective Function       total_weight
Solution Status               Optimal
Objective Value          17.111358985

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

Best Bound               17.111358985
Nodes                               1
Iterations                         12

Presolve Time                    0.11
Solution Time                   33.96
Out[2]: 17.111358984870215
```

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