# Sage Reference Manual: Numerical Optimization

Release 6.3

**The Sage Development Team** 

# **CONTENTS**

1	Knapsack Problems	]			
	1.1 Definition of Knapsack problems				
	1.2 Examples				
	1.3 Super-increasing sequences	2			
2	Mixed Integer Linear Programming	9			
	2.1 Index of functions and methods	11			
	2.2 Classes and methods	11			
3	Linear Functions and Constraints	35			
4	Numerical Root Finding and Optimization	43			
	4.1 Functions and Methods	43			
5	Interactive Simplex Method	51			
6	LP Solver backends	89			
	6.1 Generic Backend for LP solvers	89			
	6.2 GLPK Backend	102			
	6.3 GLPK Backend for access to GLPK graph functions	121			
	6.4 PPL Backend	133			
	6.5 CVXOPT Backend	143			
7	Indices and Tables	155			
	Sibliography 1				

# **KNAPSACK PROBLEMS**

This module implements a number of solutions to various knapsack problems, otherwise known as linear integer programming problems. Solutions to the following knapsack problems are implemented:

- Solving the subset sum problem for super-increasing sequences.
- General case using Linear Programming

#### **AUTHORS:**

- Minh Van Nguyen (2009-04): initial version
- Nathann Cohen (2009-08): Linear Programming version

# 1.1 Definition of Knapsack problems

You have already had a knapsack problem, so you should know, but in case you do not, a knapsack problem is what happens when you have hundred of items to put into a bag which is too small, and you want to pack the most useful of them.

When you formally write it, here is your problem:

- Your bag can contain a weight of at most W.
- Each item i has a weight  $w_i$ .
- Each item i has a usefulness  $u_i$ .

You then want to maximize the total usefulness of the items you will store into your bag, while keeping sure the weight of the bag will not go over W.

As a linear program, this problem can be represented this way (if you define  $b_i$  as the binary variable indicating whether the item i is to be included in your bag):

$$\begin{aligned} & \text{Maximize: } \sum_i b_i u_i \\ & \text{Such that: } \sum_i b_i w_i \leq W \\ & \forall i, b_i \text{ binary variable} \end{aligned}$$

(For more information, see the Wikipedia article Knapsack\_problem)

# 1.2 Examples

If your knapsack problem is composed of three items (weight, value) defined by (1,2), (1.5,1), (0.5,3), and a bag of maximum weight 2, you can easily solve it this way:

```
sage: from sage.numerical.knapsack import knapsack
sage: knapsack( [(1,2), (1.5,1), (0.5,3)], max=2)
[5.0, [(1, 2), (0.50000000000000, 3)]]
```

# 1.3 Super-increasing sequences

We can test for whether or not a sequence is super-increasing:

```
sage: from sage.numerical.knapsack import Superincreasing
sage: L = [1, 2, 5, 21, 69, 189, 376, 919]
sage: seq = Superincreasing(L)
sage: seq
Super-increasing sequence of length 8
sage: seq.is_superincreasing()
True
sage: Superincreasing().is_superincreasing([1,3,5,7])
False
```

Solving the subset sum problem for a super-increasing sequence and target sum:

```
sage: L = [1, 2, 5, 21, 69, 189, 376, 919]
sage: Superincreasing(L).subset_sum(98)
[69, 21, 5, 2, 1]
```

class sage.numerical.knapsack.Superincreasing(seg=None)

Bases: sage.structure.sage\_object.SageObject

A class for super-increasing sequences.

Let  $L=(a_1,a_2,a_3,\ldots,a_n)$  be a non-empty sequence of non-negative integers. Then L is said to be super-increasing if each  $a_i$  is strictly greater than the sum of all previous values. That is, for each  $a_i \in L$  the sequence L must satisfy the property

$$a_i > \sum_{k=1}^{i-1} a_k$$

in order to be called a super-increasing sequence, where  $|L| \ge 2$ . If L has only one element, it is also defined to be a super-increasing sequence.

If seq is None, then construct an empty sequence. By definition, this empty sequence is not super-increasing.

•seq – (default: None) a non-empty sequence.

#### **EXAMPLES:**

INPUT:

```
sage: from sage.numerical.knapsack import Superincreasing
sage: L = [1, 2, 5, 21, 69, 189, 376, 919]
sage: Superincreasing(L).is_superincreasing()
True
sage: Superincreasing().is_superincreasing([1,3,5,7])
```

```
False
sage: seq = Superincreasing(); seq
An empty sequence.
sage: seq = Superincreasing([1, 3, 6]); seq
Super-increasing sequence of length 3
sage: seq = Superincreasing(list([1, 2, 5, 21, 69, 189, 376, 919])); seq
Super-increasing sequence of length 8
```

#### is\_superincreasing(seq=None)

Determine whether or not seq is super-increasing.

If seq=None then determine whether or not self is super-increasing.

Let  $L=(a_1,a_2,a_3,\ldots,a_n)$  be a non-empty sequence of non-negative integers. Then L is said to be super-increasing if each  $a_i$  is strictly greater than the sum of all previous values. That is, for each  $a_i \in L$  the sequence L must satisfy the property

$$a_i > \sum_{k=1}^{i-1} a_k$$

in order to be called a super-increasing sequence, where  $|L| \ge 2$ . If L has exactly one element, then it is also defined to be a super-increasing sequence.

#### INPUT:

•seq - (default: None) a sequence to test

#### **OUTPUT:**

- •If seq is None, then test self to determine whether or not it is super-increasing. In that case, return True if self is super-increasing; False otherwise.
- •If seq is not None, then test seq to determine whether or not it is super-increasing. Return True if seq is super-increasing; False otherwise.

#### **EXAMPLES:**

By definition, an empty sequence is not super-increasing:

```
sage: from sage.numerical.knapsack import Superincreasing
sage: Superincreasing().is_superincreasing([])
False
sage: Superincreasing().is_superincreasing()
False
sage: Superincreasing().is_superincreasing(tuple())
False
sage: Superincreasing().is_superincreasing(())
False
```

But here is an example of a super-increasing sequence:

```
sage: L = [1, 2, 5, 21, 69, 189, 376, 919]
sage: Superincreasing(L).is_superincreasing()
True
sage: L = (1, 2, 5, 21, 69, 189, 376, 919)
sage: Superincreasing(L).is_superincreasing()
True
```

A super-increasing sequence can have zero as one of its elements:

```
sage: L = [0, 1, 2, 4]
sage: Superincreasing(L).is_superincreasing()
True
A super-increasing sequence can be of length 1:
sage: Superincreasing([randint(0, 100)]).is_superincreasing()
True
TESTS:
The sequence must contain only integers:
sage: from sage.numerical.knapsack import Superincreasing
sage: L = [1.0, 2.1, pi, 21, 69, 189, 376, 919]
sage: Superincreasing(L).is_superincreasing()
Traceback (most recent call last):
TypeError: Element e (= 1.00000000000000) of seq must be a non-negative integer.
sage: L = [1, 2.1, pi, 21, 69, 189, 376, 919]
sage: Superincreasing(L).is_superincreasing()
Traceback (most recent call last):
TypeError: Element e (= 2.10000000000000) of seg must be a non-negative integer.
```

#### $largest_less_than(N)$

Return the largest integer in the sequence self that is less than or equal to N.

This function narrows down the candidate solution using a binary trim, similar to the way binary search halves the sequence at each iteration.

#### INPUT:

•N – integer; the target value to search for.

#### **OUTPUT:**

The largest integer in self that is less than or equal to N. If no solution exists, then return None.

#### **EXAMPLES:**

When a solution is found, return it:

```
sage: from sage.numerical.knapsack import Superincreasing
sage: L = [2, 3, 7, 25, 67, 179, 356, 819]
sage: Superincreasing(L).largest_less_than(207)
179
sage: L = (2, 3, 7, 25, 67, 179, 356, 819)
sage: Superincreasing(L).largest_less_than(2)
2
```

#### But if no solution exists, return None:

```
sage: L = [2, 3, 7, 25, 67, 179, 356, 819]
sage: Superincreasing(L).largest_less_than(-1) is None
True
```

## TESTS:

The target N must be an integer:

```
sage: from sage.numerical.knapsack import Superincreasing
sage: L = [2, 3, 7, 25, 67, 179, 356, 819]
```

```
sage: Superincreasing(L).largest_less_than(2.30)
Traceback (most recent call last):
...
TypeError: N (= 2.30000000000000) must be an integer.

The sequence that self represents must also be non-empty:
sage: Superincreasing([]).largest_less_than(2)
Traceback (most recent call last):
...
ValueError: seq must be a super-increasing sequence
sage: Superincreasing(list()).largest_less_than(2)
Traceback (most recent call last):
...
ValueError: seq must be a super-increasing sequence
```

#### subset sum(N)

Solving the subset sum problem for a super-increasing sequence.

Let  $S = (s_1, s_2, s_3, \dots, s_n)$  be a non-empty sequence of non-negative integers, and let  $N \in \mathbf{Z}$  be non-negative. The subset sum problem asks for a subset  $A \subseteq S$  all of whose elements sum to N. This method specializes the subset sum problem to the case of super-increasing sequences. If a solution exists, then it is also a super-increasing sequence.

**Note:** This method only solves the subset sum problem for super-increasing sequences. In general, solving the subset sum problem for an arbitrary sequence is known to be computationally hard.

#### INPUT:

•N – a non-negative integer.

#### **OUTPUT**:

•A non-empty subset of self whose elements sum to N. This subset is also a super-increasing sequence. If no such subset exists, then return the empty list.

#### ALGORITHMS:

The algorithm used is adapted from page 355 of [HPS08].

#### **EXAMPLES:**

Solving the subset sum problem for a super-increasing sequence and target sum:

```
sage: from sage.numerical.knapsack import Superincreasing
sage: L = [1, 2, 5, 21, 69, 189, 376, 919]
sage: Superincreasing(L).subset_sum(98)
[69, 21, 5, 2, 1]
```

### TESTS:

The target N must be a non-negative integer:

```
sage: from sage.numerical.knapsack import Superincreasing
sage: L = [0, 1, 2, 4]
sage: Superincreasing(L).subset_sum(-6)
Traceback (most recent call last):
...
TypeError: N (= -6) must be a non-negative integer.
sage: Superincreasing(L).subset_sum(-6.2)
Traceback (most recent call last):
```

```
TypeError: N (= -6.2000000000000) must be a non-negative integer.

The sequence that self represents must only contain non-negative integers:

sage: L = [-10, -9, -8, -7, -6, -5, -4, -3, -2, -1, 0, 1]

sage: Superincreasing(L).subset_sum(1)

Traceback (most recent call last):
...

TypeError: Element e (= -10) of seq must be a non-negative integer.
```

#### REFERENCES:

#### Solves the knapsack problem

For more information on the knapsack problem, see the documentation of the knapsack module or the Wikipedia article Knapsack\_problem.

#### INPUT:

- •seq Two different possible types:
  - -A sequence of tuples (weight, value, something1, something2, ...). Note that only the first two coordinates (weight and values) will be taken into account. The rest (if any) will be ignored. This can be useful if you need to attach some information to the items.
  - -A sequence of reals (a value of 1 is assumed).
- •binary When set to True, an item can be taken 0 or 1 time. When set to False, an item can be taken any amount of times (while staying integer and positive).
- •max Maximum admissible weight.
- •value\_only When set to True, only the maximum useful value is returned. When set to False, both the maximum useful value and an assignment are returned.
- •solver (default: None) Specify a Linear Program (LP) solver to be used. If set to None, the default one is used. For more information on LP solvers and which default solver is used, see the documentation of class MixedIntegerLinearProgram.
- •verbose integer (default: 0). Sets the level of verbosity. Set to 0 by default, which means quiet.

#### **OUTPUT:**

If value\_only is set to True, only the maximum useful value is returned. Else (the default), the function returns a pair [value, list], where list can be of two types according to the type of seq:

- •The list of tuples  $(w_i, u_i, ...)$  occurring in the solution.
- •A list of reals where each real is repeated the number of times it is taken into the solution.

#### **EXAMPLES:**

If your knapsack problem is composed of three items (weight, value) defined by (1,2), (1.5,1), (0.5,3), and a bag of maximum weight 2, you can easily solve it this way:

```
sage: from sage.numerical.knapsack import knapsack
sage: knapsack([(1,2), (1.5,1), (0.5,3)], max=2)
[5.0, [(1, 2), (0.50000000000000, 3)]]
sage: knapsack([(1,2), (1.5,1), (0.5,3)], max=2, value_only=True)
5.0
```

Besides weight and value, you may attach any data to the items:

```
sage: from sage.numerical.knapsack import knapsack
sage: knapsack( [(1, 2, 'spam'), (0.5, 3, 'a', 'lot')])
[3.0, [(0.500000000000000, 3, 'a', 'lot')]]
```

In the case where all the values (usefulness) of the items are equal to one, you do not need embarrass yourself with the second values, and you can just type for items (1,1), (1.5,1), (0.5,1) the command:

```
sage: from sage.numerical.knapsack import knapsack
sage: knapsack([1,1.5,0.5], max=2, value_only=True)
2.0
```

Sage Reference Manual: Numerical Optimization, Release 6.3					

# MIXED INTEGER LINEAR PROGRAMMING

Mixed Integer Linear Programming

A linear program (LP) is an optimization problem in the following form

$$\max\{c^T x \mid Ax \le b, x \ge 0\}$$

with given  $A \in \mathbb{R}^{m,n}$ ,  $b \in \mathbb{R}^m$ ,  $c \in \mathbb{R}^n$  and unknown  $x \in \mathbb{R}^n$ . If some or all variables in the vector x are restricted over the integers  $\mathbb{Z}$ , the problem is called mixed integer linear program (MILP). A wide variety of problems in optimization can be formulated in this standard form. Then, solvers are able to calculate a solution.

Imagine you want to solve the following linear system of three equations:

- $w_0 + w_1 + w_2 14w_3 = 0$
- $w_1 + 2w_2 8w_3 = 0$
- $2w_2 3w_3 = 0$

and this additional inequality:

• 
$$w_0 - w_1 - w_2 \ge 0$$

where all  $w_i \in \mathbb{Z}^+$ . You know that the trivial solution is  $w_i = 0$ , but what is the first non-trivial one with  $w_3 \ge 1$ ?

A mixed integer linear program can give you an answer:

- 1. You have to create an instance of MixedIntegerLinearProgram and in our case specify that it is a minimization.
- 2. Create an dictionary w of integer variables w via w = p.new\_variable(integer=True) (note that by default all variables are non-negative, cf new\_variable()).
- 3. Add those three equations as equality constraints via add\_constraint.
- 4. Also add the inequality constraint.
- 5. Add an inequality constraint  $w_3 \ge 1$  to exclude the trivial solution.
- 6. By default, all variables are non-negative. We remove that constraint via p.set\_min(variable, None), see set\_min.
- 7. Specify the objective function via set\_objective. In our case that is just  $w_3$ . If it is a pure constraint satisfaction problem, specify it as None.
- 8. To check if everything is set up correctly, you can print the problem via show.

9. Solve it and print the solution.

The following example shows all these steps:

```
sage: p = MixedIntegerLinearProgram(maximization=False, solver = "GLPK")
sage: w = p.new_variable(integer=True, nonnegative=True)
sage: p.add_constraint(w[0] + w[1] + w[2] - 14*w[3] == 0)
sage: p.add_constraint(w[1] + 2*w[2] - 8*w[3] == 0)
sage: p.add_constraint(2*w[2] - 3*w[3] == 0)
sage: p.add_constraint(w[0] - w[1] - w[2] >= 0)
sage: p.add_constraint(w[3] >= 1)
sage: _ = [ p.set_min(w[i], None) for i in range(1,4) ]
sage: p.set_objective(w[3])
sage: p.show()
Minimization:
  x_3
Constraints:
  0.0 \le x_0 + x_1 + x_2 - 14.0 x_3 \le 0.0
  0.0 \le x_1 + 2.0 x_2 - 8.0 x_3 \le 0.0
  0.0 \le 2.0 \text{ x}_2 - 3.0 \text{ x}_3 \le 0.0
  - x_0 + x_1 + x_2 <= 0.0
  - x_3 <= -1.0
Variables:
  x_0 is an integer variable (min=0.0, max=+oo)
  x_1 is an integer variable (min=-oo, max=+oo)
  x_2 is an integer variable (min=-oo, max=+oo)
 x_3 is an integer variable (min=-oo, max=+oo)
sage: print 'Objective Value:', p.solve()
Objective Value: 2.0
sage: for i, v in p.get_values(w).iteritems():\
          print 'w_%s = %s' % (i, int(round(v)))
w_0 = 15
w_1 = 10
w_2 = 3
w_3 = 2
```

Different backends compute with different base fields, for example:

```
sage: p = MixedIntegerLinearProgram(solver = 'GLPK')
sage: p.base_ring()
Real Double Field
sage: x = p.new_variable(real=True, nonnegative=True)
sage: 0.5 + 3/2*x[1]
0.5 + 1.5*x_0

sage: p = MixedIntegerLinearProgram(solver = 'ppl')
sage: p.base_ring()
Rational Field
sage: x = p.new_variable(nonnegative=True)
sage: 0.5 + 3/2*x[1]
1/2 + 3/2*x_0
```

#### **AUTHORS**:

• Risan (2012/02): added extension for exact computation

# 2.1 Index of functions and methods

Below are listed the methods of MixedIntegerLinearProgram. This module also implements the MIPSolverException exception, as well as the MIPVariable class.

add_constraint()	Adds a constraint to the MixedIntegerLinearProgram	
base_ring()	Return the base ring	
constraints()	Returns a list of constraints, as 3-tuples	
get_backend()	Returns the backend instance used	
get_max()	Returns the maximum value of a variable	
get_max() get_min()	Returns the minimum value of a variable	
get_min() get_values()	Return values found by the previous call to solve()	
is_binary()	Tests whether the variable e is binary	
is_integer()	Tests whether the variable is an integer	
is_real()	Tests whether the variable is real	
linear_constraints_parent()	Return the parent for all linear constraints	
linear_function()	Construct a new linear function	
linear_functions_parent()	Return the parent for all linear functions	
new_variable()	Returns an instance of MIPVariable associated	
number_of_constraints()	Returns the number of constraints assigned so far	
number_of_constraints() number_of_variables()	Returns the number of variables used so far	
polyhedron()	Returns the polyhedron defined by the Linear Program  Removes a constraint from self	
remove_constraint()		
remove_constraints()	Remove several constraints	
set_binary()	Sets a variable or a MIPVariable as binary	
set_integer()	Sets a variable or a MIPVariable as integer	
set_max()	Sets the maximum value of a variable	
set_min()	Sets the minimum value of a variable	
set_objective()	Sets the objective of the MixedIntegerLinearProgram	
set_problem_name()	Sets the name of the MixedIntegerLinearProgram	
set_real()	Sets a variable or a MIPVariable as real	
show()	Displays the MixedIntegerLinearProgram in a human-readable	
solve()	Solves the MixedIntegerLinearProgram	
solver_parameter()	Return or define a solver parameter	
sum()	Efficiently computes the sum of a sequence of LinearFunction elements	
write_lp()	Write the linear program as a LP file	
write_mps()	Write the linear program as a MPS file	

## 2.2 Classes and methods

```
exception sage.numerical.mip.MIPSolverException(value)
Bases: exceptions.RuntimeError
Exception raised when the solver fails.

class sage.numerical.mip.MIPVariable
Bases: sage.structure.sage_object.SageObject
MIPVariable is a variable used by the class MixedIntegerLinearProgram.

depth()
Returns the current variable's depth.
```

```
EXAMPLE:
```

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(nonnegative=True)
sage: p.set_objective(v[0] + v[1])
sage: v.depth()
1
```

#### items()

Returns the pairs (keys, value) contained in the dictionary.

#### **EXAMPLE**:

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(nonnegative=True)
sage: p.set_objective(v[0] + v[1])
sage: v.items()
[(0, x_0), (1, x_1)]
```

#### keys()

Returns the keys already defined in the dictionary.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(nonnegative=True)
sage: p.set_objective(v[0] + v[1])
sage: v.keys()
[0, 1]
```

#### set\_max(max)

Sets an upper bound on the variable.

#### INPUT:

•max – an upper bound, or None to mean that the variable is unbounded.

#### **EXAMPLES:**

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(real=True, nonnegative=True, dim=2)
sage: p.get_max(v)
sage: p.get_max(v[0])
sage: p.get_max(v[0][0])
sage: p.set_max(v, 4)
sage: p.get_max(v)
4
sage: p.get_max(v[0])
4
sage: p.get_max(v[0])
4
sage: p.get_max(v[0][0])
4.0
```

#### set\_min(min)

Sets a lower bound on the variable.

#### INPUT:

•min – a lower bound, or None to mean that the variable is unbounded.

#### **EXAMPLES:**

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(real=True, nonnegative=True, dim=2)
```

```
sage: p.get_min(v)
0
sage: p.get_min(v[0])
0
sage: p.get_min(v[0][0])
0.0
sage: p.set_min(v,4)
sage: p.get_min(v)
4
sage: p.get_min(v[0])
4
sage: p.get_min(v[0])
4
```

#### values()

Returns the symbolic variables associated to the current dictionary.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(nonnegative=True)
sage: p.set_objective(v[0] + v[1])
sage: v.values()
[x_0, x_1]
```

#### class sage.numerical.mip.MixedIntegerLinearProgram

Bases: sage.structure.sage\_object.SageObject

The MixedIntegerLinearProgram class is the link between Sage, linear programming (LP) and mixed integer programming (MIP) solvers.

A Mixed Integer Linear Program (MILP) consists of variables, linear constraints on these variables, and an objective function which is to be maximised or minimised under these constraints.

See the Wikipedia article Linear\_programming for further information on linear programming, and the MILP module for its use in Sage.

#### INPUT:

```
•solver - selects a solver:
```

```
-GLPK (solver="GLPK"). See the GLPK web site.
```

- -COIN Branch and Cut (solver="Coin"). See the COIN-OR web site.
- -CPLEX (solver="CPLEX"). See the CPLEX web site.
- -Gurobi (solver="Gurobi"). See the Gurobi web site.
- -CVXOPT (solver="CVXOPT"). See the CVXOPT web site.
- -PPL (solver="PPL"). See the PPL web site.
- -If solver=None (default), the default solver is used (see default\_mip\_solver())

#### •maximization

- -When set to True (default), the MixedIntegerLinearProgram is defined as a maximization.
- -When set to False, the MixedIntegerLinearProgram is defined as a minimization.
- •constraint\_generation Only used when solver=None.

- -When set to True, after solving the MixedIntegerLinearProgram, it is possible to add a constraint, and then solve it again. The effect is that solvers that do not support this feature will not be used.
- -Defaults to False.

```
Warning: All LP variables are non-negative by default (see new_variable() and set_min()).
```

#### See Also:

•default mip solver() - Returns/Sets the default MIP solver.

#### **EXAMPLES:**

Computation of a maximum stable set in Petersen's graph:

#### TESTS:

Check that trac ticket #16497 is fixed:

```
sage: from sage.numerical.mip import MixedIntegerLinearProgram
sage: for type in ["binary", "integer"]:
          k = 3
. . . . :
          items = [1/5, 1/3, 2/3, 3/4, 5/7]
. . . . :
         maximum=1
. . . . :
         p=MixedIntegerLinearProgram()
. . . . :
          box=p.new_variable(nonnegative=True, **{type:True})
. . . . :
         for b in range(k):
. . . . :
                p.add_constraint(p.sum([items[i]*box[i,b] for i in range(len(items))]) <= maximum</pre>
. . . . :
          for i in range(len(items)):
. . . . :
               p.add_constraint(p.sum([box[i,b] for b in range(k)]) == 1)
. . . . :
          p.set_objective(None)
. . . . :
            _{-} = p.solve()
          box=p.get_values(box)
          print(all(v in ZZ for v in box.values()))
. . . . :
True
```

add\_constraint (linear\_function, max=None, min=None, name=None)

Adds a constraint to the MixedIntegerLinearProgram.

INPUT:

- •linear\_function Two different types of arguments are possible:
  - A linear function. In this case, arguments min or max have to be specified.
  - A linear constraint of the form A <= B, A >= B, A <= B <= C, A >= B >= C or A ==
     B. In this case, arguments min and max will be ignored.

•max – An upper bound on the constraint (set to None by default). This must be a numerical value.

•min – A lower bound on the constraint. This must be a numerical value.

•name – A name for the constraint.

To set a lower and/or upper bound on the variables use the methods set\_min and/or set\_max of MixedIntegerLinearProgram.

#### **EXAMPLE**:

Consider the following linear program:

It can be solved as follows:

```
sage: p = MixedIntegerLinearProgram(maximization=True)
sage: x = p.new_variable(nonnegative=True)
sage: p.set_objective(x[1] + 5*x[2])
sage: p.add_constraint(x[1] + 0.2*x[2], max=4)
sage: p.add_constraint(1.5*x[1] + 3*x[2], max=4)
sage: round(p.solve(),6)
6.666667
```

There are two different ways to add the constraint  $x[5] + 3*x[7] \le x[6] + 3$  to a MixedIntegerLinearProgram.

The first one consists in giving add\_constraint this very expression:

```
sage: p.add_constraint( x[5] + 3*x[7] \le x[6] + 3)
```

The second (slightly more efficient) one is to use the arguments min or max, which can only be numerical values:

```
sage: p.add_constraint( x[5] + 3*x[7] - x[6], max = 3 )
```

One can also define double-bounds or equality using symbols <=, >= and ==:

```
sage: p.add_constraint( x[5] + 3*x[7] == x[6] + 3 )
sage: p.add_constraint( x[5] + 3*x[7] <= x[6] + 3 <= x[8] + 27 )
```

The previous program can be rewritten:

```
sage: p = MixedIntegerLinearProgram(maximization=True)
sage: x = p.new_variable(nonnegative=True)
sage: p.set_objective(x[1] + 5*x[2])
sage: p.add_constraint(x[1] + 0.2*x[2] <= 4)
sage: p.add_constraint(1.5*x[1] + 3*x[2] <= 4)
sage: round(p.solve(), 5)
6.66667</pre>
```

#### TESTS:

Complex constraints:

```
sage: p = MixedIntegerLinearProgram(solver = "GLPK")
sage: b = p.new_variable(nonnegative=True)
```

```
sage: p.add_constraint( b[8] - b[15] <= 3*b[8] + 9)</pre>
sage: p.show()
Maximization:
Constraints:
  -2.0 x_0 - x_1 \le 9.0
Variables:
  x_0 is a continuous variable (min=0.0, max=+00)
 x_1 is a continuous variable (min=0.0, max=+00)
Empty constraint:
sage: p=MixedIntegerLinearProgram()
sage: p.add_constraint(sum([]),min=2)
Min/Max are numerical
sage: v = p.new_variable(nonnegative=True)
sage: p.add_constraint(v[3] + v[5], min = v[6])
Traceback (most recent call last):
ValueError: min and max arguments are required to be numerical
sage: p.add_constraint(v[3] + v[5], max = v[6])
Traceback (most recent call last):
ValueError: min and max arguments are required to be numerical
Do not add redundant elements (notice only one copy of each constraint is added):
sage: lp = MixedIntegerLinearProgram(solver = "GLPK", check_redundant=True)
sage: for each in xrange(10): lp.add_constraint(lp[0]-lp[1],min=1)
sage: lp.show()
Maximization:
Constraints:
 1.0 \le x_0 - x_1
Variables:
  x_0 is a continuous variable (min=0.0, max=+oo)
  x_1 is a continuous variable (min=0.0, max=+00)
We check for constant multiples of constraints as well:
sage: for each in xrange(10): lp.add_constraint(2*lp[0]-2*lp[1],min=2)
sage: lp.show()
Maximization:
Constraints:
 1.0 \le x_0 - x_1
Variables:
  x_0 is a continuous variable (min=0.0, max=+00)
  x_1 is a continuous variable (min=0.0, max=+oo)
But if the constant multiple is negative, we should add it anyway (once):
sage: for each in xrange(10): lp.add_constraint(-2*lp[0]+2*lp[1],min=-2)
sage: lp.show()
Maximization:
Constraints:
  1.0 \le x_0 - x_1
```

```
x_0 - x_1 <= 1.0
    Variables:
      x_0 is a continuous variable (min=0.0, max=+00)
      x_1 is a continuous variable (min=0.0, max=+oo)
    TESTS:
    Catch True / False as INPUT (trac ticket #13646):
    sage: p = MixedIntegerLinearProgram()
    sage: x = p.new_variable(nonnegative=True)
    sage: p.add_constraint(True)
    Traceback (most recent call last):
    ValueError: argument must be a linear function or constraint, got True
base_ring()
    Return the base ring.
    OUTPUT:
    A ring. The coefficients that the chosen solver supports.
    EXAMPLES:
    sage: p = MixedIntegerLinearProgram(solver='GLPK')
    sage: p.base_ring()
    Real Double Field
    sage: p = MixedIntegerLinearProgram(solver='ppl')
    sage: p.base_ring()
```

#### constraints (indices=None)

Rational Field

Returns a list of constraints, as 3-tuples.

#### INPUT:

- •indices select which constraint(s) to return
  - -If indices = None, the method returns the list of all the constraints.
  - -If indices is an integer i, the method returns constraint i.
  - -If indices is a list of integers, the method returns the list of the corresponding constraints.

#### **OUTPUT:**

Each constraint is returned as a triple lower\_bound, (indices, coefficients), upper\_bound. For each of those entries, the corresponding linear function is the one associating to variable indices[i] the coefficient coefficients[i], and 0 to all the others.

lower\_bound and upper\_bound are numerical values.

#### EXAMPLE:

#### First, let us define a small LP:

```
sage: p = MixedIntegerLinearProgram()
sage: p.add_constraint(p[0] - p[2], min = 1, max = 4)
sage: p.add_constraint(p[0] - 2*p[1], min = 1)
```

To obtain the list of all constraints:

```
sage: p.constraints()  # not tested
[(1.0, ([1, 0], [-1.0, 1.0]), 4.0), (1.0, ([2, 0], [-2.0, 1.0]), None)]

Or constraint 0 only:
sage: p.constraints(0)  # not tested
(1.0, ([1, 0], [-1.0, 1.0]), 4.0)

A list of constraints containing only 1:
sage: p.constraints([1])  # not tested
[(1.0, ([2, 0], [-2.0, 1.0]), None)]
```

#### TESTS:

As the ordering of the variables in each constraint depends on the solver used, we define a short function reordering it before it is printed. The output would look the same without this function applied:

```
sage: def reorder_constraint((lb,(ind,coef),ub)):
    d = dict(zip(ind, coef))
    ind.sort()
    return (lb, (ind, [d[i] for i in ind]), ub)
```

Running the examples from above, reordering applied:

```
sage: p = MixedIntegerLinearProgram(solver = "GLPK")
sage: p.add_constraint(p[0] - p[2], min = 1, max = 4)
sage: p.add_constraint(p[0] - 2*p[1], min = 1)
sage: sorted(map(reorder_constraint,p.constraints()))
[(1.0, ([0, 1], [1.0, -1.0]), 4.0), (1.0, ([0, 2], [1.0, -2.0]), None)]
sage: reorder_constraint(p.constraints(0))
(1.0, ([0, 1], [1.0, -1.0]), 4.0)
sage: sorted(map(reorder_constraint,p.constraints([1])))
[(1.0, ([0, 2], [1.0, -2.0]), None)]
```

#### get\_backend()

Returns the backend instance used.

This might be useful when acces to additional functions provided by the backend is needed.

#### EXAMPLE:

This example uses the simplex algorithm and prints information:

```
sage: p = MixedIntegerLinearProgram(solver="GLPK")
sage: x, y = p[0], p[1]
sage: p.add_constraint(2*x + 3*y, max = 6)
sage: p.add_constraint(3*x + 2*y, max = 6)
sage: p.set_objective(x + y + 7)
sage: b = p.get_backend()
sage: b.solver_parameter("simplex_or_intopt", "simplex_only")
sage: b.solver_parameter("verbosity_simplex", "GLP_MSG_ALL")
sage: p.solve() # tol 0.00001
GLPK Simplex Optimizer, v4.44
2 rows, 2 columns, 4 non-zeros
* 0: obj = 7.0000000000e+00 infeas = 0.000e+00 (0)
* 2: obj = 9.4000000000e+00 infeas = 0.000e+00 (0)
OPTIMAL SOLUTION FOUND
9.4
```

Returns the maximum value of a variable.

#### INPUT:

•v – a variable.

#### **OUTPUT**:

Maximum value of the variable, or None if the variable has no upper bound.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(nonnegative=True)
sage: p.set_objective(v[1])
sage: p.get_max(v[1])
sage: p.set_max(v[1],6)
sage: p.get_max(v[1])
6.0
```

#### $get_min(v)$

Returns the minimum value of a variable.

#### INPUT:

•v – a variable

#### **OUTPUT**:

Minimum value of the variable, or None if the variable has no lower bound.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(nonnegative=True)
sage: p.set_objective(v[1])
sage: p.get_min(v[1])
0.0
sage: p.set_min(v[1],6)
sage: p.get_min(v[1])
6.0
sage: p.set_min(v[1], None)
sage: p.get_min(v[1])
```

#### get\_values (\*lists)

Return values found by the previous call to  $\verb"solve"$  ().

#### INPUT:

•Any instance of MIPVariable (or one of its elements), or lists of them.

#### **OUTPUT**:

- •Each instance of MIPVariable is replaced by a dictionary containing the numerical values found for each corresponding variable in the instance.
- Each element of an instance of a MIPVariable is replaced by its corresponding numerical value.

**Note:** While a variable may be declared as binary or integer, its value as returned by the solver is of type float.

#### EXAMPLE:

```
sage: p = MixedIntegerLinearProgram()
    sage: x = p.new_variable(nonnegative=True)
    sage: y = p.new_variable(nonnegative=True)
    sage: p.set_objective(x[3] + 3*y[2,9] + x[5])
    sage: p.add_constraint(x[3] + y[2,9] + 2*x[5], max=2)
    sage: p.solve()
    6.0
    To return the optimal value of y[2, 9]:
    sage: p.get_values(y[2,9])
    2.0
    To get a dictionary identical to x containing optimal values for the corresponding variables
    sage: x_sol = p.get_values(x)
    sage: x_sol.keys()
    [3, 5]
    Obviously, it also works with variables of higher dimension:
    sage: y_sol = p.get_values(y)
    We could also have tried
    sage: [x_sol, y_sol] = p.get_values(x, y)
    Or:
    sage: [x_sol, y_sol] = p.get_values([x, y])
    TESTS:
    When 'dim' will be removed, also remove from this function the code that uses it:
    sage: p = MixedIntegerLinearProgram()
    sage: b = p.new_variable(dim=2)
    doctest:...: DeprecationWarning: The 'dim' argument will soon disappear. Fortunately variable
    See http://trac.sagemath.org/15489 for details.
    sage: p.add_constraint(b[1][2] + b[2][3] == 0)
    sage: _ = p.solve()
    sage: _ = p.get_values(b)
is_binary(e)
    Tests whether the variable e is binary. Variables are real by default.
    INPUT:
       •e - A variable (not a MIPVariable, but one of its elements.)
    OUTPUT:
    True if the variable e is binary; False otherwise.
    EXAMPLE:
    sage: p = MixedIntegerLinearProgram()
    sage: v = p.new_variable(nonnegative=True)
    sage: p.set_objective(v[1])
    sage: p.is_binary(v[1])
    False
    sage: p.set_binary(v[1])
```

```
sage: p.is_binary(v[1])
    True
is_integer(e)
    Tests whether the variable is an integer. Variables are real by default.
    INPUT:
       •e – A variable (not a MIPVariable, but one of its elements.)
    OUTPUT:
    True if the variable e is an integer; False otherwise.
    EXAMPLE:
    sage: p = MixedIntegerLinearProgram()
    sage: v = p.new_variable(nonnegative=True)
    sage: p.set_objective(v[1])
    sage: p.is_integer(v[1])
    False
    sage: p.set_integer(v[1])
    sage: p.is_integer(v[1])
is real(e)
    Tests whether the variable is real.
    INPUT:
       •e – A variable (not a MIPVariable, but one of its elements.)
    OUTPUT:
    True if the variable is real; False otherwise.
    EXAMPLE:
    sage: p = MixedIntegerLinearProgram()
    sage: v = p.new_variable(nonnegative=True)
    sage: p.set_objective(v[1])
    sage: p.is_real(v[1])
    True
    sage: p.set_binary(v[1])
    sage: p.is_real(v[1])
    False
    sage: p.set_real(v[1])
    sage: p.is_real(v[1])
    True
linear_constraints_parent()
    Return the parent for all linear constraints
    See linear_functions for more details.
    EXAMPLES:
    sage: p = MixedIntegerLinearProgram()
    sage: p.linear_constraints_parent()
    Linear constraints over Real Double Field
linear_function(x)
```

Construct a new linear function

#### **EXAMPLES:**

```
sage: p = MixedIntegerLinearProgram()
sage: p.linear_function({1:3, 4:5})
3*x_1 + 5*x_4
This is equivalent to:
```

# sage: p({1:3, 4:5}) 3\*x\_1 + 5\*x\_4

#### linear\_functions\_parent()

Return the parent for all linear functions

#### **EXAMPLES:**

```
sage: p = MixedIntegerLinearProgram()
sage: p.linear_functions_parent()
Linear functions over Real Double Field
```

**new\_variable** (real=False, binary=False, integer=False, nonnegative=None, dim=1, name='')

Returns an instance of MIPVariable associated to the current instance of MixedIntegerLinearProgram.

A new variable x is defined by:

```
sage: p = MixedIntegerLinearProgram()
sage: x = p.new_variable(nonnegative=True)
```

It behaves exactly as an usual dictionary would. It can use any key argument you may like, as x[5] or x["b"], and has methods items () and keys ().

#### INPUT:

- •dim (integer) Defines the dimension of the dictionary. If x has dimension 2, its fields will be of the form x[key1][key2]. Deprecated.
- •binary, integer, real (boolean) Set one of these arguments to True to ensure that the variable gets the corresponding type.
- •nonnegative (boolean) whether the variable should be assumed to be nonnegative. Rather useless for the binary type.
- •name (string) Associates a name to the variable. This is only useful when exporting the linear program to a file using write\_mps or write\_lp, and has no other effect.

#### See Also:

- •set\_min(),:meth: $get_min$  set/get the lower bound of a variable. Note that by default, all variables are non-negative.
- •set\_max(),:meth: $get_max$  set/get the upper bound of a variable.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()

To define two dictionaries of variables, the first being
of real type, and the second of integer type ::

sage: x = p.new_variable(real=True, nonnegative=True)
sage: y = p.new_variable(integer=True, nonnegative=True)
sage: p.add_constraint(x[2] + y[3,5], max=2)
```

```
sage: p.is_integer(x[2])
       False
       sage: p.is_integer(y[3,5])
       True
    An exception is raised when two types are supplied
    sage: z = p.new_variable(real = True, integer = True)
    Traceback (most recent call last):
    ValueError: Exactly one of the available types has to be True
    Unbounded variables:
    sage: p = MixedIntegerLinearProgram()
    sage: x = p.new_variable(real=True, nonnegative=False)
    sage: y = p.new_variable(integer=True, nonnegative=False)
    sage: p.add_constraint(x[0]+x[3] \le 8)
    sage: p.add_constraint(y[0] >= y[1])
    sage: p.show()
    Maximization:
    Constraints:
      x_0 + x_1 <= 8.0
       x_2 + x_3 <= 0.0
    Variables:
      x_0 is a continuous variable (min=-oo, max=+oo)
      x_1 is a continuous variable (min=-oo, max=+oo)
      x_2 is an integer variable (min=-oo, max=+oo)
      x_3 is an integer variable (min=-oo, max=+oo)
    TESTS:
    Default behaviour (trac ticket #15521):
    sage: x = p.new_variable(nonnegative=True)
    sage: p.get_min(x[0])
    0.0
number_of_constraints()
    Returns the number of constraints assigned so far.
    EXAMPLE:
    sage: p = MixedIntegerLinearProgram()
    sage: p.add_constraint(p[0] - p[2], min = 1, max = 4)
    sage: p.add_constraint(p[0] - 2*p[1], min = 1)
    sage: p.number_of_constraints()
number_of_variables()
```

Returns the number of variables used so far.

Note that this is backend-dependent, i.e. we count solver's variables rather than user's variables. An example of the latter can be seen below: Gurobi converts double inequalities, i.e. inequalities like  $m <= c^T x <= M$ , with m < M, into equations, by adding extra variables:  $c^T x + y = M$ , 0 <= y <= M - m.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: p.add_constraint(p[0] - p[2], max = 4)
```

```
sage: p.number_of_variables()
2
sage: p.add_constraint(p[0] - 2*p[1], min = 1)
sage: p.number_of_variables()
3
sage: p = MixedIntegerLinearProgram(solver="glpk")
sage: p.add_constraint(p[0] - p[2], min = 1, max = 4)
sage: p.number_of_variables()
2
sage: p = MixedIntegerLinearProgram(solver="gurobi")  # optional - Gurobi
sage: p.add_constraint(p[0] - p[2], min = 1, max = 4)  # optional - Gurobi
sage: p.number_of_variables()  # optional - Gurobi
```

#### polyhedron (\*\*kwds)

Returns the polyhedron defined by the Linear Program.

#### INPLIT

All arguments given to this method are forwarded to the constructor of the Polyhedron () class.

#### **OUTPUT:**

A Polyhedron () object whose *i*-th variable represents the *i*-th variable of self.

**Warning:** The polyhedron is built from the variables stored by the LP solver (i.e. the output of  $\verb|show|()$ ). While they usually match the ones created explicitly when defining the LP, a solver like Gurobi has been known to introduce additional variables to store constraints of the type  $\verb|lower_bound| <= \verb|linear_function| <= \verb|upper| bound|$ . You should be fine if you did not install Gurobi or if you do not use it as a solver, but keep an eye on the number of variables in the polyhedron, or on the output of  $\verb|show|()$ . Just in case.

### **EXAMPLES:**

#### A LP on two variables:

```
sage: p = MixedIntegerLinearProgram()
sage: p.add_constraint(2*p['x'] + p['y'] <= 1)
sage: p.add_constraint(3*p['y'] + p['x'] <= 2)
sage: P = p.polyhedron(); P
A 2-dimensional polyhedron in QQ^2 defined as the convex hull of 4 vertices</pre>
```

#### 3-D Polyhedron:

```
sage: p = MixedIntegerLinearProgram()
sage: p.add_constraint(2*p['x'] + p['y'] + 3*p['z'] <= 1)
sage: p.add_constraint(2*p['y'] + p['z'] + 3*p['x'] <= 1)
sage: p.add_constraint(2*p['z'] + p['x'] + 3*p['y'] <= 1)
sage: P = p.polyhedron(); P
A 3-dimensional polyhedron in QQ^3 defined as the convex hull of 8 vertices</pre>
```

#### An empty polyhedron:

```
sage: p = MixedIntegerLinearProgram()
sage: p.add_constraint(2*p['x'] + p['y'] + 3*p['z'] <= 1)
sage: p.add_constraint(2*p['y'] + p['z'] + 3*p['x'] <= 1)
sage: p.add_constraint(2*p['z'] + p['x'] + 3*p['y'] >= 2)
sage: P = p.polyhedron(); P
The empty polyhedron in QQ^3
```

#### An unbounded polyhedron:

```
sage: p = MixedIntegerLinearProgram()
sage: p.add_constraint(2*p['x'] + p['y'] - p['z'] <= 1)
sage: P = p.polyhedron(); P
A 3-dimensional polyhedron in QQ^3 defined as the convex hull of 3 vertices and 3 rays</pre>
```

#### A square (see trac ticket #14395)

```
sage: p = MixedIntegerLinearProgram()
sage: x,y = p['x'], p['y']
sage: p.set_min(x,None)
sage: p.set_min(y,None)
sage: p.add_constraint( x <= 1 )
sage: p.add_constraint( x >= -1 )
sage: p.add_constraint( y <= 1 )
sage: p.add_constraint( y >= -1 )
sage: p.add_constraint( y >= -1 )
```

#### $remove\_constraint(i)$

Removes a constraint from self.

#### INPUT:

•i – Index of the constraint to remove.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: x, y = p[0], p[1]
sage: p.add_constraint(x + y, max = 10)
sage: p.add_constraint(x - y, max = 0)
sage: p.add_constraint(x, max = 4)
sage: p.show()
Maximization:
Constraints:
  x_0 + x_1 \le 10.0
  x_0 - x_1 \le 0.0
  x_0 <= 4.0
sage: p.remove_constraint(1)
sage: p.show()
Maximization:
Constraints:
  x_0 + x_1 <= 10.0
  x_0 <= 4.0
sage: p.number_of_constraints()
```

#### remove\_constraints (constraints)

Remove several constraints.

#### INPUT:

•constraints – an iterable containing the indices of the rows to remove.

## EXAMPLE:

```
sage: p = MixedIntegerLinearProgram()
sage: x, y = p[0], p[1]
sage: p.add_constraint(x + y, max = 10)
sage: p.add_constraint(x - y, max = 0)
sage: p.add_constraint(x, max = 4)
sage: p.show()
Maximization:
Constraints:
  x_0 + x_1 \le 10.0
  x_0 - x_1 \le 0.0
  x_0 <= 4.0
sage: p.remove_constraints([0, 1])
sage: p.show()
Maximization:
Constraints:
  x_0 <= 4.0
sage: p.number_of_constraints()
```

When checking for redundant constraints, make sure you remove only the constraints that were actually added. Problems could arise if you have a function that builds lps non-interactively, but it fails to check whether adding a constraint actually increases the number of constraints. The function might later try to remove constraints that are not actually there:

```
sage: p = MixedIntegerLinearProgram(check_redundant=True)
    sage: x, y = p[0], p[1]
    sage: p.add_constraint(x + y, max = 10)
    sage: for each in xrange(10): p.add_constraint(x - y, max = 10)
    sage: p.add_constraint(x, max = 4)
    sage: p.number_of_constraints()
    sage: p.remove_constraints(range(1,9))
    Traceback (most recent call last):
    IndexError: pop index out of range
    sage: p.remove_constraint(1)
    sage: p.number_of_constraints()
    2
    We should now be able to add the old constraint back in:
    sage: for each in xrange(10): p.add_constraint(x - y, max = 10)
    sage: p.number_of_constraints()
set binary (ee)
    Sets a variable or a MIPVariable as binary.
    INPUT:
       •ee - An instance of MIPVariable or one of its elements.
    EXAMPLE:
    sage: p = MixedIntegerLinearProgram()
    sage: x = p.new_variable(nonnegative=True)
```

With the following instruction, all the variables from x will be binary:

```
sage: p.set_binary(x)
sage: p.set_objective(x[0] + x[1])
sage: p.add_constraint(-3*x[0] + 2*x[1], max=2)
```

It is still possible, though, to set one of these variables as integer while keeping the others as they are:

```
sage: p.set_integer(x[3])
```

#### TESTS:

When 'dim' will be removed, also remove all the is \* and set \* functions the code that uses it:

```
sage: p = MixedIntegerLinearProgram()
sage: b = p.new_variable(dim=2)
sage: p.add_constraint(b[1][2] + b[2][3] == 0)
sage: p.set_binary(b)
```

#### set\_integer(ee)

Sets a variable or a MIPVariable as integer.

#### INPUT:

•ee - An instance of MIPVariable or one of its elements.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: x = p.new_variable(nonnegative=True)
```

With the following instruction, all the variables from x will be integers:

```
sage: p.set_integer(x)
sage: p.set_objective(x[0] + x[1])
sage: p.add_constraint(-3*x[0] + 2*x[1], max=2)
```

It is still possible, though, to set one of these variables as binary while keeping the others as they are:

```
sage: p.set_binary(x[3])
```

#### $set_max(v, max)$

Sets the maximum value of a variable.

#### **INPUT**

•v – a variable.

•max – the maximum value the variable can take. When max=None, the variable has no upper bound.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(nonnegative=True)
sage: p.set_objective(v[1])
sage: p.get_max(v[1])
sage: p.set_max(v[1],6)
sage: p.get_max(v[1])
6.0
```

With a MIPVariable as an argument:

```
sage: vv = p.new_variable(real=True, nonnegative=False)
sage: p.get_max(vv)
```

```
sage: p.get_max(vv[0])
    sage: p.set_max(vv,5)
    sage: p.get_max(vv[0])
    5.0
    sage: p.get_max(vv[9])
set min (v, min)
    Sets the minimum value of a variable.
    INPUT:
       •v – a variable.
       •min – the minimum value the variable can take. When min=None, the variable has no lower bound.
    See Also:
       •get_min() – get the minimum value of a variable.
    EXAMPLE:
    sage: p = MixedIntegerLinearProgram()
    sage: v = p.new_variable(nonnegative=True)
    sage: p.set_objective(v[1])
    sage: p.get_min(v[1])
    0.0
    sage: p.set_min(v[1],6)
    sage: p.get_min(v[1])
    6.0
    sage: p.set_min(v[1], None)
    sage: p.get_min(v[1])
    With a MIPVariable as an argument:
    sage: vv = p.new_variable(real=True, nonnegative=False)
    sage: p.get_min(vv)
    sage: p.get_min(vv[0])
    sage: p.set_min(vv,5)
    sage: p.get_min(vv[0])
    5.0
    sage: p.get_min(vv[9])
    5.0
set objective (obj)
    Sets the objective of the MixedIntegerLinearProgram.
    INPUT:
       •obj - A linear function to be optimized. (can also be set to None or 0 when just looking for a
        feasible solution)
    EXAMPLE:
    Let's solve the following linear program:
```

Constraints:

x + 0.2 y <= 41.5 \* x + 3 \* y <= 4

Variables:

```
x is Real (min = 0, max = None)
      y is Real (min = 0, max = None)
    This linear program can be solved as follows:
    sage: p = MixedIntegerLinearProgram(maximization=True)
    sage: x = p.new_variable(nonnegative=True)
    sage: p.set_objective(x[1] + 5*x[2])
    sage: p.add_constraint(x[1] + 2/10*x[2], max=4)
    sage: p.add_constraint(1.5*x[1]+3*x[2], max=4)
    sage: round(p.solve(),5)
    6.66667
    sage: p.set_objective(None)
    sage: _ = p.solve()
set_problem_name (name)
    Sets the name of the MixedIntegerLinearProgram.
    INPUT:
       •name - A string representing the name of the MixedIntegerLinearProgram.
    EXAMPLE:
    sage: p=MixedIntegerLinearProgram()
    sage: p.set_problem_name("Test program")
    Mixed Integer Program "Test program" ( maximization, 0 variables, 0 constraints )
set_real(ee)
    Sets a variable or a MIPVariable as real.
    INPUT:
       •ee – An instance of MIPVariable or one of its elements.
    EXAMPLE:
    sage: p = MixedIntegerLinearProgram()
    sage: x = p.new_variable(nonnegative=True)
    With the following instruction, all the variables from x will be real:
       sage: p.set_real(x)
       sage: p.set_objective(x[0] + x[1])
       sage: p.add_constraint(-3*x[0] + 2*x[1], max=2)
    It is still possible, though, to set one of these
    variables as binary while keeping the others as they are::
       sage: p.set_binary(x[3])
show()
    Displays the MixedIntegerLinearProgram in a human-readable way.
    EXAMPLES:
    When constraints and variables have names
    sage: p = MixedIntegerLinearProgram(solver = "GLPK")
    sage: x = p.new_variable(name="Hey")
    sage: p.set_objective(x[1] + x[2])
```

```
sage: p.add_constraint(-3*x[1] + 2*x[2], max=2, name="Constraint_1")
sage: p.show()
Maximization:
  Hey[1] + Hey[2]
Constraints:
  Constraint_1: -3.0 Hey[1] + 2.0 Hey[2] <= 2.0
Variables:
  Hey[1] is a continuous variable (min=0.0, max=+oo)
  Hey[2] is a continuous variable (min=0.0, max=+oo)
Without any names
sage: p = MixedIntegerLinearProgram(solver = "GLPK")
sage: x = p.new_variable(nonnegative=True)
sage: p.set_objective(x[1] + x[2])
sage: p.add_constraint(-3*x[1] + 2*x[2], max=2)
sage: p.show()
Maximization:
  x_0 + x_1
Constraints:
  -3.0 x_0 + 2.0 x_1 \le 2.0
Variables:
  x_0 is a continuous variable (min=0.0, max=+oo)
  x_1 is a continuous variable (min=0.0, max=+oo)
With Q coefficients:
sage: p = MixedIntegerLinearProgram(solver= 'ppl')
sage: x = p.new_variable(nonnegative=True)
sage: p.set_objective(x[1] + 1/2*x[2])
sage: p.add_constraint(-3/5*x[1] + 2/7*x[2], max=2/5)
sage: p.show()
Maximization:
  x_0 + 1/2 x_1
Constraints:
  constraint_0: -3/5 \times_0 + 2/7 \times_1 <= 2/5
Variables:
  x_0 is a continuous variable (min=0, max=+00)
  x_1 is a continuous variable (min=0, max=+00)
```

#### solve (log=None, objective\_only=False)

Solves the MixedIntegerLinearProgram.

#### INPUT:

- •log integer (default: None) The verbosity level. Indicates whether progress should be printed during computation. The solver is initialized to report no progress.
- •objective\_only Boolean variable.
  - -When set to True, only the objective function is returned.
  - -When set to False (default), the optimal numerical values are stored (takes computational time).

#### **OUTPUT**:

The optimal value taken by the objective function.

Warning: By default, all variables of a LP are assumed to be non-negative. See  $set\_min()$  to change it.

#### **EXAMPLES:**

Consider the following linear program:

This linear program can be solved as follows:

```
sage: p = MixedIntegerLinearProgram(maximization=True)
   sage: x = p.new_variable(nonnegative=True)
   sage: p.set_objective(x[1] + 5*x[2])
   sage: p.add_constraint(x[1] + 0.2*x[2], max=4)
   sage: p.add_constraint(1.5\timesx[1] + 3\timesx[2], max=4)
   sage: round(p.solve(),6)
   6.666667
   sage: x = p.get_values(x)
   sage: round(x[1], 6)
   sage: round(x[2], 6)
   1.333333
Computation of a maximum stable set in Petersen's graph::
   sage: g = graphs.PetersenGraph()
   sage: p = MixedIntegerLinearProgram(maximization=True)
   sage: b = p.new_variable(nonnegative=True)
   sage: p.set_objective(sum([b[v] for v in g]))
   sage: for (u,v) in g.edges(labels=None):
            p.add_constraint(b[u] + b[v], max=1)
   sage: p.set_binary(b)
   sage: p.solve(objective_only=True)
   4.0
```

#### Constraints in the objective function are respected:

```
sage: p = MixedIntegerLinearProgram()
sage: x, y = p[0], p[1]
sage: p.add_constraint(2*x + 3*y, max = 6)
sage: p.add_constraint(3*x + 2*y, max = 6)
sage: p.set_objective(x + y + 7)
sage: p.set_integer(x); p.set_integer(y)
sage: p.solve()
9.0
```

#### solver\_parameter (name, value=None)

Return or define a solver parameter

The solver parameters are by essence solver-specific, which means their meaning heavily depends on the solver used.

(If you do not know which solver you are using, then you use use GLPK).

Aliases:

Very common parameters have aliases making them solver-independent. For example, the following:

```
sage: p = MixedIntegerLinearProgram(solver = "GLPK")
sage: p.solver_parameter("timelimit", 60)
```

Sets the solver to stop its computations after 60 seconds, and works with GLPK, CPLEX and Gurobi.

•"timelimit" – defines the maximum time spent on a computation. Measured in seconds.

Solver-specific parameters:

- •GLPK: We have implemented very close to comprehensive coverage of the GLPK solver parameters for the simplex and integer optimization methods. For details, see the documentation of GLPKBackend.solver\_parameter.
- •CPLEX's parameters are identified by a string. Their list is available on ILOG's website.

The command

```
sage: p = MixedIntegerLinearProgram(solver = "CPLEX") # optional - CPLEX
sage: p.solver_parameter("CPX_PARAM_TILIM", 60) # optional - CPLEX
```

works as intended.

•Gurobi's parameters should all be available through this method. Their list is available on Gurobi's website http://www.gurobi.com/documentation/5.5/reference-manual/node798.

#### INPUT:

- •name (string) the parameter
- •value the parameter's value if it is to be defined, or None (default) to obtain its current value.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram(solver = "GLPK")
sage: p.solver_parameter("timelimit", 60)
sage: p.solver_parameter("timelimit")
60.0
```

#### $\mathbf{sum}\,(L)$

Efficiently computes the sum of a sequence of LinearFunction elements

#### INPUT:

- •mip the MixedIntegerLinearProgram parent.
- •L list of LinearFunction instances.

**Note:** The use of the regular sum function is not recommended as it is much less efficient than this one

#### **EXAMPLES:**

```
sage: p = MixedIntegerLinearProgram()
sage: v = p.new_variable(nonnegative=True)
```

#### The following command:

```
sage: s = p.sum([v[i] for i in xrange(90)])
```

is much more efficient than:

```
sage: s = sum([v[i] for i in xrange(90)])
     write_lp (filename)
         Write the linear program as a LP file.
         This function export the problem as a LP file.
         INPUT:
            •filename – The file in which you want the problem to be written.
         EXAMPLE:
         sage: p = MixedIntegerLinearProgram(solver="GLPK")
         sage: x = p.new_variable(nonnegative=True)
         sage: p.set_objective(x[1] + x[2])
         sage: p.add_constraint(-3*x[1] + 2*x[2], max=2)
         sage: p.write_lp(os.path.join(SAGE_TMP, "lp_problem.lp"))
         Writing problem data to ...
         9 lines were written
         For more information about the LP file format: http://lpsolve.sourceforge.net/5.5/lp-format.htm
     write mps(filename, modern=True)
         Write the linear program as a MPS file.
         This function export the problem as a MPS file.
         INPUT:
            •filename – The file in which you want the problem to be written.
            •modern – Lets you choose between Fixed MPS and Free MPS
                -True - Outputs the problem in Free MPS
                -False - Outputs the problem in Fixed MPS
         EXAMPLE:
         sage: p = MixedIntegerLinearProgram(solver="GLPK")
         sage: x = p.new_variable(nonnegative=True)
         sage: p.set_objective(x[1] + x[2])
         sage: p.add_constraint(-3 \times x[1] + 2 \times x[2], max=2,name="OneConstraint")
         sage: p.write_mps(os.path.join(SAGE_TMP, "lp_problem.mps"))
         Writing problem data to ...
         17 records were written
         For information about the MPS file format: http://en.wikipedia.org/wiki/MPS %28format%29
sage.numerical.mip.Sum(x)
     Only for legacy support, use MixedIntegerLinearProgram.sum() instead.
     EXAMPLES:
     sage: from sage.numerical.mip import Sum
     sage: Sum([])
     doctest:...: DeprecationWarning: use MixedIntegerLinearProgram.sum() instead
     See http://trac.sagemath.org/13646 for details.
```

sage: Sum([x[0]+x[1], x[1]+x[2], x[2]+x[3]]) # deprecation is only shown once

 $x_0 + 2*x_1 + 2*x_2 + x_3$ 

sage: p = MixedIntegerLinearProgram()
sage: x = p.new\_variable(nonnegative=True)

Sage Reference Manual: Numerical Optimization, Release 6.3	

# LINEAR FUNCTIONS AND CONSTRAINTS

#### **Linear Functions and Constraints**

This module implements linear functions (see LinearFunction) in formal variables and chained (in)equalities between them (see LinearConstraint). By convention, these are always written as either equalities or less-oregual. For example:

```
sage: p = MixedIntegerLinearProgram()
sage: x = p.new_variable()
doctest:...: DeprecationWarning: The default value of 'nonnegative' will change, to False instead of
See http://trac.sagemath.org/15521 for details.
sage: f = 1 + x[1] + 2*x[2]; f # a linear function
1 + x_0 + 2*x_1
sage: type(f)
<type 'sage.numerical.linear_functions.LinearFunction'>

sage: c = (0 <= f); c # a constraint
0 <= 1 + x_0 + 2*x_1
sage: type(c)
<type 'sage.numerical.linear_functions.LinearConstraint'>
```

Note that you can use this module without any reference to linear programming, it only implements linear functions over a base ring and constraints. However, for ease of demonstration we will always construct them out of linear programs (see mip).

Constraints can be equations or (non-strict) inequalities. They can be chained:

```
sage: p = MixedIntegerLinearProgram()
sage: x = p.new_variable()
sage: x[0] == x[1] == x[2] == x[3]
x_0 == x_1 == x_2 == x_3

sage: ieq_01234 = x[0] <= x[1] <= x[2] <= x[3] <= x[4]
sage: ieq_01234
x_0 <= x_1 <= x_2 <= x_3 <= x_4</pre>
```

If necessary, the direction of inequality is flipped to always write inqualities as less or equal:

```
sage: x[5] >= ieq_01234
x_0 <= x_1 <= x_2 <= x_3 <= x_4 <= x_5
sage: (x[5] <= x[6]) >= ieq_01234
```

```
x_0 \le x_1 \le x_2 \le x_3 \le x_4 \le x_5 \le x_6

sage: (x[5]\le x[6]) \le ieq_01234

x_5 \le x_6 \le x_0 \le x_1 \le x_2 \le x_3 \le x_4
```

#### TESTS:

See trac ticket #12091

```
sage: p = MixedIntegerLinearProgram()
sage: b = p.new_variable()
sage: b[0] <= b[1] <= 2
x_0 <= x_1 <= 2
sage: list(b[0] <= b[1] <= 2)
[x_0, x_1, 2]
sage: 1 >= b[1] >= 2*b[0]
2*x_0 <= x_1 <= 1
sage: b[2] >= b[1] >= 2*b[0]
2*x_0 <= x_1 <= x_2</pre>
```

class sage.numerical.linear\_functions.LinearConstraint

Bases: sage.structure.element.Element

A class to represent formal Linear Constraints.

A Linear Constraint being an inequality between two linear functions, this class lets the user write  $LinearFunction1 \le LinearFunction2$  to define the corresponding constraint, which can potentially involve several layers of such inequalities ((A <= B <= C), or even equalities like A == B.

Trivial constraints (meaning that they have only one term and no relation) are also allowed. They are required for the coercion system to work.

**Warning:** This class has no reason to be instanciated by the user, and is meant to be used by instances of MixedIntegerLinearProgram.

#### INPUT:

- •parent the parent, a LinearConstraintsParent\_class
- •terms a list/tuple/iterable of two or more linear functions (or things that can be converted into linear functions).
- •equality boolean (default: False). Whether the terms are the entries of a chained less-or-equal (<=) inequality or a chained equality.

#### **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram()
sage: b = p.new_variable()
sage: b[2]+2*b[3] <= b[8]-5
x_0 + 2*x_1 <= -5 + x_2</pre>
```

#### equals (left, right)

Compare left and right.

# **OUTPUT**:

Boolean. Whether all terms of left and right are equal. Note that this is stronger than mathematical equivalence of the relations.

```
sage: p = MixedIntegerLinearProgram()
    sage: x = p.new_variable()
    sage: (x[1] + 1 \ge 2).equals(3/3 + 1*x[1] + 0*x[2] \ge 8/4)
    sage: (x[1] + 1 \ge 2).equals(x[1] + 1-1 \ge 1-1)
    False
equations()
    Iterate over the unchained(!) equations
    OUTPUT:
    An iterator over pairs (lhs, rhs) such that the individual equations are lhs == rhs.
    EXAMPLES:
    sage: p = MixedIntegerLinearProgram()
    sage: b = p.new_variable()
    sage: eqns = 1 == b[0] == b[2] == 3 == b[3]; eqns
    1 == x_0 == x_1 == 3 == x_2
    sage: for lhs, rhs in eqns.equations():
               print str(lhs) + ' == ' + str(rhs)
    1 == x_0
    x_0 == x_1
    x_1 == 3
    3 == x_2
inequalities()
    Iterate over the unchained(!) inequalities
    OUTPUT:
    An iterator over pairs (lhs, rhs) such that the individual equations are lhs <= rhs.
    EXAMPLES:
    sage: p = MixedIntegerLinearProgram()
    sage: b = p.new_variable()
    sage: ieg = 1 \le b[0] \le b[2] \le 3 \le b[3]; ieg
    1 \le x_0 \le x_1 \le 3 \le x_2
    sage: for lhs, rhs in ieq.inequalities():
               print str(lhs) + ' <= ' + str(rhs)</pre>
    1 <= x_0
    x_0 <= x_1
    x_1 <= 3
    3 <= x_2
is equation()
    Whether the constraint is a chained equation
    OUTPUT:
    Boolean.
    EXAMPLES:
    sage: p = MixedIntegerLinearProgram()
    sage: b = p.new_variable()
    sage: (b[0] == b[1]).is_equation()
    True
```

```
sage: (b[0] <= b[1]).is_equation()</pre>
         False
     is_less_or_equal()
         Whether the constraint is a chained less-or_equal inequality
         OUTPUT:
         Boolean.
         EXAMPLES:
         sage: p = MixedIntegerLinearProgram()
         sage: b = p.new_variable()
         sage: (b[0] == b[1]).is_less_or_equal()
         sage: (b[0] <= b[1]).is_less_or_equal()</pre>
     is trivial()
         Test whether the constraint is trivial.
         EXAMPLES:
         sage: p = MixedIntegerLinearProgram()
         sage: LC = p.linear_constraints_parent()
         sage: ieq = LC(1,2); ieq
         1 <= 2
         sage: ieq.is_trivial()
         False
         sage: ieq = LC(1); ieq
         trivial constraint starting with 1
         sage: ieq.is_trivial()
         True
sage.numerical.linear_functions.LinearConstraintsParent(linear_functions_parent)
     Return the parent for linear functions over base_ring.
     The output is cached, so only a single parent is ever constructed for a given base ring.
         INPUT:
            •linear_functions_parent - a LinearFunctionsParent_class. The type of lin-
             ear functions that the constraints are made out of.
         OUTPUT:
         The parent of the linear constraints with the given linear functions.
         EXAMPLES:
         sage: from sage.numerical.linear_functions import
                                                                                   LinearFunctionsParent, I
         sage: LF = LinearFunctionsParent(QQ)
         sage: LinearConstraintsParent(LF)
         Linear constraints over Rational Field
class sage.numerical.linear_functions.LinearConstraintsParent_class
     Bases: sage.structure.parent.Parent
     Parent for LinearConstraint
```

Warning: This class has no reason to be instanciated by the user, and is meant to be used by instances of MixedIntegerLinearProgram. Also, use the LinearConstraintsParent () factory function.

#### INPUT/OUTPUT:

See LinearFunctionsParent()

#### **EXAMPLES:**

```
sage: p = MixedIntegerLinearProgram()
sage: LC = p.linear_constraints_parent(); LC
Linear constraints over Real Double Field
sage: from sage.numerical.linear_functions import LinearConstraintsParent
sage: LinearConstraintsParent(p.linear_functions_parent()) is LC
True
```

#### linear\_functions\_parent()

Return the parent for the linear functions

#### **EXAMPLES:**

```
sage: LC = MixedIntegerLinearProgram().linear_constraints_parent()
sage: LC.linear_functions_parent()
Linear functions over Real Double Field
```

class sage.numerical.linear\_functions.LinearFunction

Bases: sage.structure.element.ModuleElement

An elementary algebra to represent symbolic linear functions.

Warning: You should never instantiate LinearFunction manually. Use the element constructor in the parent instead. For convenience, you can also call the MixedIntegerLinearProgram instance directly.

#### **EXAMPLES:**

```
For example, do this:
```

```
sage: p = MixedIntegerLinearProgram()
sage: p({0 : 1, 3 : -8})
x_0 - 8*x_3

or this:
sage: parent = p.linear_functions_parent()
sage: parent({0 : 1, 3 : -8})
x_0 - 8*x_3

instead of this:
sage: from sage.numerical.linear_functions import LinearFunction
sage: LinearFunction(p.linear_functions_parent(), {0 : 1, 3 : -8})
x_0 - 8*x_3
dict()
```

Returns the dictionary corresponding to the Linear Function.

#### **OUTPUT:**

The linear function is represented as a dictionary. The value are the coefficient of the variable represented by the keys ( which are integers ). The key -1 corresponds to the constant term.

```
EXAMPLE:
         sage: p = MixedIntegerLinearProgram()
         sage: lf = p({0 : 1, 3 : -8})
         sage: lf.dict()
         \{0: 1.0, 3: -8.0\}
     equals (left, right)
         Logically compare left and right.
         OUTPUT:
         Boolean.
         EXAMPLES:
         sage: p = MixedIntegerLinearProgram()
         sage: x = p.new_variable()
         sage: (x[1] + 1).equals(3/3 + 1*x[1] + 0*x[2])
         True
     is zero()
         Test whether self is zero.
         OUTPUT:
         Boolean.
         EXAMPLES:
         sage: p = MixedIntegerLinearProgram()
         sage: x = p.new_variable()
         sage: (x[1] - x[1] + 0*x[2]).is_zero()
         True
     iteritems()
         Iterate over the index, coefficient pairs
         OUTPUT:
         An iterator over the (key, coefficient) pairs. The keys are integers indexing the variables. The
         key −1 corresponds to the constant term.
         EXAMPLES:
         sage: p = MixedIntegerLinearProgram(solver = 'ppl')
         sage: x = p.new_variable()
         sage: f = 0.5 + 3/2 \times x[1] + 0.6 \times x[3]
         sage: for id, coeff in f.iteritems():
                  print 'id =', id, ' coeff =', coeff
         . . .
         id = 0 coeff = 3/2
         id = 1 coeff = 3/5
         id = -1 coeff = 1/2
sage.numerical.linear functions.LinearFunctionsParent (base ring)
     Return the parent for linear functions over base_ring.
     The output is cached, so only a single parent is ever constructed for a given base ring.
```

•base\_ring - a ring. The coefficient ring for the linear funcitons.

**OUTPUT:** 

INPUT:

The parent of the linear functions over base\_ring.

```
EXAMPLES:
```

```
sage: from sage.numerical.linear_functions import LinearFunctionsParent
sage: LinearFunctionsParent(QQ)
Linear functions over Rational Field
```

class sage.numerical.linear\_functions.LinearFunctionsParent\_class

Bases: sage.structure.parent.Parent

The parent for all linear functions over a fixed base ring.

Warning: You should use LinearFunctionsParent () to construct instances of this class.

#### INPUT/OUTPUT:

```
See LinearFunctionsParent()
```

#### **EXAMPLES:**

```
sage: from sage.numerical.linear_functions import LinearFunctionsParent_class
sage: LinearFunctionsParent_class
<type 'sage.numerical.linear_functions.LinearFunctionsParent_class'>
```

# set\_multiplication\_symbol(symbol='\*')

Set the multiplication symbol when pretty-printing linear functions.

INPUT:

•symbol – string, default: ' \*'. The multiplication symbol to be used.

# **EXAMPLES:**

```
sage: p = MixedIntegerLinearProgram()
sage: x = p.new_variable()
sage: f = -1-2*x[0]-3*x[1]
sage: LF = f.parent()
sage: LF._get_multiplication_symbol()
'*'
sage: f
-1 - 2*x_0 - 3*x_1
sage: LF.set_multiplication_symbol(' ')
sage: f
-1 - 2 x_0 - 3 x_1
sage: LF.set_multiplication_symbol()
sage: f
-1 - 2*x_0 - 3*x_1
```

 $\verb|sage.numerical.linear_functions.is_LinearConstraint|(x)$ 

Test whether x is a linear constraint

INPUT:

 $\bullet x$  – anything.

**OUTPUT**:

Boolean.

```
sage: p = MixedIntegerLinearProgram()
    sage: x = p.new_variable()
    sage: ieq = (x[0] \le x[1])
    sage: from sage.numerical.linear_functions import is_LinearConstraint
    sage: is_LinearConstraint(ieq)
    sage: is_LinearConstraint('a string')
    False
sage.numerical.linear_functions.is_LinearFunction(x)
    Test whether x is a linear function
    INPUT:
        \bullet x – anything.
    OUTPUT:
    Boolean.
    EXAMPLES:
    sage: p = MixedIntegerLinearProgram()
    sage: x = p.new_variable()
    sage: from sage.numerical.linear_functions import is_LinearFunction
    sage: is_LinearFunction(x[0] - 2*x[2])
    sage: is_LinearFunction('a string')
    False
```

# NUMERICAL ROOT FINDING AND OPTIMIZATION

#### AUTHOR:

- William Stein (2007): initial version
- Nathann Cohen (2008): Bin Packing

# 4.1 Functions and Methods

sage.numerical.optimize.binpacking(items, maximum=1, k=None) Solves the bin packing problem.

The Bin Packing problem is the following:

Given a list of items of weights  $p_i$  and a real value K, what is the least number of bins such that all the items can be put in the bins, while keeping sure that each bin contains a weight of at most K?

For more informations: http://en.wikipedia.org/wiki/Bin\_packing\_problem

#### Two version of this problem are solved by this algorithm:

- Is it possible to put the given items in L bins?
- What is the assignment of items using the least number of bins with the given list of items?

# INPUT:

- •items A list of real values (the items' weight)
- •maximum The maximal size of a bin
- •k Number of bins
  - -When set to an integer value, the function returns a partition of the items into k bins if possible, and raises an exception otherwise.
  - -When set to None, the function returns a partition of the items using the least number possible of bins

# **OUTPUT**:

A list of lists, each member corresponding to a box and containing the list of the weights inside it. If there is no solution, an exception is raised (this can only happen when k is specified or if maximum is less that the size of one item).

#### **EXAMPLES:**

Trying to find the minimum amount of boxes for 5 items of weights 1/5, 1/4, 2/3, 3/4, 5/7:

```
sage: from sage.numerical.optimize import binpacking
sage: values = [1/5, 1/3, 2/3, 3/4, 5/7]
sage: bins = binpacking(values)
sage: len(bins)
3
```

# Checking the bins are of correct size

```
sage: all([ sum(b) <= 1 for b in bins ])
True</pre>
```

# Checking every item is in a bin

```
sage: b1, b2, b3 = bins
sage: all([ (v in b1 or v in b2 or v in b3) for v in values ])
True
```

One way to use only three boxes (which is best possible) is to put 1/5 + 3/4 together in a box, 1/3 + 2/3 in another, and 5/7 by itself in the third one.

Of course, we can also check that there is no solution using only two boxes

```
sage: from sage.numerical.optimize import binpacking
sage: binpacking([0.2,0.3,0.8,0.9], k=2)
Traceback (most recent call last):
...
ValueError: This problem has no solution !
```

sage.numerical.optimize.find\_fit (data, model, initial\_guess=None, parameters=None, variables=None, solution dict=False)

Finds numerical estimates for the parameters of the function model to give a best fit to data.

#### INPUT:

- •data A two dimensional table of floating point numbers of the form  $[[x_{1,1},x_{1,2},\ldots,x_{1,k},f_1],[x_{2,1},x_{2,2},\ldots,x_{2,k},f_2],\ldots,[x_{n,1},x_{n,2},\ldots,x_{n,k},f_n]]$  given as either a list of lists, matrix, or numpy array.
- •model Either a symbolic expression, symbolic function, or a Python function. model has to be a function of the variables  $(x_1, x_2, \dots, x_k)$  and free parameters  $(a_1, a_2, \dots, a_l)$ .
- •initial\_guess (default: None) Initial estimate for the parameters  $(a_1, a_2, \dots, a_l)$ , given as either a list, tuple, vector or numpy array. If None, the default estimate for each parameter is 1.
- •parameters (default: None) A list of the parameters  $(a_1, a_2, \dots, a_l)$ . If model is a symbolic function it is ignored, and the free parameters of the symbolic function are used.
- •variables (default: None) A list of the variables  $(x_1, x_2, \dots, x_k)$ . If model is a symbolic function it is ignored, and the variables of the symbolic function are used.
- $\verb§-solution_dict-(default: False) if \verb§True*, return the solution as a dictionary rather than an equation. \\$

### **EXAMPLES:**

First we create some data points of a sine function with some random perturbations:

```
sage: data = [(i, 1.2 * sin(0.5*i-0.2) + 0.1 * normalvariate(0, 1)) for i in xsrange(0, 4*pi, 0. sage: var('a, b, c, x') (a, b, c, x)
```

We define a function with free parameters a, b and c:

```
sage: model(x) = a * sin(b * x - c)
```

We search for the parameters that give the best fit to the data:

```
sage: find_fit(data, model)
[a == 1.21..., b == 0.49..., c == 0.19...]
```

We can also use a Python function for the model:

```
sage: def f(x, a, b, c): return a * sin(b * x - c)
sage: fit = find_fit(data, f, parameters = [a, b, c], variables = [x], solution_dict = True)
sage: fit[a], fit[b], fit[c]
(1.21..., 0.49..., 0.19...)
```

We search for a formula for the n-th prime number:

```
sage: dataprime = [(i, nth_prime(i)) for i in xrange(1, 5000, 100)]
sage: find_fit(dataprime, a * x * log(b * x), parameters = [a, b], variables = [x])
[a == 1.11..., b == 1.24...]
```

#### ALGORITHM:

Uses scipy.optimize.leastsq which in turn uses MINPACK's lmdif and lmder algorithms.

```
sage.numerical.optimize.find_local_maximum (f, a, b, tol=1.48e-0.8, maxfun=500)
```

Numerically find a local maximum of the expression f on the interval [a,b] (or [b,a]) along with the point at which the maximum is attained.

Note that this function only finds a *local* maximum, and not the global maximum on that interval – see the examples with find\_local\_maximum().

See the documentation for find\_local\_maximum() for more details and possible workarounds for finding the global minimum on an interval.

#### **EXAMPLES:**

```
sage: f = lambda x: x*cos(x)
sage: find_local_maximum(f, 0, 5)
(0.561096338191..., 0.8603335890...)
sage: find_local_maximum(f, 0, 5, tol=0.1, maxfun=10)
(0.561090323458..., 0.857926501456...)
sage: find_local_maximum(8*e^(-x)*sin(x) - 1, 0, 7)
(1.579175535558..., 0.7853981...)
```

```
sage.numerical.optimize.find_local_minimum (f, a, b, tol=1.48e-0.8, maxfun=500)
```

Numerically find a local minimum of the expression f on the interval [a,b] (or [b,a]) and the point at which it attains that minimum. Note that f must be a function of (at most) one variable.

Note that this function only finds a *local* minimum, and not the global minimum on that interval – see the examples below.

# INPUT:

- •f a function of at most one variable.
- •a, b endpoints of interval on which to minimize self.
- $\bullet \texttt{tol}$  the convergence tolerance
- •maxfun maximum function evaluations

# **OUTPUT:**

- •minval (float) the minimum value that self takes on in the interval [a, b]
- $\bullet x$  (float) the point at which self takes on the minimum value

#### **EXAMPLES:**

```
sage: f = lambda x: x*cos(x)
sage: find_local_minimum(f, 1, 5)
(-3.28837139559..., 3.4256184695...)
sage: find_local_minimum(f, 1, 5, tol=1e-3)
(-3.28837136189098..., 3.42575079030572...)
sage: find_local_minimum(f, 1, 5, tol=1e-2, maxfun=10)
(-3.28837084598..., 3.4250840220...)
sage: show(plot(f, 0, 20))
sage: find_local_minimum(f, 1, 15)
(-9.4772942594..., 9.5293344109...)
```

Only local minima are found; if you enlarge the interval, the returned minimum may be *larger*! See trac ticket #2607.

```
sage: f(x) = -x*\sin(x^2)

sage: find_local_minimum(f, -2.5, -1)

(-2.182769784677722, -2.1945027498534686)
```

Enlarging the interval returns a larger minimum:

```
sage: find_local_minimum(f, -2.5, 2)
(-1.3076194129914434, 1.3552111405712108)
```

One work-around is to plot the function and grab the minimum from that, although the plotting code does not necessarily do careful numerics (observe the small number of decimal places that we actually test):

```
sage: plot(f, (x,-2.5, -1)).ymin()
-2.1827...
sage: plot(f, (x,-2.5, 2)).ymin()
-2.1827...
```

# ALGORITHM:

Uses scipy.optimize.fminbound which uses Brent's method.

#### **AUTHOR:**

•William Stein (2007-12-07)

```
sage.numerical.optimize.find_root(f, a, b, xtol=1e-12, rtol=4.5e-16, maxiter=100, full\ output=False)
```

Numerically find a root of f on the closed interval [a,b] (or [b,a]) if possible, where f is a function in the one variable. Note: this function only works in fixed (machine) precision, it is not possible to get arbitrary precision approximations with it.

# INPUT:

- •f a function of one variable or symbolic equality
- •a, b endpoints of the interval
- •xtol, rtol the routine converges when a root is known to lie within xtol of the value return. Should be  $\geq 0$ . The routine modifies this to take into account the relative precision of doubles.
- •maxiter integer; if convergence is not achieved in maxiter iterations, an error is raised. Must be  $\geq 0$ .

•full\_output - bool (default: False), if True, also return object that contains information about convergence.

#### **EXAMPLES:**

An example involving an algebraic polynomial function:

```
sage: R.<x> = QQ[]
sage: f = (x+17)*(x-3)*(x-1/8)^3
sage: find_root(f, 0,4)
2.9999999999995
sage: find_root(f, 0,1) # note -- precision of answer isn't very good on some machines.
0.124999...
sage: find_root(f, -20,-10)
-17.0
```

In Pomerance's book on primes he asserts that the famous Riemann Hypothesis is equivalent to the statement that the function f(x) defined below is positive for all  $x \ge 2.01$ :

```
sage: def f(x):
... return sqrt(x) * log(x) - abs(Li(x) - prime_pi(x))
```

We find where f equals, i.e., what value that is slightly smaller than 2.01 that could have been used in the formulation of the Riemann Hypothesis:

```
sage: find_root(f, 2, 4, rtol=0.0001)
2.0082...
```

This agrees with the plot:

```
sage: plot(f,2,2.01)
```

sage.numerical.optimize.linear\_program (c, G, h, A=None, b=None, solver=None)Solves the dual linear programs:

- •Minimize c'x subject to Gx + s = h, Ax = b, and  $s \ge 0$  where ' denotes transpose.
- •Maximize -h'z b'y subject to G'z + A'y + c = 0 and  $z \ge 0$ .

#### INPUT:

- •c − a vector
- •G a matrix
- •h − a vector
- •A a matrix
- •b a vector

•solver (optional) — solver to use. If None, the cvxopt's lp-solver is used. If it is 'glpk', then glpk's solver is used.

These can be over any field that can be turned into a floating point number.

# **OUTPUT:**

A dictionary sol with keys x, s, y, z corresponding to the variables above:

- •sol['x'] the solution to the linear program
- •sol['s'] the slack variables for the solution
- •sol['z'], sol['y'] solutions to the dual program

#### **EXAMPLES:**

```
First, we minimize -4x_1 - 5x_2 subject to 2x_1 + x_2 \le 3, x_1 + 2x_2 \le 3, x_1 \ge 0, and x_2 \ge 0:
     sage: c=vector(RDF, [-4, -5])
     sage: G=matrix(RDF,[[2,1],[1,2],[-1,0],[0,-1]])
     sage: h=vector(RDF,[3,3,0,0])
     sage: sol=linear_program(c,G,h)
     sage: sol['x']
     (0.999..., 1.000...)
     Next, we maximize x + y - 50 subject to 50x + 24y \le 2400, 30x + 33y \le 2100, x \ge 45, and y \ge 5:
     sage: v=vector([-1.0,-1.0,-1.0])
     sage: m=matrix([[50.0,24.0,0.0],[30.0,33.0,0.0],[-1.0,0.0,0.0],[0.0,-1.0,0.0],[0.0,0.0,1.0],[0.0
     sage: h=vector([2400.0,2100.0,-45.0,-5.0,1.0,-1.0])
     sage: sol=linear_program(v,m,h)
     sage: sol['x']
     (45.000000..., 6.2499999...3, 1.00000000...)
     sage: sol=linear_program(v,m,h,solver='glpk')
     GLPK Simplex Optimizer...
     OPTIMAL SOLUTION FOUND
     sage: sol['x']
     (45.0..., 6.25, 1.0...)
sage.numerical.optimize.minimize(func,
                                                 x0,
                                                       gradient=None,
                                                                        hessian=None,
                                                                                        algo-
                                         rithm='default', **args)
     This function is an interface to a variety of algorithms for computing the minimum of a function of several
     variables.
```

# INPUT:

- •func Either a symbolic function or a Python function whose argument is a tuple with n components
- •x0 Initial point for finding minimum.
- •gradient Optional gradient function. This will be computed automatically for symbolic functions. For Python functions, it allows the use of algorithms requiring derivatives. It should accept a tuple of arguments and return a NumPy array containing the partial derivatives at that point.
- •hessian Optional hessian function. This will be computed automatically for symbolic functions. For Python functions, it allows the use of algorithms requiring derivatives. It should accept a tuple of arguments and return a NumPy array containing the second partial derivatives of the function.
- •algorithm String specifying algorithm to use. Options are 'default' (for Python functions, the simplex method is the default) (for symbolic functions bfgs is the default):

```
-'simplex'
-'powell'
-'bfgs' - (Broyden-Fletcher-Goldfarb-Shanno) requires gradient
-'cg' - (conjugate-gradient) requires gradient
-'ncg' - (newton-conjugate gradient) requires gradient and hessian
```

```
sage: vars=var('x y z')
sage: f=100*(y-x^2)^2+(1-x)^2+100*(z-y^2)^2+(1-y)^2
sage: minimize(f,[.1,.3,.4],disp=0)
(1.00..., 1.00..., 1.00...)
```

```
sage: minimize(f,[.1,.3,.4],algorithm="ncg",disp=0)
(0.9999999..., 0.9999999..., 0.9999999...)
Same example with just Python functions:
sage: def rosen(x): # The Rosenbrock function
         return sum(100.0r*(x[1r:]-x[:-1r]**2.0r)**2.0r + (1r-x[:-1r])**2.0r)
sage: minimize (rosen, [.1, .3, .4], disp=0)
(1.00..., 1.00..., 1.00...)
Same example with a pure Python function and a Python function to compute the gradient:
sage: def rosen(x): # The Rosenbrock function
         return sum(100.0r*(x[1r:]-x[:-1r]**2.0r)**2.0r + (1r-x[:-1r])**2.0r)
sage: import numpy
sage: from numpy import zeros
sage: def rosen_der(x):
        xm = x[1r:-1r]
         xm_m1 = x[:-2r]
         xm_p1 = x[2r:]
         der = zeros(x.shape,dtype=float)
         der[1r:-1r] = 200r*(xm-xm_m1**2r) - 400r*(xm_p1 - xm**2r)*xm - 2r*(1r-xm)
. . .
         der[0] = -400r*x[0r]*(x[1r]-x[0r]**2r) - 2r*(1r-x[0])
. . .
         der[-1] = 200r*(x[-1r]-x[-2r]**2r)
         return der
sage: minimize(rosen,[.1,.3,.4],gradient=rosen_der,algorithm="bfgs",disp=0)
(1.00..., 1.00..., 1.00...)
```

sage.numerical.optimize.minimize\_constrained(func, cons, x0, gradient=None, algorithm='default', \*\*args)

Minimize a function with constraints.

#### INPUT:

- •func Either a symbolic function, or a Python function whose argument is a tuple with n components
- •cons constraints. This should be either a function or list of functions that must be positive. Alternatively, the constraints can be specified as a list of intervals that define the region we are minimizing in. If the constraints are specified as functions, the functions should be functions of a tuple with n components (assuming n variables). If the constraints are specified as a list of intervals and there are no constraints for a given variable, that component can be (None, None).
- •x0 Initial point for finding minimum
- •algorithm Optional, specify the algorithm to use:
  - -'default' default choices
  - -'l-bfgs-b' only effective if you specify bound constraints. See [ZBN97].
- •gradient Optional gradient function. This will be computed automatically for symbolic functions. This is only used when the constraints are specified as a list of intervals.

#### **EXAMPLES:**

Let us maximize x+y-50 subject to the following constraints:  $50x+24y \le 2400$ ,  $30x+33y \le 2100$ ,  $x \ge 45$ , and  $y \ge 5$ :

```
sage: y = var('y')
sage: f = lambda p: -p[0]-p[1]+50
sage: c_1 = lambda p: p[0]-45
sage: c_2 = lambda p: p[1]-5
```

```
sage: c_3 = lambda p: -50*p[0]-24*p[1]+2400
sage: c_4 = lambda p: -30*p[0]-33*p[1]+2100
sage: a = minimize\_constrained(f, [c_1, c_2, c_3, c_4], [2,3])
sage: a
(45.0, 6.25)
Let's find a minimum of sin(xy):
sage: x, y = var('x y')
sage: f = sin(x*y)
sage: minimize_constrained(f, [(None, None), (4, 10)], [5, 5])
(4.8..., 4.8...)
Check, if L-BFGS-B finds the same minimum:
sage: minimize_constrained(f, [(None, None), (4,10)], [5,5], algorithm='l-bfgs-b')
(4.7..., 4.9...)
Rosenbrock function, [http://en.wikipedia.org/wiki/Rosenbrock_function]:
sage: from scipy.optimize import rosen, rosen_der
sage: minimize_constrained(rosen, [(-50,-10),(5,10)],[1,1], gradient=rosen_der, algorithm='l-bfgs-
(-10.0, 10.0)
sage: minimize_constrained(rosen, [(-50,-10),(5,10)],[1,1],algorithm='l-bfgs-b')
(-10.0, 10.0)
```

**REFERENCES:** 

# INTERACTIVE SIMPLEX METHOD

The purpose of this module is to support learning and exploring of the simplex method. While it does allow solving Linear Programming Problems (LPPs) in a number of ways, it may require explicit (and correct!) description of steps and is likely to be much slower than "regular" LP solvers. Therefore, do not use this module if all you want is the result. If, however, you want to learn how the simplex method works and see what happens in different situations using different strategies, but don't want to deal with tedious arithmetic, this module is for you!

Historically it was created to complement the Math 373 course on Mathematical Programming and Optimization at the University of Alberta, Edmonton, Canada.

#### **AUTHORS:**

• Andrey Novoseltsev (2013-03-16): initial version.

#### **EXAMPLES:**

Most of the module functionality is demonstrated on the following problem.

### Corn & Barley

A farmer has 1000 acres available to grow corn and barley. Corn has a net profit of 10 dollars per acre while barley has a net profit of 5 dollars per acre. The farmer has 1500 kg of fertilizer available with 3 kg per acre needed for corn and 1 kg per acre needed for barley. The farmer wants to maximize profit. (Sometimes we also add one more constraint to make the initial dictionary infeasible: the farmer has to use at least 40% of the available land.)

Using variables C and B for land used to grow corn and barley respectively, in acres, we can construct the following LP problem:

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
sage: P
LP problem (use typeset mode to see details)
```

It is recommended to copy-paste such examples into your own worksheet, so that you can run these commands with typeset mode on and get

$$\begin{array}{ccc} \max \ 10C + 5B & \\ C + & B \leq 1000 \\ 3C + & B \leq 1500 \\ C, B > 0 & \end{array}$$

Since it has only two variables, we can solve it graphically:

```
sage: P.plot()
```

The simplex method can be applied only to problems in standard form, which can be created either directly

```
sage: LPProblemStandardForm(A, b, c, ["C", "B"])
LP problem (use typeset mode to see details)
```

or from an already constructed problem of "general type":

```
sage: P = P.standard_form()
```

In this case the problem does not require any modifications to be written in standard form, but this step is still necessary to enable methods related to the simplex method.

The simplest way to use the simplex method is:

```
sage: P.run_simplex_method()
'...'
```

(This method produces quite long formulas which have been omitted here.) But, of course, it is much more fun to do most of the steps by hand. Let's start by creating the initial dictionary:

```
sage: D = P.initial_dictionary()
sage: D
LP problem dictionary (use typeset mode to see details)
```

Using typeset mode as recommended, you'll see

$$x_3 = 1000 - C - B$$

$$x_4 = 1500 - 3C - B$$

$$z = 0 + 10C + 5B$$

With the initial or any other dictionary you can perform a number of checks:

```
sage: D.is_feasible()
True
sage: D.is_optimal()
False
```

You can look at many of its pieces and associated data:

```
sage: D.basic_variables()
(x3, x4)
sage: D.basic_solution()
(0, 0)
sage: D.objective_value()
0
```

Most importantly, you can perform steps of the simplex method by picking an entering variable, a leaving variable, and updating the dictionary:

```
sage: D.enter("C")
sage: D.leave(4)
sage: D.update()
```

If everything was done correctly, the new dictionary is still feasible and the objective value did not decrease:

```
sage: D.is_feasible()
True
sage: D.objective_value()
5000
```

If you are unsure about picking entering and leaving variables, you can use helper methods that will try their best to tell you what are your next options:

```
sage: D.possible_entering()
[B]
sage: D.possible_leaving()
Traceback (most recent call last):
...
ValueError: leaving variables can be determined
for feasible dictionaries with a set entering variable
or for dual feasible dictionaries
```

It is also possible to obtain feasible sets and final dictionaries of problems, work with revised dictionaries, and use the dual simplex method!

Note: Currently this does not have a display format for the terminal.

```
class sage.numerical.interactive_simplex_method.LPAbstractDictionary
    Bases: sage.structure.sage_object.SageObject
```

Abstract base class for dictionaries for LP problems.

Instantiating this class directly is meaningless, see LPDictionary and LPRevisedDictionary for useful extensions.

#### base\_ring()

Return the base ring of self, i.e. the ring of coefficients.

### **OUTPUT**:

•a ring

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.base_ring()
Rational Field
sage: D = P.revised_dictionary()
sage: D.base_ring()
Rational Field
```

# basic\_solution (include\_slack\_variables=False)

Return the basic solution of self.

The basic solution associated to a dictionary is obtained by setting to zero all nonbasic\_variables(), in which case basic\_variables() have to be equal to constant\_terms() in equations. It may refer to values of decision\_variables() only or include slack\_variables() as well.

INPUT:

•include\_slack\_variables - (default: False) if True, values of slack variables will be appended at the end

#### **OUTPUT:**

•a vector

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.basic_solution()
(0, 0)
sage: D.basic_solution(True)
(0, 0, 1000, 1500)
sage: D = P.revised_dictionary()
sage: D.basic_solution()
(0, 0)
sage: D.basic_solution(True)
(0, 0, 1000, 1500)
```

#### coordinate\_ring()

Return the coordinate ring of self.

#### **OUTPUT**:

•a polynomial ring in auxiliary\_variable(), decision\_variables(), and slack\_variables() of self over the base\_ring()

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.coordinate_ring()
Multivariate Polynomial Ring in x0, x1, x2, x3, x4
over Rational Field
sage: D = P.revised_dictionary()
sage: D.coordinate_ring()
Multivariate Polynomial Ring in x0, x1, x2, x3, x4
over Rational Field
```

# dual\_ratios()

Return ratios used to determine the entering variable based on leaving.

#### **OUTPUT:**

•A list of pairs  $(r_j, x_j)$  where  $x_j$  is a non-basic variable and  $r_j = c_j/a_{ij}$  is the ratio of the objective coefficient  $c_j$  to the coefficient  $a_{ij}$  of  $x_j$  in the relation for the leaving variable  $x_i$ :

$$x_i = b_i - \dots - a_{ij}x_j - \dots$$

The order of pairs matches the order of nonbasic\_variables(), but only  $x_j$  with negative  $a_{ij}$  are considered.

```
sage: A = ([1, 1], [3, 1], [-1, -1])
sage: b = (1000, 1500, -400)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.dictionary(2, 3, 5)
sage: D.leave(3)
sage: D.dual_ratios()
[(5/2, x1), (5, x4)]
sage: D = P.revised_dictionary(2, 3, 5)
sage: D.leave(3)
sage: D.dual_ratios()
[(5/2, x1), (5, x4)]
```

#### enter(v)

Set v as the entering variable of self.

#### INPUT:

•v – a non-basic variable of self, can be given as a string, an actual variable, or an integer interpreted as the index of a variable

# **OUTPUT**:

•none, but the selected variable will be used as entering by methods that require an entering variable and the corresponding column will be typeset in green

#### EXAMPLES:

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.enter("x1")
```

We can also use indices of variables:

```
sage: D.enter(1)
```

Or variable names without quotes after injecting them:

```
sage: P.inject_variables()
Defining x0, x1, x2, x3, x4
sage: D.enter(x1)
```

The same works for revised dictionaries as well:

```
sage: D = P.revised_dictionary()
sage: D.enter(x1)
```

#### is dual feasible()

Check if self is dual feasible.

# **OUTPUT**:

•True if all objective\_coefficients() are non-positive, False otherwise

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
```

```
sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.initial_dictionary()
    sage: D.is_dual_feasible()
    False
    sage: D = P.revised_dictionary()
    sage: D.is_dual_feasible()
    False
is_feasible()
    Check if self is feasible.
    OUTPUT:
       •True if all constant_terms () are non-negative, "False" otherwise
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.initial_dictionary()
    sage: D.is_feasible()
    sage: D = P.revised_dictionary()
    sage: D.is_feasible()
    True
is_optimal()
    Check if self is optimal.
    OUTPUT:
       •True if self is_feasible() and is_dual_feasible() (i.e. all constant_terms()
        are non-negative and all objective_coefficients() are non-positive), False otherwise.
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.initial_dictionary()
    sage: D.is_optimal()
    False
    sage: D = P.revised_dictionary()
    sage: D.is_optimal()
    False
    sage: D = P.revised_dictionary(1, 2)
    sage: D.is_optimal()
    True
leave (v)
    Set v as the leaving variable of self.
    INPUT:
       •v - a basic variable of self, can be given as a string, an actual variable, or an integer interpreted as
        the index of a variable
    OUTPUT:
```

•none, but the selected variable will be used as leaving by methods that require a leaving variable and the corresponding row will be typeset in red

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.leave("x4")
```

We can also use indices of variables:

```
sage: D.leave(4)
```

Or variable names without quotes after injecting them:

```
sage: P.inject_variables()
Defining x0, x1, x2, x3, x4
sage: D.leave(x4)
```

The same works for revised dictionaries as well:

```
sage: D = P.revised_dictionary()
sage: D.leave(x4)
```

#### possible dual simplex method steps()

Return possible dual simplex method steps for self.

#### **OUTPUT:**

•A list of pairs (leaving, entering), where leaving is a basic variable that may leave () and entering is a list of non-basic variables that may enter() when leaving leaves. Note that entering may be empty, indicating that the problem is infeasible (since the dual one is unbounded).

# **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.dictionary(2, 3)
sage: D.possible_dual_simplex_method_steps()
[(x3, [x1])]
sage: D = P.revised_dictionary(2, 3)
sage: D.possible_dual_simplex_method_steps()
[(x3, [x1])]
```

#### possible\_entering()

Return possible entering variables for self.

# **OUTPUT**:

•a list of non-basic variables of self that can enter () on the next step of the (dual) simplex method

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
```

```
sage: D.possible_entering()
[x1, x2]
sage: D = P.revised_dictionary()
sage: D.possible_entering()
[x1, x2]
```

# possible\_leaving()

Return possible leaving variables for self.

#### **OUTPUT:**

 $\bullet$ a list of basic variables of self that can leave() on the next step of the (dual) simplex method

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.enter(1)
sage: D.possible_leaving()
[x4]
sage: D = P.revised_dictionary()
sage: D.enter(1)
sage: D.possible_leaving()
[x4]
```

# possible\_simplex\_method\_steps()

Return possible simplex method steps for self.

#### **OUTPUT**:

•A list of pairs (entering, leaving), where entering is a non-basic variable that may enter() and leaving is a list of basic variables that may leave() when entering enters. Note that leaving may be empty, indicating that the problem is unbounded.

# **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.possible_simplex_method_steps()
[(x1, [x4]), (x2, [x3])]
sage: D = P.revised_dictionary()
sage: D.possible_simplex_method_steps()
[(x1, [x4]), (x2, [x3])]
```

# ratios()

Return ratios used to determine the leaving variable based on entering.

#### **OUTPUT:**

•A list of pairs  $(r_i, x_i)$  where  $x_i$  is a basic variable and  $r_i = b_i/a_{ik}$  is the ratio of the constant term  $b_i$  to the coefficient  $a_{ik}$  of the entering variable  $x_k$  in the relation for  $x_i$ :

```
x_i = b_i - \dots - a_{ik}x_k - \dots
```

The order of pairs matches the order of basic\_variables(), but only  $x_i$  with positive  $a_{ik}$  are considered.

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.enter(1)
sage: D.ratios()
[(1000, x3), (500, x4)]
sage: D = P.revised_dictionary()
sage: D.enter(1)
sage: D.ratios()
[(1000, x3), (500, x4)]
```

Bases: sage.numerical.interactive\_simplex\_method.LPAbstractDictionary

Construct a dictionary for an LP problem.

A dictionary consists of the following data:

$$x_B = b - Ax_N$$
$$z = z^* + cx_N$$

#### INPUT:

- •A a matrix of relation coefficients
- •b a vector of relation constant terms
- •c a vector of objective coefficients
- •objective\_value current value of the objective  $z^*$
- •basic\_variables a list of basic variables  $x_B$
- ullet nonbasic\_variables a list of non-basic variables  $x_N$
- •objective\_variable an objective variable z

# **OUTPUT:**

•a dictionary for an LP problem

**Note:** This constructor does not check correctness of input, as it is intended to be used internally by LPProblemStandardForm.

# **EXAMPLES:**

The intended way to use this class is indirect:

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D
LP problem dictionary (use typeset mode to see details)
```

But if you want you can create a dictionary without starting with an LP problem, here is construction of the same dictionary as above:

```
sage: A = matrix(QQ, ([1, 1], [3, 1]))
sage: b = vector(QQ, (1000, 1500))
sage: c = vector(QQ, (10, 5))
sage: R = PolynomialRing(QQ, "x1, x2, x3, x4", order="neglex")
sage: from sage.numerical.interactive_simplex_method \
...: import LPDictionary
sage: D2 = LPDictionary(A, b, c, 0, R.gens()[2:], R.gens()[:2], "z")
sage: D2 == D
True
```

#### **ELLUL** (*entering*, *leaving*)

Perform the Enter-Leave-LaTeX-Update-LaTeX step sequence on self.

#### INPUT:

- •entering the entering variable
- •leaving the leaving variable

#### **OUTPUT:**

•a string with LaTeX code for self before and after update

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.ELLUL("x1", "x4")
\renewcommand{\arraystretch}{1.5} \setlength{\arraycolsep}{0.125em}
\begin{array}{|rcrcrcr|}
x_{3} &= & 1000 & - & \color{green} & x_{1} & - & x_{2} \
\label{eq:color} $$ \color{red} x_{4} &\color{red} = &\color{red} 1500 &\color{red} - &\color{blue} 3 x_{1} &\color{red} = &\color{red} - &\color{blue} 3 x_{1} &\color{red} = &\color{red} - &\color{blue} 
\hline
z \& = \& 0 \& + \& \color{green} 10 x_{1} \& + \& 5 x_{2} \
\hline
\mbox{multicolumn{2}{c}{}} \mbox{c}{} \mbox{-3ex]}
\hline
x_{3} & = 6500 & + 6 \frac{1}{3} x_{4} & - 6 \frac{2}{3} x_{2}
x_{1} &= 6500 & - 6 \frac{1}{3} x_{4} & - 6 \frac{1}{3} x_{2}
\hline
z \& = \& 5000 \& - \& \frac{10}{3} x_{4} \& + \& \frac{5}{3} x_{2} \
\hline
\end{array}
```

This is how the above output looks when rendered:

$$x_{3} = 1000 - x_{1} - x_{2}$$

$$x_{4} = 1500 - 3x_{1} - x_{2}$$

$$z = 0 + 10x_{1} + 5x_{2}$$

$$x_{3} = 500 + \frac{1}{3}x_{4} - \frac{2}{3}x_{2}$$

$$x_{1} = 500 - \frac{1}{3}x_{4} - \frac{1}{3}x_{2}$$

$$z = 5000 - \frac{10}{3}x_{4} + \frac{5}{3}x_{2}$$

The column of the entering variable is green, while the row of the leaving variable is red in the original dictionary state on the top. The new state after the update step is shown on the bottom.

#### basic variables()

Return the basic variables of self.

OUTPUT:

•a vector

```
EXAMPLES:
```

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.basic_variables()
(x3, x4)
```

# constant\_terms()

Return the constant terms of relations of self.

**OUTPUT**:

•a vector.

```
EXAMPLES:
```

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.constant_terms()
(1000, 1500)
```

# entering\_coefficients()

Return coefficients of the entering variable.

**OUTPUT**:

•a vector

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
```

```
sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.initial_dictionary()
    sage: D.enter(1)
    sage: D.entering_coefficients()
    (1, 3)
leaving_coefficients()
    Return coefficients of the leaving variable.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.dictionary(2, 3)
    sage: D.leave(3)
    sage: D.leaving_coefficients()
    (-2, -1)
nonbasic_variables()
    Return non-basic variables of self.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.initial_dictionary()
    sage: D.nonbasic_variables()
    (x1, x2)
objective_coefficients()
    Return coefficients of the objective of self.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.initial_dictionary()
    sage: D.objective_coefficients()
    (10, 5)
objective_value()
    Return the value of the objective at the basic_solution() of self.
    OUTPUT:
```

#### •a number

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.objective_value()
0
```

# update()

Update self using previously set entering and leaving variables.

# **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
sage: D.objective_value()
0
sage: D.enter("x1")
sage: D.leave("x4")
sage: D.update()
sage: D.objective_value()
```

class sage.numerical.interactive\_simplex\_method.LPProblem  $(A, b, c, x='x', constraint_type='<=', variable_type='', problem_type='max', prefix='x', base_ring=None)$ 

 $Bases: \verb|sage_object.SageObject| \\$ 

Construct an LP (Linear Programming) problem.

This class supports LP problems with "variables on the left" constraints.

#### INPUT:

- •A a matrix of constraint coefficients
- •b a vector of constraint constant terms
- •c a vector of objective coefficients
- •x (default: "x") a vector of decision variables or a string giving the base name
- •constraint\_type-(default: "<=") a string specifying constraint type(s): either "<=", ">=", "==", or a list of them
- •variable\_type (default: "") a string specifying variable type(s): either ">=", "<=", " " (the empty string), or a list of them, corresponding, respectively, to non-negative, non-positive, and free variables
- •problem\_type (default: "max") a string specifying the problem type: "max", "min", "-max", or "-min"
- •prefix (default: parameter x if it was given as a string, string "x" otherwise) a string giving the base name of automatically created variables in standard\_form()

•base\_ring - (default: the fraction field of a common ring for all input coefficients) a field to which all input coefficients will be converted

#### **EXAMPLES:**

We will construct the following problem:

Using the last form you should be able to represent any LP problem, as long as all like terms are collected and in constraints variables and constants are on different sides.

#### **A**()

Return coefficients of constraints of self, i.e. A.

# **OUTPUT:**

•a matrix

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
sage: P.constraint_coefficients()
[1 1]
[3 1]
sage: P.A()
[1 1]
[3 1]
```

#### Abcx()

Return A, b, c, and x of self as a tuple.

#### **OUTPUT**:

•a tuple

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
```

```
sage: P.Abcx()
    [1 1]
    [3 1], (1000, 1500), (10, 5), (C, B)
b()
    Return constant terms of constraints of self, i.e. b.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.constant_terms()
    (1000, 1500)
    sage: P.b()
    (1000, 1500)
base_ring()
    Return the base ring of self.
    Note: The base ring of LP problems is always a field.
    OUTPUT:
       •a ring
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.base_ring()
    Rational Field
    sage: c = (10, 5.)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
```

**c**()

Return coefficients of the objective of self, i.e. c.

Real Field with 53 bits of precision

**OUTPUT**:

•a vector

sage: P.base\_ring()

```
EXAMPLES:
```

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
sage: P.objective_coefficients()
```

```
(10, 5)
    sage: P.c()
    (10, 5)
constant_terms()
    Return constant terms of constraints of self, i.e. b.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.constant_terms()
    (1000, 1500)
    sage: P.b()
    (1000, 1500)
constraint_coefficients()
    Return coefficients of constraints of self, i.e. A.
    OUTPUT:
       •a matrix
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.constraint_coefficients()
    [1 1]
    [3 1]
    sage: P.A()
    [1 1]
    [3 1]
decision_variables()
    Return decision variables of self, i.e. x.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.decision_variables()
    (C, B)
    sage: P.x()
    (C, B)
dual (y=None)
    Construct the dual LP problem for self.
```

# INPUT:

•y – (default: "x" if the prefix of self is "y", "y" otherwise) a vector of dual decision variables or a string giving the base name

# **OUTPUT**:

```
•an LPProblem
```

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
sage: DP = P.dual()
sage: DP.b() == P.c()
True
sage: DP.dual(["C", "B"]) == P
```

#### feasible\_set()

Return the feasible set of self.

# **OUTPUT**:

•a Polyhedron

#### **EXAMPLES**:

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
sage: P.feasible_set()
A 2-dimensional polyhedron in QQ^2
defined as the convex hull of 4 vertices
```

# is\_bounded()

Check if self is bounded.

# **OUTPUT**:

•True is self is bounded, False otherwise

#### **EXAMPLES**:

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
sage: P.is_bounded()
True
```

# is\_feasible()

Check if self is feasible.

#### **OUTPUT**:

•True is self is feasible, False otherwise

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
```

```
sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.is_feasible()
    True
m()
    Return the number of constraints of self, i.e. m.
    OUTPUT:
       •an integer
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.n_constraints()
    sage: P.m()
n()
    Return the number of decision variables of self, i.e. n.
    OUTPUT:
       •an integer
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.n_variables()
    sage: P.n()
n_constraints()
    Return the number of constraints of self, i.e. m.
    OUTPUT:
       •an integer
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.n_constraints()
    sage: P.m()
n_variables()
    Return the number of decision variables of self, i.e. n.
    OUTPUT:
```

```
•an integer
```

```
EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.n_variables()
    sage: P.n()
    2
objective_coefficients()
    Return coefficients of the objective of self, i.e. c.
    OUTPUT:
       ·a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.objective_coefficients()
    (10, 5)
    sage: P.c()
    (10, 5)
optimal_solution()
    Return an optimal solution of self.
    OUTPUT:
       •a vector or None if there are no optimal solutions
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
    sage: P.optimal_solution()
    (250, 750)
optimal_value()
    Return the optimal value for self.
    OUTPUT:
       •a number if the problem is bounded, \pm \infty if it is unbounded, or None if it is infeasible
    EXAMPLES:
```

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
sage: P.optimal_value()
6250
```

```
plot (*args, **kwds)
```

Return a plot for solving self graphically.

#### INPUT:

- •xmin, xmax, ymin, ymax bounds for the axes, if not given, an attempt will be made to pick reasonable values
- •alpha (default: 0.2) determines how opaque are shadows

#### **OUTPUT:**

•a plot

This only works for problems with two decision variables. On the plot the black arrow indicates the direction of growth of the objective. The lines perpendicular to it are level curves of the objective. If there are optimal solutions, the arrow originates in one of them and the corresponding level curve is solid: all points of the feasible set on it are optimal solutions. Otherwise the arrow is placed in the center. If the problem is infeasible or the objective is zero, a plot of the feasible set only is returned.

# **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
sage: p = P.plot()
sage: p.show()
```

In this case the plot works better with the following axes ranges:

```
sage: p = P.plot(0, 1000, 0, 1500)
sage: p.show()
```

# TESTS:

We check that zero objective can be dealt with:

```
sage: LPProblem(A, b, (0, 0), ["C", "B"], variable_type=">=").plot()
```

plot\_feasible\_set (xmin=None, xmax=None, ymin=None, ymax=None, alpha=0.2)

Return a plot of the feasible set of self.

#### INPUT:

- •xmin, xmax, ymin, ymax bounds for the axes, if not given, an attempt will be made to pick reasonable values
- •alpha (default: 0.2) determines how opaque are shadows

# **OUTPUT**:

•a plot

This only works for a problem with two decision variables. The plot shows boundaries of constraints with a shadow on one side for inequalities. If the  $feasible\_set()$  is not empty and at least part of it is in the given boundaries, it will be shaded gray and F will be placed in its middle.

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
```

```
sage: p = P.plot_feasible_set()
         sage: p.show()
         In this case the plot works better with the following axes ranges:
         sage: p = P.plot_feasible_set(0, 1000, 0, 1500)
         sage: p.show()
     standard_form()
         Construct the LP problem in standard form equivalent to self.
         OUTPUT:
            •an LPProblemStandardForm
         EXAMPLES:
         sage: A = ([1, 1], [3, 1])
         sage: b = (1000, 1500)
         sage: c = (10, 5)
         sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
         sage: DP = P.dual()
         sage: DPSF = DP.standard_form()
         sage: DPSF.b()
         (-10, -5)
     x()
         Return decision variables of self, i.e. x.
         OUTPUT:
            •a vector
         EXAMPLES:
         sage: A = ([1, 1], [3, 1])
         sage: b = (1000, 1500)
         sage: c = (10, 5)
         sage: P = LPProblem(A, b, c, ["C", "B"], variable_type=">=")
         sage: P.decision_variables()
         (C, B)
         sage: P.x()
         (C, B)
{f class} sage.numerical.interactive_simplex_method.LPProblemStandardForm (A, b, c,
                                                                                 x='x'
                                                                                 prob-
                                                                                 lem type='max',
                                                                                 slack_variables=None,
                                                                                 auxil-
                                                                                 iary_variable=None,
                                                                                 objec-
                                                                                 tive='z',
                                                                                 base_ring=None)
     Bases: sage.numerical.interactive_simplex_method.LPProblem
```

Construct an LP (Linear Programming) problem in standard form.

The used standard form is:

#### INPUT:

- •A a matrix of constraint coefficients
- •b a vector of constraint constant terms
- •c a vector of objective coefficients
- •x (default: "x") a vector of decision variables or a string the base name giving
- •problem\_type (default: "max") a string specifying the problem type: either "max" or "-max"
- •slack\_variables (default: same as x parameter, if it was given as a string, otherwise string "x") a vector of slack variables or a sting giving the base name
- •auxiliary\_variable (default: same as x parameter with adjoined "0" if it was given as a string, otherwise "x0") the auxiliary name, expected to be the same as the first decision variable for auxiliary problems
- •objective (default: "z") the objective variable (used for the initial dictionary)
- •base\_ring (default: the fraction field of a common ring for all input coefficients) a field to which all input coefficients will be converted

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
```

Unlike LPProblem, this class does not allow you to adjust types of constraints (they are always "<=") and variables (they are always ">="), and the problem type may only be "max" or "-max". You may give custom names to slack and auxiliary variables, but in most cases defaults should work:

```
sage: P.decision_variables()
(x1, x2)
sage: P.slack_variables()
(x3, x4)
```

## auxiliary\_problem()

Construct the auxiliary problem for self.

#### **OUTPUT:**

```
•an LP problem in standard form
```

The auxiliary problem with the auxiliary variable  $x_0$  is

$$\begin{aligned} \max & -x_0 \\ -x_0 + A_i x \leq b_i \text{ for all } i \\ x \geq 0 \end{aligned} .$$

Such problems are used when the initial\_dictionary () is infeasible.

```
sage: A = ([1, 1], [3, 1], [-1, -1])
    sage: b = (1000, 1500, -400)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: AP = P.auxiliary_problem()
auxiliary_variable()
    Return the auxiliary variable of self.
    Note that the auxiliary variable may or may not be among decision_variables().
    OUTPUT:
       •a variable of the coordinate_ring() of self
    EXAMPLES:
    sage: A = ([1, 1], [3, 1], [-1, -1])
    sage: b = (1000, 1500, -400)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: P.auxiliary_variable()
    sage: P.decision_variables()
    (x1, x2)
    sage: AP = P.auxiliary_problem()
    sage: AP.auxiliary_variable()
    sage: AP.decision_variables()
    (x0, x1, x2)
coordinate_ring()
    Return the coordinate ring of self.
    OUTPUT:
       •a polynomial ring over the base_ring() of self in the auxiliary_variable(),
        decision_variables(), and slack_variables() with "neglex" order
    EXAMPLES:
    sage: A = ([1, 1], [3, 1], [-1, -1])
    sage: b = (1000, 1500, -400)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: P.coordinate_ring()
    Multivariate Polynomial Ring in x0, x1, x2, x3, x4, x5
    over Rational Field
    sage: P.base_ring()
    Rational Field
    sage: P.auxiliary_variable()
    sage: P.decision_variables()
    (x1, x2)
    sage: P.slack_variables()
    (x3, x4, x5)
dictionary(*x_B)
    Construct a dictionary for self with given basic variables.
```

INPUT:

73

•basic variables for the dictionary to be constructed

#### **OUTPUT**:

```
•a dictionary
```

**Note:** This is a synonym for  $self.revised\_dictionary(x_B).dictionary(), but basic variables are mandatory.$ 

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.dictionary("x1", "x2")
sage: D.basic_variables()
(x1, x2)
```

# feasible\_dictionary (auxiliary\_dictionary)

Construct a feasible dictionary for self.

#### INPUT:

•auxiliary\_dictionary - an optimal dictionary for the auxiliary\_problem() of self with the optimal value 0 and a non-basic auxiliary variable

#### **OUTPUT:**

•a feasible dictionary for self

```
sage: A = ([1, 1], [3, 1], [-1, -1])
sage: b = (1000, 1500, -400)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: AP = P.auxiliary_problem()
sage: D = AP.initial_dictionary()
sage: D.enter(0)
sage: D.leave(5)
sage: D.update()
sage: D.enter(1)
sage: D.leave(0)
sage: D.update()
sage: D.is_optimal()
sage: D.objective_value()
sage: D.basic_solution()
(0, 400, 0)
sage: D = P.feasible_dictionary(D)
sage: D.is_optimal()
False
sage: D.is_feasible()
True
sage: D.objective_value()
sage: D.basic_solution()
(400, 0)
```

#### final dictionary()

Return the final dictionary of the simplex method applied to self.

See run\_simplex\_method() for the description of possibilities.

#### **OUTPUT**:

```
•a dictionary
```

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.final_dictionary()
sage: D.is_optimal()
True
```

#### TESTS:

```
sage: P.final_dictionary() is P.final_dictionary()
False
```

# final\_revised\_dictionary()

Return the final dictionary of the revised simplex method applied to self.

See run\_revised\_simplex\_method() for the description of possibilities.

#### **OUTPUT:**

```
•a revised dictionary
```

# EXAMPLES:

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.final_revised_dictionary()
sage: D.is_optimal()
True
```

#### TESTS:

```
sage: P.final_revised_dictionary() is P.final_revised_dictionary()
False
```

# initial\_dictionary()

Construct the initial dictionary of self.

The initial dictionary "defines" slack\_variables() in terms of the decision\_variables(), i.e. it has slack variables as basic ones.

# **OUTPUT:**

```
•a dictionary
```

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.initial_dictionary()
```

inject\_variables (scope=None, verbose=True)

```
Inject variables of self into scope.
    INPUT:
       •scope - namespace (default: global)
       •verbose – if True (default), names of injected variables will be printed
    OUTPUT:
       •none
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: P.inject_variables()
    Defining x0, x1, x2, x3, x4
    sage: 3*x1 + x2
    x2 + 3*x1
revised_dictionary(*x_B)
    Construct a revised dictionary for self.
    INPUT:
       •basic variables for the dictionary to be constructed; if not given, slack_variables() will be
        used, perhaps with the auxiliary_variable() to give a feasible dictionary
    OUTPUT:
       •a revised dictionary
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary("x1", "x2")
    sage: D.basic_variables()
    (x1, x2)
    If basic variables are not given the initial dictionary is constructed:
    sage: P.revised_dictionary().basic_variables()
    (x3, x4)
    sage: P.initial_dictionary().basic_variables()
    (x3, x4)
    Unless it is infeasible, in which case a feasible dictionary for the auxiliary problem is constructed:
    sage: A = ([1, 1], [3, 1], [-1, -1])
    sage: b = (1000, 1500, -400)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: P.initial_dictionary().is_feasible()
    sage: P.revised_dictionary().basic_variables()
    (x3, x4, x0)
```

#### run revised simplex method()

Apply the revised simplex method to solve self and show the steps.

#### **OUTPUT:**

•a string with LATEX code of intermediate dictionaries

Note: You can access the final\_revised\_dictionary(), which can be one of the following:

- •an optimal dictionary with the auxiliary\_variable() among basic\_variables() and a non-zero optimal value indicating that self is infeasible;
- •a non-optimal dictionary that has marked entering variable for which there is no choice of the leaving variable, indicating that self is unbounded;
- •an optimal dictionary.

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1], [-1, -1])
sage: b = (1000, 1500, -400)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: P.run_revised_simplex_method()
\renewcommand{\arraystretch}{1.500000}
\begin{array}{1}
...
\text{Entering: $x_{1}$. Leaving: $x_{0}$.}\\
...
\text{Entering: $x_{5}$. Leaving: $x_{4}$.}\\
...
\text{Entering: $x_{2}$. Leaving: $x_{3}$.}\\
...
\text{The optimal value: $6250$. An optimal solution: $\left(250,\,750\right)$.}\\
\end{array}
```

#### run simplex method()

Apply the simplex method to solve self and show the steps.

# **OUTPUT:**

•a string with LATEX code of intermediate dictionaries

**Note:** You can access the final\_dictionary(), which can be one of the following:

- •an optimal dictionary for the auxiliary\_problem() with a non-zero optimal value indicating that self is infeasible;
- •a non-optimal dictionary for self that has marked entering variable for which there is no choice of the leaving variable, indicating that self is unbounded;
- •an optimal dictionary for self.

```
sage: A = ([1, 1], [3, 1], [-1, -1])
sage: b = (1000, 1500, -400)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: P.run_simplex_method() # not tested
```

You should use the typeset mode as the command above generates long LATEX code:

```
sage: print P.run_simplex_method()
\begin{gather*}
...
\text{The initial dictionary is infeasible, solving auxiliary problem.}\displaybreak[0]\\
...
\text{Entering: $x_{0}$. Leaving: $x_{5}$.}\displaybreak[0]\\
...
\text{Entering: $x_{1}$. Leaving: $x_{0}$.}\displaybreak[0]\\
...
\text{Back to the original problem.}\displaybreak[0]\\
...
\text{Entering: $x_{5}$. Leaving: $x_{4}$.}\displaybreak[0]\\
...
\text{Entering: $x_{2}$. Leaving: $x_{3}$.}\displaybreak[0]\\
...
\text{Entering: $x_{2}$. Leaving: $x_{3}$.}\displaybreak[0]\\
...
\text{The optimal value: $6250$. An optimal solution: $\left(250,\,750\right)$.}
\end{gather*}
```

#### slack variables()

Return slack variables of self.

Slack variables are differences between the constant terms and left hand sides of the constraints.

If you want to give custom names to slack variables, you have to do so during construction of the problem.

## **OUTPUT**:

•a tuple

# **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: P.slack_variables()
(x3, x4)
sage: P = LPProblemStandardForm(A, b, c, ["C", "B"],
....: slack_variables=["L", "F"])
sage: P.slack_variables()
(L, F)
```

class sage.numerical.interactive\_simplex\_method.LPRevisedDictionary (problem,

basic\_variables)

Bases: sage.numerical.interactive simplex method.LPAbstractDictionary

Construct a revised dictionary for an LP problem.

#### INPUT:

```
•problem - an LP problem in standard form
```

•basic\_variables - a list of basic variables or their indices

# **OUTPUT:**

```
ullet a revised dictionary for an LP problem
```

A revised dictionary encodes the same relations as a regular dictionary, but stores only what is "necessary to efficiently compute data for the simplex method".

Let the original problem be

Let  $\bar{x}$  be the vector of decision\_variables() x followed by the slack\_variables(). Let  $\bar{c}$  be the vector of objective\_coefficients() c followed by zeroes for all slack variables. Let  $\bar{A}=(A|I)$  be the matrix of constraint\_coefficients() A augmented by the identity matrix as columns corresponding to the slack variables. Then the problem above can be written as

$$\begin{array}{l} \pm \max \bar{c}\bar{x} \\ \bar{A}\bar{x} = b \\ \bar{x} > 0 \end{array}$$

and any dictionary is a system of equations equivalent to  $\bar{A}\bar{x}=b$ , but resolved for basic\_variables()  $x_B$  in terms of nonbasic\_variables()  $x_N$  together with the expression for the objective in terms of  $x_N$ . Let c\_B() and c\_N() be vectors "splitting  $\bar{c}$  into basic and non-basic parts". Let B() and A\_N() be the splitting of  $\bar{A}$ . Then the corresponding dictionary is

$$x_B = B^{-1}b - B^{-1}A_N x_N z = yb + (c_N - y^T A_N) x_N$$

where  $y=c_B^TB^{-1}$ . To proceed with the simplex method, it is not necessary to compute all entries of this dictionary. On the other hand, any entry is easy to compute, if you know  $B^{-1}$ , so we keep track of it through the update steps.

# **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: from sage.numerical.interactive_simplex_method \
...: import LPRevisedDictionary
sage: D = LPRevisedDictionary(P, [1, 2])
sage: D.basic_variables()
(x1, x2)
sage: D
LP problem dictionary (use typeset mode to see details)
```

The same dictionary can be constructed through the problem:

```
sage: P.revised_dictionary(1, 2) == D
True
```

When this dictionary is typeset, you will see two tables like these ones:

$$\begin{array}{c|cccc} x_N & x_3 & x_4 \\ \hline c_N^T & 0 & 0 \\ y^T A_N & \frac{5}{2} & \frac{5}{2} \\ \hline c_N^T - y^T A_N & -\frac{5}{2} & -\frac{5}{2} \end{array}$$

More details will be shown if entering and leaving variables are set, but in any case the top table shows  $B^{-1}$  and a few extra columns, while the bottom one shows several rows: these are related to columns and rows of dictionary entries.

```
\mathbf{A}(v)
```

Return the column of constraint coefficients corresponding to v.

#### INPUT:

 $\bullet_{V}$  – a variable, its name, or its index

#### **OUTPUT**:

•a vector

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary()
sage: D.A(1)
(1, 3)
sage: D.A(0)
(-1, -1)
sage: D.A("x3")
(1, 0)
```

#### **A\_N**()

Return the  $A_N$  matrix, constraint coefficients of non-basic variables.

# **OUTPUT:**

•a matrix

# **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary()
sage: D.A_N()
[1 1]
[3 1]
```

#### **B**()

Return the B matrix, i.e. constraint coefficients of basic variables.

# **OUTPUT**:

•a matrix

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary(1, 2)
sage: D.B()
[1 1]
[3 1]
```

#### B inverse()

Return the inverse of the B () matrix.

This inverse matrix is stored and computed during dictionary update in a more efficient way than generic inversion.

# **OUTPUT**:

•a matrix

#### **EXAMPLES:**

# **E**()

Return the eta matrix between self and the next dictionary.

#### **OUTPUT:**

•a matrix

If  $B_{\text{old}}$  is the current matrix B and  $B_{\text{new}}$  is the B matrix of the next dictionary (after the update step), then  $B_{\text{new}} = B_{\text{old}} E$ .

# **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary()
sage: D.enter(1)
sage: D.leave(4)
sage: D.E()
[1 1]
[0 3]
```

# E\_inverse()

Return the inverse of the matrix  $\mathbb{E}$  ().

This inverse matrix is computed in a more efficient way than generic inversion.

# **OUTPUT**:

•a matrix

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary()
sage: D.enter(1)
sage: D.leave(4)
sage: D.E_inverse()
```

```
[ 1 -1/3]
[ 0 1/3]
```

## basic\_indices()

Return the basic indices of self.

**Note:** Basic indices are indices of basic\_variables() in the list of generators of the coordinate\_ring() of the problem() of self, they may not coincide with the indices of variables which are parts of their names. (They will for the default indexed names.)

```
OUTPUT:
       •a list.
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary()
    sage: D.basic_indices()
    [3, 4]
basic_variables()
    Return the basic variables of self.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary()
    sage: D.basic_variables()
    (x3, x4)
c_B()
    Return the c_B vector, objective coefficients of basic variables.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary(1, 2)
    sage: D.c_B()
    (10, 5)
```

 $\mathbf{c}_{\mathbf{N}}()$ 

Return the  $c_N$  vector, objective coefficients of non-basic variables.

```
OUTPUT:
       ·a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary()
    sage: D.c_N()
    (10, 5)
constant_terms()
    Return constant terms in the relations of self.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary()
    sage: D.constant_terms()
    (1000, 1500)
dictionary()
    Return a regular LP dictionary matching self.
    OUTPUT:
       •an LP dictionary
    EXAMPLES:
    sage: A = ([1, 1], [3, 1], [-1, -1])
    sage: b = (1000, 1500, -400)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary()
    sage: D.dictionary()
    LP problem dictionary (use typeset mode to see details)
entering_coefficients()
    Return coefficients of the entering variable.
    OUTPUT:
       ·a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary()
    sage: D.enter(1)
```

```
sage: D.entering_coefficients()
    (1, 3)
leaving_coefficients()
    Return coefficients of the leaving variable.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary(2, 3)
    sage: D.leave(3)
    sage: D.leaving_coefficients()
    (-2, -1)
nonbasic indices()
```

Return the non-basic indices of self.

**Note:** Non-basic indices are indices of nonbasic\_variables() in the list of generators of the coordinate\_ring() of the problem() of self, they may not coincide with the indices of variables which are parts of their names. (They will for the default indexed names.)

```
OUTPUT:
       •a list
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary()
    sage: D.nonbasic_indices()
    [1, 2]
nonbasic_variables()
    Return non-basic variables of self.
    OUTPUT:
       •a vector
    EXAMPLES:
    sage: A = ([1, 1], [3, 1])
    sage: b = (1000, 1500)
    sage: c = (10, 5)
    sage: P = LPProblemStandardForm(A, b, c)
    sage: D = P.revised_dictionary()
    sage: D.nonbasic_variables()
    (x1, x2)
```

```
objective_coefficients()
```

Return coefficients of the objective of self.

#### **OUTPUT**:

•a vector

These are coefficients of non-basic variables when basic variables are eliminated.

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary()
sage: D.objective_coefficients()
(10, 5)
```

## objective\_value()

Return the value of the objective at the basic solution of self.

# **OUTPUT:**

a number

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary()
sage: D.objective_value()
0
```

## problem()

Return the original problem.

# **OUTPUT**:

```
•an LP problem in standard form
```

#### **EXAMPLES:**

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary()
sage: D.problem() is P
True
```

# update()

Update self using previously set entering and leaving variables.

```
sage: A = ([1, 1], [3, 1])
sage: b = (1000, 1500)
sage: c = (10, 5)
sage: P = LPProblemStandardForm(A, b, c)
sage: D = P.revised_dictionary()
sage: D.objective_value()
```

```
sage: D.enter("x1")
         sage: D.leave("x4")
         sage: D.update()
         sage: D.objective_value()
         5000
    x B()
         Return the basic variables of self.
         OUTPUT:
            •a vector
         EXAMPLES:
         sage: A = ([1, 1], [3, 1])
         sage: b = (1000, 1500)
         sage: c = (10, 5)
         sage: P = LPProblemStandardForm(A, b, c)
         sage: D = P.revised_dictionary()
         sage: D.basic_variables()
         (x3, x4)
    x N()
         Return non-basic variables of self.
         OUTPUT:
            •a vector
         EXAMPLES:
         sage: A = ([1, 1], [3, 1])
         sage: b = (1000, 1500)
         sage: c = (10, 5)
         sage: P = LPProblemStandardForm(A, b, c)
         sage: D = P.revised_dictionary()
         sage: D.nonbasic_variables()
         (x1, x2)
    y()
         Return the y vector, the product of c_B() and B_inverse().
         OUTPUT:
            •a vector
         EXAMPLES:
         sage: A = ([1, 1], [3, 1])
         sage: b = (1000, 1500)
         sage: c = (10, 5)
         sage: P = LPProblemStandardForm(A, b, c)
         sage: D = P.revised_dictionary()
         sage: D.y()
         (0, 0)
sage.numerical.interactive_simplex_method.random_dictionary (m, n, bound=5, spe-
                                                                       cial probability=0.2)
    Construct a random dictionary.
    INPUT:
```

- •m the number of constraints/basic variables
- •n the number of decision/non-basic variables
- •bound (default: 5) a bound on dictionary entries
- •special\_probability (default: 0.2) probability of constructing a potentially infeasible or potentially optimal dictionary

#### **OUTPUT:**

```
•an LP problem dictionary
```

#### **EXAMPLES:**

```
sage: from sage.numerical.interactive_simplex_method \
....: import random_dictionary
sage: random_dictionary(3, 4)
LP problem dictionary (use typeset mode to see details)
```

 $\verb|sage.numerical.interactive\_simplex\_method. \textbf{variable} (R, v)|\\$ 

Interpret v as a variable of R.

#### **INPUT:**

- •R a polynomial ring
- $\bullet_{V}$  a variable of R or convertible into R, a string with the name of a variable of R or an index of a variable in R

#### **OUTPUT:**

•a variable of R

```
sage: from sage.numerical.interactive_simplex_method \
         import variable
sage: R = PolynomialRing(QQ, "x3, y5, x5, y")
sage: R.inject_variables()
Defining x3, y5, x5, y
sage: variable(R, "x3")
хЗ
sage: variable(R, x3)
xЗ
sage: variable(R, 3)
sage: variable(R, 0)
Traceback (most recent call last):
ValueError: there is no variable with the given index
sage: variable(R, 5)
Traceback (most recent call last):
ValueError: the given index is ambiguous
sage: variable(R, 2 * x3)
Traceback (most recent call last):
ValueError: cannot interpret given data as a variable
sage: variable(R, "z")
Traceback (most recent call last):
ValueError: cannot interpret given data as a variable
```

Sage Reference Manual: Numerical Optimization, Release 6.3	

# LP SOLVER BACKENDS

# 6.1 Generic Backend for LP solvers

Generic Backend for LP solvers

This class only lists the methods that should be defined by any interface with a LP Solver. All these methods immediately raise NotImplementedError exceptions when called, and are obviously meant to be replaced by the solver-specific method. This file can also be used as a template to create a new interface: one would only need to replace the occurrences of "Nonexistent\_LP\_solver" by the solver's name, and replace GenericBackend by SolverName (GenericBackend) so that the new solver extends this class.

# **AUTHORS:**

- Nathann Cohen (2010-10): initial implementation
- Risan (2012-02): extension for PPL backend
- Ingolfur Edvardsson (2014-06): extension for CVXOPT backend

class sage.numerical.backends.generic\_backend.GenericBackend
 Bases: object
 x.\_\_init\_\_(...) initializes x; see help(type(x)) for signature
 add\_col (indices, coeffs)
 Add a column.

# INPUT:

- •indices (list of integers) this list constains the indices of the constraints in which the variable's coefficient is nonzero
- •coeffs (list of real values) associates a coefficient to the variable in each of the constraints in which it appears. Namely, the ith entry of coeffs corresponds to the coefficient of the variable in the constraint represented by the ith entry in indices.

**Note:** indices and coeffs are expected to be of the same length.

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.ncols() # optional - Nonexistent_LP_solver
0
sage: p.nrows() # optional - Nonexistent_LP_solver
```

```
sage: p.add_linear_constraints(5, 0, None) # optional - Nonexistent_LP_solver
sage: p.add_col(range(5), range(5)) # optional - Nonexistent_LP_solver
sage: p.nrows() # optional - Nonexistent_LP_solver
```

add\_linear\_constraint (coefficients, lower\_bound, upper\_bound, name=None)

Add a linear constraint.

#### INPUT:

- •coefficients an iterable with (c, v) pairs where c is a variable index (integer) and v is a value (real value).
- •lower\_bound a lower bound, either a real value or None
- •upper\_bound an upper bound, either a real value or None
- •name an optional name for this row (default: None)

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_variables(5)
                                                        # optional - Nonexistent_LP_solver
sage: p.add_linear_constraint(zip(range(5), range(5)), 2.0, 2.0) # optional - Nonexistent_LB
                                                        # optional - Nonexistent_LP_solver
sage: p.row(0)
([4, 3, 2, 1], [4.0, 3.0, 2.0, 1.0])
                                                        # optional - Nonexistent_LP_solver
                                                        # optional - Nonexistent_LP_solver
sage: p.row_bounds(0)
(2.0, 2.0)
sage: p.add_linear_constraint( zip(range(5), range(5)), 1.0, 1.0, name='foo') # optional - N
sage: p.row_name(-1)
                                                                               # optional - 1
"foo"
```

add\_linear\_constraints (number, lower\_bound, upper\_bound, names=None)

Add constraints.

# INPUT:

- •number (integer) the number of constraints to add.
- •lower\_bound a lower bound, either a real value or None
- •upper\_bound an upper bound, either a real value or None
- •names an optional list of names (default: None)

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver")  # optional - Nonexistent_LP_solver
sage: p.add_variables(5)  # optional - Nonexistent_LP_solver

sage: p.add_linear_constraints(5, None, 2)  # optional - Nonexistent_LP_solver
sage: p.row(4)  # optional - Nonexistent_LP_solver
([], [])
sage: p.row_bounds(4)  # optional - Nonexistent_LP_solver
(None, 2.0)
```

 $\begin{tabular}{ll} \textbf{add\_variable} (lower\_bound=None, & upper\_bound=None, & binary=False, & continuous=True, & integer=False, & obj=None, & name=None) \\ \end{tabular}$ 

Add a variable.

This amounts to adding a new column to the matrix. By default, the variable is both positive and real.

#### INPUT:

- •lower\_bound the lower bound of the variable (default: 0)
- •upper\_bound the upper bound of the variable (default: None)
- •binary True if the variable is binary (default: False).
- •continuous True if the variable is binary (default: True).
- •integer True if the variable is binary (default: False).
- •ob j (optional) coefficient of this variable in the objective function (default: 0.0)
- •name an optional name for the newly added variable (default: None).

OUTPUT: The index of the newly created variable

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver")
                                                            # optional - Nonexistent_LP_solver
                                                            # optional - Nonexistent_LP_solver
sage: p.ncols()
                                                            # optional - Nonexistent_LP_solver
sage: p.add_variable()
                                                            # optional - Nonexistent_LP_solver
sage: p.ncols()
sage: p.add_variable(binary=True)
                                                            # optional - Nonexistent_LP_solver
sage: p.add_variable(lower_bound=-2.0, integer=True)
                                                            # optional - Nonexistent_LP_solver
sage: p.add_variable(continuous=True, integer=True)
                                                            # optional - Nonexistent_LP_solver
Traceback (most recent call last):
ValueError: ...
sage: p.add_variable(name='x',obj=1.0)
                                                            # optional - Nonexistent_LP_solver
                                                            # optional - Nonexistent_LP_solver
sage: p.col_name(3)
' x'
sage: p.objective_coefficient(3)
                                                            # optional - Nonexistent_LP_solver
1.0
```

 $add\_variables$  (n, lower\_bound=None, upper\_bound=None, binary=False, continuous=True, integer=False, obj=None, names=None)

Add n variables.

This amounts to adding new columns to the matrix. By default, the variables are both positive and real.

#### INPUT:

- •n the number of new variables (must be > 0)
- •lower\_bound the lower bound of the variable (default: 0)
- •upper\_bound the upper bound of the variable (default: None)
- •binary True if the variable is binary (default: False).
- •continuous True if the variable is binary (default: True).
- •integer True if the variable is binary (default: False).
- •ob j (optional) coefficient of all variables in the objective function (default: 0.0)

•names - optional list of names (default: None)

OUTPUT: The index of the variable created last.

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import
sage: p = get_solver(solver = "Nonexistent_LP_solver")  # optional - Nonexistent_LP_solver
sage: p.ncols()  # optional - Nonexistent_LP_solver
sage: p.add_variables(5)  # optional - Nonexistent_LP_solver
sage: p.ncols()  # optional - Nonexistent_LP_solver
sage: p.ncols()  # optional - Nonexistent_LP_solver
sage: p.add_variables(2, lower_bound=-2.0, integer=True, names=['a','b']) # optional - Nonexistent_Solver
sage: p.add_variables(2, lower_bound=-2.0, integer=True, names=['a','b']) # optional - Nonexistent_Solver
```

#### base\_ring()

#### col bounds (index)

Return the bounds of a specific variable.

#### **INPUT:**

•index (integer) – the variable's id.

#### **OUTPUT**:

A pair (lower\_bound, upper\_bound). Each of them can be set to None if the variable is not bounded in the corresponding direction, and is a real value otherwise.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_variable() # optional - Nonexistent_LP_solver

sage: p.col_bounds(0) # optional - Nonexistent_LP_solver
(0.0, None)
sage: p.variable_upper_bound(0, 5) # optional - Nonexistent_LP_solver
sage: p.col_bounds(0) # optional - Nonexistent_LP_solver
(0.0, 5.0)
```

# col\_name (index)

Return the index th col name

#### INPUT:

- •index (integer) the col's id
- •name (char \*) its name. When set to NULL (default), the method returns the current name.

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import
sage: p = get_solver(solver = "Nonexistent_LP_solver")  # optional - Nonexistent_LP_solver
sage: p.add_variable(name="I am a variable")  # optional - Nonexistent_LP_solver
1
sage: p.col_name(0)  # optional - Nonexistent_LP_solver
'I am a variable'
```

# get\_objective\_value()

Return the value of the objective function.

**Note:** Behaviour is undefined unless solve has been called before.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
                                                        # optional - Nonexistent_LP_solver
sage: p.add_variables(2)
sage: p.add_linear_constraint([(0,1), (1,2)], None, 3) # optional - Nonexistent_LP_solver
sage: p.set_objective([2, 5])
                                                        # optional - Nonexistent_LP_solver
sage: p.solve()
                                                        # optional - Nonexistent_LP_solver
0
sage: p.get_objective_value()
                                                        # optional - Nonexistent_LP_solver
7.5
sage: p.get_variable_value(0)
                                                        # optional - Nonexistent_LP_solver
                                                        # optional - Nonexistent_LP_solver
sage: p.get_variable_value(1)
1.5
```

#### get\_variable\_value(variable)

Return the value of a variable given by the solver.

**Note:** Behaviour is undefined unless solve has been called before.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_variables(2)
                                                       # optional - Nonexistent_LP_solver
sage: p.add_linear_constraint([(0,1), (1, 2)], None, 3) # optional - Nonexistent_LP_solver
                                                       # optional - Nonexistent_LP_solver
sage: p.set_objective([2, 5])
                                                       # optional - Nonexistent_LP_solver
sage: p.solve()
sage: p.get_objective_value()
                                                       # optional - Nonexistent_LP_solver
                                                       # optional - Nonexistent_LP_solver
sage: p.get_variable_value(0)
0.0
sage: p.get_variable_value(1)
                                                       # optional - Nonexistent_LP_solver
1.5
```

## is maximization()

Test whether the problem is a maximization

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.is_maximization() # optional - Nonexistent_LP_solver
True
sage: p.set_sense(-1) # optional - Nonexistent_LP_solver
sage: p.is_maximization() # optional - Nonexistent_LP_solver
False
```

# is\_variable\_binary(index)

Test whether the given variable is of binary type.

INPUT:

•index (integer) - the variable's id

```
EXAMPLE:
```

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver")  # optional - Nonexistent_LP_solver
sage: p.ncols()  # optional - Nonexistent_LP_solver
0
sage: p.add_variable()  # optional - Nonexistent_LP_solver
1
sage: p.set_variable_type(0,0)  # optional - Nonexistent_LP_solver
sage: p.is_variable_binary(0)  # optional - Nonexistent_LP_solver
True
```

## is\_variable\_continuous (index)

Test whether the given variable is of continuous/real type.

#### INPUT:

•index (integer) - the variable's id

#### EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.ncols() # optional - Nonexistent_LP_solver
0
sage: p.add_variable() # optional - Nonexistent_LP_solver
1
sage: p.is_variable_continuous(0) # optional - Nonexistent_LP_solver
True
sage: p.set_variable_type(0,1) # optional - Nonexistent_LP_solver
sage: p.is_variable_continuous(0) # optional - Nonexistent_LP_solver
False
```

# is\_variable\_integer(index)

Test whether the given variable is of integer type.

## INPUT:

•index (integer) - the variable's id

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver")  # optional - Nonexistent_LP_solver
sage: p.ncols()  # optional - Nonexistent_LP_solver
0
sage: p.add_variable()  # optional - Nonexistent_LP_solver
1
sage: p.set_variable_type(0,1)  # optional - Nonexistent_LP_solver
sage: p.is_variable_integer(0)  # optional - Nonexistent_LP_solver
True
```

# ncols()

Return the number of columns/variables.

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.ncols() # optional - Nonexistent_LP_solver
0
```

# optional - Nonexistent\_LP\_solver

```
sage: p.ncols()
                                                              # optional - Nonexistent_LP_solver
nrows()
    Return the number of rows/constraints.
    EXAMPLE:
    sage: from sage.numerical.backends.generic backend import get_solver
    sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
    sage: p.nrows()
                                                               # optional - Nonexistent_LP_solver
    0
    sage: p.add_linear_constraints(2, 2.0, None)
                                                            # optional - Nonexistent_LP_solver
                                                            # optional - Nonexistent_LP_solver
    sage: p.nrows()
objective_coefficient (variable, coeff=None)
    Set or get the coefficient of a variable in the objective function
    INPUT:
       •variable (integer) - the variable's id
       •coeff (double) - its coefficient
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
                                                               # optional - Nonexistent_LP_solver
    sage: p.add_variable()
    sage: p.objective_coefficient(0)
                                                                 # optional - Nonexistent_LP_solver
    0.0
    sage: p.objective_coefficient(0,2)
                                                                 # optional - Nonexistent_LP_solver
    sage: p.objective_coefficient(0)
                                                                 # optional - Nonexistent_LP_solver
    2.0
problem_name (name='NULL')
    Return or define the problem's name
    INPUT:
       •name (char *) - the problem's name. When set to NULL (default), the method returns the problem's
        name.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
    sage: p.problem_name("There once was a french fry") # optional - Nonexistent_LP_solver
    sage: print p.get_problem_name()
                                                                # optional - Nonexistent_LP_solver
    There once was a french fry
remove_constraint(i)
    Remove a constraint.
    INPUT:
    - ''i'' -- index of the constraint to remove.
```

sage: p.add\_variables(2)

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_constraint(p[0] + p[1], max = 10) # optional - Nonexistent_LP_solver
sage: p.remove_constraint(0) # optional - Nonexistent_LP_solver
```

#### remove constraints (constraints)

Remove several constraints.

#### INPUT:

•constraints – an iterable containing the indices of the rows to remove.

### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_constraint(p[0] + p[1], max = 10) # optional - Nonexistent_LP_solver
sage: p.remove_constraints([0]) # optional - Nonexistent_LP_solver
```

#### row(i)

Return a row

#### INPUT:

•index (integer) - the constraint's id.

# **OUTPUT**:

A pair (indices, coeffs) where indices lists the entries whose coefficient is nonzero, and to which coeffs associates their coefficient on the model of the add\_linear\_constraint method.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_variables(5) # optional - Nonexistent_LP_solver

sage: p.add_linear_constraint(zip(range(5), range(5)), 2, 2) # optional - Nonexistent_LP_solver

sage: p.row(0) # optional - Nonexistent_LP_solver

([4, 3, 2, 1], [4.0, 3.0, 2.0, 1.0])
sage: p.row_bounds(0) # optional - Nonexistent_LP_solver

(2.0, 2.0)
```

# row\_bounds (index)

Return the bounds of a specific constraint.

#### INPUT:

•index (integer) – the constraint's id.

# **OUTPUT:**

A pair (lower\_bound, upper\_bound). Each of them can be set to None if the constraint is not bounded in the corresponding direction, and is a real value otherwise.

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_variables(5) # optional - Nonexistent_LP_solver
5
sage: p.add_linear_constraint(range(5), range(5), 2, 2) # optional - Nonexistent_LP_solver
```

# optional - Nonexistent\_LP\_solver

```
([4, 3, 2, 1], [4.0, 3.0, 2.0, 1.0])
    sage: p.row_bounds(0)
                                                           # optional - Nonexistent_LP_solver
    (2.0, 2.0)
row name (index)
    Return the index th row name
    INPUT:
       •index (integer) - the row's id
    EXAMPLE:
    sage: from sage.numerical.backends.generic backend import get_solver
    sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
    sage: p.add_linear_constraints(1, 2, None, name="Empty constraint 1") # optional - Nonexist
                                                                # optional - Nonexistent_LP_solver
    sage: p.row_name(0)
    'Empty constraint 1'
set\_objective(coeff, d=0.0)
    Set the objective function.
    INPUT:
       •coeff – a list of real values, whose ith element is the coefficient of the ith variable in the objective
       •d (double) – the constant term in the linear function (set to 0 by default)
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "Nonexistent_LP_solver")
                                                                 # optional - Nonexistent_LP_solver
                                                                  # optional - Nonexistent_LP_solver
    sage: p.add_variables(5)
    sage: p.set_objective([1, 1, 2, 1, 3])
                                                                 # optional - Nonexistent_LP_solver
    sage: map(lambda x :p.objective_coefficient(x), range(5)) # optional - Nonexistent_LP_solve
    [1.0, 1.0, 2.0, 1.0, 3.0]
    Constants in the objective function are respected:
    sage: p = MixedIntegerLinearProgram(solver='Nonexistent_LP_solver') # optional - Nonexistent
    sage: x, y = p[0], p[1]
                                                           # optional - Nonexistent_LP_solver
    sage: p.add_constraint(2*x + 3*y, max = 6)
                                                            # optional - Nonexistent_LP_solver
    sage: p.add_constraint(3*x + 2*y, max = 6)
                                                           # optional - Nonexistent_LP_solver
    sage: p.set_objective(x + y + 7)
                                                            # optional - Nonexistent_LP_solver
                                                            # optional - Nonexistent LP solver
    sage: p.set_integer(x); p.set_integer(y)
                                                            # optional - Nonexistent_LP_solver
    sage: p.solve()
    9.0
set sense (sense)
    Set the direction (maximization/minimization).
    INPUT:
       •sense (integer):
          -+1 => Maximization
          -1 \Rightarrow Minimization
    EXAMPLE:
```

sage: p.row(0)

```
sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
                                                               # optional - Nonexistent_LP_solver
    sage: p.is_maximization()
    True
    sage: p.set_sense(-1)
                                                          # optional - Nonexistent_LP_solver
                                                               # optional - Nonexistent_LP_solver
    sage: p.is_maximization()
    False
set_variable_type (variable, vtype)
    Set the type of a variable
    INPUT:
       •variable (integer) – the variable's id
       •vtype (integer):
          -1 Integer
          -0 Binary
                -1
                                 Continuous
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "Nonexistent_LP_solver")
                                                               # optional - Nonexistent_LP_solver
    sage: p.ncols()
                                                               # optional - Nonexistent_LP_solver
    sage: p.add_variable()
                                                                # optional - Nonexistent_LP_solver
                                                               # optional - Nonexistent_LP_solver
    sage: p.set_variable_type(0,1)
                                                               # optional - Nonexistent_LP_solver
    sage: p.is_variable_integer(0)
    True
set_verbosity(level)
    Set the log (verbosity) level
    INPUT:
       •level (integer) – From 0 (no verbosity) to 3.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
    sage: p.set_verbosity(2)
                                                                # optional - Nonexistent_LP_solver
solve()
    Solve the problem.
```

**Note:** This method raises MIPSolverException exceptions when the solution can not be computed for any reason (none exists, or the LP solver was not able to find it, etc...)

```
EXAMPLE:
```

```
sage: from sage.numerical.backends.generic_backend import
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_linear_constraints(5, 0, None) # optional - Nonexistent_LP_solver
sage: p.add_col(range(5), range(5)) # optional - Nonexistent_LP_solver
sage: p.solve() # optional - Nonexistent_LP_solver
```

```
sage: p.objective_coefficient(0,1) # optional - Nonexistent_LP_solver
sage: p.solve() # optional - Nonexistent_LP_solver
Traceback (most recent call last):
...
MIPSolverException: ...
```

# solver\_parameter (name, value=None)

Return or define a solver parameter

#### INPUT:

- •name (string) the parameter
- •value the parameter's value if it is to be defined, or None (default) to obtain its current value.

**Note:** The list of available parameters is available at solver\_parameter().

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.solver_parameter("timelimit") # optional - Nonexistent_LP_solver
sage: p.solver_parameter("timelimit", 60) # optional - Nonexistent_LP_solver
sage: p.solver_parameter("timelimit") # optional - Nonexistent_LP_solver
```

#### variable\_lower\_bound (index, value=None)

Return or define the lower bound on a variable

## INPUT:

- •index (integer) the variable's id
- •value real value, or None to mean that the variable has not lower bound. When set to None (default), the method returns the current value.

## EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
sage: p.add_variable() # optional - Nonexistent_LP_solver

sage: p.col_bounds(0) # optional - Nonexistent_LP_solver
(0.0, None)
sage: p.variable_lower_bound(0, 5) # optional - Nonexistent_LP_solver
sage: p.col_bounds(0) # optional - Nonexistent_LP_solver
(5.0, None)
```

# variable\_upper\_bound(index, value=None)

Return or define the upper bound on a variable

# INPUT:

- •index (integer) the variable's id
- •value real value, or None to mean that the variable has not upper bound. When set to None (default), the method returns the current value.

```
sage: from sage.numerical.backends.generic_backend import get_solver
         sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
                                                                  # optional - Nonexistent_LP_solver
         sage: p.add_variable()
         sage: p.col_bounds(0)
                                                              # optional - Nonexistent_LP_solver
         (0.0, None)
         sage: p.variable_upper_bound(0, 5)
                                                              # optional - Nonexistent_LP_solver
         sage: p.col_bounds(0)
                                                              # optional - Nonexistent_LP_solver
         (0.0, 5.0)
    write_lp(name)
         Write the problem to a .lp file
         INPUT:
           •filename (string)
         EXAMPLE:
         sage: from sage.numerical.backends.generic_backend import get_solver
         sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
                                                                  # optional - Nonexistent_LP_solver
         sage: p.add_variables(2)
         sage: p.add_linear_constraint([(0, 1], (1, 2)], None, 3) # optional - Nonexistent_LP_solver
         sage: p.set_objective([2, 5])
                                                                  # optional - Nonexistent_LP_solver
         sage: p.write_lp(os.path.join(SAGE_TMP, "lp_problem.lp"))
                                                                                 # optional - Nonexister
    write_mps (name, modern)
         Write the problem to a .mps file
         INPUT:
           •filename (string)
        EXAMPLE:
         sage: from sage.numerical.backends.generic_backend import get_solver
         sage: p = get_solver(solver = "Nonexistent_LP_solver") # optional - Nonexistent_LP_solver
         sage: p.add_variables(2)
                                                                  # optional - Nonexistent_LP_solver
         sage: p.add_linear_constraint([(0, 1), (1, 2)], None, 3) # optional - Nonexistent_LP_solver
         sage: p.set_objective([2, 5])
                                                                  # optional - Nonexistent_LP_solver
         sage: p.write_lp(os.path.join(SAGE_TMP, "lp_problem.lp"))
                                                                                 # optional - Nonexister
    zero()
sage.numerical.backends.generic_backend.default_mip_solver(solver=None)
    Returns/Sets the default MILP Solver used by Sage
    INPUT:
        •solver – defines the solver to use:
              -GLPK (solver="GLPK"). See the GLPK web site.
              -COIN Branch and Cut (solver="Coin"). See the COIN-OR web site.
              -CPLEX (solver="CPLEX"). See the CPLEX web site.
              -CVXOPT (solver="CVXOPT"). See the CVXOPT web site.
              -PPL (solver="PPL"). See the PPL web site.
```

solver=None)

```
-Gurobi (solver="Gurobi"). See the Gurobi web site.

solver should then be equal to one of "GLPK", "Coin", "CPLEX", "CVXOPT", "Gurobi" or "PPL".

-If solver=None (default), the current default solver's name is returned.
```

# OUTPUT:

This function returns the current default solver's name if solver = None (default). Otherwise, it sets the default solver to the one given. If this solver does not exist, or is not available, a ValueError exception is raised.

#### **EXAMPLE:**

```
sage: former_solver = default_mip_solver()
sage: default_mip_solver("GLPK")
sage: default_mip_solver()
'Glpk'
sage: default_mip_solver("PPL")
sage: default_mip_solver()
'Ppl'
sage: default_mip_solver()
'Ppl'
sage: default_mip_solver("GUROBI")
Traceback (most recent call last):
...
ValueError: Gurobi is not available. Please refer to the documentation to install it.
sage: default_mip_solver("Yeahhhhhhhhhh")
Traceback (most recent call last):
...
ValueError: 'solver' should be set to 'GLPK', 'Coin', 'CPLEX', 'Gurobi', 'CVXOPT', 'PPL' or None sage: default_mip_solver(former_solver)
```

Return a solver according to the given preferences

# INPUT:

- •solver 6 solvers should be available through this class:
  - -GLPK (solver="GLPK"). See the GLPK web site.
  - -COIN Branch and Cut (solver="Coin"). See the COIN-OR web site.
  - -CPLEX (solver="CPLEX"). See the CPLEX web site.
  - -CVXOPT (solver="CVXOPT"). See the CVXOPT web site.
  - -Gurobi (solver="Gurobi"). See the Gurobi web site.
  - -PPL (solver="PPL"). See the PPL web site.

solver should then be equal to one of "GLPK", "COin", "CPLEX", "CVXOPT", "Gurobi", ""PPL", or None. If solver=None (default), the default solver is used (see default\_mip\_solver method.

- •constraint\_generation Only used when solver=None.
  - -When set to True, after solving the MixedIntegerLinearProgram, it is possible to add a constraint, and then solve it again. The effect is that solvers that do not support this feature will not be used.
  - -Defaults to False.

# See Also:

•default mip solver() - Returns/Sets the default MIP solver.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver()
```

# 6.2 GLPK Backend

**GLPK Backend** 

#### **AUTHORS:**

- Nathann Cohen (2010-10): initial implementation
- John Perry (2012-01): glp\_simplex preprocessing
- John Perry and Raniere Gaia Silva (2012-03): solver parameters
- Christian Kuper (2012-10): Additions for sensitivity analysis

```
class sage.numerical.backends.glpk_backend.GLPKBackend
```

Bases: sage.numerical.backends.generic\_backend.GenericBackend

x.\_\_init\_\_(...) initializes x; see help(type(x)) for signature

```
add_col (indices, coeffs)
```

Add a column.

#### INPUT:

- •indices (list of integers) this list constains the indices of the constraints in which the variable's coefficient is nonzero
- •coeffs (list of real values) associates a coefficient to the variable in each of the constraints in which it appears. Namely, the ith entry of coeffs corresponds to the coefficient of the variable in the constraint represented by the ith entry in indices.

Note: indices and coeffs are expected to be of the same length.

# EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.ncols()
0
sage: p.nrows()
0
sage: p.add_linear_constraints(5, 0, None)
sage: p.add_col(range(5), range(5))
sage: p.nrows()
5
```

add\_linear\_constraint (coefficients, lower\_bound, upper\_bound, name=None)

Add a linear constraint.

#### INPUT:

•coefficients an iterable with (c, v) pairs where c is a variable index (integer) and v is a value (real value).

- •lower\_bound a lower bound, either a real value or None
- •upper\_bound an upper bound, either a real value or None
- •name an optional name for this row (default: None)

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variables(5)
4
sage: p.add_linear_constraint( zip(range(5), range(5)), 2.0, 2.0)
sage: p.row(0)
([4, 3, 2, 1], [4.0, 3.0, 2.0, 1.0])
sage: p.row_bounds(0)
(2.0, 2.0)
sage: p.add_linear_constraint( zip(range(5), range(5)), 1.0, 1.0, name='foo')
sage: p.row_name(1)
'foo'
```

add\_linear\_constraints (number, lower\_bound, upper\_bound, names=None)

Add 'number linear constraints.

#### INPUT:

- •number (integer) the number of constraints to add.
- •lower\_bound a lower bound, either a real value or None
- •upper\_bound an upper bound, either a real value or None
- •names an optional list of names (default: None)

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variables(5)
4
sage: p.add_linear_constraints(5, None, 2)
sage: p.row(4)
([], [])
sage: p.row_bounds(4)
(None, 2.0)
sage: p.add_linear_constraints(2, None, 2, names=['foo','bar'])
```

 $\begin{tabular}{ll} {\tt add\_variable} (lower\_bound=0.0, & upper\_bound=None, & binary=False, & continuous=False, & integer=False, & obj=0.0, & name=None) \end{tabular}$ 

Add a variable.

This amounts to adding a new column to the matrix. By default, the variable is both positive, real and the coefficient in the objective function is 0.0.

# INPUT:

- •lower\_bound the lower bound of the variable (default: 0)
- •upper bound the upper bound of the variable (default: None)
- •binary True if the variable is binary (default: False).
- •continuous True if the variable is binary (default: True).
- •integer True if the variable is binary (default: False).

6.2. GLPK Backend 103

- •ob j (optional) coefficient of this variable in the objective function (default: 0.0)
- •name an optional name for the newly added variable (default: None).

OUTPUT: The index of the newly created variable

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.ncols()
1
sage: p.add_variable(binary=True)
1
sage: p.add_variable(lower_bound=-2.0, integer=True)
2
sage: p.add_variable(continuous=True, integer=True)
Traceback (most recent call last):
...
ValueError: ...
sage: p.add_variable(name='x', obj=1.0)
3
sage: p.col_name(3)
'x'
sage: p.objective_coefficient(3)
1.0
```

Add number new variables.

This amounts to adding new columns to the matrix. By default, the variables are both positive, real and theor coefficient in the objective function is 0.0.

## INPUT:

- •n the number of new variables (must be > 0)
- •lower\_bound the lower bound of the variable (default: 0)
- •upper\_bound the upper bound of the variable (default: None)
- •binary True if the variable is binary (default: False).
- •continuous True if the variable is binary (default: True).
- •integer True if the variable is binary (default: False).
- •obj (optional) coefficient of all variables in the objective function (default: 0.0)
- •names optional list of names (default: None)

OUTPUT: The index of the variable created last.

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.ncols()
0
sage: p.add_variables(5)
```

```
4
    sage: p.ncols()
    sage: p.add_variables(2, lower_bound=-2.0, integer=True, names=['a','b'])
col bounds (index)
    Return the bounds of a specific variable.
    INPUT:
       •index (integer) – the variable's id.
    OUTPUT:
    A pair (lower_bound, upper_bound). Each of them can be set to None if the variable is not
    bounded in the corresponding direction, and is a real value otherwise.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "GLPK")
    sage: p.add_variable()
    sage: p.col_bounds(0)
    (0.0, None)
    sage: p.variable_upper_bound(0, 5)
    sage: p.col_bounds(0)
    (0.0, 5.0)
col name (index)
    Return the index th col name
    INPUT:
       •index (integer) – the col's id
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "GLPK")
    sage: p.add_variable(name='I am a variable')
    sage: p.col_name(0)
    'I am a variable'
copy()
    Returns a copy of self.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = MixedIntegerLinearProgram(solver = "GLPK")
    sage: b = p.new_variable()
    sage: p.add_constraint(b[1] + b[2] <= 6)</pre>
    sage: p.set_objective(b[1] + b[2])
    sage: copy(p).solve()
    6.0
```

105

Returns the dual value (reduced cost) of a variable

get\_col\_dual (variable)

The dual value is the reduced cost of a variable. The reduced cost is the amount by which the objective coefficient of a non basic variable has to change to become a basic variable.

#### INPUT:

•variable - The number of the variable

**Note:** Behaviour is undefined unless solve has been called before. If the simplex algorithm has not been used for solving just a 0.0 will be returned.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variables(3)
2
sage: p.add_linear_constraint(zip([0, 1, 2], [8, 6, 1]), None, 48)
sage: p.add_linear_constraint(zip([0, 1, 2], [4, 2, 1.5]), None, 20)
sage: p.add_linear_constraint(zip([0, 1, 2], [2, 1.5, 0.5]), None, 8)
sage: p.set_objective([60, 30, 20])
sage: import sage.numerical.backends.glpk_backend as backend
sage: p.solver_parameter(backend.glp_simplex_or_intopt, backend.glp_simplex_only)
sage: p.solve()
0
sage: p.get_col_dual(1)
-5.0
```

#### get\_objective\_value()

Returns the value of the objective function.

**Note:** Behaviour is undefined unless solve has been called before.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variables(2)
1
sage: p.add_linear_constraint([[0, 1], [1, 2]], None, 3)
sage: p.set_objective([2, 5])
sage: p.solve()
0
sage: p.get_objective_value()
7.5
sage: p.get_variable_value(0)
0.0
sage: p.get_variable_value(1)
1.5
```

#### get\_row\_dual (variable)

Returns the dual value of a constraint.

The dual value of the ith row is also the value of the ith variable of the dual problem.

The dual value of a constraint is the shadow price of the constraint. The shadow price is the amount by which the objective value will change if the constraints bounds change by one unit under the precondition that the basis remains the same.

INPUT:

•variable - The number of the constraint

**Note:** Behaviour is undefined unless solve has been called before. If the simplex algorithm has not been used for solving 0.0 will be returned.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic backend import get_solver
sage: lp = get_solver(solver = "GLPK")
sage: lp.add_variables(3)
sage: lp.add_linear_constraint(zip([0, 1, 2], [8, 6, 1]), None, 48)
sage: lp.add_linear_constraint(zip([0, 1, 2], [4, 2, 1.5]), None, 20)
sage: lp.add_linear_constraint(zip([0, 1, 2], [2, 1.5, 0.5]), None, 8)
sage: lp.set_objective([60, 30, 20])
sage: import sage.numerical.backends.glpk_backend as backend
sage: lp.solver_parameter(backend.glp_simplex_or_intopt, backend.glp_simplex_only)
sage: lp.solve()
sage: lp.get_row_dual(0)
                           # tolerance 0.00001
0.0
sage: lp.get_row_dual(1)
                          # tolerance 0.00001
10.0
```

## get\_variable\_value(variable)

Returns the value of a variable given by the solver.

**Note:** Behaviour is undefined unless solve has been called before.

# EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variables(2)
1
sage: p.add_linear_constraint([[0, 1], [1, 2]], None, 3)
sage: p.set_objective([2, 5])
sage: p.solve()
0
sage: p.get_objective_value()
7.5
sage: p.get_variable_value(0)
0.0
sage: p.get_variable_value(1)
1.5
```

## is\_maximization()

Test whether the problem is a maximization

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.is_maximization()
True
sage: p.set_sense(-1)
sage: p.is_maximization()
False
```

#### is\_variable\_binary (index)

Test whether the given variable is of binary type.

#### INPUT:

•index (integer) - the variable's id

#### **EXAMPLE**:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.set_variable_type(0,0)
sage: p.is_variable_binary(0)
```

## is\_variable\_continuous (index)

Test whether the given variable is of continuous/real type.

#### INPUT:

•index (integer) - the variable's id

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.is_variable_continuous(0)
True
sage: p.set_variable_type(0,1)
sage: p.is_variable_continuous(0)
False
```

# is\_variable\_integer(index)

Test whether the given variable is of integer type.

# INPUT:

•index (integer) - the variable's id

# **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.set_variable_type(0,1)
sage: p.is_variable_integer(0)
True
```

#### ncols()

Return the number of columns/variables.

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.ncols()
0
sage: p.add_variables(2)
1
sage: p.ncols()
2
```

#### nrows()

Return the number of rows/constraints.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.nrows()
0
sage: p.add_linear_constraints(2, 2, None)
sage: p.nrows()
```

#### objective\_coefficient (variable, coeff=None)

Set or get the coefficient of a variable in the objective function

#### **INPUT:**

```
•variable (integer) - the variable's id
```

•coeff (double) – its coefficient or None for reading (default: None)

# **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variable()
0
sage: p.objective_coefficient(0)
0.0
sage: p.objective_coefficient(0,2)
sage: p.objective_coefficient(0)
2.0
```

#### print\_ranges (filename='NULL')

Print results of a sensitivity analysis

If no filename is given as an input the results of the sensitivity analysis are displayed on the screen. If a filename is given they are written to a file.

#### INPUT:

 $\bullet$ filename – (optional) name of the file

#### **OUTPUT:**

Zero if the operations was successful otherwise nonzero.

**Note:** This method is only effective if an optimal solution has been found for the lp using the simplex algorithm. In all other cases an error message is printed.

**EXAMPLE:** 

```
sage: from sage.numerical.backends.generic_backend import get_solver
   sage: p = get_solver(solver = "GLPK")
   sage: p.add_variables(2)
   sage: p.add_linear_constraint(zip([0, 1], [1, 2]), None, 3)
   sage: p.set_objective([2, 5])
   sage: import sage.numerical.backends.glpk_backend as backend
   sage: p.solver_parameter(backend.glp_simplex_or_intopt, backend.glp_simplex_only)
   sage: p.print_ranges()
   glp_print_ranges: optimal basic solution required
   sage: p.solve()
   sage: p.print_ranges()
   Write sensitivity analysis report to...
   GLPK ... - SENSITIVITY ANALYSIS REPORT
   Problem:
   Objective: 7.5 (MAXimum)
      No. Row name St Activity
                                          Slack Lower bound Activity Obj coe
                                          Marginal Upper bound
                                                                      range
                                                                                    rang
                    NU 3.00000
                                                                                   -2.5000
       1
                                                            -Inf
                                           2.50000
                                                       3.00000
                                                                         +Inf
   GLPK ... - SENSITIVITY ANALYSIS REPORT
   Problem:
   Objective: 7.5 (MAXimum)
                                                                     Activity
                                                                                  Obj coe
      No. Column name St Activity
                                          Obj coef Lower bound
                                          Marginal Upper bound
                                                                       range
                                                                                   rang
                                           2.00000
        1
                      NT.
                                                                          -Inf
                                                          +Inf
                                            -.50000
                                                                      3.00000
                                                                                   2.5000
                    BS 1.50000 5.00000
                                                                         -Inf
                                                                                    4.0000
                                                           +Inf 1.50000
   End of report
problem name (name='NULL')
   Return or define the problem's name
   INPUT:
      •name (char *) - the problem's name. When set to NULL (default), the method returns the problem's
      name.
   EXAMPLE:
   sage: from sage.numerical.backends.generic_backend import get_solver
   sage: p = get_solver(solver = "GLPK")
   sage: p.problem_name("There once was a french fry")
   sage: print p.problem_name()
   There once was a french fry
```

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```
remove constraint(i)
```

Remove a constraint from self.

#### INPUT:

•i – index of the constraint to remove

```
EXAMPLE:
```

```
sage: p = MixedIntegerLinearProgram(solver='GLPK')
sage: x,y = p[0], p[1]
doctest:...: DeprecationWarning: The default value of 'nonnegative' will change, to False in
See http://trac.sagemath.org/15521 for details.
sage: p.add_constraint(2*x + 3*y, max = 6)
sage: p.add_constraint(3*x + 2*y, max = 6)
sage: p.set_objective(x + y + 7)
sage: p.set_integer(x); p.set_integer(y)
sage: p.solve()
9.0
sage: p.remove_constraint(0)
```

#### Removing fancy constraints does not make Sage crash:

```
sage: MixedIntegerLinearProgram(solver = "GLPK").remove_constraint(-2)
Traceback (most recent call last):
...
ValueError: The constraint's index i must satisfy 0 <= i < number_of_constraints</pre>
```

# remove\_constraints (constraints)

Remove several constraints.

sage: p.solve()

#### INPUT:

10.0

•constraints – an iterable containing the indices of the rows to remove.

#### **EXAMPLE**:

```
sage: p = MixedIntegerLinearProgram(solver='GLPK')
sage: x,y = p[0], p[1]
sage: p.add_constraint(2*x + 3*y, max = 6)
sage: p.add_constraint(3*x + 2*y, max = 6)
sage: p.set_objective(x + y + 7)
sage: p.set_integer(x); p.set_integer(y)
sage: p.solve()
9.0
sage: p.remove_constraints([1])
sage: p.solve()
10.0
sage: p.get_values([x,y])
[3.0, 0.0]
```

#### TESTS:

# Removing fancy constraints does not make Sage crash:

```
sage: MixedIntegerLinearProgram(solver= "GLPK").remove_constraints([0, -2])
Traceback (most recent call last):
...
ValueError: The constraint's index i must satisfy 0 <= i < number_of_constraints</pre>
```

#### row (index)

Return a row

#### INPUT:

•index (integer) - the constraint's id.

## **OUTPUT**:

A pair (indices, coeffs) where indices lists the entries whose coefficient is nonzero, and to which coeffs associates their coefficient on the model of the add linear constraint method.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variables(5)
4
sage: p.add_linear_constraint(zip(range(5), range(5)), 2, 2)
sage: p.row(0)
([4, 3, 2, 1], [4.0, 3.0, 2.0, 1.0])
sage: p.row_bounds(0)
(2.0, 2.0)
```

#### row bounds (index)

Return the bounds of a specific constraint.

#### INPUT:

•index (integer) – the constraint's id.

## **OUTPUT**:

A pair (lower\_bound, upper\_bound). Each of them can be set to None if the constraint is not bounded in the corresponding direction, and is a real value otherwise.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variables(5)
4
sage: p.add_linear_constraint(zip(range(5), range(5)), 2, 2)
sage: p.row(0)
([4, 3, 2, 1], [4.0, 3.0, 2.0, 1.0])
sage: p.row_bounds(0)
(2.0, 2.0)
```

#### row\_name (index)

Return the index th row name

#### INPUT:

•index (integer) - the row's id

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_linear_constraints(1, 2, None, names=['Empty constraint 1'])
sage: p.row_name(0)
'Empty constraint 1'
```

```
set\_objective (coeff, d=0.0)
    Set the objective function.
    INPUT:
       •coeff - a list of real values, whose ith element is the coefficient of the ith variable in the objective
        function.
       •d (double) – the constant term in the linear function (set to 0 by default)
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "GLPK")
    sage: p.add_variables(5)
    sage: p.set_objective([1, 1, 2, 1, 3])
    sage: map(lambda x :p.objective_coefficient(x), range(5))
    [1.0, 1.0, 2.0, 1.0, 3.0]
set_sense(sense)
    Set the direction (maximization/minimization).
    INPUT:
       •sense (integer):
           -+1 => Maximization
           -1 \Rightarrow Minimization
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "GLPK")
    sage: p.is_maximization()
    True
    sage: p.set_sense(-1)
    sage: p.is_maximization()
    False
set_variable_type (variable, vtype)
    Set the type of a variable
    INPUT:
       •variable (integer) - the variable's id
       •vtype (integer):
           -1 Integer
           -0 Binary
           -- 1 Real
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "GLPK")
    sage: p.ncols()
    sage: p.add_variable()
    sage: p.set_variable_type(0,1)
```

**Note:** This method raises MIPSolverException exceptions when the solution can not be computed for any reason (none exists, or the LP solver was not able to find it, etc...)

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_linear_constraints(5, 0, None)
sage: p.add_col(range(5), range(5))
sage: p.solve()
0
sage: p.objective_coefficient(0,1)
sage: p.solve()
Traceback (most recent call last):
...
MIPSolverException: ...
```

**Warning:** Sage uses GLPK's <code>glp\_intopt</code> to find solutions. This routine sometimes FAILS CATASTROPHICALLY when given a system it cannot solve. (Ticket #12309.) Here, "catastrophic" can mean either "infinite loop" or segmentation fault. Upstream considers this behavior "essentially innate" to their design, and suggests preprocessing it with <code>glpk\_simplex</code> first. Thus, if you suspect that your system is infeasible, set the <code>preprocessing</code> option first.

```
sage: lp = MixedIntegerLinearProgram(solver = "GLPK")
sage: lp.add_constraint( lp[1] +lp[2] -2.0 *lp[3] , max =-1.0)
sage: lp.add_constraint( lp[0] -4.0/3 *lp[1] +1.0/3 *lp[2] , max =-1.0/3)
sage: lp.add_constraint( lp[0] +0.5 *lp[1] -0.5 *lp[2] +0.25 *lp[3] , max =-0.25)
sage: lp.solve()
0.0
sage: lp.add_constraint( lp[0] +4.0 *lp[1] -lp[2] +lp[3] , max =-1.0)
sage: lp.solve()
Traceback (most recent call last):
...
RuntimeError: GLPK : Signal sent, try preprocessing option
sage: lp.solver_parameter("simplex_or_intopt", "simplex_then_intopt")
sage: lp.solve()
Traceback (most recent call last):
```

```
MIPSolverException: 'GLPK: Simplex cannot find a feasible solution'
```

The user can ask sage to solve via simplex or intopt. The default solver is intopt, so we get integer solutions.

#### **EXAMPLE:**

```
sage: lp = MixedIntegerLinearProgram(solver = 'GLPK', maximization = False)
sage: x, y = lp[0], lp[1]
sage: lp.add_constraint(-2*x + y <= 1)
sage: lp.add_constraint(x - y <= 1)
sage: lp.add_constraint(x + y >= 2)
sage: lp.set_objective(x + y)
sage: lp.set_integer(x)
sage: lp.set_integer(y)
sage: lp.solve()
2.0
sage: lp.get_values([x, y])
[1.0, 1.0]
```

If we switch to simplex, we get continuous solutions.

#### **EXAMPLE:**

```
sage: lp.solver_parameter("simplex_or_intopt", "simplex_only") # use simplex only
sage: lp.solve()
2.0
sage: lp.get_values([x, y])
[1.5, 0.5]
```

# solver\_parameter (name, value=None)

Return or define a solver parameter

# INPUT:

```
•name (string) – the parameter
```

•value – the parameter's value if it is to be defined, or None (default) to obtain its current value.

You can supply the name of a parameter and its value using either a string or a glp\_constant (which are defined as Cython variables of this module).

In most cases, you can use the same name for a parameter as that given in the GLPK documentation, which is available by downloading GLPK from <a href="http://www.gnu.org/software/glpk/">http://www.gnu.org/software/glpk/</a>. The exceptions relate to parameters common to both methods; these require you to append \_simplex or \_intopt to the name to resolve ambiguity, since the interface allows access to both.

We have also provided more meaningful names, to assist readability.

Parameter **names** are specified in lower case. To use a constant instead of a string, prepend glp\_to the name. For example, both glp\_gmi\_cuts or "gmi\_cuts" control whether to solve using Gomory cuts.

Parameter **values** are specificed as strings in upper case, or as constants in lower case. For example, both glp\_on and "GLP\_ON" specify the same thing.

Naturally, you can use True and False in cases where glp\_on and glp\_off would be used.

A list of parameter names, with their possible values:

#### **General-purpose parameters:**

timelimit	specify the time limit IN SECONDS. This affects both simplex and
	intopt.
timelimit_simplex and	specify the time limit IN MILLISECONDS. (This is glpk's default.)
timelimit_intopt	
simplex_or_intopt	whether to use the simplex or intopt routines in GLPK. This is
	<pre>controlled by using glp_simplex_only, glp_intopt_only,</pre>
	and glp_simplex_then_intopt. The latter is useful to deal
	with a problem in GLPK where problems with no solution hang
	when using integer optimization; if you specify
	glp_simplex_then_intopt, sage will try simplex first, then
	perform integer optimization only if a solution of the LP relaxation
	exists.
verbosity_intopt and	one of GLP_MSG_OFF, GLP_MSG_ERR, GLP_MSG_ON, or
verbosity_simplex	GLP_MSG_ALL. The default is GLP_MSG_OFF.
output_frequency_intoptthe output frequency, in milliseconds. Default is 5000.	
and	
output_frequency_simple	ex
output_delay_intopt	the output delay, in milliseconds, regarding the use of the simplex
and	method on the LP relaxation. Default is 10000.
output_delay_simplex	

# intopt-specific parameters:

branching	
Dranening	•GLP_BR_FFV first fractional variable •GLP_BR_LFV last fractional variable •GLP_BR_MFV most fractional variable •GLP_BR_DTH Driebeck-Tomlin heuristic (default) •GLP_BR_PCH hybrid pseudocost heuristic
backtracking	•GLP_BT_DFS depth first search •GLP_BT_BFS breadth first search •GLP_BT_BLB best local bound (default) •GLP_BT_BPH best projection heuristic
preprocessing	•GLP_PP_NONE •GLP_PP_ROOT preprocessing only at root level •GLP_PP_ALL (default)
feasibility_pump	GLP_ON or GLP_OFF (default)
gomory_cuts	GLP_ON or GLP_OFF (default)
mixed_int_rounding_cuts	GLP_ON or GLP_OFF (default)
mixed_cover_cuts	GLP_ON or GLP_OFF (default)
clique_cuts	GLP_ON or GLP_OFF (default)
absolute_tolerance	(double) used to check if optimal solution to LP relaxation is integer feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."
relative_tolerance	(double) used to check if objective value in LP re- laxation is not better than best known integer so- lution. GLPK manual advises, "do not change without detailed understanding of its purpose."
mip_gap_tolerance	(double) relative mip gap tolerance. Default is 0.0.
presolve_intopt	GLP_ON (default) or GLP_OFF.
binarize	GLP_ON or GLP_OFF (default)

# simplex-specific parameters:

### Pricing  ### Pricing  ### OGLP_PT_STD standard (textbook)  ### OGLP_PT_STD standard (textbook)  ### OGLP_PT_PSE projected steepest edge (default)  ### PSE projected steepest edge (default)  #### PSE projected steepest edge (default)  #### OGLP_RT_STD standard (textbook)  #### OGLP_RT_HAR Harris' two-pass ratio test (default)  ##### Took of the passe ratio test (default)  ####### Took of the passe ratio test (default)  ###################################	primal_v_dual	
Pricing  *GLP_DUALP  *GLP_DUALP  *GLP_DUALP  *GLP_PT_STD standard (textbook)  *GLP_PT_PSE projected steepest edge (default)  *GLP_RT_STD standard (textbook)  *GLP_RT_STD standard (textbook)  *GLP_RT_HAR Harris' two-pass ratio test (default)  tolerance_primal  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_dual  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_pivot  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  obj_lower_limit  (double) lower limit of the objective function. The default is DBL_MAX.  obj_upper_limit  (double) upper limit of the objective function. The default is DBL_MAX.  (int) iteration limit of the simplex algorithm. The default is INT_MAX.	primar_v_dddi	•GLP PRIMAL (default)
pricing  *GLP_PT_STD standard (textbook) *GLP_PT_PSE projected steepest edge (default)  ratio_test  *GLP_RT_STD standard (textbook) *GLP_RT_HAR Harris' two-pass ratio test (default)  tolerance_primal  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_dual  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_pivot  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  obj_lower_limit  (double) lower limit of the objective function. The default is DBL_MAX.  (double) upper limit of the objective function. The default is DBL_MAX.  (int) iteration_limit of the simplex algorithm. The default is INT_MAX.		_ ` '
•GLP_PT_STD standard (textbook) •GLP_PT_PSE projected steepest edge (default)  ratio_test  •GLP_RT_STD standard (textbook) •GLP_RT_HAR Harris' two-pass ratio test (default)  tolerance_primal  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_dual  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_pivot  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) lower limit of the objective function. The default is ¬DBL_MAX.  (idouble) upper limit of the objective function. The default is DBL_MAX.  (int) iteration limit of the simplex algorithm. The default is INT_MAX.		_
•GLP_PT_STD standard (textbook) •GLP_PT_PSE projected steepest edge (default)  ratio_test  •GLP_RT_STD standard (textbook) •GLP_RT_HAR Harris' two-pass ratio test (default)  tolerance_primal  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_dual  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_pivot  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) lower limit of the objective function. The default is ¬DBL_MAX.  (idouble) upper limit of the objective function. The default is DBL_MAX.  (int) iteration limit of the simplex algorithm. The default is INT_MAX.		_
*GLP_PT_PSE projected steepest edge (default)  ratio_test  *GLP_RT_STD standard (textbook) *GLP_RT_HAR Harris' two-pass ratio test (default)  tolerance_primal  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_dual  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_pivot  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) lower_limit of the objective function. The default is DBL_MAX.  (double) upper limit of the objective function. The default is DBL_MAX.  (int) iteration_limit of the simplex algorithm. The default is INT_MAX.	pricing	
ratio_test  *GLP_RT_STD standard (textbook) *GLP_RT_HAR Harris' two-pass ratio test (default)  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_dual  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_pivot  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  obj_lower_limit  (double) lower limit of the objective function. The default is -DBL_MAX.  (double) upper limit of the objective function. The default is DBL_MAX.  iteration_limit  (int) iteration limit of the simplex algorithm. The default is INT_MAX.		•GLP_PT_STD standard (textbook)
ratio_test  *GLP_RT_STD standard (textbook) *GLP_RT_HAR Harris' two-pass ratio test (default)  tolerance_primal  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_dual  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_pivot  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) lower_limit of the objective function. The default is -DBL_MAX.  (int) iteration_limit of the simplex algorithm. The default is INT_MAX.		
•GLP_RT_STD standard (textbook) •GLP_RT_HAR Harris' two-pass ratio test (default)  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) lower limit of the objective function. The default is -DBL_MAX.  (double) upper limit of the objective function. The default is DBL_MAX.  (int) iteration limit of the simplex algorithm. The default is INT_MAX.		fault)
•GLP_RT_STD standard (textbook) •GLP_RT_HAR Harris' two-pass ratio test (default)  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  (double) lower limit of the objective function. The default is -DBL_MAX.  (double) upper limit of the objective function. The default is DBL_MAX.  (int) iteration limit of the simplex algorithm. The default is INT_MAX.		
*GLP_RT_HAR Harris' two-pass ratio test (default)  tolerance_primal  (double) tolerance used to check if basic solution is primal feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_dual  (double) tolerance used to check if basic solution is dual feasible. GLPK manual advises, "do not change without detailed understanding of its purpose."  tolerance_pivot  (double) tolerance used to choose pivot. GLPK manual advises, "do not change without detailed understanding of its purpose."  obj_lower_limit  (double) lower limit of the objective function. The default is -DBL_MAX.  obj_upper_limit  (double) upper limit of the objective function. The default is DBL_MAX.  iteration_limit  (int) iteration limit of the simplex algorithm. The default is INT_MAX.	ratio_test	ACT D. D.M. CMD atom double (touth and)
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default is INT_MAX.	iteration limit	
presorve_srmprex   GLP_ON OF GLP_OFF (default).	presolve_simplex	GLP_ON or GLP_OFF (default).

**Note:** The coverage for GLPK's control parameters for simplex and integer optimization is nearly complete. The only thing lacking is a wrapper for callback routines.

To date, no attempt has been made to expose the interior point methods.

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.solver_parameter("timelimit", 60)
sage: p.solver_parameter("timelimit")
60.0
```

•Don't forget the difference between timelimit and timelimit\_intopt

```
sage: p.solver_parameter("timelimit_intopt")
60000
```

If you don't care for an integer answer, you can ask for an lp relaxation instead. The default solver performs integer optimization, but you can switch to the standard simplex algorithm through the glp\_simplex\_or\_intopt parameter.

#### **EXAMPLE:**

```
sage: lp = MixedIntegerLinearProgram(solver = 'GLPK', maximization = False)
sage: x, y = lp[0], lp[1]
sage: lp.add_constraint(-2*x + y \le 1)
sage: lp.add_constraint(x - y <= 1)</pre>
sage: lp.add_constraint(x + y \geq 2)
sage: lp.set_integer(x); lp.set_integer(y)
sage: lp.set_objective(x + y)
sage: lp.solve()
2.0
sage: lp.get_values([x,y])
[1.0, 1.0]
sage: import sage.numerical.backends.glpk backend as backend
sage: lp.solver_parameter(backend.glp_simplex_or_intopt, backend.glp_simplex_only)
sage: lp.solve()
2.0
sage: lp.get_values([x,y])
[1.5, 0.5]
```

You can get glpk to spout all sorts of information at you. The default is to turn this off, but sometimes (debugging) it's very useful:

```
sage: lp.solver_parameter(backend.glp_simplex_or_intopt, backend.glp_simplex_then_intopt)
sage: lp.solver_parameter(backend.glp_mir_cuts, backend.glp_on)
sage: lp.solver_parameter(backend.glp_msg_lev_intopt, backend.glp_msg_all)
sage: lp.solver_parameter(backend.glp_mir_cuts)
1
```

If you actually try to solve lp, you will get a lot of detailed information.

#### variable\_lower\_bound (index, value=False)

Return or define the lower bound on a variable

# INPUT:

- •index (integer) the variable's id
- •value real value, or None to mean that the variable has not lower bound. When set to False (default), the method returns the current value.

#### EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "GLPK")
sage: p.add_variable()
sage: p.col_bounds(0)
(0.0, None)
sage: p.variable_lower_bound(0, 5)
sage: p.col_bounds(0)
(5.0, None)
TESTS:
trac ticket #14581:
sage: P = MixedIntegerLinearProgram(solver="GLPK")
sage: x = P["x"]
sage: P.set_min(x, 5)
sage: P.set_min(x, 0)
sage: P.get_min(x)
0.0
```

sage: p = get\_solver(solver = "GLPK")

sage: p.add\_variables(2)

```
variable upper bound(index, value=False)
    Return or define the upper bound on a variable
    INPUT:
       •index (integer) - the variable's id
       •value - real value, or None to mean that the variable has not upper bound. When set to False
        (default), the method returns the current value.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "GLPK")
    sage: p.add_variable()
    sage: p.col_bounds(0)
    (0.0, None)
    sage: p.variable_upper_bound(0, 5)
    sage: p.col_bounds(0)
    (0.0, 5.0)
    TESTS:
    trac ticket #14581:
    sage: P = MixedIntegerLinearProgram(solver="GLPK")
    sage: x = P["x"]
    sage: P.set_max(x, 0)
    sage: P.get_max(x)
    0.0
write_lp (filename)
    Write the problem to a .lp file
    INPUT:
       •filename (string)
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "GLPK")
    sage: p.add_variables(2)
    sage: p.add_linear_constraint([[0, 1], [1, 2]], None, 3)
    sage: p.set_objective([2, 5])
    sage: p.write_lp(os.path.join(SAGE_TMP, "lp_problem.lp"))
    Writing problem data to ...
    9 lines were written
write_mps (filename, modern)
    Write the problem to a .mps file
    INPUT:
       •filename (string)
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
```

```
sage: p.add_linear_constraint([[0, 1], [1, 2]], None, 3)
sage: p.set_objective([2, 5])
sage: p.write_mps(os.path.join(SAGE_TMP, "lp_problem.mps"), 2)
Writing problem data to...
17 records were written
```

# 6.3 GLPK Backend for access to GLPK graph functions

GLPK Backend for access to GLPK graph functions

# **AUTHORS:**

• Christian Kuper (2012-11): Initial implementation

# 6.3.1 Methods index

# Graph creation and modification operations:

add_vertex()	Adds an isolated vertex to the graph.	
add_vertices()	Adds vertices from an iterable container of vertices.	
set_vertex_demand()	Sets the vertex parameters.	
set_vertices_demand()	Sets the parameters of selected vertices.	
get_vertex()	Returns a specific vertex as a dict Object.	
get_vertices()	Returns a dictionary of the dictonaries associated to each vertex.	
vertices()	Returns a list of all vertices.	
delete_vertex()	Removes a vertex from the graph.	
delete_vertices()	Removes vertices from the graph.	
add_edge()	Adds an edge between vertices u and v.	
add_edges()	Adds edges to the graph.	
get_edge()	Returns an edge connecting two vertices.	
edges()	Returns a list of all edges in the graph.	
delete_edge()	Deletes an edge from the graph.	
delete_edges()	Deletes edges from the graph.	

# **Graph writing operations:**

write_graph()	Writes the graph to a plain text file.
write_ccdata()	Writes the graph to a text file in DIMACS format.
write_mincost()	Writes the mincost flow problem data to a text file in DIMACS format.
write_maxflow()	Writes the maximum flow problem data to a text file in DIMACS format.

# **Network optimization operations:**

<pre>mincost_okalg()</pre>	Finds solution to the mincost problem with the out-of-kilter algorithm.
<pre>maxflow_ffalg()</pre>	Finds solution to the maxflow problem with Ford-Fulkerson algorithm.
cpp()	Solves the critical path problem of a project network.

# 6.3.2 Classes and methods

 ${\bf class} \ {\tt sage.numerical.backends.glpk\_graph\_backend.GLPKGraphBackend} \\ Bases: \ {\tt object}$ 

GLPK Backend for access to GLPK graph functions

The constructor can either be called without arguments (which results in an empty graph) or with arguments to read graph data from a file.

#### INPUT:

- •data a filename or a Graph object.
- •format when data is a filename, specifies the format of the data read from a file. The format parameter is a string and can take values as described in the table below.

# **Format parameters:**

plain	Read data from a plain text file containing the following information:  nv na  i[1] j[1]  i[2] j[2]   i[na] j[na]  where:  •nv is the number of vertices (nodes);  •na is the number of arcs;  •i[k], k = 1,, na, is the index of tail vertex of arc k;  •j[k], k = 1,, na, is the index of head vertex of arc k.
dimacs	Read data from a plain ASCII text file in DIMACS format. A discription of the DIMACS format can be found at http://dimacs.rutgers.edu/Challenges/.
mincost	Reads the mincost flow problem data from a text file in DIMACS format
maxflow	Reads the maximum flow problem data from a text file in DIMACS format

Note: When data is a Graph, the following restrictions are applied.

- •vertices the value of the demand of each vertex (see set\_vertex\_demand()) is obtained from the numerical value associated with the key "rhs" if it is a dictionary.
- •edges The edge values used in the algorithms are read from the edges labels (and left undefined if the edge labels are equal to None). To be defined, the labels must be dict objects with keys "low", "cap" and "cost". See get\_edge() for details.

# **EXAMPLES:**

The following example creates an empty graph:

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
```

The following example creates an empty graph, adds some data, saves the data to a file and loads it:

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: gbe.add_vertices([None, None])
['0', '1']
sage: a = gbe.add_edge('0', '1')
sage: gbe.write_graph(SAGE_TMP+"/graph.txt")
```

```
Writing graph to ...
2 lines were written
0
sage: gbe1 = GLPKGraphBackend(SAGE_TMP+"/graph.txt", "plain")
Reading graph from ...
Graph has 2 vertices and 1 arc
2 lines were read
```

The following example imports a Sage Graph and then uses it to solve a maxflow problem:

# add\_edge (u, v, params=None)

Adds an edge between vertices u and v.

Allows adding an edge and optionally providing parameters used by the algorithms. If a vertex does not exist it is created.

## INPUT:

- •u The name (as str) of the tail vertex
- •v The name (as str) of the head vertex
- •params An optional dict containing the edge parameters used for the algorithms. The following keys are used:
  - **-**low − The minimum flow through the edge
  - -cap The maximum capacity of the edge
  - -cost The cost of transporting one unit through the edge

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: gbe.add_edge("A", "B", {"low":0.0, "cap":10.0, "cost":5})
sage: gbe.vertices()
['A', 'B']
sage: for ed in gbe.edges():
...     print ed[0], ed[1], ed[2]['cap'], ed[2]['cost'], ed[2]['low']
A B 10.0 5.0 0.0
sage: gbe.add_edge("B", "C", {"low":0.0, "cap":10.0, "cost":'5'})
Traceback (most recent call last):
...
TypeError: Invalid edge parameter.
```

# add\_edges (edges)

Adds edges to the graph.

#### INPUT:

•edges – An iterable container of pairs of the form (u, v), where u is name (as str) of the tail vertex and v is the name (as str) of the head vertex or an interable container of triples of the form (u, v, params) where params is a dict as described in add\_edge.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: edges = [("A", "B", {"low":0.0, "cap":10.0, "cost":5})]
sage: edges.append(("B", "C"))
sage: gbe.add_edges(edges)
sage: for ed in gbe.edges():
         print ed[0], ed[1], ed[2]['cap'], ed[2]['cost'], ed[2]['low']
A B 10.0 5.0 0.0
B C 0.0 0.0 0.0
sage: edges = [("C", "D", {"low":0.0, "cap":10.0, "cost":5})]
sage: edges.append(("C", "E", 5))
sage: gbe.add_edges(edges)
Traceback (most recent call last):
TypeError: Argument 'params' has incorrect type ...
sage: for ed in qbe.edges():
         print ed[0], ed[1], ed[2]['cap'], ed[2]['cost'], ed[2]['low']
A B 10.0 5.0 0.0
B C 0.0 0.0 0.0
C D 10.0 5.0 0.0
```

#### add vertex(name='NULL')

Adds an isolated vertex to the graph.

If the vertex already exists, nothing is done.

#### INPUT:

•name – String of max 255 chars length. If no name is specified, then the vertex will be represented by the string representation of the ID of the vertex or - if this already exists - a string representation of the least integer not already representing a vertex.

## **OUTPUT**:

If no name is passed as an argument, the new vertex name is returned. None otherwise.

# **EXAMPLE:**

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: gbe.add_vertex()
'0'
sage: gbe.add_vertex("2")
sage: gbe.add_vertex()
'1'
```

#### add vertices (vertices)

Adds vertices from an iterable container of vertices.

Vertices that already exist in the graph will not be added again.

### INPUT:

•vertices – iterator of vertex labels (str). A label can be None.

# **OUTPUT**:

Generated names of new vertices if there is at least one None value present in vertices. None otherwise.

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: vertices = [None for i in range(3)]
sage: gbe.add_vertices(vertices)
['0', '1', '2']
sage: gbe.add_vertices(['A', 'B', None])
['5']
sage: gbe.add_vertices(['A', 'B', 'C'])
sage: gbe.vertices()
['0', '1', '2', 'A', 'B', '5', 'C']

TESTS:
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: gbe.add_vertices([None, None, None, '1'])
['0', '2', '3']
```

# $\mathbf{cpp}()$

Solves the critical path problem of a project network.

#### **OUTPUT:**

The length of the critical path of the network

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: gbe.add_vertices([None for i in range(3)])
['0', '1', '2']
sage: gbe.set_vertex_demand('0', 3)
sage: gbe.set_vertex_demand('1', 1)
sage: gbe.set_vertex_demand('2', 4)
sage: a = gbe.add_edge('0', '2')
sage: a = gbe.add_edge('1', '2')
sage: gbe.cpp()
7.0
sage: v = gbe.get_vertex('1')
sage: print 1, v["rhs"], v["es"], v["ls"] # abs tol 1e-6
1 1.0 0.0 2.0
```

# delete\_edge (u, v, params=None)

Deletes an edge from the graph.

If an edge does not exist it is ignored.

# INPUT:

- •u The name (as str) of the tail vertex of the edge
- •v The name (as str) of the tail vertex of the edge
- •params params An optional dict containing the edge parameters (see meth:add\_edge). If this parameter is not provided, all edges connecting u and v are deleted. Otherwise only edges with matching parameters are deleted.

## See Also:

```
delete_edges()
```

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
    sage: gbe = GLPKGraphBackend()
    sage: edges = [("A", "B", {"low":0.0, "cap":10.0, "cost":5})]
    sage: edges.append(("A", "B", {"low":0.0, "cap":15.0, "cost":10}))
    sage: edges.append(("B", "C", {"low":0.0, "cap":20.0, "cost":1}))
    sage: edges.append(("B", "C", {"low":0.0, "cap":10.0, "cost":20}))
    sage: gbe.add_edges(edges)
                                "B")
    sage: gbe.delete_edge("A",
    sage: gbe.delete_edge("B", "C", {"low":0.0, "cap":10.0, "cost":20})
    sage: print gbe.edges()[0][0], gbe.edges()[0][1], gbe.edges()[0][2]['cost']
    B C 1.0
delete_edges (edges)
    Deletes edges from the graph.
    Non existing edges are ignored.
    INPUT:
       •edges – An iterable container of edges.
    See Also:
    delete edge()
    EXAMPLE:
    sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
    sage: gbe = GLPKGraphBackend()
    sage: edges = [("A", "B", {"low":0.0, "cap":10.0, "cost":5})]
    sage: edges.append(("A", "B", {"low":0.0, "cap":15.0, "cost":10}))
    sage: edges.append(("B", "C", {"low":0.0, "cap":20.0, "cost":1}))
    sage: edges.append(("B", "C", {"low":0.0, "cap":10.0, "cost":20}))
    sage: gbe.add_edges(edges)
    sage: gbe.delete_edges(edges[1:])
    sage: len(gbe.edges())
    sage: print gbe.edges()[0][0], gbe.edges()[0][1], gbe.edges()[0][2]['cap']
    A B 10.0
delete vertex(vert)
    Removes a vertex from the graph.
    Trying to delete a non existing vertex will raise an exception.
    INPUT:
       •vert – The name (as str) of the vertex to delete.
    EXAMPLE:
    sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
    sage: gbe = GLPKGraphBackend()
    sage: verts = ["A", "D"]
    sage: gbe.add_vertices(verts)
    sage: gbe.delete_vertex("A")
    sage: qbe.vertices()
    ['D']
```

sage: gbe.delete\_vertex("A")
Traceback (most recent call last):

RuntimeError: Vertex A does not exist.

## delete\_vertices (verts)

Removes vertices from the graph.

Trying to delete a non existing vertex will raise an exception.

#### INPUT:

•verts – iterable container containing names (as str) of the vertices to delete

#### EXAMPLE:

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: verts = ["A", "B", "C", "D"]
sage: gbe.add_vertices(verts)
sage: v_d = ["A", "B"]
sage: gbe.delete_vertices(v_d)
sage: gbe.vertices()
['C', 'D']
sage: gbe.delete_vertices(["C", "A"])
Traceback (most recent call last):
...
RuntimeError: Vertex A does not exist.
sage: gbe.vertices()
['C', 'D']
```

#### edges()

Returns a list of all edges in the graph

#### **OUTPUT:**

A list of triples representing the edges of the graph.

# **EXAMPLE:**

## $get\_edge(u, v)$

Returns an edge connecting two vertices.

**Note:** If multiple edges connect the two vertices only the first edge found is returned.

# INPUT:

- •u Name (as str) of the tail vertex
- $\bullet$ v Name (as str) of the head vertex

#### **OUTPUT:**

A triple describing if edge was found or None if not. The third value of the triple is a dict containing the following edge parameters:

•low – The minimum flow through the edge

- •cap The maximum capacity of the edge
- •cost The cost of transporting one unit through the edge
- •x The actual flow through the edge after solving

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: edges = [("A", "B"), ("A", "C"), ("B", "C")]
sage: gbe.add_edges(edges)
sage: ed = gbe.get_edge("A", "B")
sage: print ed[0], ed[1], ed[2]['x']
A B 0.0
sage: gbe.get_edge("A", "F") is None
True
```

#### get vertex(vertex)

Returns a specific vertex as a dict Object.

#### INPUT:

•vertex - The vertex label as str.

#### **OUTPUT:**

The vertex as a dict object or None if the vertex does not exist. The dict contains the values used or created by the different algorithms. The values associated with the keys following keys contain:

- •"rhs" The supply / demand value the vertex (mincost alg)
- •"pi" The node potential (mincost alg)
- •"cut" The cut flag of the vertex (maxflow alg)
- •"es" The earliest start of task (cpp alg)
- •"ls" The latest start of task (cpp alg)

# **EXAMPLE:**

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: verts = ["A", "B", "C", "D"]
sage: gbe.add_vertices(verts)
sage: sorted(gbe.get_vertex("A").items())
[('cut', 0), ('es', 0.0), ('ls', 0.0), ('pi', 0.0), ('rhs', 0.0)]
sage: gbe.get_vertex("F") is None
True
```

# get\_vertices (verts)

Returns a dictionary of the dictonaries associated to each vertex.

#### INPUT:

•verts – iterable container of vertices

## **OUTPUT**:

A list of pairs (vertex, properties) where properties is a dictionary containing the numerical values associated with a vertex. For more information, see the documentation of GLPKGraphBackend.get\_vertex().

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: verts = ['A', 'B']
sage: gbe.add_vertices(verts)
sage: sorted(gbe.get_vertices(verts)['B'].items())
[('cut', 0), ('es', 0.0), ('ls', 0.0), ('pi', 0.0), ('rhs', 0.0)]
sage: gbe.get_vertices(["C", "D"])
{}
```

#### maxflow ffalg(u=None, v=None)

Finds solution to the maxflow problem with Ford-Fulkerson algorithm.

#### INPUT:

- •u Name (as str) of the tail vertex. Default is None.
- •v Name (as str) of the head vertex. Default is None.

If u or v are None, the currently stored values for the head or tail vertex are used. This behavior is useful when reading maxflow data from a file. When calling this function with values for u and v, the head and tail vertex are stored for later use.

#### OUTPUT:

The solution to the maxflow problem, i.e. the maximum flow.

#### Note:

- •If the source or sink vertex does not exist, an IndexError is raised.
- •If the source and sink are identical, a ValueError is raised.
- •This method raises MIPSolverException exceptions when the solution can not be computed for any reason (none exists, or the LP solver was not able to find it, etc...)

## **EXAMPLE:**

## mincost okalq()

Finds solution to the mincost problem with the out-of-kilter algorithm.

The out-of-kilter algorithm requires all problem data to be integer valued.

# **OUTPUT:**

The solution to the mincost problem, i.e. the total cost, if operation was successful.

**Note:** This method raises MIPSolverException exceptions when the solution can not be computed for any reason (none exists, or the LP solver was not able to find it, etc...)

#### EXAMPLE:

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: vertices = (35, 50, 40, -45, -20, -30, -30)
sage: vs = gbe.add_vertices([None for i in range(len(vertices))])
sage: v_dict = {}
sage: for i, v in enumerate(vs):
          v_dict[v] = vertices[i]
sage: gbe.set_vertices_demand(v_dict.items())
sage: cost = ((8, 6, 10, 9), (9, 12, 13, 7), (14, 9, 16, 5))
sage: lcost = range(len(cost))
sage: lcost_0 = range(len(cost[0]))
sage: for i in lcost:
         for j in lcost_0:
                gbe.add_edge(str(i), str(j + len(cost)), {"cost":cost[i][j], "cap":100})
. . .
sage: gbe.mincost_okalg()
1020.0
sage: for ed in qbe.edges():
          print ed[0], "->", ed[1], ed[2]["x"]
. . .
0 \rightarrow 6 \ 0.0
0 \rightarrow 5 25.0
0 \rightarrow 4 10.0
0 \rightarrow 3 0.0
1 \rightarrow 6 0.0
1 \rightarrow 5.0
1 \rightarrow 4 0.0
1 -> 3 45.0
2 -> 6 30.0
2 \rightarrow 5 0.0
2 \rightarrow 4 10.0
2 \rightarrow 3 0.0
```

# set\_vertex\_demand(vertex, demand)

Sets the demand of the vertex in a mincost flow algorithm.

#### INPUT:

- •vertex Name of the vertex
- •demand the numerical value representing demand of the vertex in a mincost flow alorithm (it could be for instance -1 to represent a sink, or 1 to represent a source and 0 for a neutral vertex). This can either be an int or float value.

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: vertices = [None for i in range(3)]
sage: gbe.add_vertices(vertices)
['0', '1', '2']
sage: gbe.set_vertex_demand('0', 2)
sage: gbe.get_vertex('0')['rhs']
2.0
sage: gbe.set_vertex_demand('3', 2)
Traceback (most recent call last):
```

```
KeyError: 'Vertex 3 does not exist.'
```

## set\_vertices\_demand(pairs)

Sets the parameters of selected vertices.

#### INPUT:

•pairs - A list of pairs (vertex, demand) associating a demand to each vertex. For more information, see the documentation of set\_vertex\_demand().

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: vertices = [None for i in range(3)]
sage: gbe.add_vertices(vertices)
['0', '1', '2']
sage: gbe.set_vertices_demand([('0', 2), ('1', 3), ('3', 4)])
sage: sorted(gbe.get_vertex('1').items())
[('cut', 0), ('es', 0.0), ('ls', 0.0), ('pi', 0.0), ('rhs', 3.0)]
```

## vertices()

Returns the list of all vertices

**Note:** Changing elements of the list will not change anything in the the graph.

**Note:** If a vertex in the graph does not have a name / label it will appear as None in the resulting list.

## EXAMPLE:

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: verts = ["A", "B", "C"]
sage: gbe.add_vertices(verts)
sage: a = gbe.vertices(); a
['A', 'B', 'C']
sage: a.pop(0)
'A'
sage: gbe.vertices()
['A', 'B', 'C']
```

# write\_ccdata(fname)

Writes the graph to a text file in DIMACS format.

Writes the data to plain ASCII text file in DIMACS format. A discription of the DIMACS format can be found at http://dimacs.rutgers.edu/Challenges/.

### INPUT:

•fname - full name of the file

#### **OUTPUT:**

Zero if the operations was successful otherwise nonzero

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
```

```
sage: a = gbe.add_edge("0", "1")
    sage: gbe.write_ccdata(SAGE_TMP+"/graph.dat")
    Writing graph to ...
    6 lines were written
write_graph (fname)
    Writes the graph to a plain text file
    INPUT:
       •fname - full name of the file
    OUTPUT:
    Zero if the operations was successful otherwise nonzero
    EXAMPLE:
    sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
    sage: gbe = GLPKGraphBackend()
    sage: a = gbe.add_edge("0", "1")
    sage: gbe.write_graph(SAGE_TMP+"/graph.txt")
    Writing graph to ...
    2 lines were written
write_maxflow(fname)
    Writes the maximum flow problem data to a text file in DIMACS format.
    INPUT:
       •fname - Full name of file
    OUTPUT:
    Zero if successful, otherwise non-zero
    EXAMPLE:
    sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
    sage: gbe = GLPKGraphBackend()
    sage: gbe.add_vertices([None for i in range(2)])
    ['0', '1']
    sage: a = gbe.add_edge('0', '1')
    sage: gbe.maxflow_ffalg('0', '1')
    sage: gbe.write_maxflow(SAGE_TMP+"/graph.max")
    Writing maximum flow problem data to ...
    6 lines were written
    sage: gbe = GLPKGraphBackend()
    sage: gbe.write_maxflow(SAGE_TMP+"/graph.max")
    Traceback (most recent call last):
    IOError: Cannot write empty graph
write mincost(fname)
    Writes the mincost flow problem data to a text file in DIMACS format
    INPUT:
       •fname - Full name of file
```

## **OUTPUT**:

Zero if successful, otherwise nonzero

## **EXAMPLE:**

```
sage: from sage.numerical.backends.glpk_graph_backend import GLPKGraphBackend
sage: gbe = GLPKGraphBackend()
sage: a = gbe.add_edge("0", "1")
sage: gbe.write_mincost(SAGE_TMP+"/graph.min")
Writing min-cost flow problem data to ...
4 lines were written
0
```

# 6.4 PPL Backend

PPL Backend

#### **AUTHORS:**

• Risan (2012-02): initial implementation

```
class sage.numerical.backends.ppl_backend.PPLBackend
    Bases: sage.numerical.backends.generic_backend.GenericBackend
    x.__init__(...) initializes x; see help(type(x)) for signature
    add_col (indices, coeffs)
        Add a column.
```

# INPUT:

- •indices (list of integers) this list constains the indices of the constraints in which the variable's coefficient is nonzero
- •coeffs (list of real values) associates a coefficient to the variable in each of the constraints in which it appears. Namely, the ith entry of coeffs corresponds to the coefficient of the variable in the constraint represented by the ith entry in indices.

**Note:** indices and coeffs are expected to be of the same length.

# **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.ncols()
0
sage: p.nrows()
0
sage: p.add_linear_constraints(5, 0, None)
sage: p.add_col(range(5), range(5))
sage: p.nrows()
5
```

add\_linear\_constraint (coefficients, lower\_bound, upper\_bound, name=None)

Add a linear constraint.

INPUT:

6.4. PPL Backend 133

- •coefficients an iterable with (c, v) pairs where c is a variable index (integer) and v is a value (real value).
- •lower\_bound a lower bound, either a real value or None
- •upper\_bound an upper bound, either a real value or None
- •name an optional name for this row (default: None)

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.add_variables(5)
4
sage: p.add_linear_constraint(zip(range(5), range(5)), 2.0, 2.0)
sage: p.row(0)
([1, 2, 3, 4], [1, 2, 3, 4])
sage: p.row_bounds(0)
(2.000000000000000, 2.0000000000000)
sage: p.add_linear_constraint( zip(range(5), range(5)), 1.0, 1.0, name='foo')
sage: p.row_name(-1)
'foo'
```

add\_linear\_constraints (number, lower\_bound, upper\_bound, names=None)

Add constraints.

## INPUT:

- •number (integer) the number of constraints to add.
- •lower\_bound a lower bound, either a real value or None
- •upper\_bound an upper bound, either a real value or None
- •names an optional list of names (default: None)

# EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.add_variables(5)
4
sage: p.add_linear_constraints(5, None, 2)
sage: p.row(4)
([], [])
sage: p.row_bounds(4)
(None, 2)
```

 $\begin{tabular}{ll} \textbf{add\_variable} (lower\_bound=0, & upper\_bound=None, & binary=False, & continuous=True, & integer=False, & obj=0, & name=None) \end{tabular}$ 

Add a variable.

This amounts to adding a new column to the matrix. By default, the variable is both positive and real.

It has not been implemented for selecting the variable type yet.

## INPUT:

- •lower\_bound the lower bound of the variable (default: 0)
- •upper\_bound the upper bound of the variable (default: None)
- •binary True if the variable is binary (default: False).

```
•continuous – True if the variable is binary (default: True).
```

- •integer True if the variable is binary (default: False).
- •obj (optional) coefficient of this variable in the objective function (default: 0)
- •name an optional name for the newly added variable (default: None).

OUTPUT: The index of the newly created variable

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.ncols()
1
sage: p.add_variable(lower_bound=-2)
1
sage: p.add_variable(name='x',obj=2/3)
2
sage: p.col_name(2)
'x'
sage: p.objective_coefficient(2)
```

 $add\_variables(n, lower\_bound=0, upper\_bound=None, binary=False, continuous=True, inte-ger=False, obj=0, names=None)$ 

Add n variables.

This amounts to adding new columns to the matrix. By default, the variables are both positive and real.

It has not been implemented for selecting the variable type yet.

## INPUT:

- •n the number of new variables (must be > 0)
- •lower\_bound the lower bound of the variable (default: 0)
- •upper\_bound the upper bound of the variable (default: None)
- •binary True if the variable is binary (default: False).
- •continuous True if the variable is binary (default: True).
- •integer True if the variable is binary (default: False).
- •obj (optional) coefficient of all variables in the objective function (default: 0)
- •names optional list of names (default: None)

OUTPUT: The index of the variable created last.

#### EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.ncols()
0
sage: p.add_variables(5)
4
sage: p.ncols()
```

6.4. PPL Backend 135

```
5
    sage: p.add_variables(2, lower_bound=-2.0, names=['a','b'])
base_ring()
col_bounds (index)
    Return the bounds of a specific variable.
    INPUT:
       •index (integer) - the variable's id.
    OUTPUT:
    A pair (lower_bound, upper_bound). Each of them can be set to None if the variable is not
    bounded in the corresponding direction, and is a real value otherwise.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.add_variable()
    sage: p.col_bounds(0)
    (0, None)
    sage: p.variable_upper_bound(0, 5)
    sage: p.col_bounds(0)
    (0, 5)
col name (index)
    Return the index th col name
    INPUT:
       •index (integer) – the col's id
       •name (char *) - its name. When set to NULL (default), the method returns the current name.
    EXAMPLE:
    sage: from sage.numerical.backends.generic backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.add_variable(name="I am a variable")
    sage: p.col_name(0)
    'I am a variable'
get_objective_value()
    Return the exact value of the objective function.
    Note: Behaviour is undefined unless solve has been called before.
    EXAMPLE:
    sage: from sage.numerical.backends.generic backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.add_variables(2)
```

sage: p.add\_linear\_constraint([(0,1), (1,2)], None, 3)

sage: p.set\_objective([2, 5])

sage: p.solve()

```
osage: p.get_objective_value()
15/2
sage: p.get_variable_value(0)
osage: p.get_variable_value(1)
3/2
```

## get\_variable\_value(variable)

Return the value of a variable given by the solver.

**Note:** Behaviour is undefined unless solve has been called before.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.add_variables(2)
1
sage: p.add_linear_constraint([(0,1), (1, 2)], None, 3)
sage: p.set_objective([2, 5])
sage: p.solve()
0
sage: p.get_objective_value()
15/2
sage: p.get_variable_value(0)
0
sage: p.get_variable_value(1)
3/2
```

# init\_mip()

Converting the matrix form of the MIP Problem to PPL MIP\_Problem.

#### **EXAMPLE**:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.base_ring()
Rational Field
sage: type(p.zero())
<type 'sage.rings.rational.Rational'>
sage: p.init_mip()
```

# is\_maximization()

Test whether the problem is a maximization

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.is_maximization()
True
sage: p.set_sense(-1)
sage: p.is_maximization()
False
```

# is\_variable\_binary (index)

Test whether the given variable is of binary type.

6.4. PPL Backend 137

## **INPUT:**

•index (integer) - the variable's id

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.is_variable_binary(0)
False
```

## is\_variable\_continuous (index)

Test whether the given variable is of continuous/real type.

#### INPUT:

•index (integer) - the variable's id

## **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.is_variable_continuous(0)
True
```

# is\_variable\_integer (index)

Test whether the given variable is of integer type.

### INPUT:

•index (integer) - the variable's id

# EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.is_variable_integer(0)
False
```

# ncols()

Return the number of columns/variables.

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.ncols()
0
sage: p.add_variables(2)
1
sage: p.ncols()
2
```

```
nrows()
```

Return the number of rows/constraints.

```
EXAMPLE:
```

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.nrows()
0
sage: p.add_linear_constraints(2, 2.0, None)
sage: p.nrows()
2
```

# objective\_coefficient (variable, coeff=None)

Set or get the coefficient of a variable in the objective function

## **INPUT:**

```
•variable (integer) - the variable's id
```

•coeff (integer) - its coefficient

#### **EXAMPLE**:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.add_variable()
0
sage: p.objective_coefficient(0)
0
sage: p.objective_coefficient(0,2)
sage: p.objective_coefficient(0)
```

### problem name(name='NULL')

Return or define the problem's name

# INPUT:

•name (char  $\star$ ) – the problem's name. When set to NULL (default), the method returns the problem's name.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.problem_name("There once was a french fry")
sage: print p.problem_name()
There once was a french fry
```

#### row(i)

Return a row

## INPUT:

•index (integer) – the constraint's id.

#### **OUTPUT:**

A pair (indices, coeffs) where indices lists the entries whose coefficient is nonzero, and to which coeffs associates their coefficient on the model of the add\_linear\_constraint method.

EXAMPLE:

6.4. PPL Backend 139

```
sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.add_variables(5)
    sage: p.add_linear_constraint(zip(range(5), range(5)), 2, 2)
    sage: p.row(0)
    ([1, 2, 3, 4], [1, 2, 3, 4])
    sage: p.row_bounds(0)
    (2, 2)
row_bounds (index)
    Return the bounds of a specific constraint.
    INPUT:
       •index (integer) - the constraint's id.
    OUTPUT:
    A pair (lower bound, upper bound). Each of them can be set to None if the constraint is not
    bounded in the corresponding direction, and is a real value otherwise.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.add_variables(5)
    sage: p.add_linear_constraint(zip(range(5), range(5)), 2, 2)
    sage: p.row(0)
    ([1, 2, 3, 4], [1, 2, 3, 4])
    sage: p.row_bounds(0)
    (2, 2)
row name (index)
    Return the index th row name
    INPUT:
       •index (integer) - the row's id
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.add_linear_constraints(1, 2, None, names="Empty constraint 1")
    sage: p.row_name(0)
    'Empty constraint 1'
set\_objective (coeff, d=0)
    Set the objective function.
    INPUT:
       •coeff – a list of real values, whose ith element is the coefficient of the ith variable in the objective
        function.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
```

4

sage: p.add\_variables(5)

```
sage: p.set_objective([1, 1, 2, 1, 3])
    sage: map(lambda x :p.objective_coefficient(x), range(5))
    [1, 1, 2, 1, 3]
set_sense(sense)
    Set the direction (maximization/minimization).
    INPUT:
       •sense (integer):
          -+1 => Maximization
          -1 \Rightarrow Minimization
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.is_maximization()
    True
    sage: p.set_sense(-1)
    sage: p.is_maximization()
    False
set_variable_type (variable, vtype)
    Set the type of a variable.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.add_variables(5)
    sage: p.set_variable_type(3, -1)
    sage: p.set_variable_type(3, -2)
    Traceback (most recent call last):
    Exception: ...
set_verbosity(level)
    Set the log (verbosity) level. Not Implemented.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
    sage: p.set_verbosity(0)
solve()
    Solve the problem.
    Note: This method raises MIPSolverException exceptions when the solution can not be computed
    for any reason (none exists, or the LP solver was not able to find it, etc...)
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "PPL")
```

6.4. PPL Backend 141

sage: p.add\_linear\_constraints(5, 0, None)

```
sage: p.add_col(range(5), range(5))
sage: p.solve()
0
sage: p.objective_coefficient(0,1)
sage: p.solve()
Traceback (most recent call last):
...
MIPSolverException: ...
```

#### variable\_lower\_bound(index, value=False)

Return or define the lower bound on a variable

#### INPUT:

- •index (integer) the variable's id
- •value real value, or None to mean that the variable has not lower bound. When set to None (default), the method returns the current value.

#### EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.add_variable()
0
sage: p.col_bounds(0)
(0, None)
sage: p.variable_lower_bound(0, 5)
sage: p.col_bounds(0)
(5, None)
sage: p.variable_lower_bound(0, None)
sage: p.col_bounds(0)
(None, None)
```

# variable\_upper\_bound(index, value=False)

Return or define the upper bound on a variable

#### INPUT:

- •index (integer) the variable's id
- •value real value, or None to mean that the variable has not upper bound. When set to None (default), the method returns the current value.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "PPL")
sage: p.add_variable()
0
sage: p.col_bounds(0)
(0, None)
sage: p.variable_upper_bound(0, 5)
sage: p.col_bounds(0)
(0, 5)
sage: p.variable_upper_bound(0, None)
sage: p.col_bounds(0)
(0, None)
```

zero()

# 6.5 CVXOPT Backend

#### **CVXOPT** Backend

#### **AUTHORS:**

• Ingolfur Edvardsson (2014-05): initial implementation

```
class sage.numerical.backends.cvxopt_backend.CVXOPTBackend
    Bases: sage.numerical.backends.generic_backend.GenericBackend
    x.__init__(...) initializes x; see help(type(x)) for signature
    add_col (indices, coeffs)
    Add a column.
```

#### INPUT:

- •indices (list of integers) this list constains the indices of the constraints in which the variable's coefficient is nonzero
- •coeffs (list of real values) associates a coefficient to the variable in each of the constraints in which it appears. Namely, the ith entry of coeffs corresponds to the coefficient of the variable in the constraint represented by the ith entry in indices.

Note: indices and coeffs are expected to be of the same length.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.ncols()
0
sage: p.nrows()
0
sage: p.add_linear_constraints(5, 0, None)
sage: p.add_col(range(5), range(5))
sage: p.nrows()
```

add\_linear\_constraint (coefficients, lower\_bound, upper\_bound, name=None)

Add a linear constraint.

#### INPUT:

- •coefficients an iterable with (c, v) pairs where c is a variable index (integer) and v is a value (real value).
- •lower bound a lower bound, either a real value or None
- •upper\_bound an upper bound, either a real value or None
- •name an optional name for this row (default: None)

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variables(5)
4
sage: p.add_linear_constraint(zip(range(5), range(5)), 2.0, 2.0)
sage: p.row(0)
```

```
([1, 2, 3, 4], [1, 2, 3, 4])
    sage: p.row_bounds(0)
    (2.00000000000000, 2.0000000000000)
    sage: p.add_linear_constraint( zip(range(5), range(5)), 1.0, 1.0, name='foo')
    sage: p.row_name(-1)
    'foo'
add_linear_constraints (number, lower_bound, upper_bound, names=None)
    Add constraints.
    INPUT:
       •number (integer) - the number of constraints to add.
       •lower_bound - a lower bound, either a real value or None
       •upper_bound - an upper bound, either a real value or None
       •names - an optional list of names (default: None)
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "CVXOPT")
    sage: p.add_variables(5)
    sage: p.add_linear_constraints(5, None, 2)
    sage: p.row(4)
    ([], [])
    sage: p.row_bounds(4)
     (None, 2)
add_variable(lower_bound=0.0, upper_bound=None, binary=False, continuous=True, inte-
                ger=False, obj=None, name=None)
    Add a variable.
    This amounts to adding a new column to the matrix. By default, the variable is both positive and real.
    INPUT:
       •lower_bound - the lower bound of the variable (default: 0)
       •upper_bound - the upper bound of the variable (default: None)
       •binary - True if the variable is binary (default: False).
       •continuous - True if the variable is binary (default: True).
       •integer - True if the variable is binary (default: False).
       •obj - (optional) coefficient of this variable in the objective function (default: 0.0)
       •name - an optional name for the newly added variable (default: None).
    OUTPUT: The index of the newly created variable
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "CVXOPT")
    sage: p.ncols()
    sage: p.add_variable()
```

sage: p.ncols()

```
sage: p.add_variable(binary=True)
    sage: p.add_variable(lower_bound=-2.0, integer=True)
    sage: p.add_variable(continuous=True, integer=True)
                                                                       # optional - CVXOPT
    Traceback (most recent call last):
    ValueError: ...
    sage: p.add_variable(name='x',obj=1.0)
    sage: p.col_name(3)
    ' x'
    sage: p.objective_coefficient(3)
    1.000000000000000
add_variables (n, lower_bound=None, upper_bound=None, binary=False, continuous=True, inte-
                  ger=False, obj=None, names=None)
    Add n variables.
    This amounts to adding new columns to the matrix. By default, the variables are both positive and real.
    INPUT:
        •n - the number of new variables (must be > 0)
        •lower_bound - the lower bound of the variable (default: 0)
        •upper_bound - the upper bound of the variable (default: None)
        •binary - True if the variable is binary (default: False).
        •continuous - True if the variable is binary (default: True).
        •integer - True if the variable is binary (default: False).
        •obj - (optional) coefficient of all variables in the objective function (default: 0.0)
        •names - optional list of names (default: None)
    OUTPUT: The index of the variable created last.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "CVXOPT")
    sage: p.ncols()
    sage: p.add_variables(5)
    sage: p.ncols()
    sage: p.add_variables(2, lower_bound=-2.0, integer=True, names=['a','b'])
col_bounds (index)
    Return the bounds of a specific variable.
        •index (integer) - the variable's id.
    OUTPUT:
```

A pair (lower\_bound, upper\_bound). Each of them can be set to None if the variable is not bounded in the corresponding direction, and is a real value otherwise.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variable()
0
sage: p.col_bounds(0)
(0.0, None)
sage: p.variable_upper_bound(0, 5)
sage: p.col_bounds(0)
(0.0, 5)
```

#### col\_name (index)

Return the index th col name

#### INPUT:

```
•index (integer) - the col's id
```

•name (char \*) - its name. When set to NULL (default), the method returns the current name.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variable(name="I am a variable")
0
sage: p.col_name(0)
'I am a variable'
```

#### get\_objective\_value()

Return the value of the objective function.

**Note:** Behaviour is undefined unless solve has been called before.

#### **EXAMPLE**:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "cvxopt")
sage: p.add_variables(2)
1
sage: p.add_linear_constraint([(0,1), (1,2)], None, 3)
sage: p.set_objective([2, 5])
sage: p.solve()
0
sage: round(p.get_objective_value(),4)
7.5
sage: round(p.get_variable_value(0),4)
0.0
sage: round(p.get_variable_value(1),4)
1.5
```

#### get\_variable\_value(variable)

Return the value of a variable given by the solver.

Note: Behaviour is undefined unless solve has been called before.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variables(2)
1
sage: p.add_linear_constraint([(0,1), (1, 2)], None, 3)
sage: p.set_objective([2, 5])
sage: p.solve()
0
sage: round(p.get_objective_value(),4)
7.5
sage: round(p.get_variable_value(0),4)
0.0
sage: round(p.get_variable_value(1),4)
1.5
```

#### is\_maximization()

Test whether the problem is a maximization

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.is_maximization()
True
sage: p.set_sense(-1)
sage: p.is_maximization()
False
```

#### is\_variable\_binary(index)

Test whether the given variable is of binary type.

#### INPUT:

•index (integer) - the variable's id

#### EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.ncols()
0
sage: p.add_variable()
0
sage: p.set_variable_type(0,0)  # optional - CVXOPT
sage: p.is_variable_binary(0)  # optional - CVXOPT
```

### is\_variable\_continuous (index)

Test whether the given variable is of continuous/real type.

#### INPUT:

•index (integer) - the variable's id

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.ncols()
0
sage: p.add_variable()
```

```
0
sage: p.is_variable_continuous(0)  # optional - CVXOPT
True
sage: p.set_variable_type(0,1)  # optional - CVXOPT
sage: p.is_variable_continuous(0)  # optional - CVXOPT
False
```

#### is\_variable\_integer(index)

Test whether the given variable is of integer type.

#### INPUT:

•index (integer) - the variable's id

#### EXAMPLE:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT") # optional - CVXOPT
sage: p.ncols() # optional - CVXOPT
0
sage: p.add_variable() # optional - CVXOPT
1
sage: p.set_variable_type(0,1) # optional - CVXOPT
sage: p.is_variable_integer(0) # optional - CVXOPT
True
```

#### ncols()

Return the number of columns/variables.

#### **EXAMPLE**:

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.ncols()
0
sage: p.add_variables(2)
1
sage: p.ncols()
2
```

#### nrows()

Return the number of rows/constraints.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.nrows()
0
sage: p.add_variables(5)
4
sage: p.add_linear_constraints(2, 2.0, None)
sage: p.nrows()
2
```

## objective\_coefficient (variable, coeff=None)

Set or get the coefficient of a variable in the objective function

#### INPUT:

•variable (integer) – the variable's id

```
•coeff (double) - its coefficient
```

```
EXAMPLE:
```

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variable()
0
sage: p.objective_coefficient(0)
0.0
sage: p.objective_coefficient(0,2)
sage: p.objective_coefficient(0)
2.0
```

#### problem\_name (name='NULL')

Return or define the problem's name

#### INPUT:

•name (char \*) - the problem's name. When set to NULL (default), the method returns the problem's name.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.problem_name("There once was a french fry")
sage: print p.problem_name()
There once was a french fry
```

#### row(i)

Return a row

#### INPUT:

•index (integer) – the constraint's id.

#### **OUTPUT**:

A pair (indices, coeffs) where indices lists the entries whose coefficient is nonzero, and to which coeffs associates their coefficient on the model of the add\_linear\_constraint method.

#### **EXAMPLE**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variables(5)
4
sage: p.add_linear_constraint(zip(range(5), range(5)), 2, 2)
sage: p.row(0)
([1, 2, 3, 4], [1, 2, 3, 4])
sage: p.row_bounds(0)
(2, 2)
```

#### row\_bounds (index)

Return the bounds of a specific constraint.

## INPUT:

•index (integer) – the constraint's id.

#### **OUTPUT**:

A pair (lower\_bound, upper\_bound). Each of them can be set to None if the constraint is not bounded in the corresponding direction, and is a real value otherwise.

```
EXAMPLE:
```

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variables(5)
sage: p.add_linear_constraint(zip(range(5), range(5)), 2, 2)
sage: p.row(0)
([1, 2, 3, 4], [1, 2, 3, 4])
sage: p.row_bounds(0)
(2, 2)
```

#### row\_name (index)

Return the index th row name

#### INPUT:

•index (integer) - the row's id

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_linear_constraints(1, 2, None, names="Empty constraint 1")
sage: p.row_name(0)
'Empty constraint 1'
```

#### set objective (coeff, d=0.0)

Set the objective function.

### INPUT:

- •coeff a list of real values, whose ith element is the coefficient of the ith variable in the objective function.
- •d (double) the constant term in the linear function (set to 0 by default)

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variables(5)
sage: p.set_objective([1, 1, 2, 1, 3])
sage: map(lambda x :p.objective_coefficient(x), range(5))
[1, 1, 2, 1, 3]
```

### set\_sense(sense)

Set the direction (maximization/minimization).

#### INPUT:

**EXAMPLE:** 

```
•sense (integer):
    -+1 => Maximization
    -1 \Rightarrow Minimization
```

```
sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "CVXOPT")
    sage: p.is_maximization()
    True
    sage: p.set_sense(-1)
    sage: p.is_maximization()
    False
set_variable_type (variable, vtype)
    Set the type of a variable.
    EXAMPLE:
    sage: from sage.numerical.backends.generic_backend import get_solver
    sage: p = get_solver(solver = "cvxopt")
    sage: p.add_variables(5)
    sage: p.set_variable_type(3, -1)
    sage: p.set_variable_type(3, -2)
    Traceback (most recent call last):
    Exception: ...
set_verbosity(level)
    Does not apply for the cvxopt solver
solve()
    Solve the problem.
```

**Note:** This method raises MIPSolverException exceptions when the solution can not be computed for any reason (none exists, or the LP solver was not able to find it, etc...)

# **EXAMPLE:**

```
sage: p = MixedIntegerLinearProgram(solver = "cvxopt", maximization=False)
sage: x=p.new_variable(nonnegative=True)
sage: p.set_objective(-4 \times x[0] - 5 \times x[1])
sage: p.add_constraint(2 \times x[0] + x[1] \le 3)
sage: p.add_constraint(2 \times x[1] + x[0] \le 3)
sage: round(p.solve(), 2)
-9.0
sage: p = MixedIntegerLinearProgram(solver = "cvxopt", maximization=False)
sage: x=p.new_variable(nonnegative=True)
sage: p.set_objective(x[0] + 2*x[1])
sage: p.add_constraint(-5*x[0] + x[1]
sage: p.add_constraint(-5*x[0] + x[1] >=
sage: p.add_constraint(x[0] + x[1] >= 26 )
sage: p.add_constraint( x[0] >= 3)
sage: p.add_constraint( x[1] >= 4)
sage: round(p.solve(),2)
48.83
sage: p = MixedIntegerLinearProgram(solver = "cvxopt")
sage: x=p.new_variable(nonnegative=True)
sage: p.set_objective(x[0] + x[1] + 3*x[2])
sage: p.solver_parameter("show_progress", True)
sage: p.add_constraint(x[0] + 2*x[1] <= 4)
sage: p.add_constraint(5*x[2] - x[1] \le 8)
sage: round(p.solve(), 2)
```

```
pcost
                          dcost
                                               pres
                                                       dres
                                                              k/t
                                        gap
         . . .
        8.8
    sage: #CVXOPT gives different values for variables compared to the other solvers.
    sage: c = MixedIntegerLinearProgram(solver = "cvxopt")
    sage: p = MixedIntegerLinearProgram(solver = "ppl")
    sage: g = MixedIntegerLinearProgram()
    sage: xc=c.new_variable(nonnegative=True)
    sage: xp=p.new_variable(nonnegative=True)
    sage: xg=g.new_variable(nonnegative=True)
    sage: c.set_objective(xc[2])
    sage: p.set_objective(xp[2])
    sage: g.set_objective(xg[2])
    sage: #we create a cube for all three solvers
    sage: c.add_constraint(xc[0] <= 100)</pre>
    sage: c.add_constraint(xc[1] <= 100)</pre>
    sage: c.add_constraint(xc[2] <= 100)</pre>
    sage: p.add_constraint(xp[0] <= 100)</pre>
    sage: p.add_constraint(xp[1] <= 100)</pre>
    sage: p.add_constraint(xp[2] <= 100)</pre>
    sage: g.add_constraint(xg[0] <= 100)</pre>
    sage: g.add_constraint(xg[1] <= 100)</pre>
    sage: g.add_constraint(xg[2] <= 100)</pre>
    sage: round(c.solve(),2)
    100.0
    sage: round(c.get_values(xc[0]),2)
    50.0
    sage: round(c.get_values(xc[1]),2)
    50.0
    sage: round(c.get_values(xc[2]),2)
    100.0
    sage: round(p.solve(),2)
    100.0
    sage: round(p.get_values(xp[0]),2)
    0.0
    sage: round(p.get_values(xp[1]),2)
    0.0
    sage: round(p.get_values(xp[2]),2)
    100.0
    sage: round(g.solve(),2)
    100.0
    sage: round(g.get_values(xg[0]),2)
    sage: round(g.get_values(xg[1]),2)
    sage: round(g.get_values(xg[2]),2)
    100.0
solver parameter(name, value=None)
    Return or define a solver parameter
```

#### INPUT:

•name (string) – the parameter

•value – the parameter's value if it is to be defined, or None (default) to obtain its current value.

**Note:** The list of available parameters is available at solver\_parameter().

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.solver_parameter("show_progress")
False
sage: p.solver_parameter("show_progress", True)
sage: p.solver_parameter("show_progress")
True
```

#### variable lower bound(index, value=None)

Return or define the lower bound on a variable

#### INPUT:

- •index (integer) the variable's id
- •value real value, or None to mean that the variable has not lower bound. When set to None (default), the method returns the current value.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variable()
0
sage: p.col_bounds(0)
(0.0, None)
sage: p.variable_lower_bound(0, 5)
sage: p.col_bounds(0)
(5, None)
```

## variable\_upper\_bound (index, value=None)

Return or define the upper bound on a variable

#### INPUT:

- •index (integer) the variable's id
- •value real value, or None to mean that the variable has not upper bound. When set to None (default), the method returns the current value.

#### **EXAMPLE:**

```
sage: from sage.numerical.backends.generic_backend import get_solver
sage: p = get_solver(solver = "CVXOPT")
sage: p.add_variable()
0
sage: p.col_bounds(0)
(0.0, None)
sage: p.variable_upper_bound(0, 5)
sage: p.col_bounds(0)
(0.0, 5)
```

Sage also supports CBC (COIN-OR), CPLEX (ILOG), Gurobi, CVXOPT and PPL. In order to find out how to use them in Sage, please refer to the Thematic Tutorial on Linear Programming.

age Reference Manual: Numerical Optimization, Release 6.3	
- <b>-</b>	

**CHAPTER** 

**SEVEN** 

# **INDICES AND TABLES**

- Index
- Module Index
- Search Page

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158 Bibliography

# **PYTHON MODULE INDEX**

### n

```
sage.numerical.backends.cvxopt_backend, 143
sage.numerical.backends.generic_backend, 89
sage.numerical.backends.glpk_backend, 102
sage.numerical.backends.glpk_graph_backend, 121
sage.numerical.backends.ppl_backend, 133
sage.numerical.interactive_simplex_method, 51
sage.numerical.knapsack, 1
sage.numerical.linear_functions, 35
sage.numerical.mip, 9
sage.numerical.optimize, 43
```

160 Python Module Index

# INDEX

# Α

```
A() (sage.numerical.interactive_simplex_method.LPProblem method), 64
A() (sage.numerical.interactive_simplex_method.LPRevisedDictionary method), 80
A N() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 80
Abcx() (sage.numerical.interactive simplex method.LPProblem method), 64
add col() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 143
add col() (sage.numerical.backends.generic backend.GenericBackend method), 89
add_col() (sage.numerical.backends.glpk_backend.GLPKBackend method), 102
add_col() (sage.numerical.backends.ppl_backend.PPLBackend method), 133
add constraint() (sage.numerical.mip.MixedIntegerLinearProgram method), 14
add_edge() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 123
add edges() (sage.numerical.backends.glpk graph backend.GLPKGraphBackend method), 123
add linear constraint() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 143
add_linear_constraint() (sage.numerical.backends.generic_backend.GenericBackend method), 90
add_linear_constraint() (sage.numerical.backends.glpk_backend.GLPKBackend method), 102
add linear constraint() (sage.numerical.backends.ppl backend.PPLBackend method), 133
add linear constraints() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 144
add linear constraints() (sage.numerical.backends.generic backend.GenericBackend method), 90
add_linear_constraints() (sage.numerical.backends.glpk_backend.GLPKBackend method), 103
add_linear_constraints() (sage.numerical.backends.ppl_backend.PPLBackend method), 134
add variable() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 144
add_variable() (sage.numerical.backends.generic_backend.GenericBackend method), 90
add_variable() (sage.numerical.backends.glpk_backend.GLPKBackend method), 103
add variable() (sage.numerical.backends.ppl backend.PPLBackend method), 134
add_variables() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 145
add_variables() (sage.numerical.backends.generic_backend.GenericBackend method), 91
add variables() (sage.numerical.backends.glpk backend.GLPKBackend method), 104
add variables() (sage.numerical.backends.ppl backend.PPLBackend method), 135
add_vertex() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 124
add_vertices() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 124
auxiliary_problem() (sage.numerical.interactive_simplex_method.LPProblemStandardForm method), 72
auxiliary variable() (sage.numerical.interactive simplex method.LPProblemStandardForm method), 73
```

# В

b() (sage.numerical.interactive\_simplex\_method.LPProblem method), 65 B() (sage.numerical.interactive\_simplex\_method.LPRevisedDictionary method), 80

```
B inverse() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 80
base_ring() (sage.numerical.backends.generic_backend.GenericBackend method), 92
base_ring() (sage.numerical.backends.ppl_backend.PPLBackend method), 136
base ring() (sage.numerical.interactive simplex method.LPAbstractDictionary method), 53
base_ring() (sage.numerical.interactive_simplex_method.LPProblem method), 65
base_ring() (sage.numerical.mip.MixedIntegerLinearProgram method), 17
basic indices() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 82
basic solution() (sage.numerical.interactive simplex method.LPAbstractDictionary method), 53
basic_variables() (sage.numerical.interactive_simplex_method.LPDictionary method), 61
basic variables() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 82
binpacking() (in module sage.numerical.optimize), 43
C
c() (sage.numerical.interactive simplex method.LPProblem method), 65
c B() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 82
c N() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 82
col bounds() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 145
col bounds() (sage.numerical.backends.generic backend.GenericBackend method), 92
col_bounds() (sage.numerical.backends.glpk_backend.GLPKBackend method), 105
col_bounds() (sage.numerical.backends.ppl_backend.PPLBackend method), 136
col name() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 146
col_name() (sage.numerical.backends.generic_backend.GenericBackend method), 92
col_name() (sage.numerical.backends.glpk_backend.GLPKBackend method), 105
col_name() (sage.numerical.backends.ppl_backend.PPLBackend method), 136
constant terms() (sage.numerical.interactive simplex method.LPDictionary method), 61
constant terms() (sage.numerical.interactive simplex method.LPProblem method), 66
constant terms() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 83
constraint_coefficients() (sage.numerical.interactive_simplex_method.LPProblem method), 66
constraints() (sage.numerical.mip.MixedIntegerLinearProgram method), 17
coordinate_ring() (sage.numerical.interactive_simplex_method.LPAbstractDictionary method), 54
coordinate ring() (sage.numerical.interactive simplex method.LPProblemStandardForm method), 73
copy() (sage.numerical.backends.glpk_backend.GLPKBackend method), 105
cpp() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 125
CVXOPTBackend (class in sage.numerical.backends.cvxopt backend), 143
D
decision variables() (sage.numerical.interactive simplex method.LPProblem method), 66
default_mip_solver() (in module sage.numerical.backends.generic_backend), 100
delete_edge() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 125
delete_edges() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 126
delete_vertex() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 126
delete vertices() (sage.numerical.backends.glpk graph backend.GLPKGraphBackend method), 126
depth() (sage.numerical.mip.MIPVariable method), 11
dict() (sage.numerical.linear_functions.LinearFunction method), 39
dictionary() (sage.numerical.interactive simplex method.LPProblemStandardForm method), 73
dictionary() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 83
dual() (sage.numerical.interactive_simplex_method.LPProblem method), 66
dual_ratios() (sage.numerical.interactive_simplex_method.LPAbstractDictionary method), 54
```

```
F
E() (sage.numerical.interactive_simplex_method.LPRevisedDictionary method), 81
E inverse() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 81
edges() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 127
ELLUL() (sage.numerical.interactive simplex method.LPDictionary method), 60
enter() (sage.numerical.interactive simplex method.LPAbstractDictionary method), 55
entering_coefficients() (sage.numerical.interactive_simplex_method.LPDictionary method), 61
entering_coefficients() (sage.numerical.interactive_simplex_method.LPRevisedDictionary method), 83
equals() (sage.numerical.linear_functions.LinearConstraint method), 36
equals() (sage.numerical.linear functions.LinearFunction method), 40
equations() (sage.numerical.linear functions.LinearConstraint method), 37
F
feasible dictionary() (sage.numerical.interactive simplex method.LPProblemStandardForm method), 74
feasible_set() (sage.numerical.interactive_simplex_method.LPProblem method), 67
final_dictionary() (sage.numerical.interactive_simplex_method.LPProblemStandardForm method), 74
final_revised_dictionary() (sage.numerical.interactive_simplex_method.LPProblemStandardForm method), 75
find_fit() (in module sage.numerical.optimize), 44
find local maximum() (in module sage.numerical.optimize), 45
find_local_minimum() (in module sage.numerical.optimize), 45
find root() (in module sage.numerical.optimize), 46
G
GenericBackend (class in sage.numerical.backends.generic_backend), 89
get backend() (sage.numerical.mip.MixedIntegerLinearProgram method), 18
get_col_dual() (sage.numerical.backends.glpk_backend.GLPKBackend method), 105
get edge() (sage.numerical.backends.glpk graph backend.GLPKGraphBackend method), 127
get max() (sage.numerical.mip.MixedIntegerLinearProgram method), 18
get_min() (sage.numerical.mip.MixedIntegerLinearProgram method), 19
get_objective_value() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 146
get objective value() (sage.numerical.backends.generic backend.GenericBackend method), 92
get_objective_value() (sage.numerical.backends.glpk_backend.GLPKBackend method), 106
get objective value() (sage.numerical.backends.ppl backend.PPLBackend method), 136
get_row_dual() (sage.numerical.backends.glpk_backend.GLPKBackend method), 106
get solver() (in module sage.numerical.backends.generic backend), 101
get values() (sage.numerical.mip.MixedIntegerLinearProgram method), 19
get_variable_value() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 146
get_variable_value() (sage.numerical.backends.generic_backend.GenericBackend method), 93
get variable value() (sage.numerical.backends.glpk backend.GLPKBackend method), 107
get_variable_value() (sage.numerical.backends.ppl_backend.PPLBackend method), 137
get_vertex() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 128
get_vertices() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 128
GLPKBackend (class in sage.numerical.backends.glpk_backend), 102
GLPKGraphBackend (class in sage.numerical.backends.glpk_graph_backend), 121
inequalities() (sage.numerical.linear functions.LinearConstraint method), 37
init_mip() (sage.numerical.backends.ppl_backend.PPLBackend method), 137
```

initial\_dictionary() (sage.numerical.interactive\_simplex\_method.LPProblemStandardForm method), 75 inject\_variables() (sage.numerical.interactive\_simplex\_method.LPProblemStandardForm method), 75

```
is binary() (sage.numerical.mip.MixedIntegerLinearProgram method), 20
is_bounded() (sage.numerical.interactive_simplex_method.LPProblem method), 67
is dual feasible() (sage.numerical.interactive simplex method.LPAbstractDictionary method), 55
is equation() (sage.numerical.linear functions.LinearConstraint method), 37
is_feasible() (sage.numerical.interactive_simplex_method.LPAbstractDictionary method), 56
is_feasible() (sage.numerical.interactive_simplex_method.LPProblem method), 67
is integer() (sage.numerical.mip.MixedIntegerLinearProgram method), 21
is less or equal() (sage.numerical.linear functions.LinearConstraint method), 38
is_LinearConstraint() (in module sage.numerical.linear_functions), 41
is LinearFunction() (in module sage.numerical.linear functions), 42
is maximization() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 147
is maximization() (sage.numerical.backends.generic backend.GenericBackend method), 93
is_maximization() (sage.numerical.backends.glpk_backend.GLPKBackend method), 107
is maximization() (sage.numerical.backends.ppl backend.PPLBackend method), 137
is optimal() (sage.numerical.interactive simplex method.LPAbstractDictionary method), 56
is_real() (sage.numerical.mip.MixedIntegerLinearProgram method), 21
is_superincreasing() (sage.numerical.knapsack.Superincreasing method), 3
is trivial() (sage.numerical.linear functions.LinearConstraint method), 38
is variable binary() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 147
is_variable_binary() (sage.numerical.backends.generic_backend.GenericBackend method), 93
is_variable_binary() (sage.numerical.backends.glpk_backend.GLPKBackend method), 107
is variable binary() (sage.numerical.backends.ppl backend.PPLBackend method), 137
is_variable_continuous() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 147
is_variable_continuous() (sage.numerical.backends.generic_backend.GenericBackend method), 94
is_variable_continuous() (sage.numerical.backends.glpk_backend.GLPKBackend method), 108
is variable continuous() (sage.numerical.backends.ppl backend.PPLBackend method), 138
is_variable_integer() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 148
is_variable_integer() (sage.numerical.backends.generic_backend.GenericBackend method), 94
is variable integer() (sage.numerical.backends.glpk backend.GLPKBackend method), 108
is variable integer() (sage.numerical.backends.ppl backend.PPLBackend method), 138
is zero() (sage.numerical.linear functions.LinearFunction method), 40
items() (sage.numerical.mip.MIPVariable method), 12
iteritems() (sage.numerical.linear functions.LinearFunction method), 40
K
keys() (sage.numerical.mip.MIPVariable method), 12
knapsack() (in module sage.numerical.knapsack), 6
L
largest less than() (sage.numerical.knapsack.Superincreasing method), 4
leave() (sage.numerical.interactive simplex method.LPAbstractDictionary method), 56
leaving coefficients() (sage.numerical.interactive simplex method.LPDictionary method), 62
leaving coefficients() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 84
linear_constraints_parent() (sage.numerical.mip.MixedIntegerLinearProgram method), 21
linear_function() (sage.numerical.mip.MixedIntegerLinearProgram method), 21
linear_functions_parent() (sage.numerical.linear_functions.LinearConstraintsParent_class method), 39
linear_functions_parent() (sage.numerical.mip.MixedIntegerLinearProgram method), 22
linear_program() (in module sage.numerical.optimize), 47
LinearConstraint (class in sage.numerical.linear_functions), 36
LinearConstraintsParent() (in module sage.numerical.linear functions), 38
```

```
LinearConstraintsParent class (class in sage.numerical.linear functions), 38
LinearFunction (class in sage.numerical.linear_functions), 39
LinearFunctionsParent() (in module sage.numerical.linear functions), 40
LinearFunctionsParent class (class in sage.numerical.linear functions), 41
LPAbstractDictionary (class in sage.numerical.interactive_simplex_method), 53
LPDictionary (class in sage.numerical.interactive_simplex_method), 59
LPProblem (class in sage.numerical.interactive simplex method), 63
LPProblemStandardForm (class in sage.numerical.interactive simplex method), 71
LPRevisedDictionary (class in sage.numerical.interactive_simplex_method), 78
M
m() (sage.numerical.interactive_simplex_method.LPProblem method), 68
maxflow ffalg() (sage.numerical.backends.glpk graph backend.GLPKGraphBackend method), 129
mincost okalg() (sage.numerical.backends.glpk graph backend.GLPKGraphBackend method), 129
minimize() (in module sage.numerical.optimize), 48
minimize_constrained() (in module sage.numerical.optimize), 49
MIPSolverException, 11
MIPVariable (class in sage.numerical.mip), 11
MixedIntegerLinearProgram (class in sage.numerical.mip), 13
Ν
n() (sage.numerical.interactive_simplex_method.LPProblem method), 68
n constraints() (sage.numerical.interactive simplex method.LPProblem method), 68
n_variables() (sage.numerical.interactive_simplex_method.LPProblem method), 68
ncols() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 148
ncols() (sage.numerical.backends.generic_backend.GenericBackend method), 94
ncols() (sage.numerical.backends.glpk backend.GLPKBackend method), 108
ncols() (sage.numerical.backends.ppl backend.PPLBackend method), 138
new variable() (sage.numerical.mip.MixedIntegerLinearProgram method), 22
nonbasic indices() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 84
nonbasic variables() (sage.numerical.interactive simplex method.LPDictionary method), 62
nonbasic_variables() (sage.numerical.interactive_simplex_method.LPRevisedDictionary method), 84
nrows() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 148
nrows() (sage.numerical.backends.generic backend.GenericBackend method), 95
nrows() (sage.numerical.backends.glpk_backend.GLPKBackend method), 109
nrows() (sage.numerical.backends.ppl_backend.PPLBackend method), 138
number_of_constraints() (sage.numerical.mip.MixedIntegerLinearProgram method), 23
number of variables() (sage.numerical.mip.MixedIntegerLinearProgram method), 23
\mathbf{O}
objective_coefficient() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 148
objective coefficient() (sage.numerical.backends.generic backend.GenericBackend method), 95
objective_coefficient() (sage.numerical.backends.glpk_backend.GLPKBackend method), 109
objective_coefficient() (sage.numerical.backends.ppl_backend.PPLBackend method), 139
objective coefficients() (sage.numerical.interactive simplex method.LPDictionary method), 62
objective coefficients() (sage.numerical.interactive simplex method.LPProblem method), 69
objective coefficients() (sage.numerical.interactive simplex method.LPRevisedDictionary method), 84
objective_value() (sage.numerical.interactive_simplex_method.LPDictionary method), 62
objective_value() (sage.numerical.interactive_simplex_method.LPRevisedDictionary method), 85
optimal solution() (sage.numerical.interactive simplex method.LPProblem method), 69
```

```
optimal value() (sage.numerical.interactive simplex method.LPProblem method), 69
plot() (sage.numerical.interactive simplex method.LPProblem method), 69
plot feasible set() (sage.numerical.interactive simplex method.LPProblem method), 70
polyhedron() (sage.numerical.mip.MixedIntegerLinearProgram method), 24
possible_dual_simplex_method_steps() (sage.numerical.interactive_simplex_method.LPAbstractDictionary method),
possible entering() (sage.numerical.interactive simplex method.LPAbstractDictionary method), 57
possible leaving() (sage.numerical.interactive simplex method.LPAbstractDictionary method), 58
possible_simplex_method_steps() (sage.numerical.interactive_simplex_method.LPAbstractDictionary method), 58
PPLBackend (class in sage.numerical.backends.ppl backend), 133
print ranges() (sage.numerical.backends.glpk backend.GLPKBackend method), 109
problem() (sage.numerical.interactive_simplex_method.LPRevisedDictionary method), 85
problem name() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 149
problem_name() (sage.numerical.backends.generic_backend.GenericBackend method), 95
problem_name() (sage.numerical.backends.glpk_backend.GLPKBackend method), 110
problem name() (sage.numerical.backends.ppl backend.PPLBackend method), 139
R
random_dictionary() (in module sage.numerical.interactive_simplex_method), 86
ratios() (sage.numerical.interactive_simplex_method.LPAbstractDictionary method), 58
remove constraint() (sage.numerical.backends.generic backend.GenericBackend method), 95
remove_constraint() (sage.numerical.backends.glpk_backend.GLPKBackend method), 110
remove constraint() (sage.numerical.mip.MixedIntegerLinearProgram method), 25
remove constraints() (sage.numerical.backends.generic backend.GenericBackend method), 96
remove constraints() (sage.numerical.backends.glpk backend.GLPKBackend method), 111
remove_constraints() (sage.numerical.mip.MixedIntegerLinearProgram method), 25
revised dictionary() (sage.numerical.interactive simplex method.LPProblemStandardForm method), 76
row() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 149
row() (sage.numerical.backends.generic backend.GenericBackend method), 96
row() (sage.numerical.backends.glpk_backend.GLPKBackend method), 111
row() (sage.numerical.backends.ppl_backend.PPLBackend method), 139
row bounds() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 149
row_bounds() (sage.numerical.backends.generic_backend.GenericBackend method), 96
row_bounds() (sage.numerical.backends.glpk_backend.GLPKBackend method), 112
row bounds() (sage.numerical.backends.ppl backend.PPLBackend method), 140
row name() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 150
row_name() (sage.numerical.backends.generic_backend.GenericBackend method), 97
row name() (sage.numerical.backends.glpk backend.GLPKBackend method), 112
row name() (sage.numerical.backends.ppl backend.PPLBackend method), 140
run_revised_simplex_method() (sage.numerical.interactive_simplex_method.LPProblemStandardForm method), 76
run_simplex_method() (sage.numerical.interactive_simplex_method.LPProblemStandardForm method), 77
sage.numerical.backends.cvxopt_backend (module), 143
sage.numerical.backends.generic backend (module), 89
sage.numerical.backends.glpk backend (module), 102
sage.numerical.backends.glpk_graph_backend (module), 121
sage.numerical.backends.ppl_backend (module), 133
```

```
sage.numerical.interactive simplex method (module), 51
sage.numerical.knapsack (module), 1
sage.numerical.linear functions (module), 35
sage.numerical.mip (module), 9
sage.numerical.optimize (module), 43
set_binary() (sage.numerical.mip.MixedIntegerLinearProgram method), 26
set integer() (sage.numerical.mip.MixedIntegerLinearProgram method), 27
set max() (sage.numerical.mip.MIPVariable method), 12
set max() (sage.numerical.mip.MixedIntegerLinearProgram method), 27
set min() (sage.numerical.mip.MIPVariable method), 12
set min() (sage.numerical.mip.MixedIntegerLinearProgram method), 28
set multiplication symbol() (sage.numerical.linear functions.LinearFunctionsParent class method), 41
set objective() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 150
set objective() (sage.numerical.backends.generic backend.GenericBackend method), 97
set objective() (sage.numerical.backends.glpk backend.GLPKBackend method), 112
set_objective() (sage.numerical.backends.ppl_backend.PPLBackend method), 140
set_objective() (sage.numerical.mip.MixedIntegerLinearProgram method), 28
set problem name() (sage.numerical.mip.MixedIntegerLinearProgram method), 29
set real() (sage.numerical.mip.MixedIntegerLinearProgram method), 29
set sense() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 150
set sense() (sage.numerical.backends.generic backend.GenericBackend method), 97
set sense() (sage.numerical.backends.glpk backend.GLPKBackend method), 113
set_sense() (sage.numerical.backends.ppl_backend.PPLBackend method), 141
set variable type() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 151
set_variable_type() (sage.numerical.backends.generic_backend.GenericBackend method), 98
set variable type() (sage.numerical.backends.glpk backend.GLPKBackend method), 113
set_variable_type() (sage.numerical.backends.ppl_backend.PPLBackend method), 141
set_verbosity() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 151
set verbosity() (sage.numerical.backends.generic backend.GenericBackend method), 98
set verbosity() (sage.numerical.backends.glpk backend.GLPKBackend method), 114
set verbosity() (sage.numerical.backends.ppl backend.PPLBackend method), 141
set vertex demand() (sage.numerical.backends.glpk graph backend.GLPKGraphBackend method), 130
set vertices demand() (sage.numerical.backends.glpk graph backend.GLPKGraphBackend method), 131
show() (sage.numerical.mip.MixedIntegerLinearProgram method), 29
slack variables() (sage.numerical.interactive simplex method.LPProblemStandardForm method), 78
solve() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 151
solve() (sage.numerical.backends.generic_backend.GenericBackend method), 98
solve() (sage.numerical.backends.glpk backend.GLPKBackend method), 114
solve() (sage.numerical.backends.ppl_backend.PPLBackend method), 141
solve() (sage.numerical.mip.MixedIntegerLinearProgram method), 30
solver parameter() (sage.numerical.backends.cvxopt backend.CVXOPTBackend method), 152
solver parameter() (sage.numerical.backends.generic backend.GenericBackend method), 99
solver_parameter() (sage.numerical.backends.glpk_backend.GLPKBackend method), 115
solver parameter() (sage.numerical.mip.MixedIntegerLinearProgram method), 31
standard form() (sage.numerical.interactive simplex method.LPProblem method), 71
subset sum() (sage.numerical.knapsack.Superincreasing method), 5
Sum() (in module sage.numerical.mip), 33
sum() (sage.numerical.mip.MixedIntegerLinearProgram method), 32
Superincreasing (class in sage.numerical.knapsack), 2
```

# U

update() (sage.numerical.interactive\_simplex\_method.LPDictionary method), 63 update() (sage.numerical.interactive\_simplex\_method.LPRevisedDictionary method), 85

# ٧

```
variable() (in module sage.numerical.mip.MIPVariable method), 13
variable() (in module sage.numerical.interactive_simplex_method), 87
variable_lower_bound() (sage.numerical.backends.cvxopt_backend.CVXOPTBackend method), 153
variable_lower_bound() (sage.numerical.backends.generic_backend.GenericBackend method), 99
variable_lower_bound() (sage.numerical.backends.glpk_backend.GLPKBackend method), 119
variable_lower_bound() (sage.numerical.backends.cvxopt_backend.PPLBackend method), 142
variable_upper_bound() (sage.numerical.backends.generic_backend.GenericBackend method), 153
variable_upper_bound() (sage.numerical.backends.glpk_backend.GLPKBackend method), 199
variable_upper_bound() (sage.numerical.backends.ppl_backend.PPLBackend method), 119
variable_upper_bound() (sage.numerical.backends.ppl_backend.PPLBackend method), 142
vertices() (sage.numerical.backends.glpk_graph_backend.GLPKGraphBackend method), 131
```

# W

write\_ccdata() (sage.numerical.backends.glpk\_graph\_backend.GLPKGraphBackend method), 131 write\_graph() (sage.numerical.backends.glpk\_graph\_backend.GLPKGraphBackend method), 132 write\_lp() (sage.numerical.backends.generic\_backend.GenericBackend method), 100 write\_lp() (sage.numerical.backends.glpk\_backend.GLPKBackend method), 120 write\_lp() (sage.numerical.mip.MixedIntegerLinearProgram method), 33 write\_maxflow() (sage.numerical.backends.glpk\_graph\_backend.GLPKGraphBackend method), 132 write\_mincost() (sage.numerical.backends.glpk\_graph\_backend.GLPKGraphBackend method), 132 write\_mps() (sage.numerical.backends.glpk\_graph\_backend.GLPKBackend method), 100 write\_mps() (sage.numerical.backends.glpk\_backend.GLPKBackend method), 120 write\_mps() (sage.numerical.mip.MixedIntegerLinearProgram method), 33

# Χ

x() (sage.numerical.interactive\_simplex\_method.LPProblem method), 71 x\_B() (sage.numerical.interactive\_simplex\_method.LPRevisedDictionary method), 86 x\_N() (sage.numerical.interactive\_simplex\_method.LPRevisedDictionary method), 86

#### Υ

y() (sage.numerical.interactive\_simplex\_method.LPRevisedDictionary method), 86

# Ζ

zero() (sage.numerical.backends.generic\_backend.GenericBackend method), 100 zero() (sage.numerical.backends.ppl\_backend.PPLBackend method), 142