

INTRODUCTION TO THE USE OF SOLVERS WITH PYTHON

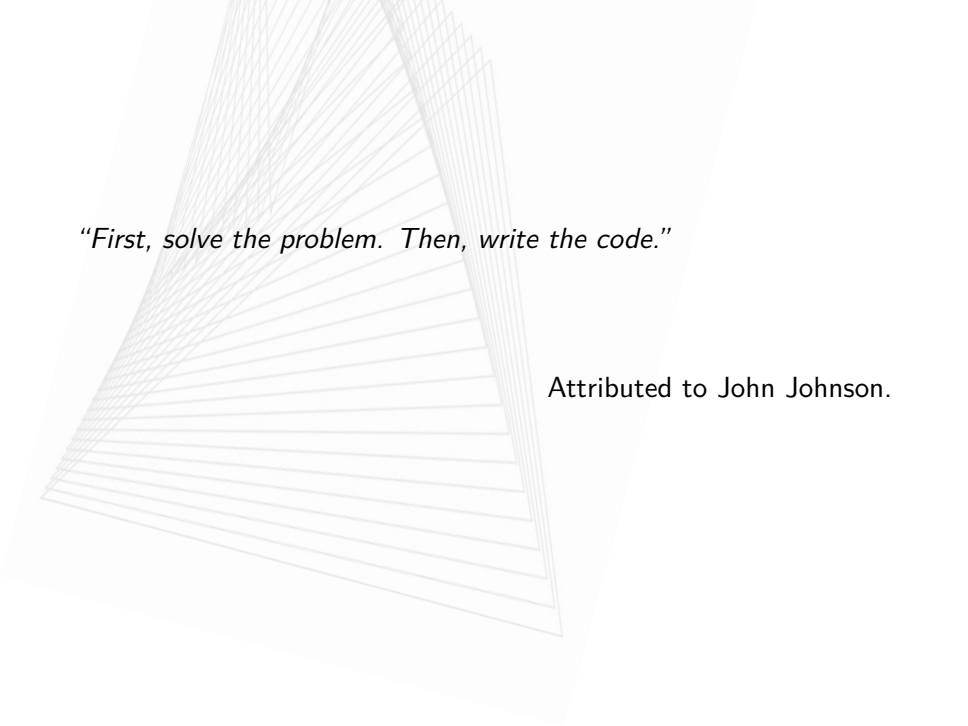
Integer linear programming:
formulations, techniques and
applications.

14

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October,
2020



The background features a series of overlapping, semi-transparent triangles and lines that create a sense of depth and movement. The lines are thin and light gray, while the triangles are slightly more opaque. The overall effect is a modern, minimalist geometric design.

“First, solve the problem. Then, write the code.”

Attributed to John Johnson.



1 Introduction

2 PuLP

- Coding formulations
- Solving formulations

3 DipPy

The background features a series of overlapping, semi-transparent triangles and lines that create a sense of depth and geometric complexity. The lines are thin and light gray, while the triangles are slightly darker, all set against a white background.

INTRODUCTION

Commercial solvers

IBM
CPLEX

FICOTM



GUROBI
OPTIMIZATION

Non-commercial solvers



[Home](#) / [Browse](#) / [Development](#) / [Algorithms](#) / [Ipsolve](#)





Ipsolve

Mixed Integer Linear Programming (MILP) solver
Brought to you by: [keikland](#), [peno64](#)

GLPK (GNU Linear Programming Kit)



Why python?

- ▶ Very intuitive and easy-to-program language.
- ▶ Growing community and popularity:
 - ▶ 3rd in TIOBE index .
 - ▶ 2nd in GitHub .
- ▶ Common interfaces for different solvers (e.g., **PuLP/DipPy**):
 - ▶ Simplifies the formulations coding.
 - ▶ Facilitates to embed solvers calls in algorithm solutions (e.g., matheuristics) or in software applications.



PuLP

Description

PuLP is a linear programming modeler written in Python and able to integrate with different solvers.

The main classes for coding formulations are **LpProblem**, **LpVariable**, **LpConstraint** and **LpConstraintVar**.

The solvers interfaces are given by the classes **LpSolver** and **LpSolver_CMD**.

Access documentation here 

Coding formulations

Import **PuLP** classes and functions: `from pulp import *`

Define the variables:

- ▶ `myVariable = LpVariable(name, lowBound = None, upBound = None, cat = 'Continuous', e = None)`
- ▶ `myVariables = LpVariable.dicts(name, indexs, lowBound = None, upBound = None, cat = 0)`

Define the problem:

- ▶ `myProblem = LpProblem("name", LpMinimize)`
- ▶ `myProblem = LpProblem("name", LpMaximize)`

Define the objective function: `myProblem += expression, name`

Define the constraints:

- ▶ `myProblem += expression <= value`
- ▶ `myProblem += expression == value`
- ▶ `myProblem += expression >= value`

Coding formulations. Simple example

Consider the following problem:

$$\max \quad 3 \times x + 2 \times y$$

s.t. :

$$x - y + z = 1$$

$$x + 2 \times y \leq 14$$

$$4 \times x + y \leq 20$$

$$x, y \in \mathbb{Z}_+, z \in \mathbb{R}_+$$

Coding formulations. Simple example

$\max \quad 3 \times x + 2 \times y$
 $s.t. : \quad$
 $x - y + z = 1$
 $x + 2 \times y \leq 14$
 $4 \times x + y \leq 20$
 $x, y \in \mathbb{Z}_+, z \in \mathbb{R}_+$

```
1 from pulp import *
2
3 x = LpVariable("x", lowBound = 0, cat = 'Integer')
4 y = LpVariable("y", lowBound = 0, cat = 'Integer')
5 z = LpVariable("z", lowBound = 0)
6
7 problem = LpProblem("myProblem", LpMaximize)
8
9 problem += 3 * x + 2 * y, "myObjective"
10
11 problem += x - y + z == 1
12 problem += x + 2 * y <= 14
13 problem += 4 * x + y <= 20
```

Coding formulations. Knapsack

Instance: $O, \nu : O \rightarrow \mathbb{R}_+, \omega : O \rightarrow \mathbb{R}_+, W \in \mathbb{R}_+$.

$$\begin{aligned} \max \quad & \sum_{o \in O} \nu(o) \times x_o \\ \text{s.t. :} \quad & \sum_{o \in O} \omega(o) \times x_o \leq W \\ & x_o \in \{0, 1\}, \forall o \in O \end{aligned}$$

Coding formulations. Knapsack

```
1 from pulp import *
2
3 def knapsack(values, weights, W):
4     x = LpVariable.dicts("x", [o for o in range(len(values))], lowBound = 0, upBound = 1,
5         ↳ cat='Integer')
6
7     problem = LpProblem("BinaryKnapsack", LpMaximize)
8
9     problem += lpSum(values[o] * x[o] for o in range(len(values))), "profit"
10    problem += lpSum(weights[o] * x[o] for o in range(len(values))) <= W
```

Coding formulations. Multiple knapsack

Instance: $O, \nu : O \rightarrow \mathbb{R}_+, \omega : O \rightarrow \mathbb{R}_+, W \in \mathbb{R}_+^m$.

$$\begin{aligned} \max \quad & \sum_{o \in O} \sum_{i=1}^m \nu(o) \times x_{oi} \\ \text{s.t. :} \quad & \sum_{o \in O} \omega(o) \times x_{oi} \leq W_i \quad \forall 1 \leq i \leq m \\ & \sum_{i=1}^m x_{oi} \leq 1 \quad \forall o \in O \\ & x_{oi} \in \{0, 1\} \quad \forall o \in O, 1 \leq i \leq m \end{aligned}$$

Coding formulations. Multiple knapsack

```
1 from pulp import *
2
3 def multipleKnapsack(values, weights, W):
4     x = LpVariable.dicts("x", [(o, i) for o in range(len(values)) for i in range(len(W))],
5         ↳ lowBound = 0, upBound = 1, cat='Integer')
6
7     problem = LpProblem("MultipleKnapsack", LpMaximize)
8
9     problem += lpSum(values[o] * x[o, i] for o in range(len(values)) for i in range(len(W))),
10        ↳ "profit"
11
12     for i in range(len(W)):
13         problem += lpSum(weights[o] * x[o, i] for o in range(len(values))) <= W[i]
14
15     for o in range(len(W)):
16         problem += lpSum(x[o, i] for i in range(len(W))) <= 1
```


Solving formulations

The function `list_solvers()` returns the available solvers:

- ▶ e.g., `['GLPK_CMD', 'PYGLPK', 'CPLEX_CMD', 'CPLEX_PY', 'GUROBI', 'GUROBI_CMD', 'XPRESS', 'COIN_CMD', 'SCIP_CMD']`

Get the solver:

- ▶ e.g., `solver = GUROBI(parameters)`.
- ▶ Some of the parameters may include: `timeLimit` in seconds, `Cuts`, `Heuristics` and `Presolve` to indicate if there will be used, respectively, standard cut generation, embedded heuristics and preprocessing.

Solve the problem:

- ▶ `myProblem.solve(solver)`
- ▶ `solver.buildSolverModel(myProblem)`, `solver.callSolver(myProblem)` and `solver.findSolutionValues(myProblem)`

Get solution value: `value(myProblem.objective)`.

The variables are elements in `myProblem.variables()` each one with attributes `name` and `varValue`.

Solving formulations. Simple example

```
1 from pulp import *
2
3 x = LpVariable("x", lowBound = 0, cat = 'Integer')
4 y = LpVariable("y", lowBound = 0, cat = 'Integer')
5 z = LpVariable("z", lowBound = 0)
6
7 problem = LpProblem("myProblem", LpMaximize)
8
9 problem += 3 * x + 2 * y, "myObjective"
10
11 problem += x - y + z == 1
12 problem += x + 2 * y <= 14
13 problem += 4 * x + y <= 20
14
15 problem.solve(GUROBI_CMD())
16
17 print('Optimal value: ' + str(value(problem.objective)))
18 print('Optimal solution: ')
19 for variable in problem.variables():
20     print('    ' + variable.name + " = " + str(variable.varValue))
```

Solving formulations. Knapsack

```
1 from pulp import *
2
3 def knapsack(values, weights, W):
4     x = LpVariable.dicts("x", [o for o in range(len(values))], lowBound = 0, upBound = 1,
5         ↪ cat='Integer')
6
7     problem = LpProblem("BinaryKnapsack", LpMaximize)
8
9     problem += lpSum(values[o] * x[o] for o in range(len(values))), "profit"
10
11     problem += lpSum(weights[o] * x[o] for o in range(len(values))) <= W
12
13     solver = GUROBI(timeLimit = 3600)
14
15     solver.buildSolverModel(problem)
16     solver.callSolver(problem)
17     solver.findSolutionValues(problem)
18
19     print('Optimal value: ' + str(value(problem.objective)))
20     print('Optimal solution: ')
21     for variable in problem.variables():
22         print('    ' + variable.name + " = " + str(variable.varValue))
```



DIPPy

PuLP extension

- ▶ **Advanced branching.** Includes `branch_method`.
- ▶ **Customized cuts.** Includes `generate_cuts` and `is_solution_feasible`.
- ▶ **Customized columns.** Includes `relaxed_solver` and `init_vars`.
- ▶ **Heuristics.** Includes `heuristics`.

* Michael O'Sullivan, Qi-Shan Lim, Cameron Walker and Iain Dunning "Dippy – a simplified interface for advanced mixed integer programming". (2012).

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