Modeling with the Gurobi-Python Interface

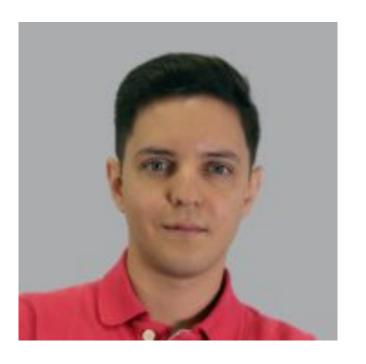
Juan Antonio Orozco Guzman



The World's Fastest Solver

About the Speaker





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Gurobi Optimization

Modeling with the Gurobi-Python Interface

Introduction



The World's Fastest Solver

Objectives



- Discuss the motivation for using Python in mathematical optimization (MO) applications
- Help you understand the importance of parameterizing a MO model
- Review some of the best practices for deploying MO models in Python

Agenda



- Introduction
- Elements of a MO model
- Motivation for using Python
- Gurobi-Python interface
- Sparsity and best practices
- Conclusion

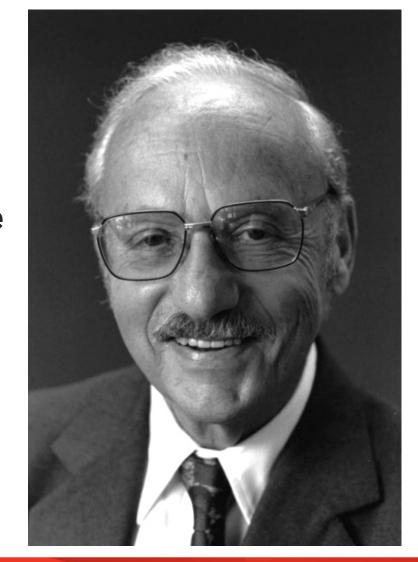
Modeling with the Gurobi-Python Interface

Introduction

What is Mathematical Optimization?



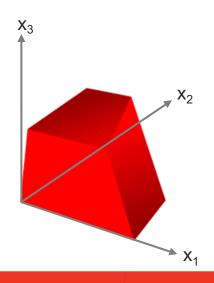
Its origins can be traced back to the invention of **linear programming** shortly after World War II in 1947 by **George Dantzig**.



What is Mathematical Optimization?



- A declarative approach where the modeler:
 - States all the properties associated with a solution.
 - Defines a **criterion** to guide the search.
- Other algorithmic approaches specify the necessary steps to build and test a solution.



Mathematical Optimization Modeling

Elements of a MO model

Example: Assignment Problem



Maximize total matching score:

At most, one person can be assigned to each job

At most, one job can be assigned to each person

1 if person i is assigned to job j; 0 otherwise

$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j}$$

$$s.t. \sum_{i \in I} x_{i,j} \leq 1 \quad \forall j \in J$$

$$\sum_{j \in J} x_{i,j} \leq 1 \quad \forall i \in I$$

$$x_{i,j} \in \{0,1\} \quad \forall i \in I, j \in J$$



$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j} \qquad \text{Decision Variables}$$

$$s.t. \quad \sum_{i \in I} x_{i,j} \leq 1 \quad \forall j \in J$$

$$\sum_{j \in J} x_{i,j} \leq 1 \quad \forall i \in I$$

$$x_{i,j} \in \{0,1\} \quad \forall i \in I, j \in J$$



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$$x_{i,j} \in \{0,1\} \quad \forall i \in I, j \in J$$

Objective Function



$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j} \qquad \text{Constraints}$$

$$s.t. \sum_{i \in I} x_{i,j} \leq 1 \quad \forall j \in J$$

$$\sum_{j \in J} x_{i,j} \leq 1 \quad \forall i \in I$$

$$x_{i,j} \in \{0,1\} \quad \forall i \in I, j \in J$$



$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j} \qquad \text{Data Coefficients}$$

$$s.t. \sum_{i \in I} x_{i,j} \leq \boxed{1} \ \forall j \in J$$

$$\sum_{j \in J} x_{i,j} \leq \boxed{1} \ \forall i \in I$$

$$x_{i,j} \in \{0,1\} \qquad \forall i \in I, j \in J$$



$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j} \qquad \text{Index Sets}$$

$$s.t. \qquad \sum_{i \in I} x_{i,j} \leq 1 \quad \forall j \in J$$

$$\sum_{j \in J} x_{i,j} \leq 1 \quad \forall i \in I$$

$$x_{i,j} \in \{0,1\} \qquad \forall i \in I, j \in J$$



$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} \lambda_{i,j} \qquad \text{Subscripts}$$

$$s.t. \qquad \sum_{i \in I} \chi_{i,j} \qquad \leq \qquad 1 \quad \forall j \in J$$

$$\sum_{j \in J} \chi_{i,j} \qquad \leq \qquad 1 \quad \forall i \in I$$

$$\chi_{i,j} \in \{0,1\} \qquad \forall i \in I, j \in J$$



$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j} \qquad \text{Arithmetic Operators}$$

$$s.t. \qquad \sum_{i \in I} x_{i,j} \qquad \leq \qquad 1 \quad \forall j \in J$$

$$\sum_{j \in J} x_{i,j} \qquad \leq \qquad 1 \quad \forall i \in I$$

$$x_{i,j} \in \{0,1\} \qquad \forall i \in I, j \in J$$



$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j} \qquad \text{Constraint Operators}$$

$$s.t. \sum_{i \in I} x_{i,j} \quad \leqq \quad 1 \quad \forall j \in J$$

$$\sum_{j \in J} x_{i,j} \quad \leqq \quad 1 \quad \forall i \in I$$

$$x_{i,j} \in \{0,1\} \quad \forall i \in I, j \in J$$



$$\max \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j} \qquad \text{For-all Operators}$$

$$s.t. \sum_{i \in I} x_{i,j} \leq 1 \quad \forall j \in J$$

$$\sum_{j \in J} x_{i,j} \leq 1 \quad \forall i \in I$$

$$x_{i,j} \in \{0,1\} \qquad \forall i \in I, j \in J$$



$$\max \quad \sum_{i \in I} \sum_{j \in J} c_{i,j} x_{i,j} \qquad \text{Aggregate-sum Operators}$$
 $s.t. \quad \sum_{i \in I} x_{i,j} \leq 1 \quad \forall j \in J$
$$\sum_{i \in J} x_{i,j} \leq 1 \quad \forall i \in I$$

$$x_{i,j} \in \{0,1\} \qquad \forall i \in I, j \in J$$

Elements of a MO Model



- Decision variables
- Objective function
- Constraints

- Coefficients
- Sets and subscripts
- Operators:
 - Arithmetic (+, -, *, /)
 - Constraint $(\leq, \geq, =)$
 - For-all (∀)
 - Aggregate-sum (Σ)

Mathematical Optimization Modeling

Motivation for Using Python

Desired Modeling Traits



Translate a math formulation into a machine-readable format:

- Code is easy to write and maintain
- Covers all solver and programming needs
- Low overhead as compared with solver alone

Why Python?



- Fast and powerful; Easy to learn, use, and read
- Extendible with vast library of prewritten modules
 - Statistics
 - GUIs
 - Web development and web services
 - Data connections
 - File compression
 - Data encryption
- In top-3 most popular programming languages (<u>TIOBE index</u>)
- Large community
- Free and open-source with license that is business-friendly



Jupyter Notebook



- Web application to create and share documents that contain:
 - Live code
 - Explanatory text
 - Equations
 - Visualizations
- Excellent for reproducible research
- Free software with an active community
- Learn more at http://jupyter.org



Mathematical Optimization Modeling

Gurobi-Python Interface

Gurobi Modeling Objects



- Mode1: an optimization model
- Var: a decision variable
- Constr: a constraint
- Overloaded operators
 - Arithmetic
 - Constraint
- Aggregate sum operator (quicksum)
- Tuplelists and multidicts
- Python provides the rest:
 - Read data
 - Print out / write solutions
 - Define control and looping statements

Simple Python Example



```
import gurobipy as gp
from gurobipy import GRB
model = gp.Model("mip1")
x = model.addVar(vtype=GRB.BINARY, name="x")
y = model.addVar(vtype=GRB.BINARY, name="y")
z = model.addVar(vtype=GRB.BINARY, name="z")
model.setObjective(x + y + 2*z, GRB.MAXIMIZE)
model.addConstr(x + 2*y + 3*z <= 4, name="Constraint1")
model.addConstr(x + y >= 1, name="Constraint2")
model.optimize()
```

$$Max \quad x + y + 2z$$

$$s.t. \quad x + 2y + 3z \le 4$$

$$x + y \ge 1$$

$$x, y, z \in \{0,1\}$$

Indexing and Subscripts in Python



- Python provides data structures that are well-suited for indexing and subscripts:
 - List
 - Dictionary
 - Tuple
- Gurobi also provides:
 - Tuplelist
 - Multidict

Python Tuple



A fixed, compound grouping

```
• arc = ("CHI", "NYC")
```

- A tuple cannot be modified once it is created
- Ideal for representing multi-dimensional subscripts

```
("CHI", "NYC", "Prod1")("CHI", "NYC", "Prod2")("CHI", "NYC", "ProdN")
```

Python List



- An ordered group
 - cities = ["CHI", "NYC", "ATL", "MIA"]
- Lists can be modified
 - Add, delete, sort elements
- Unlike sets, a list can have repeated elements
 - Python has a set type to represent sets

Python Dictionary



- A mapping from keys to values
 - Cost[("CHI", "NYC")] = 100
 - Cost[("ATL", "NYC")] = 110
- Keys can be basic values or tuples
- Ideal for representing indexed data

Gurobi Tuplelist



- Gurobi's extension of lists
- Efficient for storing a list of tuples

```
arcs = gp.tuplelist([("CHI", "NYC"), ("CHI", "ATL"), ("ATL", "MIA"),
("ATL", "NYC")])
```

Select() method finds matching subsets

```
• print(arcs.select("CHI", "*"))
    [("CHI", "NYC"), ("CHI", "ATL")]
```

• Select() uses efficient indexing

Gurobi Multidict



Convenience function to initialize dictionaries and their indices in one statement

```
• cities, supply, demand = gp.multidict({
    "ATL": [100, 20],
    "CHI": [150, 50],
    "NYC": [20, 300],
    "MIA": [10, 200]})
```

Index is returned as a tuplelist

The Diet Model



$$Min \sum_{f \in Foods} cost_f \cdot buy_f$$

s.t. $\sum_{f \in Foods} nutrition_value_{c,f} \cdot buy_f \ge \min_nutrition_c \quad \forall c \in Categories$

 $\sum_{f \in Foods} nutrition_value_{c,f} \cdot buy_f \leq \max_nutrition_c \quad \forall c \in Categories$

 $buy_f \in \mathbb{R}^+$



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Mathematical Optimization Modeling

Sparsity and Best Practices

Sparsity, Part 1



Mistake

```
availability = tuplelist([
  ("Amy", "Tue2"), ("Amy", "Wed3"),
 ("Amy", "Fri5"), ("Amy", "Sun7"),
X = \{\}
for w in workers:
  for s in shifts:
    x[w,s] = model.addVar(ub=1,
obj=pay[w])
    if (w,s) not in availability:
      x[w,s].ub = 0
   Overhead for both modeling and solving
```

Done Right

```
availability = tuplelist([
    ("Amy", "Tue2"), ("Amy", "Wed3"),
    ("Amy", "Fri5"), ("Amy", "Sun7"),
...])

x = {}
for w,s in availability:
    x[w,s] = model.addVar(ub=1,
obj=pay[w])
```

Variables represent only valid combinations of workers and shifts

Sparsity, Part 2



Mistake

```
# Constraint: assign exactly
shiftRequirements[s] workers to
shift s
```

```
model.addConstrs((shiftRequirements
[s] == gp.quicksum(x[w,s] for w in
workers if (w,s) in availability)
for s in shifts),
name="requirement")
```

Modeling step iterates over all workers, rather than only valid combinations

Done Right

```
# Constraint: assign exactly
shiftRequirements[s] workers to
shift s
```

```
model.addConstrs((shiftRequirements
[s] == gp.quicksum(x[w,s] for w,s
in availability.select("*",s)) for
s in shifts), name="requirement")
```

Iterates over only valid combinations of workers and shifts

Exploiting Sparsity



- Use tuplelists to specify valid combinations
- Create variables and data as dictionaries that are indexed by these tuplelists
- Use tuplelist.select() to efficiently iterate over valid combinations

Best Practices for Python Models



- Sparsity
- List comprehension and generator syntax
- gp.quicksum()
- Model / data separation and external sources of data
 - dietmodel.py (module with logic for model deployment)
 - diet2.py (data hard-coded in a separate script)
 - diet3.py (data read from a SQLite database)

Mathematical Optimization Modeling

Conclusion

Modeling Languages vs Gurobi-Python Interface



- Concise, readable syntax for building models
- Interative model and data manipulation
- Efficient handling of dense and sparse data
- Convenient connections to external data sources

Modeling Languages

- Specialized language for math programming
 - Syntax and primitives designed for optimization
 - Best practices built into the language
 - Error handling tailored for optimization

Gurobi-Python Interface

- Part of a general-purpose language
 - Greater flexibility
 - Designed with deployment in mind
 - Build complex programs in one language
 - Integrate easily with databases, web servers, etc.
 - Covers all features in Gurobi Optimizer
 - Large user community

Resources

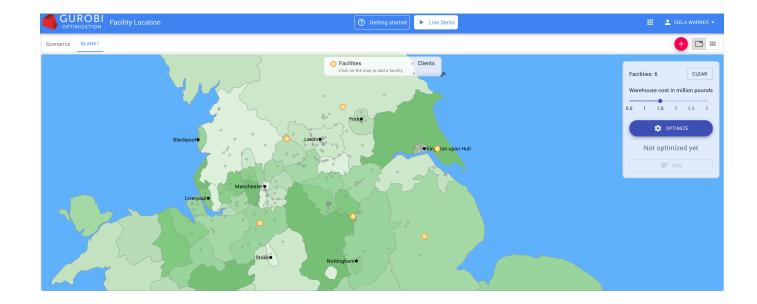


Optimization Application Demos

- Cell Tower Coverage
- Cutting Stock Problem with Multiple Master Rolls
- Facility Location
- Offshore Wind Farming
- Resource Matching Optimization
- The Traveling Salesman Problem
- Workforce Scheduling

Jupyter Notebook Modeling Examples

- <u>Cell Tower Coverage</u>
- Customer Assignment
- Facility Location
- HP Williams Modeling Examples
- L0-Regression
- Offshore Wind Farming
- Standard Pooling
- Traveling Salesman



Resources



- Get a free 30-day trial of the Gurobi Optimizer
 - www.gurobi.com/eval
- Need help leveraging Optimization for your business?
 - Contact us at info@gurobi.com

Thank You



The World's Fastest Solver