Basics of COPTPY Solver

AIE1901 - AI Exploration - LLM for Optimization

Key Ingredients of an Optimization Problem

- 1. Decision Variables: The choices we can make
- 2. Objective: The thing we want to minimize or maximize
- 3. Constraints: The rules or limitations we have to follow

Meet the Solver: COPT

Cardinal Optimizer (COPT): The Ultimate Optimizatiom Engine for Your Enterprise

- What is COPT? Cardinal Optimizer (COPT) is a high-performance mathematical solver developed by Cardinal Operations
- What does it do? It takes your problem and uses advanced algorithms to find the provably best solution
- COPTPY: A python package that enables us to talk with COPT solver using Python.

Our Coding Environment: Google Colab

- Action: Go to colab.research.google.com
- Step 1: Create a new notebook
- Step 2: Install COPTPY

The "Hello World" of Optimization

Maximize_{$$x,y$$} $x + y$
Subject to $x + 2y \le 10$
 $2x + y \le 10$
 $x \ge 0, y \ge 0$

Step 1: Import and Create Environment

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
1 # import the coptpy package
2 import coptpy as cp
3 from coptpy import COPT
4 # Create COPT environment
5 env = cp.Envr()
6
7 # Create COPT model
8 model = env.createModel("Hello_World")
9

Cardinal Optimizer v8.0.1. Build date Oct 22 2025
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```

- Envr() is our connection to the COPT Solver
- createModel() creates a new "container" for our problem

Step 2: Add Variables

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
1 # Create variables. They have a name and a lower bound (lb)
2 # "x" and "y" are our decision variables
3 x = model.addVar(lb=0, name="x")
4 y = model.addVar(lb=0, name="y")
```

- Create variables. They have a name and a lower bound (lb)
- These variables can be any number from o to infinity

Step 3: Set the Objective

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
1 # set the objective: Maximize (x+y)
2 model.setObjective(x+y, sense=COPT.MAXIMIZE)
```

- Our goal is to maximize the objective x + y
- COPT.MAXIMIZE tells the solver we want the largest possible value

Step 4: Add Constraints

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
1  # Add the constriants
2  model.addConstr(x + 2*y <= 10, name = "c1") # constraint 1
3  model.addConstr(2*x + y <= 10, name = "c2") # constriant 2
</pre>
<coptpy.Constraint: c2>
```

- Add two linear constraints
- Give each constraint a name for clarity

Step 5: Solve and Get Results

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
# solve the model
model.solve()

# check if the solution is optimal
if model.status == COPT.OPTIMAL:
    print("Optimal solution found")
    print("Objective value: {}".format(model.ObjVal))

# print("x: {}".format(x.x)) # .x gets the value of the variable print("y: {}".format(y.x))
else:
    print("No solution found")
```

- Run the entire code block in Colab.
- Show the output:
 - Optimal Solution:
 - Optimal Value:
- Visualize the solution

Rethinking the Example

Problem Statement:

Maximize_{$$x,y$$} $x + y$
Subject to $x + 2y \le 10$
 $2x + y \le 10$
 $x \ge 0, y \ge 0$

Objective coefficient:

$$c = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Constraint coefficient:

$$A = \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}, b = \begin{bmatrix} 10 \\ 10 \end{bmatrix}$$

Decision variable:

$$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

What is a Matrix?

Let $A = (a_{ij})$ be an $m \times n$ matrix.

• The jth column of A is denoted by a column vector \mathbf{a}_j , i.e.,

$$\mathbf{a}_{j} = \begin{bmatrix} a_{1j} \\ a_{2j} \\ \vdots \\ a_{mj} \end{bmatrix}$$

 $A^2 \begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix}$

• The *i*th row of A is denoted by a row vector $\vec{\mathbf{a}}_i$, i.e.,

$$\vec{\mathbf{a}}_i = (a_{i1}, a_{i2}, \dots, a_{in})$$

ullet Matrix A can be represented in terms of either its columns and rows:

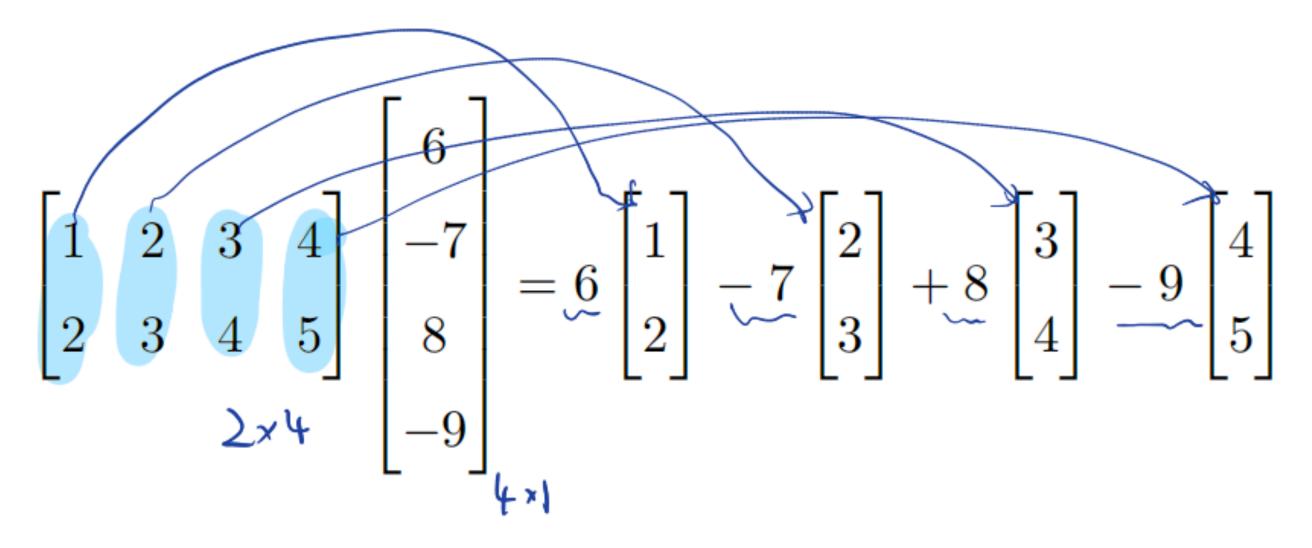
$$A = [\mathbf{a}_1, \cdots, \mathbf{a}_n] = egin{bmatrix} ec{\mathbf{a}}_1 \ ec{\mathbf{a}}_2 \ dots \ ec{\mathbf{a}}_m \ \end{pmatrix}$$

Matrix-Vector Multiplication

For an $m \times n$ matrix A with the ith column \mathbf{a}_i , and a vector $\mathbf{u} = (u_1, u_2, \dots, u_n)^{\top}$, the multiplication of A and \mathbf{u} is defined as

$$\mathbf{A}\mathbf{u} = u_1\mathbf{a}_1 + u_2\mathbf{a}_2 + \dots + u_n\mathbf{a}_n$$

Example



Inner Product

• Given a vector $\mathbf{a} = (a_1, \dots, a_n)^{\top}$ and a vector $\mathbf{b} = (b_1, \dots, b_n)^{\top}$, following the rule of matrix-vector product, we have

$$\mathbf{a}^{\top}\mathbf{b} = a_1b_1 + a_2b_2 + \cdots + a_nb_n$$

- We call this special vector-vector multiplication the inner product (scalar product) of \mathbf{a} and \mathbf{b} (denoted by $\mathbf{a}^{\top}\mathbf{b}$ or $\langle \mathbf{a}, \mathbf{b} \rangle$)
- Properties: Commutative, bilinear
- Application: Cosine similarity, $\cos \theta = \frac{\mathbf{a}^{\top} \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$

Row Perspective of Multiplication

The matrix-vector multiplication $A\mathbf{u}$ has a row formula as

$$A\mathbf{u} = egin{bmatrix} ec{\mathbf{a}}_1\mathbf{u} \ ec{\mathbf{a}}_2\mathbf{u} \ dots \ dots \ dots \ ec{\mathbf{a}}_m\mathbf{u} \end{bmatrix}$$

- We calculate

$$\vec{\mathbf{a}}_1 \mathbf{u} = 6 \cdot 1 - 7 \cdot 2 + 8 \cdot 3 - 9 \cdot 4 = -20$$

$$\vec{\mathbf{a}}_2 \mathbf{u} = 6 \cdot 2 - 7 \cdot 3 + 8 \cdot 4 - 9 \cdot 5 = -22$$

• We see that $A\mathbf{u} = \begin{bmatrix} -20 & -22 \end{bmatrix}^{\mathsf{T}}$

Linear Systems as Matrix Equations

Write the following linear systems into compact matrix form:

$$\begin{cases} 2x_1 + x_2 + x_3 = 5 \\ 4x_1 - 6x_2 = -2 \\ -2x_1 + 7x_2 + 2x_3 = 9 \end{cases} \Rightarrow A\mathbf{x} = \mathbf{b}$$

where

$$A = \begin{bmatrix} 2 & 1 & 1 \\ 4 & -6 & 0 \\ -2 & 7 & 2 \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 5 \\ -2 \\ 9 \end{bmatrix}$$

Rethinking the Example

Problem Statement:

Maximize_{$$x,y$$} $x + y$

Subject to
$$x + 2y \le 10$$

$$2x + y \le 10$$

$$x \ge 0, y \ge 0$$

Compact Form:

 $\begin{aligned} &\text{Maximize}_{\mathbf{x}} \quad c^{\mathsf{T}}\mathbf{x} \\ &\text{Subject to} \quad A\mathbf{x} \leq b \end{aligned}$

Objective coefficient:

$$c = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

• Constraint coefficient:

$$A = \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}, b = \begin{bmatrix} 10 \\ 10 \end{bmatrix}$$

Decision variable:

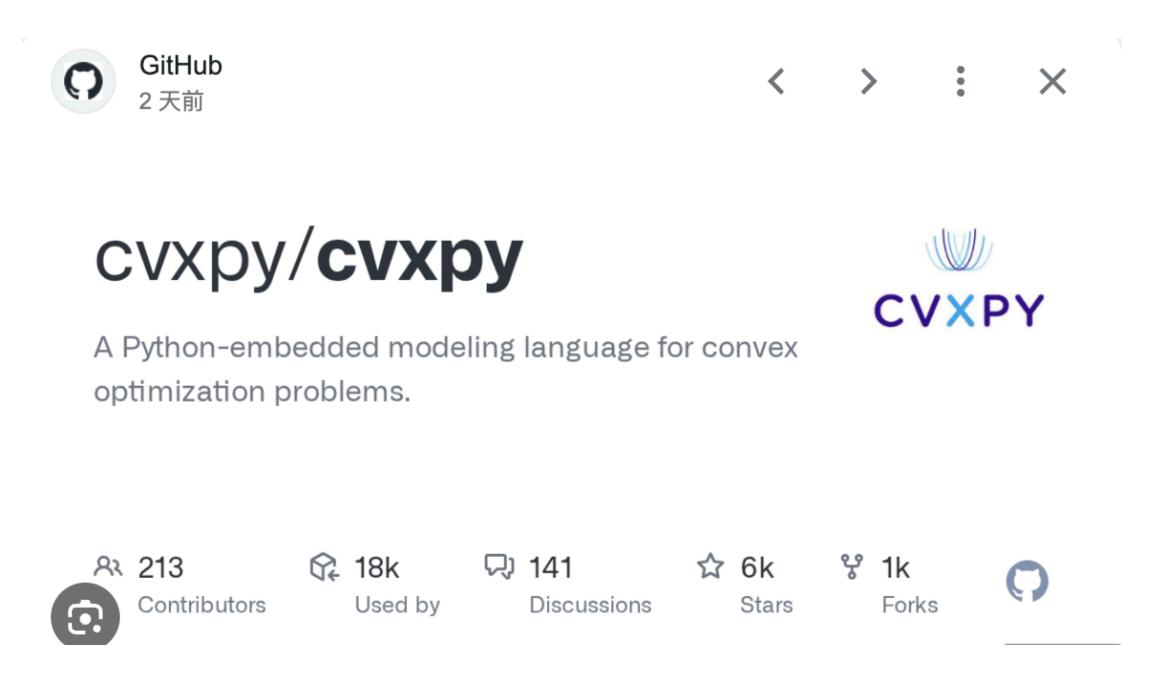
$$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

Full Coding Demo

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

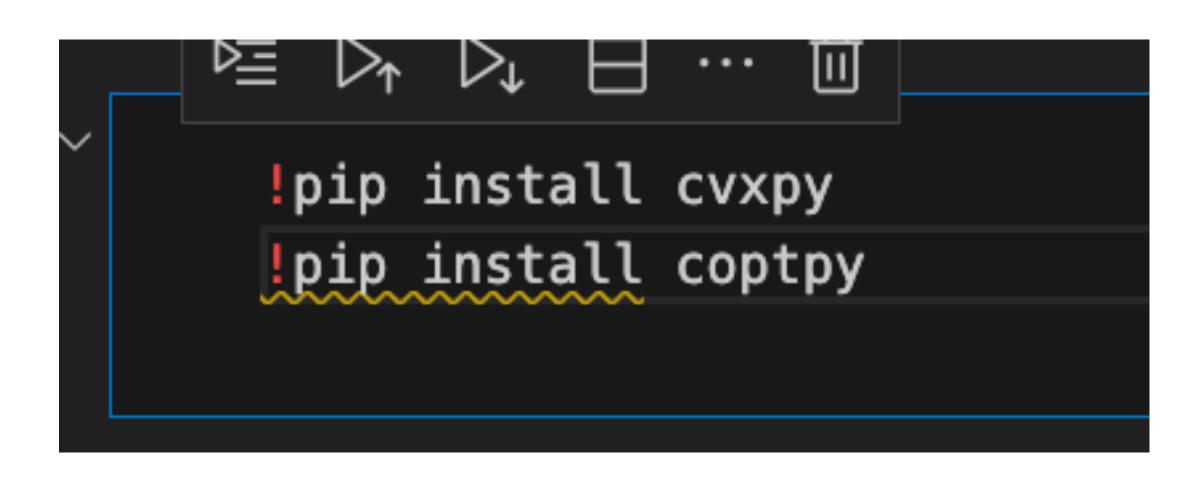
```
# import the coptpy package
    import coptpy as cp
    from coptpy import COPT
    # Create COPT environment
    env = cp.Envr()
    # Create COPT model
    model = env.createModel("Hello_World")
    # Create variables. They have a name and a lower bound (lb)
    # "x" and "y" are our decision variables
    x = model.addVar(lb=0, name="x")
    y = model.addVar(lb=0, name="y")
14
    # Add the constriants
    model.addConstr(x + 2*y <= 10, name = "c1") # constraint 1</pre>
    model.addConstr(2*x + y \le 10, name = "c2") # constriant 2
18
    model.setObjective(x+y, sense=COPT.MAXIMIZE)
    # solve the model
    model.solve()
22
    # check if the solution is optimal
    if model.status == COPT.OPTIMAL:
        print("Optimal solution found")
        print("Objective value: {}".format(model.ObjVal))
28
         print("Optimal solution: ")
        print("x: {}".format(x.x)) # .x gets the value of the variable
         print("y: {}".format(y.x))
    else:
31
        print("No solution found")
32
```

Alternative Modeling: CVXPY



- What is CVXPY? a Python-embedded modeling language for convex optimization that:
- Provides intuitive mathematical expression syntax
- Supports multiple backend solvers (including COPT, ECOS, SCS, etc.)
- Easy to learn and use, ideal for rapid prototyping and education

Installing CVXPY in Google Colab



Note: CVXPY comes with free solvers by default, but can also interface with commercial solvers like COPT.

CVXPY Modeling Approach - Comparison with COPTPY

COPT-PY	CVXPY
model.addVar()	<pre>cp.Variable()</pre>
model.addConstr()	Constraints with <= , == , >=
<pre>model.setObjective()</pre>	<pre>cp.Maximize() or cp.Minimize()</pre>
model.solve()	problem.solve()

Step 1: Import and Create Variables

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
import cvxpy as cp

# Create decision variables

x = cp.Variable(nonneg=True, name="x")

y = cp.Variable(nonneg=True, name="y")
```

- nonneg=True automatically sets lower bound to zero
- Variable names are optional but helpful for debugging

Step 2: Define Constraints

Problem Statement:

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
# Define constraints

vonstraints = [

x + 2*y <= 10,  # First constraint

2*x + y <= 10,  # Second constraint

x >= 0,  # Non-negativity (redundant but explicit)

y >= 0  # Non-negativity

]
```

• Note: Constraints are defined using natural mathematical syntax with Python operators.

Step 3: Formulate the Problem

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
# Define objective function
objective = cp.Maximize(x + y)

# Create optimization problem
problem = cp.Problem(objective, constraints)
```

- cp.Maximize() for maximization problems
- cp.Minimize() for minimization problems
- Problem combines objective and constraints into one object

Step 4: Solve and Get Results

Problem Statement:

Maximize_{$$x,y$$} $x + y$
Subject to $x + 2y \le 10$
 $2x + y \le 10$
 $x \ge 0, y \ge 0$

```
# Solve the problem
problem.solve(solver=cp.COPT) # Specify COPT as solver

# Display results
print("Status:", problem.status)
print("Optimal value:", problem.value)
print("Optimal solution:")
print(f"x = {x.value:.2f}")

print(f"y = {y.value:.2f}")
```

Alternative solvers:

- solver=cp.ECOS (free, for convex problems)
- solver=cp.SCS (free, for larger problems)
- solver=cp.COPT (commercial, high-performance)

Full Coding Demo using CVXPY

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
!pip install cvxpy
!pip install coptpy
import cvxpy as cp
# Step 1: Create variables
x = cp.Variable(nonneg=True, name="x")
y = cp.Variable(nonneg=True, name="y")
# Step 2: Define constraints
constraints = [x + 2*y <= 10, 2*x + y <= 10]
# Step 3: Formulate problem
objective = cp.Maximize(x + y)
problem = cp.Problem(objective, constraints)
# Step 4: Solve
problem.solve(solver=cp.COPT)
# Step 5: Output results
print("Status:", problem.status)
print("Optimal value: {:.2f}".format(problem.value))
print("x = {:.2f}, y = {:.2f}".format(x.value, y.value))
```

Matrix Form with CVXPY

```
Maximize<sub>x,y</sub> x + y
Subject to x + 2y \le 10
2x + y \le 10
x \ge 0, y \ge 0
```

```
import cvxpy as cp
import numpy as np
# Problem data in matrix form
c = np.array([1, 1]) # Objective coefficients
A = np.array([[1, 2], [2, 1]]) # Constraint matrix
b = np.array([10, 10]) # RHS values
# Variables
x = cp.Variable(2, nonneg=True) # Vector of 2 variables
# Problem formulation
objective = cp.Maximize(c.T @ x) # c^Tx
constraints = [A @ x \le b] # Ax \le b
problem = cp.Problem(objective, constraints)
problem.solve()
print("Solution:", x.value)
```

COPTPY versus CVXPY

COPT-PY (Direct Interface)

- Pros: Full control, access to advanced solver features, better for large-scale problems
- Cons: More verbose syntax, steeper learning curve

CVXPY (Modeling Language)

- Pros: Clean mathematical syntax, easy prototyping, solver-agnostic
- Cons: Some overhead for very large problems, limited to convex problems

Recommendation:

- CVXPY for education, research, and rapid prototyping
- COPT-PY for production systems and performance-critical applications

When to use Which?

Choose CVXPY when:

- Learning optimization concepts
- Rapid prototyping and experimentation
- Working with multiple solvers
- Solving convex optimization problems

Choose COPT-PY when:

- Building production systems
- Need maximum performance
- Require advanced solver features
- Working exclusively with COPT solver

Summary

- CVXPY provides a high-level, intuitive interface for optimization modeling
- Natural mathematical syntax makes code readable and maintainable
- Same optimization problem can be solved with identical results
- Choice depends on your specific needs: education vs production

Next: Try converting more complex problems between both interfaces!