

## **OMIS 6000**



- The Python Programming Language
- Optimization with Python (Gurobi)
- Transportation and Transshipment
- Multi-period Optimization Models
- Large Language Models (LLMs)

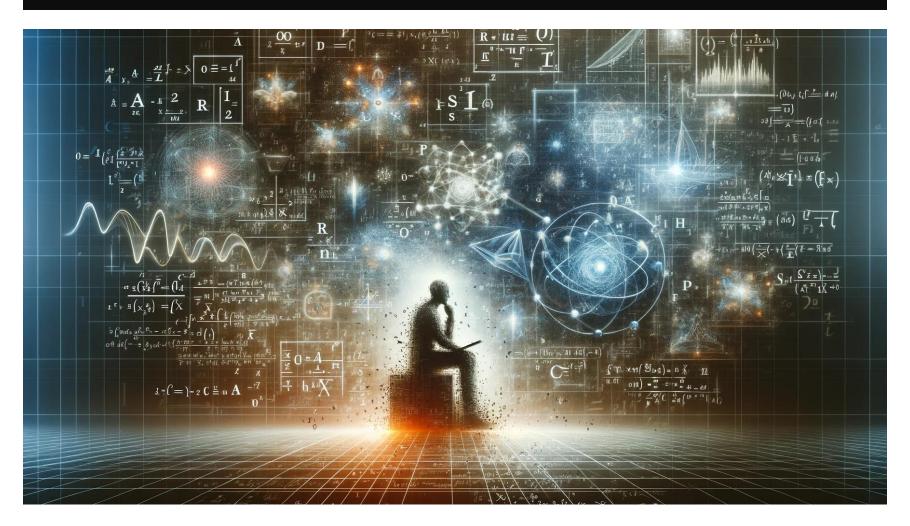






Adam Diamant, Schulich School of Business, Winter 2025

# Optimization in Python



# **Optimization in Python**

## Packages for Linear Models:

PulP

## Packages for Nonlinear Models:

- pyOpt
- CVXOPT
- ipopt

## Packages for both:

- Gurobi (Lots of documentation @ Knowledge Center)
- pyscipopt

## **Gurobi for Python**

 A commercial optimization tool that is free for academic use and has Python bindings. It is the the fastest optimization solver in the world!



# Installing Gurobi

- Register for a <u>Gurobi</u> account <u>here</u> using your Schulich email (schulich.yorku.ca):
  - Make sure to select <u>Academic</u> user.
- Download the <u>Latest Version of Gurobi</u> of the <u>Gurobi Optimizer</u> and install.
  - Make sure to select **Academic** user.
- Request an <u>Academic License</u>.
  - Open a <u>terminal/command prompt</u> window and run 'grbgetkey' using the argument provided to register your machine.

# Installing Gurobi

- This <u>Gurobi</u> academic license can be set up only a single physical machine. Users may install and license <u>Gurobi</u> for their own use on more than one machine.
- You will be able to access and use <u>Gurobi</u> as long as your have a Schulich email.
- Licenses must be renewed every year.
  - The academic licensing program gives you free access to commercial software that is used by more than <u>2,400 companies</u>.

# Installing Gurobi Python

The <u>Guorbipy</u> python library must be installed before using the software to communicate with the <u>Gurobi</u> optimization suite.

 If you have installed <u>Anaconda</u>, type the following into the <u>Spyder</u> console window.
 conda install -c gurobi gurobi

 If you are using another IDE, type this into the <u>Spyder</u> console. Make sure you have <u>pip</u>.
 pip install gurobipy

# Installing Gurobi Python

The <u>Guorbipy</u> python library must be installed before using the software to communicate with the <u>Gurobi</u> optimization suite.

- If you have installed <u>Anaconda</u>, open an <u>Anaconda Prompt</u> window and type:
   conda install -c gurobi gurobi
- If you are using another IDE, open a terminal/command prompt window, scroll to the corresponding Python directory and type:

# **Gurobi for Python**

There are 3 components to a Python model:

- A. The Gurobi <u>model</u> object represents the optimization model expressed in Python.
- B. Elements of the optimization model.
  - Decision Variables
  - 2. Objective Function
  - Constraints
- C. An <u>optimized</u> model and the methods that support <u>inspecting</u> the optimal solution.

# Linear Programming with Gurobi and Python

LG Production Example
Transportation and Transshipment
Multi-Period Optimization



LG is one of the world's largest LCD panel maker, in particular, those based on LED's (*light-emitting diodes*). The company recently received an order for three types of LED displays. Each display type requires time for assembling and packaging. The table summarizes the requirements for each LED type.

	Type A	Type B	Type C
Numbers Ordered	3,000	2,000	900
Assembling (Hours)	2	1.5	3
Packaging (Hours)	1	2	1
Profit per unit	\$60	\$75	\$80

LG has only 10,000 hours of assembly and 5,000 hours of packaging available which is not enough to satisfy all orders.

How many units of each type should LG produce to maximize profits?12

#### **Final Formulation**

Maximize 
$$Z =$$

(Assembly)

(Packaging)

(Order limits)

(Non-negativity)

#### $x_A \ge 0$ , $x_B \ge 0$ , $x_C \ge 0$

## **Optimal Solution:**

#### **Final Formulation**

$$\mathbf{Maximize} \quad \mathbf{Z} = \mathbf{60} x_A + 75 x_B + 80 x_C$$

(Assembly)

(Packaging)

(Order limits)

(Non-negativity)

#### $x_A \ge 0$ , $x_B \ge 0$ , $x_C \ge 0$

#### **Optimal Solution:**

#### **Final Formulation**

$$\mathbf{Maximize} \quad Z = 60x_A + 75x_B + 80x_C$$

$$2x_A+1.5x_B+3x_C\leq 10,000$$
 (Assembly)  $x_A+2x_B+x_C\leq 5,000$  (Packaging)  $x_A\leq 3000, x_B\leq 2000, x_C\leq 900$  (Order limits)  $x_A\geq 0, \quad x_B\geq 0, \quad x_C\geq 0$  (Non-negativity)

### **Optimal Solution:**

#### **Final Formulation**

$$\mathbf{Maximize} \quad Z = 60x_A + 75x_B + 80x_C$$

$$2x_A+1.5x_B+3x_C\leq 10,000$$
 (Assembly)  $x_A+2x_B+x_C\leq 5,000$  (Packaging)  $x_A\leq 3000, x_B\leq 2000, x_C\leq 900$  (Order limits)  $x_A\geq 0, \quad x_B\geq 0, \quad x_C\geq 0$  (Non-negativity)

Optimal Solution: The highest profit that can be obtained is \$293,250 producing 3000 units of type A, 550 units of type B, and 900 units of type C.

# LG Production Example: Python Solution

- Make sure you remember to actually solve the Gurobi model after formulating it.
- When/if an error occurs, pay attention to what line is generating the error.
  - Typically, errors are syntax-related.
  - You can also progressively add constraints (comment the others out) to the problem until you figure out which constraint is problematic.

# What managerial intuition do you get from the Python solution?

## How does Gurobi do it?

## Basic concept of the **Simplex algorithm**:

- 1. Start at a vertex (corner point).
- 2. If there is an adjacent corner point that yields a better objective function value, move to that point.
- 3. Otherwise, stop. The current solution is optimal.

A quick description of the <u>Simplex algorithm</u> including the <u>Simplex Tableau</u> as well as <u>basic</u> and <u>non-basic solutions</u> can be found <u>here</u>.

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- 3. Otherwise, stop. The current solution is optimal.

**Theorem:** If the <u>Simplex algorithm</u> does not contain cycles (i.e., there is no <u>degeneracy</u>), it will monotonically converge to the optimal solution in a finite number of iterations. No cycling can be guaranteed using <u>Bland's Rule</u>.

## How does Gurobi do it?

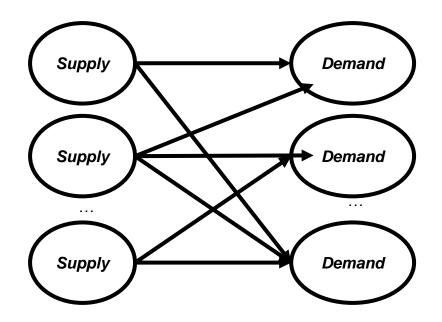
## Basic concept of the **Simplex algorithm**:

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- 3. Otherwise, stop. The current solution is optimal.

Proof of Convergence: In-Class.



Two classes of nodes: supply and demand

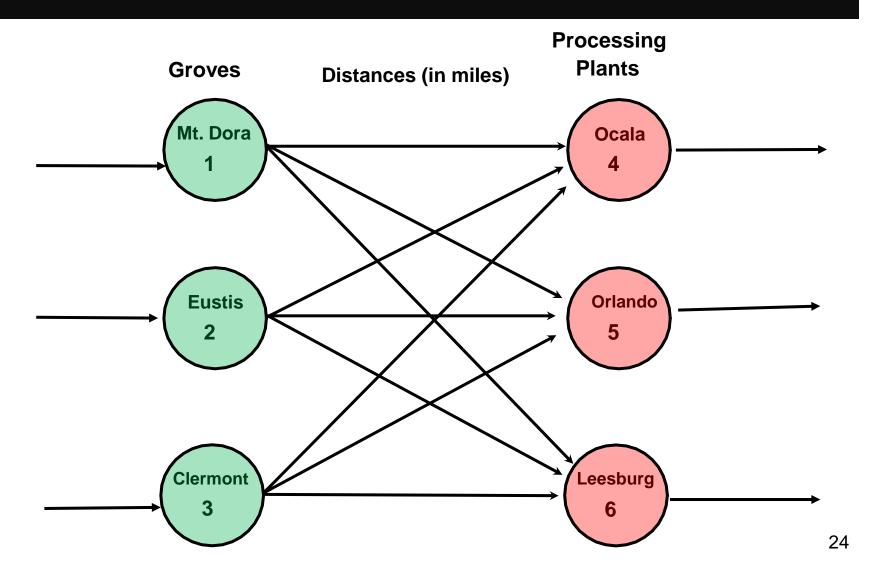


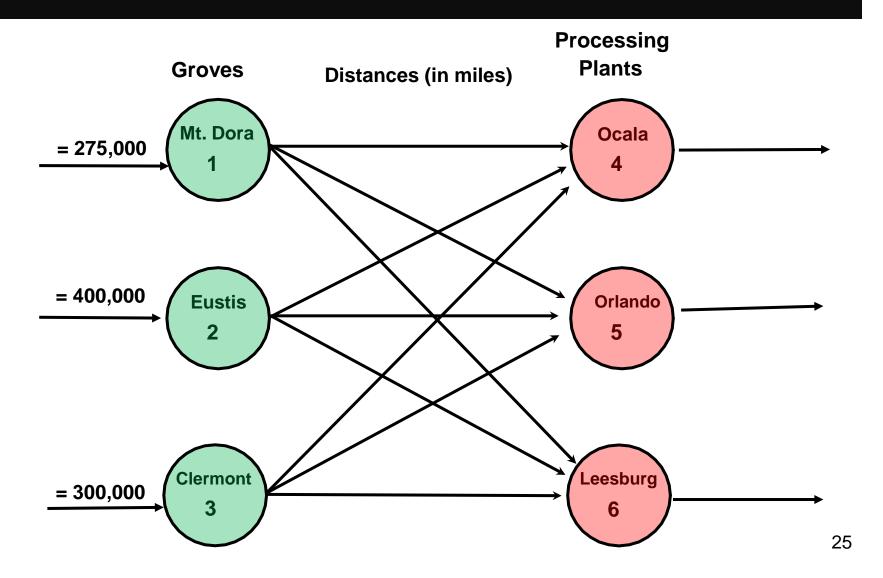
 The objective is to transport products/goods from the supply nodes to the demand nodes.

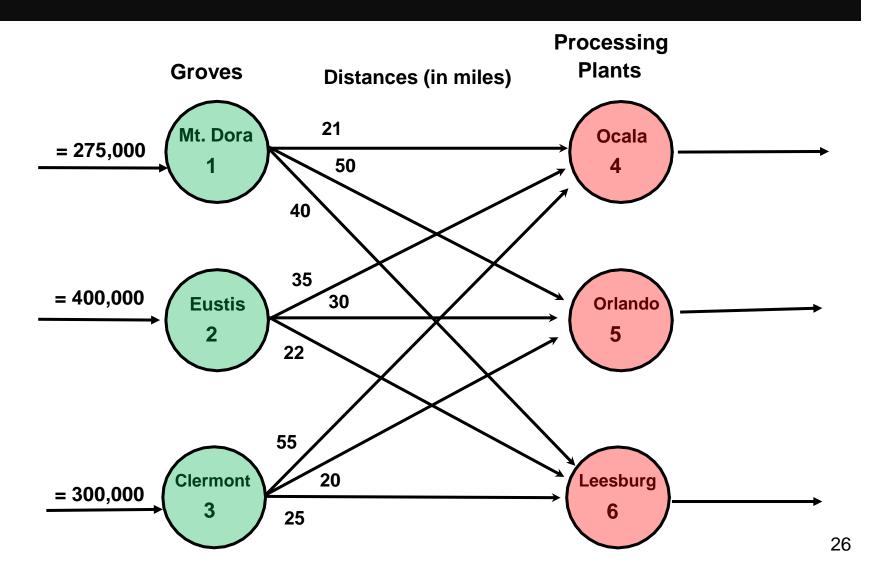
The juice company *Grovestand*® has three orange groves and three processing plants. Each grove has oranges that must enter the market immediately (storage would degrade the quality of the orange). Each plant has a processing capacity. The amount of supply, capacity, and the distances between the groves and the plants are:

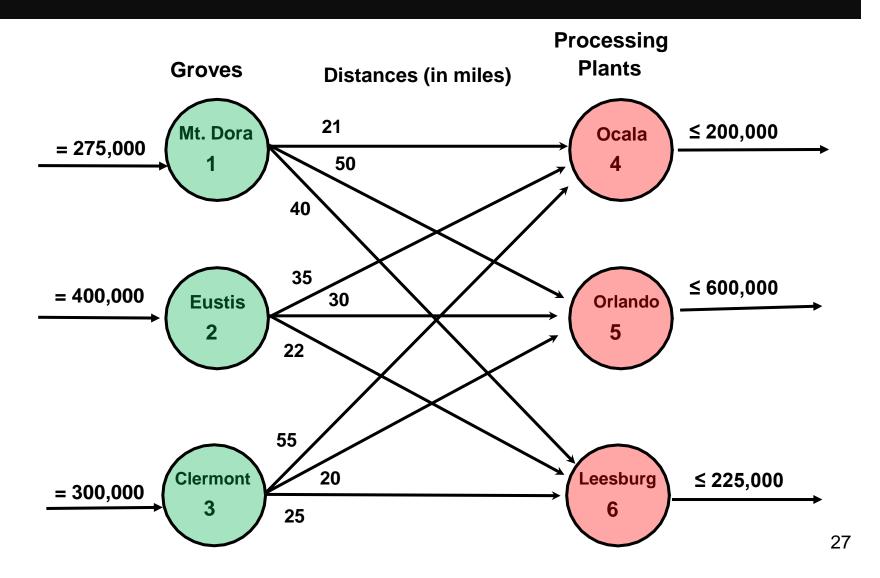
Grove	Supply	Plant	<b>Capacity</b>	<b>Distance</b>	Ocala	Orlando	Leesburg
Mt. Dora	275,000	Ocala	200,000	Mt. Dora	21	50	40
Eustis	400,000	Orlando	600,000	Eustis	35	30	22
Clermont	300,000	Leesburg	225,000	Clermon	55	20	25

- How can we transport the entire supply of oranges from the groves to the plants such that the total distance is minimized?
- Formulate the transportation network and solve the LP model.









Define the objective:

**Decision variables:** 

## Define the objective:

Minimize the total distance that all oranges travel

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#### **Decision variables:**

```
x_{ij}: amount of oranges sent <u>from</u> node i <u>to</u> node j where i = \{Mt, Eu, Cl\} and j = \{Oc, Or, Le\}.
```

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Minimize the total distance that all oranges travel

#### **Decision variables:**

```
x_{ij}: amount of oranges sent <u>from</u> node i <u>to</u> node j where i = \{Mt, Eu, Cl\} and j = \{Oc, Or, Le\}.
```

Minimize 
$$Z = 21x_{Mt,Oc} + 50x_{Mt,Or} + ... + 25x_{Cl,Le}$$

## Formulating the constraints

There are three types of constraints:

- 1. Supply constraints
- 2. Demand constraints
- 3. Non-negativity constraints

## Formulating the supply constraints

Transport the entire supply of oranges from the groves to the processing plants.

## Formulating the supply constraints

Transport the entire supply of oranges from the groves to the processing plants.

$$x_{Mt,Oc} + x_{Mt,Or} + x_{Mt,Le} = 275000$$
  
 $x_{Eu,Oc} + x_{Eu,Or} + x_{Eu,Le} = 400000$   
 $x_{Cl,Oc} + x_{Cl,Or} + x_{Cl,Le} = 300000$ 

## Formulating the demand constraints

The processing plants can only accept so many oranges (they have a capacity limit).

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The processing plants can only accept so many oranges (they have a capacity limit).

$$x_{Mt,Oc} + x_{Eu,Oc} + x_{Cl,Oc} \le 200000$$
  
 $x_{Mt,Or} + x_{Eu,Or} + x_{Cl,Or} \le 600000$   
 $x_{Mt,Le} + x_{Eu,Le} + x_{Cl,Le} \le 225000$ 

## **Transportation Example**

$$Z = 21x_{Mt,Oc} + 50x_{Mt,Or} + ... + 25x_{Cl,Le}$$

#### Subject to:

```
x_{Mt,Oc} + x_{Mt,Or} + x_{Mt,Le} = 275000 (Supply for Mt.Dora grove) x_{Eu,Oc} + x_{Eu,Or} + x_{Eu,Le} = 400000 (Supply for Eustis grove) x_{Cl,Oc} + x_{Cl,Or} + x_{Cl,Le} = 300000 (Supply for Clermont grove) x_{Mt,Oc} + x_{Eu,Oc} + x_{Cl,Oc} \leq 200000 (Demand capacity of Ocala) x_{Mt,Or} + x_{Eu,Or} + x_{Cl,Or} \leq 600000 (Demand capacity of Orlando) x_{Mt,Le} + x_{Eu,Le} + x_{Cl,Le} \leq 225000 (Demand capacity of Leesburg) x_{Mt,Oc} \geq 0, ..., x_{Cl,Le} \geq 0 (Non-negativity constraints)
```

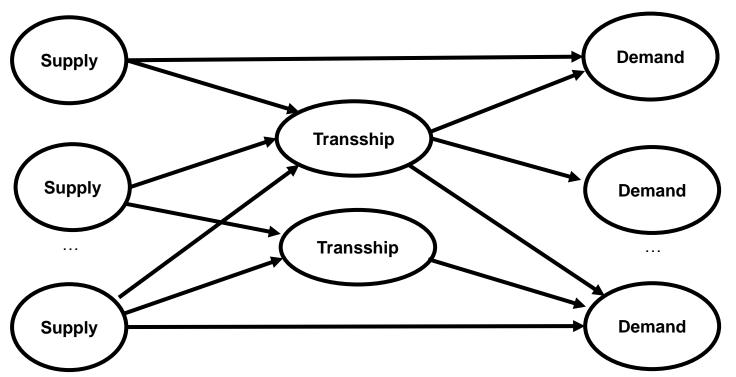
# Transportation Example: Python Solution

- Involves minimizing the cost of sending flow (e.g., people, products, oil) subject to:
  - Processing limitations, transportation capacity, management constraints, and both supply and demand restrictions.
- It is a very common optimization problem especially in supply chain management.

What managerial intuition do you get from the Python solution?



- Generalizes transportation problems by adding extra intermediate nodes called transshipment nodes.
  - Intermediate nodes may represent <u>warehouses</u>, <u>cross-docking facilities</u>, <u>refinement or finishing centers</u>, etc.



GE produces special digital components that are used in expensive electrical appliances like washers, dryers, microwaves, and dishwashers. They have two plants. One is in Dallas and the other is in Houston. GE ships the digital components to two wholesalers that distribute the products all over the world. The wholesalers are based in New York City and San Francisco. All products are shipped by air. Because of the pricing system of the airline, it can be cheaper to first ship to intermediate cities, Chicago or Los Angeles, rather than taking a direct flight. However, there is limited capacity to use these routes.

City	<b>Max Production</b>
Dallas	200
Houston	160

City	Capacity		
Chicago	90		
LA	80		

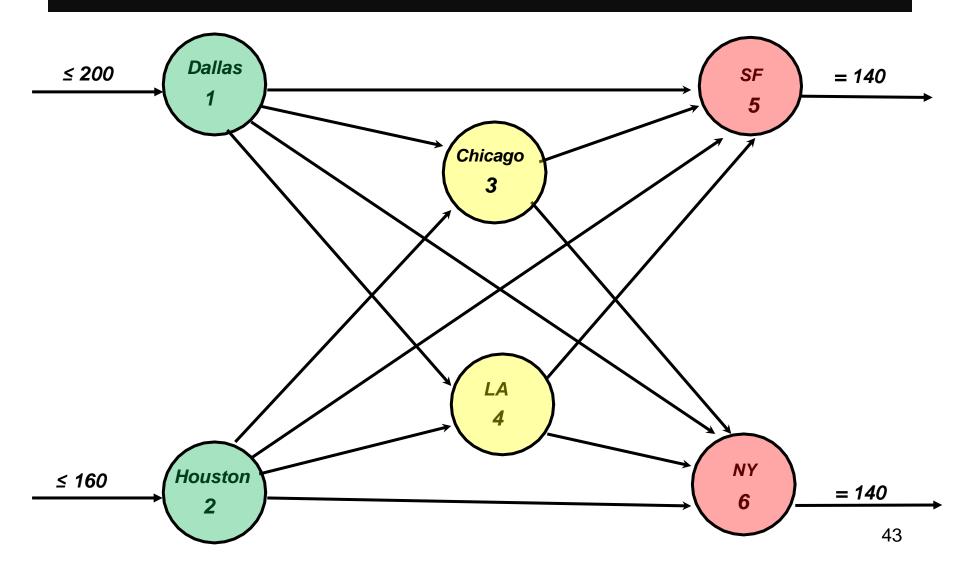
City	Demand
SF	140
NY	140

FROM	Dallas	Houston	Chicago	LA	SF	NY
Dallas	\$0	_	\$11	\$10	\$26	\$29
Houston	-	\$0	\$9	\$12	\$27	\$26
Chicago	-	_	\$0	-	\$12	\$16
LA	_	_	_	\$0	\$13	\$15
SF	_	_	_	-	\$0	_
NY	-	_	_	-	_	\$0

Production, capacity, and demand figures are in units of 1000.

airfreight cost per unit

How should GE transport products such that the shipping cost is minimized, the wholesalers are able to satisfy *all* of their demand, and no more than 40% of all products are shipped through Chicago and LA?



Define the objective:

Minimize the total shipping cost

**Decision variables:** 

#### Define the objective:

Minimize the total shipping cost

#### **Decision variables:**

```
x_{ij}: number of products sent <u>from</u> node i <u>to</u> node j where i = \{Da, Ho\} and j = \{Ch, LA, SF, NY\}.
```

#### Define the objective:

Minimize the total shipping cost

#### **Decision variables:**

```
y_{ij}: number of products sent \underline{from} node i \underline{to} node j where i = \{Ch, LA\} and j = \{SF, NY\}.
```

#### Define the objective:

Minimize the total shipping cost

#### **Decision variables:**

```
x_{ij}: number of products sent \underline{from} node i \underline{to} node j where i = \{Da, Ho\} and j = \{Ch, LA, SF, NY\}. y_{ij}: number of products sent \underline{from} node i \underline{to} node j where i = \{Ch, LA\} and j = \{SF, NY\}.
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#### Define the objective:

Minimize the total shipping cost

#### **Decision variables:**

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x_{ij}: number of products sent \underline{from} node i \underline{to} node j where i = \{Da, Ho\} and j = \{Ch, LA, SF, NY\}. y_{ij}: number of products sent \underline{from} node i \underline{to} node j where i = \{Ch, LA\} and j = \{SF, NY\}.
```

#### Write the mathematical objective function:

Minimize  $Z = 11x_{Da,Ch} + 10x_{Da,LA} + ... + 15y_{LA,NY}$ 

### Formulating the constraints

There are five types of constraints:

- 1. Supply constraints
- 2. Demand constraints
- 3. Transship constraints
- 4. Ratio constraint
- 5. Non-negativity constraints

### Formulating the supply constraints

There is a capacity limit on how many units can be transported out of the production facilities in Dallas and Houston.

### Formulating the supply constraints

There is a capacity limit on how many units can be transported out of the production facilities in Dallas and Houston.

$$x_{Da,Ch} + x_{Da,LA} + x_{Da,SF} + x_{Da,NY} \le 200$$
  
 $x_{Ho,Ch} + x_{Ho,LA} + x_{Ho,SF} + x_{Ho,NY} \le 160$ 

### Formulating the demand constraints

The wholesalers in San Francisco and New York must process all supply they receive.

### Formulating the demand constraints

The wholesalers in San Francisco and New York must process all supply they receive.

$$x_{Da,SF} + x_{Ho,SF} + y_{Ch,SF} + y_{LA,SF} = 140$$
  
 $x_{Da,NY} + x_{Ho,NY} + y_{Ch,NY} + y_{LA,NY} = 140$ 

### Formulating the transship constraints

If products are shipped to Chicago and LA, they must satisfy the capacity constraints.

### Formulating the transship constraints

If products are shipped to Chicago and LA, they must satisfy the capacity constraints.

$$x_{Da,Ch} + x_{Ho,Ch} \le 90$$
$$x_{Da,LA} + x_{Ho,LA} \le 80$$

### Formulating the transship constraints

If products are shipped to Chicago and LA, they must eventually be distributed to San Francisco and New York.

### Formulating the transship constraints

If products are shipped to Chicago and LA, they must eventually be distributed to San Francisco and New York.

$$x_{Da,Ch} + x_{Ho,Ch} = y_{Ch,SF} + y_{Ch,NY}$$
  
 $x_{Da,LA} + x_{Ho,LA} = y_{LA,SF} + y_{LA,NY}$ 

### Formulating the ratio constraint

No more than 40% of all products can be transshipped through Chicago and LA.

### Formulating the ratio constraint

No more than 40% of all products can be transshipped through Chicago and LA.

$$\frac{y_{Ch,SF} + y_{Ch,NY} + y_{LA,SF} + y_{LA,NY}}{y_{Ch,SF} + y_{Ch,NY} + y_{LA,SF} + y_{LA,NY} + x_{Da,SF} + x_{Ho,SF} + x_{Da,NY} + x_{Ho,NY}} \le 0.4$$

### Formulating the ratio constraint

No more than 40% of all products can be transshipped through Chicago and LA.

$$0.6(y_{Ch,SF} + y_{Ch,NY} + y_{LA,SF} + y_{LA,NY})$$

$$\leq 0.4(x_{Da,SF} + x_{Ho,SF} + x_{Da,NY} + x_{Ho,NY})$$

#### **Minimize**

$$Z = 11x_{Da,Ch} + 10x_{Da,LA} + ... + 15y_{LA,NY}$$

#### Subject to:

$$x_{Da,Ch} + x_{Da,LA} + x_{Da,SF} + x_{Da,NY} \le 200$$
  
 $x_{Ho,Ch} + x_{Ho,LA} + x_{Ho,SF} + x_{Ho,NY} \le 160$   
 $x_{Da,Ch} + x_{Ho,Ch} \le 90$   
 $x_{Da,LA} + x_{Ho,LA} \le 80$   
 $x_{Da,Ch} + x_{Ho,Ch} = y_{Ch,SF} + y_{Ch,NY}$   
 $x_{Da,LA} + x_{Ho,LA} = y_{LA,SF} + y_{LA,NY}$   
 $x_{Da,SF} + x_{Ho,SF} + y_{Ch,SF} + y_{LA,SF} = 140$   
 $x_{Da,NY} + x_{Ho,NY} + y_{Ch,NY} + y_{LA,NY} = 140$   
 $0.6(y_{Ch,SF} + y_{Ch,NY} + y_{LA,SF} + y_{LA,NY})$   
 $\le 0.4(x_{Da,SF} + x_{Ho,SF} + x_{Da,NY} + x_{Ho,NY})$   
 $x_{Da,Ch} \ge 0, ..., y_{LA,NY} \ge 0$ 

(Dallas production capacity)

(Houston production capacity)

(Chicago distribution capacity)

(LA distribution capacity)

(Chicago flow constraint)

(LA flow constraint)

(SF demand constraint)

(NY demand constraint)

(Ratio constraint)

(Non-negativity constraints)

# Transshipment Example: Python Solution

- Notice how the constraints reflect the mathematical formulation of the problem.
  - This is not the case for all optimization solvers and is one reason why Gurobi is so popular.
- There is a difference between a variable in Python (a memory location) and a variable in an optimization model (a decision variable that will be optimized by Gurobi).

What managerial intuition do you get from the Python solution?



Tower Research® must define its investment portfolio for 4 months.

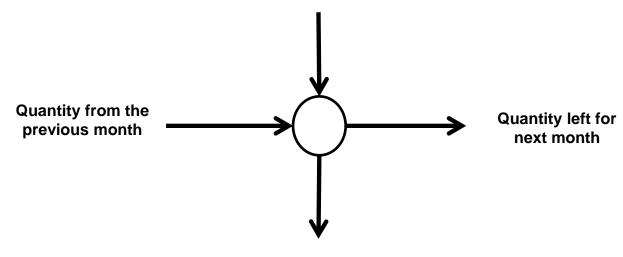
- It initially has \$4,000 in deposits (figures in millions of dollars).
- After each month, the company has the option to invest in a 2month growth fund that gives a 2% (total) rate of return.
- The company can borrow, at most, \$3,000 every month but must pay it back the following month at a 3% (total) rate.
- The expected investment revenues/expenses per month:

Month	1	2	3	4
Revenues	\$1,000	\$4,400	\$5,800	\$3,000
Expenses	\$1,200	\$4,800	\$4,212	\$1,000

What should Tower Research® do to maximize the amount that it generates at the end of the fourth month while never having a negative balance? 64

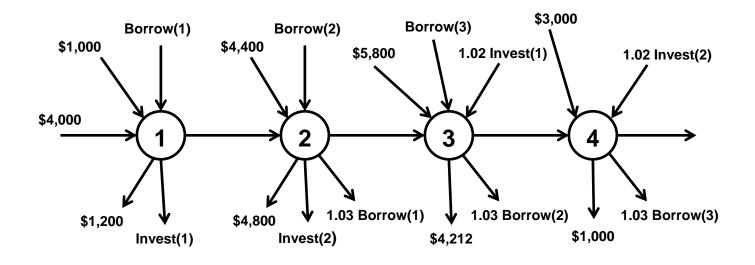
Before solving multiperiod problems, it is a good practice to draw a diagram of the problem. For each month, we have:

Incoming quantities (dividends, etc.)



Outgoing quantities (payments, funds etc.)

#### Four each of the four months:



Month	1	2	3	4
Revenues	\$1,000	\$4,400	\$5,800	\$3,000
Expenses	\$1,200	\$4,800	\$4,212	\$1,000

#### **Define the objective:**

Maximize the amount of money at the end of period 4.

**Decision variables:** 

**Auxiliary decision variables:** 

#### **Define the objective:**

Maximize the amount of money at the end of period 4.

#### **Decision variables:**

 $I_t = \text{how much we will invest}$  in period t = 1, 2.

 $B_t = \text{how much we will borrow in period } t = 1, 2, 3.$ 

#### **Auxiliary decision variables:**

#### **Define the objective:**

Maximize the amount of money at the end of period 4.

#### **Decision variables:**

 $I_t = \text{how much we will invest}$  in period t = 1, 2.

 $B_t = \text{how much we will borrow in period } t = 1, 2, 3.$ 

#### **Auxiliary decision variables:**

 $w_t$  = total wealth at the end of period t = 1, 2, 3, 4.

#### **Define the objective:**

Maximize the amount of money at the end of period 4.

#### **Decision variables:**

 $I_t = \text{how much we will invest in period } t = 1, 2.$ 

 $B_t = \text{how much we will borrow in period } t = 1, 2, 3.$ 

#### **Auxiliary decision variables:**

 $w_t$  = total wealth at the end of period t = 1, 2, 3, 4.

#### Write the mathematical objective function:

Maximize  $Z = w_4$ 

### Formulating the constraints

There are three types of constraints:

- 1. Borrowing constraints
- 2. Balance constraints
- 3. Non-negativity constraints

### Formulating the borrowing constraints

How do you ensure the company cannot borrow more than \$3000 in any period?

### Formulating the borrowing constraints

How do you ensure the company cannot borrow more than \$3000 in any period?

$$B_t \leq 3000 \ for \ t = 1, ..., 3$$

### Formulating the balance constraints

- Ensure that the amount of money in each period is consistent. The amount at the end of a period is:
  - 1. The amount at the beginning of the period.
  - 2. Plus the deposits that are entering.
  - 3. Minus the withdrawals that are leaving.
- They are of the form:

$$w_t = w_{t-1} + inputs - outputs$$

Period 1:

Period 2:

Period 3:

Month	Start	1	2	3	4
Revenues	4000	\$1,000	\$4,400	\$5,800	\$3,000
Expenses	N/A	\$1,200	\$4,800	\$4,212	\$1,000

#### Period 1:

$$w_1 = 4000 + 1000 + B_1 - 1200 - I_1$$

#### Period 2:

#### Period 3:

Month	Start	1	2	3	4
Revenues	4000	\$1,000	\$4,400	\$5,800	\$3,000
Expenses	N/A	\$1,200	\$4,800	\$4,212	\$1,000

#### Period 1:

$$w_1 = 4000 + 1000 + B_1 - 1200 - I_1$$

#### Period 2:

$$w_2 = w_1 + B_2 + 4400 - 1.03B_1 - 4800 - I_2$$

#### Period 3:

Month	Start	1	2	3	4
Revenues	4000	\$1,000	\$4,400	\$5,800	\$3,000
Expenses	N/A	\$1,200	\$4,800	\$4,212	\$1,000

#### Period 1:

$$w_1 = 4000 + 1000 + B_1 - 1200 - I_1$$

#### Period 2:

$$w_2 = w_1 + B_2 + 4400 - 1.03B_1 - 4800 - I_2$$

#### Period 3:

$$w_3 = w_2 + B_3 + 5800 + 1.02I_1 - 4212 - 1.03B_2$$

Month	Start	1	2	3	4
Revenues	4000	\$1,000	\$4,400	\$5,800	\$3,000
Expenses	N/A	\$1,200	\$4,800	\$4,212	\$1,000

#### Period 1:

$$w_1 = 4000 + 1000 + B_1 - 1200 - I_1$$

#### Period 2:

$$w_2 = w_1 + B_2 + 4400 - 1.03B_1 - 4800 - I_2$$

#### Period 3:

$$w_3 = w_2 + B_3 + 5800 + 1.02I_1 - 4212 - 1.03B_2$$

$$w_4 = w_3 + 3000 + 1.02I_2 - 1000 - 1.03B_3$$

Month	Start	1	2	3	4
Revenues	4000	\$1,000	\$4,400	\$5,800	\$3,000
Expenses	N/A	\$1,200	\$4,800	\$4,212	\$1,000

#### **Maximize**

$$Z = w_4$$

#### Subject to:

```
w_1 = 4000 + 1000 + B_1 - 1200 - I_1 (Balance constraint #1)

w_2 = w_1 + B_2 + 4400 - 1.03B_1 - 4800 - I_2 (Balance constraint #2)

w_3 = w_2 + B_3 + 5800 + 1.02I_1 - 4212 - 1.03B_2 (Balance constraint #3)

w_4 = w_3 + 3000 + 1.02I_2 - 1000 - 1.03B_3 (Balance constraint #4)

B_t \le 3000 \ for \ t = 1, ..., 3 (Borrowing constraints)

I_t \ge 0 \ for \ t = 1, ..., 2 (Non-negativity constraints)

w_t \ge 0 \ for \ t = 1, ..., 4 (Non-negativity constraints)
```

# Tower Research® Example: Python Solution

- Be careful of keeping track of the <u>variable</u> <u>indices</u> and the mathematical <u>notation</u>.
- Linear programming models can be used to determine optimal decisions for multiperiod problems. More complicated formulations can even include <u>uncertainty</u>.
  - Examples: Inventory planning, production scheduling, or workforce assignment.

What managerial intuition do you get from the Python solution?

# Python Programming: Gurobi Cheat Sheet

**Basic Functionality** 

### Modeling with Python and Gurobi:

#### Import and create a new instance of a Gurobi model:

```
import gurobipy as gb
from gurobipy import GRB
lp = gb.Model("Name of Problem")
```

#### Define a single decision variable:

```
x = model.addVar(<lb>, <ub>, <vtype>, "Name")
```

- <1b> Lower bound on value (e.g., lb=-GRB.INFINITY, lb=0).
- <ub> Upper bound on value (e.g., ub=1, ub=GRB.INFINITY).
- <vtype> GRB.CONTINUOUS, GRB.BINARY, GRB.INTEGER

### Modeling with Python and Gurobi:

#### Import and create a new instance of a Gurobi model:

```
import gurobipy as gb
from gurobipy import GRB
lp = gb.Model("Name of Problem")
```

#### Define multiple decision variables:

```
x = model.addVars(<num>, <lb>, <ub>, <vtype>, "Name")
```

- <num> Number of decision variables (e.g., 100 or 2,100).
- <1b> Lower bound on value (e.g., lb=-GRB.INFINITY, lb=0).
- <ub> Upper bound on value (e.g., ub=1, ub=GRB.INFINITY).
- <vtype> GRB.CONTINUOUS, GRB.BINARY, GRB.INTEGER

### Modeling with Python and Gurobi:

#### Add the objective to the Gurobi model:

```
lp = set.Objective(<function>, <sense>)
```

Examples:

```
lp. addConstr(x[0] + x[1] + x[2] + x[3] + x[4], GRB. MAXIMIZE) lp. addConstr(gb. quicksum(x[i] for i in range(4)), GRB.MINIMIZE)
```

#### Add the constraints to the Gurobi model:

```
lp.addConstr(<equation>, "Name")
```

Examples:

```
lp. addConstr(x[0] + x[3] <= 10, "Constraint")
lp. addConstr(gb. quicksum(x[i] for i in range(100)) >= 100, "Cons")
```

### Modeling with Python and Gurobi:

#### Solve the optimization problem:

lp.optimize()

#### Return the number of decision variables in the model:

lp.numVars

#### Return the number of constraints in the model:

lp.numConstrs

#### Return the status code of the model:

lp.status

### Modeling with Python and Gurobi:

#### Return optimal values from the solved model:

lp.printAttr('X') #print objective/optimal solution

```
x[0].x or x[1].x #one-dimensional variables x[0,0].x or x[0,1].x #two-dimensional variables lp.getVars() #returns all problem variables
```

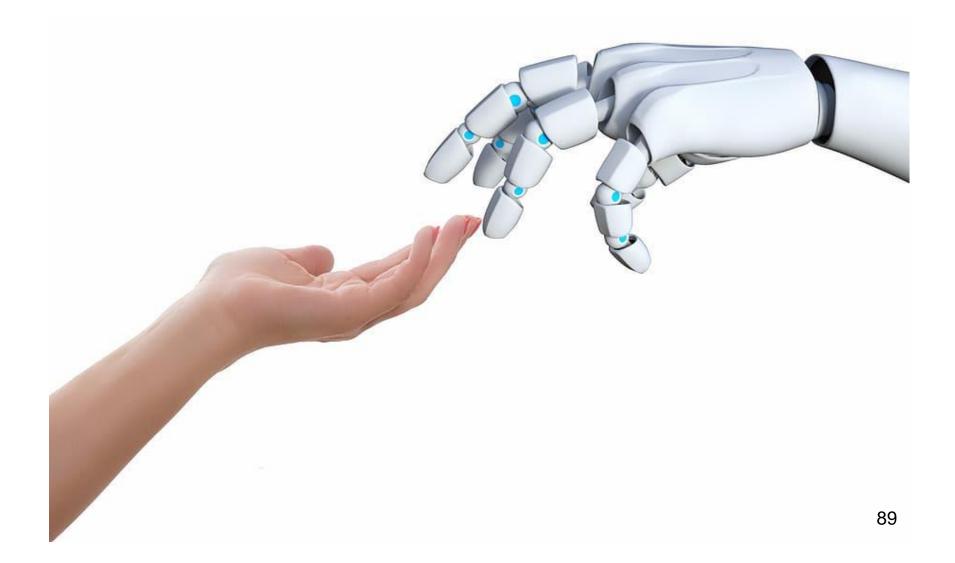
#### Return the objective function value from the model:

lp.objVal

To see what else can be queried from the model, see this <u>link</u>.

### Modeling with Python and Gurobi:

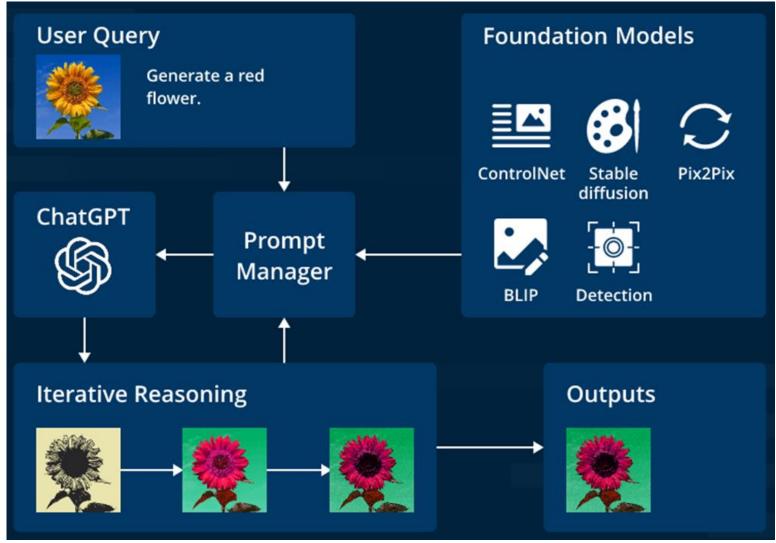
- Large-scale models: In some instances, the solver may experience slow convergence toward the optimal solution, potentially taking hours or days to complete.
- Sometimes this can be rectified by parameter tuning.
- This is an advanced topic, see this <u>webinar</u> for details:
  - Set a <u>time limit</u> to solve the model. Analyze the <u>optimality gap</u>.
  - Control constraint tolerances (i.e., numerical precision).
  - Try a different <u>optimization algorithm</u> (e.g., <u>concurrent optimizer</u>).
  - Set the <u>bounds</u> of the decision variables upon instantiation.
  - Do not have <u>large ranges</u> in coefficient/parameter values.
  - Be careful when choosing certain parameter values.

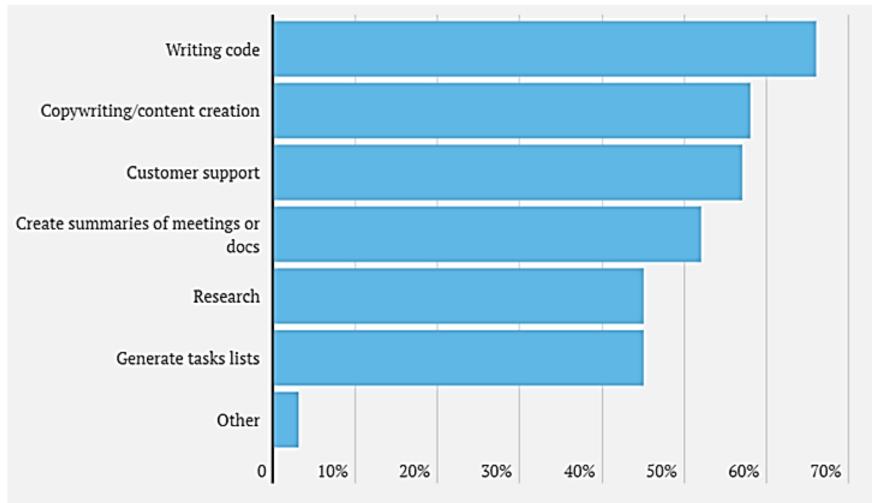


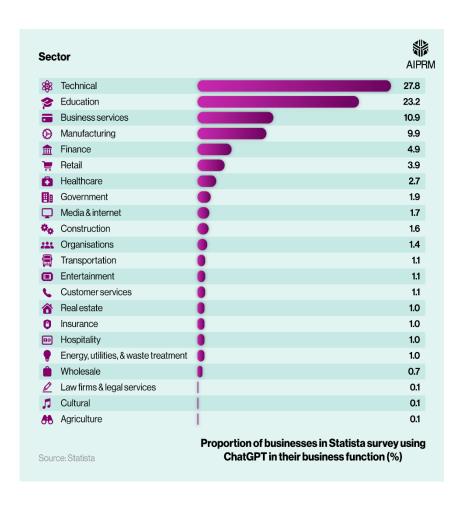
**Generative AI:** Any set of artificial intelligence (AI) algorithms or tools that can <u>create</u> new content using pre-existing data (text, audio, video, images).

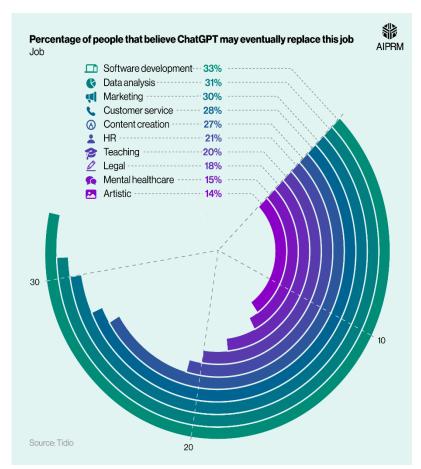
**LLMs:** All systems that generate new content by interacting with users using <u>written/spoken language</u>.

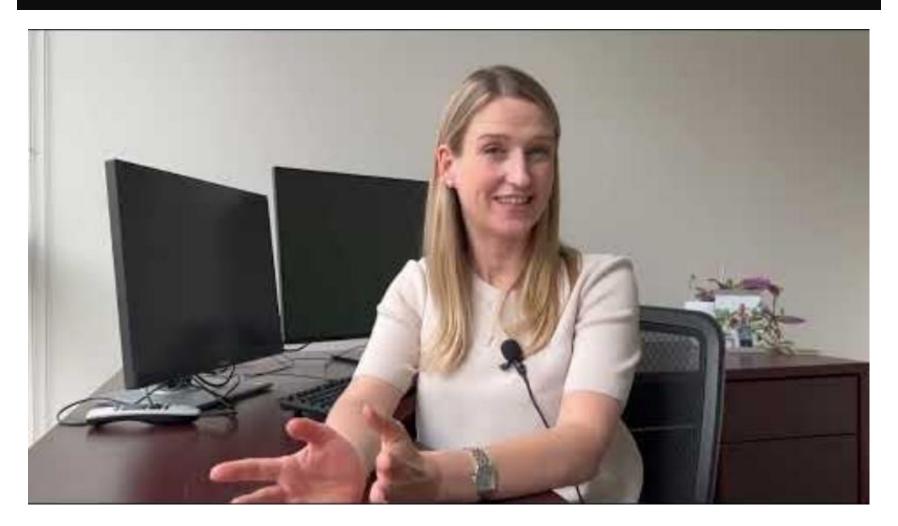






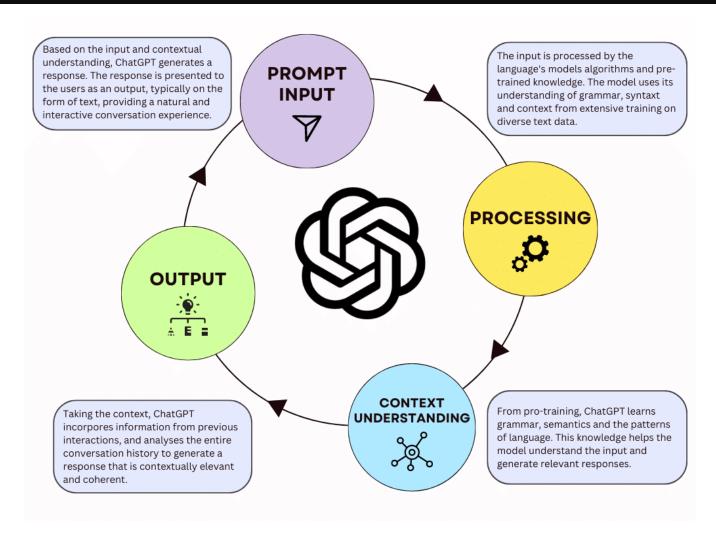






- Fundamentally, <u>ChatGPT</u> is an algorithm that predicts the most "correct sounding" answer to any question. It may not actually be <u>correct</u>...
- ChatGPT excels at generating lots of suggestions to answer <u>any</u> possible question. However, determining what the <u>best solution</u> is remains a uniquely human endeavor.
- The optimal workflow involves using <u>ChatGPT</u>
  as a personal assistant (known as a <u>Co-Pilot</u>).

<sup>&</sup>quot;It is both smarter and dumber than any person you've ever met."



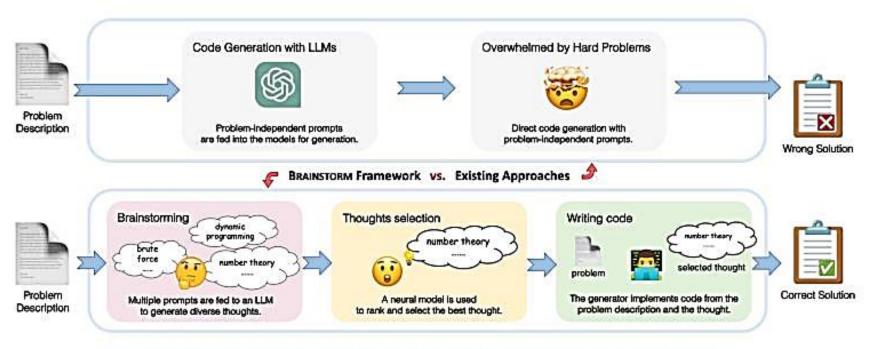
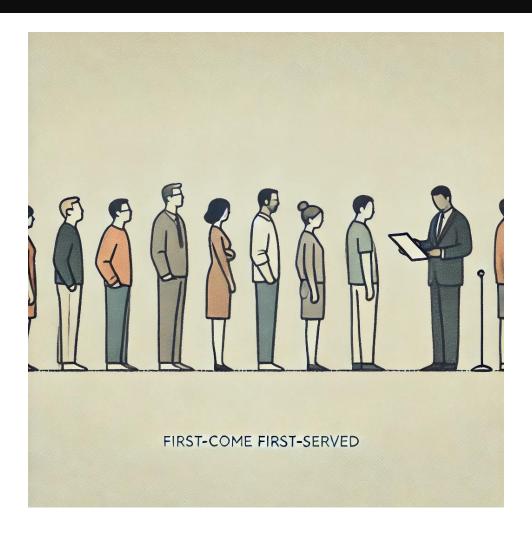
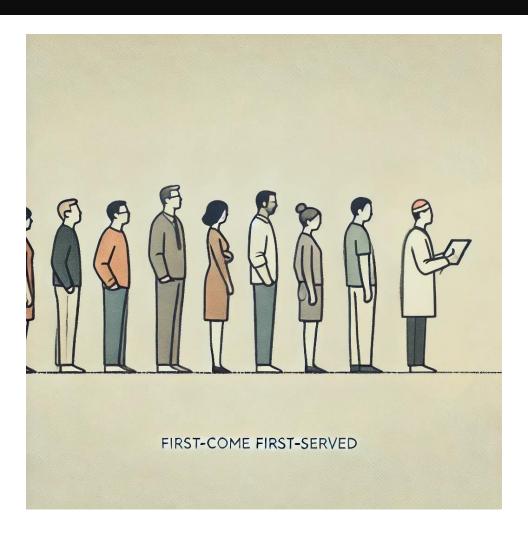
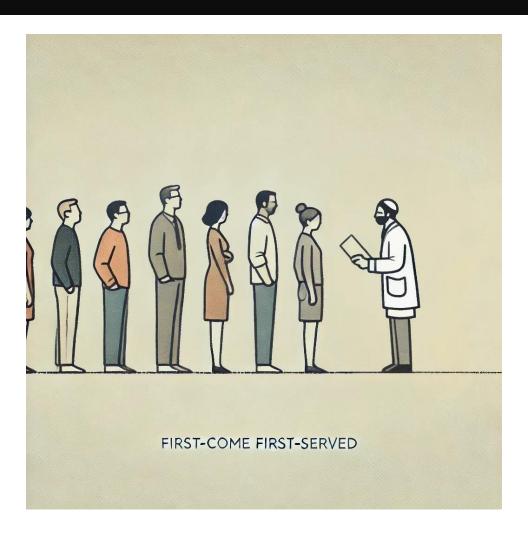


Figure 1: An illustrative example for the BRAINSTORM framework.









- You are the arbiter of truth!
  - Al tools do not know if they are <u>right or wrong</u>.
  - You need to determine whether the response is correct and useful. If not, rephrase your question or provide more context!
- When developing software, coders use unit testing to validate the expected behavior of the code. Many tests ensure that the code is correct in all cases.

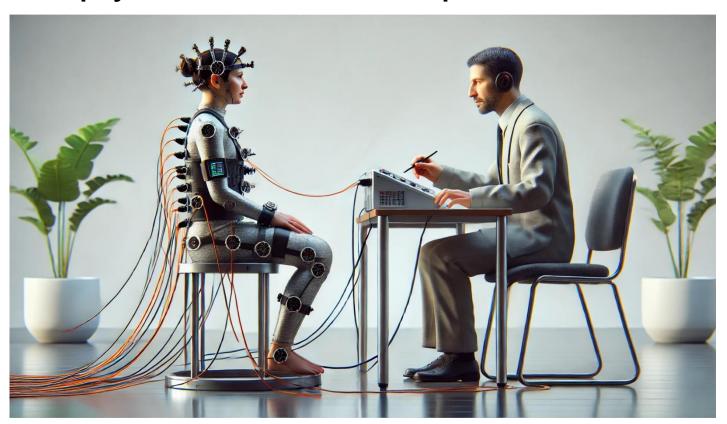
### Verifying the correctness of an LLM answer:

- Regenerate the response to see if the LLM returns a different answer than the one it gave you.
  - Rephrase the question and ask it again.
- In more recent versions, ask the LLM to verify the information online and check the links it provides.
- Paste the solution in a new chat window and ask the LLM to evaluate inaccuracies in the answer.
- Provide contradictory statements to see if the LLM can identify which one is true and why.
- Analyze the response for "<a href="hedging">hedging</a>" words like "may, might, possibly, potentially, uncertain..."

### Prompting tips and tricks:

- Show the LLM examples with the solution.
  - This technique is called <u>multi-shot prompting</u>.
- Decompose a large problem into simpler tasks where it is easier for you to verify correctness.
- Ask whether the proposed solution exhibits
   structure that is associated with a correct response.
- Use domain knowledge to identify issues in the solution. Explain to the LLM why the answer is incorrect and what a correct response looks like.
- Directly use the provided solution and modify it using your knowledge of the problem domain.

- 1. Level-up your prompt engineering skills.
- 2. Deeply understand the problem domain.



### Programming with <a href="ChatGPT">ChatGPT</a>

### 1. Understand the purpose of the code.

– What are the objectives and data requirements?

### 2. Clearly define the inputs and outputs.

- What is the <u>data schema</u> and where does it come from?
- What information should the script return to the user?

### 3. Define the appropriate programming logic.

– Do you want comments? Should the code be able to handle errors? How readable or performant should it be?

### 4. Test and refine the prompt/code.

 Do not expect code for complex systems to automatically work. Always assume ChatGPT provides a "<u>first-draft</u>".

## Programming with <a href="ChatGPT">ChatGPT</a>

#### **Example:** Define an LP using Python and gurobiypy

- Load a dataset from a csv file called "Coefficients.csv"
   that has the parameter values for the objective function.
- Maximize an objective function consisting of the sum of 20 continuous, non-negative decision variables where the first ten variables have an upper bound of 40 and the rest of the variables have an upper bound of 45.
- The sum of all decision variables is less than 100.
- Include constraints such that the sum of any three of the twenty decision variables is equal to no more than 66% of the total allocation in the optimal solution.

# Programming with <a href="ChatGPT">ChatGPT</a>

```
import gurobipy as gp
import pandas as pd
# Load dataset from CSV file
dataset = pd.read csv("Coefficients.csv")
# Create a new model
model = gp.Model("Linear Program")
# Create decision variables
variables = []
for i in range(20):
    if i < 10:
        ub = 40
    else:
        ub = 45
    variable = model.addVar(vtype=gp.GRB.CONTINUOUS, lb=0, ub=upper bound)
                                                                            108
    variables.append(variable)
```

# Programming with **ChatGPT**

```
# Extract the coefficients for the objective function
objective coefficients = coefficients df.values.flatten()
# Set the objective function to maximize
model.setObjective(gp.quicksum(objective coefficients[i] * variables[i] for
i in 20)), GRB.MAXIMIZE)
# Add the constraint: the sum of all decision variables is less than 100
model.addConstr(gp.quicksum(variables[i] for i in range(20)) <= 100)</pre>
# Add the constraint: the sum of any three variables is equal to no more
than 66% of the total allocation
for i in range(num variables):
    for j in range(i + 1, num variables):
        for k in range(j + 1, num variables):
            model.addConstr(variables[i] + variables[j] + variables[k] <=</pre>
0.66 * gp.quicksum(variables), f"constraint {i} {j} {k}")
```

# Programming with **ChatGPT**

Using <a href="ChatGPT">ChatGPT</a> as a programming assistant is powerful!

#### Benefits:

- Quickly create a functional and moderately efficient codebase.
- Can explain why/how certain snippets of code work.
- Acts as a personal tutor/assistant for completing projects.
- It can suggest alternative Python libraries and ways of coding.

#### Drawbacks:

- Requires you to clearly explain code functionality in great detail.
- It sometimes <u>hallucinates</u> code/libraries that do not exist.
- Does not tell you what logic may be missing from your code.
- Typically requires extensive testing to ensure correctness for all use cases (although you can use <u>ChatGPT</u> to help with <u>this</u>).
- There are persistent <u>privacy</u> and <u>cybersecurity</u> concerns.

### Next Class: Linear Programming Duality

Different problem formulations that give identical optimal solutions! The difference is that the number of variables in the **dual problem** is equal to the number of constraints in the original (**primal**) problem. The number of constraints in the **dual problem** is equal to the number of variables in the **primal problem**. Both are linear programs!

- Weak and strong duality: Relating the objective functions and using them as optimality certificates.
- Reduced costs and shadow prices.
- Complementary slackness theory.