

An Overview of Optimization

History, Classification and Methods Part 1

MORSC Tutorial

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Outline

- ▶ What is Optimization?
- ▶ History of Optimization
 - ▶ Pre Simplex Era
 - ▶ Modern Optimization and applications
- ▶ NEOS server

What is optimization?

- ▶ an act, process, or methodology of making something (as a design, system, or decision) as fully perfect, functional, or effective as possible; specifically : the mathematical procedures (as finding the maximum of a function) involved in this.
- *Merriam Webster Dictionary*.

In Operations Research

Optimization=Mathematical Optimization

No Heuristics or Metaheuristics in this part.

Mathematical Optimization

A Mathematical Optimization Problem:

$$\begin{aligned} \text{(P)} \quad & \min h(x) \\ \text{s.t.} \quad & f_t(x) \leq 0 \quad \forall t \in T \\ & g_s(x) = 0 \quad \forall s \in S \\ & x \in X \end{aligned}$$

$$h, f, g : X \rightarrow \mathbb{R}$$

X is a finite dimensioned space
 T, S are arbitrary index sets

Mathematical Optimization refers to the study of these problems' properties, development and implementation of solution algorithms and their application to real world problems.

-*Mathematical Optimization Society (INFORMS)*

Mathematical Optimization

A Mathematical Optimization Problem:

$$\begin{array}{llll}
 \text{(P)} & \min h(x) & & \text{Objective Function} \\
 \text{s.t.} & f_t(x) \leq 0 & \forall t \in T & \text{Inequality Constraints} \\
 & g_s(x) = 0 & \forall s \in S & \text{Equality Constraints} \\
 & x \in X & & \text{Variable Definition}
 \end{array}
 \left. \vphantom{\begin{array}{l} \text{Inequality Constraints} \\ \text{Equality Constraints} \end{array}} \right\} \text{Constraints}$$

Mathematical Optimization refers to the study of these problems' properties, development and implementation of solution algorithms and their application to real world problems.

-*Mathematical Optimization Society (INFORMS)*

Some Applications of Optimization

Finance

- ▶ Portfolio Management
- ▶ Asset Pricing
- ▶ Risk Management
- ▶ Financial Valuation

Manufacturing

- ▶ Product Mix Planning
- ▶ Inventory Management
- ▶ Job Scheduling
- ▶ Maintenance Scheduling

Health Care

- ▶ Staff Scheduling
- ▶ Radiation Exposure
- ▶ Blood Bank collection
- ▶ Ambulance Scheduling

Transportation- Airlines

- ▶ Fleet assignment
- ▶ Crew Scheduling
- ▶ Fuel Allocation
- ▶ Airport Traffic Planning

Transportation- Other

- ▶ Vehicle Routing
- ▶ Depot/Warehouse location
- ▶ Transportation System Man.
- ▶ Fleet Management

Communications/Computing

- ▶ Circuit Design
- ▶ Office Automation
- ▶ Telephone Operator Scheduling

ETC...

The History of Optimization

- ▶ Can be traced back as far as 300 BC
- ▶ Can be divided into two eras:

Pre Simplex Era



Joseph Fourier



Pierre de Fermat

1947

Modern Optimization



George Dantzig



Ralph Gomory

The History of Optimization

Pre Simplex Era



Joseph Fourier



Pierre de Fermat



Leonid Kantorovich



Tjalling Koopmans

Pre Simplex Era

300 BC	Euclid of Alexandria	<ul style="list-style-type: none">• Minimal Distance b/w a point and a line• Square is rectangle with max area given perimeter
200 BC	Zenodorus	<ul style="list-style-type: none">• Dido's Problem- Semicircle
1615	Johannes Kepler	<ul style="list-style-type: none">• Wine Barrel Problem• Secretary Problem
1636	Pierre de Fermat	<ul style="list-style-type: none">• Derivative vanishes at local optimum
1660s	I. Newton, G. Leibniz	<ul style="list-style-type: none">• Calculus of Variations

Pre Simplex Era

- | | | |
|------|-----------------|---|
| 1736 | Leonard Euler | <ul style="list-style-type: none">• Foundations of Graph Theory |
| 1754 | Joseph Lagrange | <ul style="list-style-type: none">• Maximum and Minimum w/ Constraints |
| 1823 | Joseph Fourier | <ul style="list-style-type: none">• Rudimentary LP Programming algorithm |
| 1902 | Gyula Farkas | <ul style="list-style-type: none">• Farkas Lemma |
| 1905 | Johan Jensen | <ul style="list-style-type: none">• Convex Functions |
| 1917 | Harris Hancock | <ul style="list-style-type: none">• Published Theory of Maxima and Minima |

Pre Simplex Era

- | | | |
|------|--------------------|---|
| 1927 | Karl Menger | <ul style="list-style-type: none">• Max number of p-q paths=Minimum Cut |
| 1931 | Dénes König | <ul style="list-style-type: none">• Maximum matching= Minimum vertex cover in bipartite graphs |
| 1935 | Hassler Whitney | <ul style="list-style-type: none">• Matroids |
| 1939 | Leonid Kantorovich | <ul style="list-style-type: none">• Linear Programming Methods• Transportation Problem |
| 1941 | Frank Hitchcock | <ul style="list-style-type: none">• Transportation Problem |
| 1942 | Tjalling Koopmans | <ul style="list-style-type: none">• Sensitivity Analysis• Transportation Problem |

The History of Optimization

Modern Optimizaion



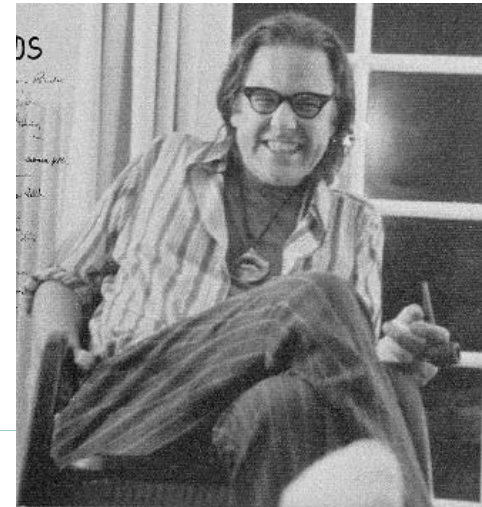
George Dantzig



Ralph Gomory



Martin Grötschel



Jack Edmonds

The first problem of Modern Optimization

Given a set of Recommended Dietary Allowances and a list of 77 foods with their prices and nutrition content what is the cheapest survival diet possible?

Table 1. 1943 RDAs for a moderately active 154-pound man.

Nutrient	RDA
Calories	3,000 kcalories
Protein	70 grams
Calcium	0.8 grams
Iron	12 milligrams
Vitamin A	5,000 IU
Thiamine (Vitamin B ₁)	1.8 milligrams
Riboflavin (Vitamin B ₂)	2.7 milligrams
Niacin	18 milligrams
Ascorbic Acid (Vitamin C)	75 milligrams

Linear Programming (Optimization)

Stigler's Diet (1943)

$$(P) \quad \min \sum_{j \in J} c_j x_j$$

$$\text{s.t.} \quad \sum_{j \in J} a_{ij} x_j \geq RDA_i \quad \forall i \in I$$

$$x_j \geq 0 \quad \forall j \in J$$

J denote the set of 77 food items

c_j denote the cost of food item $j \in J$.

I denote the set of 9 essential nutrients in a diet

RDA_i denote the amount of nutrient $i \in I$ necessary to survive.

a_{ij} denote the amount of nutrient $i \in I$ contained in 1 unit of food item $j \in J$.

x_j denote the amount of food item $j \in J$ to be consumed in the diet.

Linear Programming (Optimization)

Stigler's Diet (1943)

$$(P) \quad \min \sum_{j \in J} c_j x_j$$

$$\text{s.t.} \quad \sum_{j \in J} a_{ij} x_j \geq RDA_i \quad \forall i \in I$$

$$x_j \geq 0 \quad \forall j \in J$$

Linear Programming

Objective Function- Linear

Constraints- Finite and Linear

Variable Definition- Continuous

Solved by Trial and Error with Mathematical intuition

Solving LPs Today

Linear Programming (Algorithms)

1947	George Dantzig	<ul style="list-style-type: none"> • Primal Simplex 	
1954	Carlton Lemke	<ul style="list-style-type: none"> ★ Dual Simplex 	
1954	G. Dantzig and W. Orchard Hays	<ul style="list-style-type: none"> • Revised Simplex Method 	
1958	L. Ford and D. Fulkerson	<ul style="list-style-type: none"> • Column Generation 	
1979	Leonid Khachiyan	<ul style="list-style-type: none"> • Ellipsoid Method 	} Polynomial running time
1984	Narendra Karmarkar	<ul style="list-style-type: none"> ★ Interior Point Method 	

Problem Definition- Salesperson assignment

Assume you have 3 salespersons in different cities and three other cities to which you would like them to visit with the below cost matrix of flights. To which city should I assign each salesperson to minimize cost?

From \ To	Denver	Edmonton	Fargo
Austin	250	400	350
Boston	400	600	350
Chicago	200	400	250

Combinatorial Optimization

The Assignment Problem

$$(P) \quad \min \sum_{i \in V_1} \sum_{j \in V_2} c_{ij} x_{ij}$$

$$\text{s.t.} \quad \sum_{i \in V_1} x_{ij} = 1 \quad \forall j \in V_2$$

$$\sum_{j \in V_2} x_{ij} = 1 \quad \forall i \in V_1$$

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

V_1 denote the set of salesperson

V_2 denote the set of cities salespersons must visit.

c_{ij} denote the cost of travelling for salesperson $i \in V_1$ to travel to city $j \in V_2$.

x_{ij} denote whether salesperson $i \in V_1$ will travel to city $j \in V_2$.

Combinatorial Optimization

The Assignment Problem

$$(P) \quad \min \sum_{i \in V_1} \sum_{j \in V_2} c_{ij} x_{ij}$$

Objective Function- Linear

$$\text{s.t.} \quad \sum_{i \in V_1} x_{ij} = 1 \quad \forall j \in V_2$$

Constraints- Finite and Linear

$$\sum_{j \in V_2} x_{ij} = 1 \quad \forall i \in V_1$$

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

Variable Definition- Binary

Combinatorial Optimization

The Assignment Problem

Current state of the art solution method

$$(P) \quad \min \sum_{i \in V_1} \sum_{j \in V_2} c_{ij} x_{ij}$$

$$\text{s.t.} \quad \sum_{i \in V_1} x_{ij} = 1 \quad \forall j \in V_2$$

$$\sum_{j \in V_2} x_{ij} = 1 \quad \forall i \in V_1$$

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

- **The Hungarian Method** Harold Kuhn

Combinatorial Optimization

The Assignment Problem

Interesting Result

$$(P) \quad \min \sum_{i \in V_1} \sum_{j \in V_2} c_{ij} x_{ij}$$

$$\text{s.t.} \quad \sum_{i \in V_1} x_{ij} = 1 \quad \forall j \in V_2$$

$$\sum_{j \in V_2} x_{ij} = 1 \quad \forall i \in V_1$$

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



$$(\bar{P}) \quad \min \sum_{i \in V_1} \sum_{j \in V_2} c_{ij} x_{ij}$$

$$\text{s.t.} \quad \sum_{i \in V_1} x_{ij} = 1 \quad \forall j \in V_2$$

$$\sum_{j \in V_2} x_{ij} = 1 \quad \forall i \in V_1$$

$$x_{ij} \in [0, 1] \quad \forall i \in V_1, j \in V_2$$

Solving the Assignment Problem

Linear Programming (Algorithms)

- | | | |
|------|--------------------------------|--|
| 1947 | George Dantzig | <ul style="list-style-type: none">• Primal Simplex |
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| 1984 | Narendra Karmarkar | <ul style="list-style-type: none">• Interior Point Method |

Problem Definition- Depot Location

There are 4 potential depot locations, each with a different installation cost, that must serve a set of 8 retail stores. Each depot has a restricted list of possible stores it can serve as below. What is the minimum cost of installing depots such that each store has at least one depot?

Store	Depot 1	Depot 2	Depot 3	Depot 4
1	Yes	No	No	Yes
2	No	Yes	No	Yes
3	No	Yes	Yes	Yes
4	No	No	Yes	Yes
5	Yes	Yes	No	No
6	No	No	Yes	Yes
7	Yes	No	No	No
8	Yes	Yes	No	No

Combinatorial Optimization

The Set Covering Problem

$$(P) \quad \min \sum_{j \in J} f_j x_j$$

$$\text{s.t.} \quad \sum_{j \in J} a_{ij} x_j \geq 1 \quad \forall i \in I$$

$$x_j \in \{0, 1\} \quad \forall j \in J$$

J denote the set of depots.

f_j denote the cost of opening depot $j \in J$.

I denote the set of retail stores.

a_{ij} is 1 if depot $j \in J$ can serve store $i \in I$.

x_j denote whether depot j is open.

Combinatorial Optimization

The Set Covering Problem

$$(P) \quad \min \sum_{j \in J} f_j x_j$$

$$\text{s.t.} \quad \sum_{j \in J} a_{ij} x_j \geq 1 \quad \forall i \in I$$

$$x_j \in \{0, 1\} \quad \forall j \in J$$

Objective Function- Linear

Constraints- Finite and Linear

Variable Definition- Binary

Combinatorial Optimization

The Set Covering Problem

Question

$$(P) \quad \min \sum_{j \in J} f_j x_j$$

$$\text{s.t.} \quad \sum_{j \in J} a_{ij} x_j \geq 1 \quad \forall i \in I$$

$$x_j \in \{0, 1\} \quad \forall j \in J$$



$$(P) \quad \min \sum_{j \in J} f_j x_j$$

$$\text{s.t.} \quad \sum_{j \in J} a_{ij} x_j \geq 1 \quad \forall i \in I$$

$$x_j \in [0, 1] \quad \forall j \in J$$

Combinatorial Optimization

The Set Covering Problem

Question

$$(P) \quad \min \sum_{j \in J} f_j x_j$$

$$\text{s.t.} \quad \sum_{j \in J} a_{ij} x_j \geq 1 \quad \forall i \in I$$

$$x_j \in \{0, 1\} \quad \forall j \in J$$



$$(P) \quad \min \sum_{j \in J} f_j x_j$$

$$\text{s.t.} \quad \sum_{j \in J} a_{ij} x_j \geq 1 \quad \forall i \in I$$

$$x_j \in [0, 1] \quad \forall j \in J$$

Cannot use LP Methods

Is NP Hard

Combinatorial Optimization

Question

What changed between

The Set Covering Problem & The Assignment Problem ?
Totally Unimodular Matrix

Total Unimodularity = Easy Problems

Solving Combinatorial Problems

Easy Problems

- Specialized Algorithms that run in Polynomial Time
- Find a complete formulation and solve the LP model
 - Model may be polynomial in size.
 - Model may have exponential number of inequalities but can be separated in polynomial time.

Solving Combinatorial Problems

Difficult Problems (NP hard)

- Approximation Algorithms
- Cutting Plane Methods
- Branch and Bound/ Branch and Cut **Most often used in practice**
- Group Theoretic Approach **Seldom used in practice**

Problem Definition- A 24 hour restaurant

In a 24 hour restaurant they have established shifts for their full time workers to cover the day. However, demand for workers varies for each 3 hour time window. Due to the time of day, the wage for a full time worker in each shift varies. What is the minimum cost of employing workers to satisfy demand?

TABLE 2.1 Time Windows for Shift Workers

Time Window	Shift				Workers Required
	1	2	3	4	
6 a.m.–9 a.m.	X			X	55
9 a.m.–12 noon	X				46
12 noon–3 p.m.	X	X			59
3 p.m.–6 p.m.		X			23
6 p.m.–9 p.m.		X	X		60
9 p.m.–12 a.m.			X		38
12 a.m.–3 a.m.			X	X	20
3 a.m.–6 a.m.				X	30
Wage rate per 9 h shift	\$135	\$140	\$190	\$188	

Integer Programming (Optimization)

The Set Covering Problem

$$\begin{aligned}
 \text{(P)} \quad & \min \sum_{j \in J} f_j x_j \\
 \text{s.t.} \quad & \sum_{j \in J} a_{jt} x_j \geq d_t \quad \forall t \in T \\
 & x_j \geq 0 \text{ and integer} \quad \forall j \in J
 \end{aligned}$$

J denote the set of shifts.

f_j denote the wage of an employee on that shift

T denote the set of 3 hour time windows.

d_t is the # of workers needed in time window t

a_{jt} is 1 if shift $j \in J$ covers time window $t \in T$.

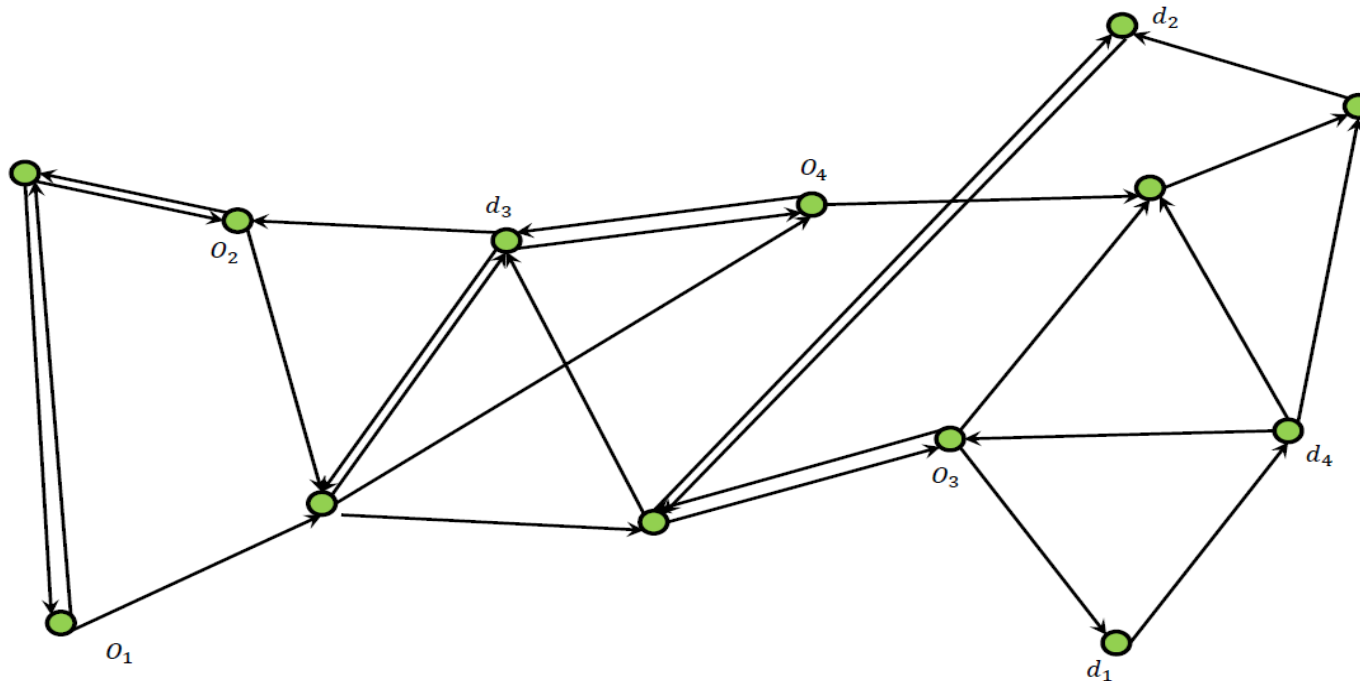
x_j denote the number of employees in shift $j \in J$.

Solving Pure Integer Programs

- Approximation Algorithms
- Branch and Bound/ Branch and Cut
- Cutting Plane Methods
 - Gomory Cuts
 - Valid Inequalities
 - Lift and Project
- Decomposition Methods
- Group Theoretic Approach

Problem Definition- Network Loading Problem

Suppose you are given a network and a set of requests with different origin and destination nodes and demand quantity that you have to route. For each link you can install a structure that allows a number u of units to pass. The cost of each structure varies per link. What is the minimum cost of installation to send all the requests?



Problem Definition- Network Loading Problem

Suppose you are given a network and a set of requests with different origin and destination nodes and demand quantity that you have to route. For each link you can install a structure that allows a number u of units to pass. The cost of each structure varies per link. What is the minimum cost of installation to send all the requests?

Notation

A denote the set of arcs.

c_{ij} is the cost of installing a structure on arc $(i, j) \in A$

u is the flow capacity of a structure installed

N denote the set of nodes

f_{ij}^k is the portion of commodity k routed on arc $(i, j) \in A$.

x_{ij} denotes the number of structures installed on arc $(i, j) \in A$.

K denote the set of commodities.

$o(k)$ is the origin of a commodity k .

$d(k)$ is the destination of a commodity k .

W_k is the demand quantity of a commodity k .

Mixed Integer Programming (Optimization)

$$(P) \quad \min \sum_{ij \in A} c_{ij} x_{ij}$$

$$\text{s.t.} \quad \sum_{j \in N: (j,i) \in A} f_{ji}^k - \sum_{j \in N: (i,j) \in A} f_{ij}^k = \begin{cases} -1 & \text{if } i = o(k) \\ 0 & \text{if } i \notin \{o(k), d(k)\} \\ 1 & \text{if } i = d(k) \end{cases} \quad \forall i \in N, \forall k \in K$$

$$\sum_{k \in K} W_k f_{ij}^k \leq u x_{ij} \quad \forall ij \in A$$

$$f_{ij}^k \geq 0 \quad \forall ij \in A, k \in K$$

$$x_{ij} \geq 0 \text{ and integer} \quad \forall ij \in A$$

Solving Mixed Integer Programs

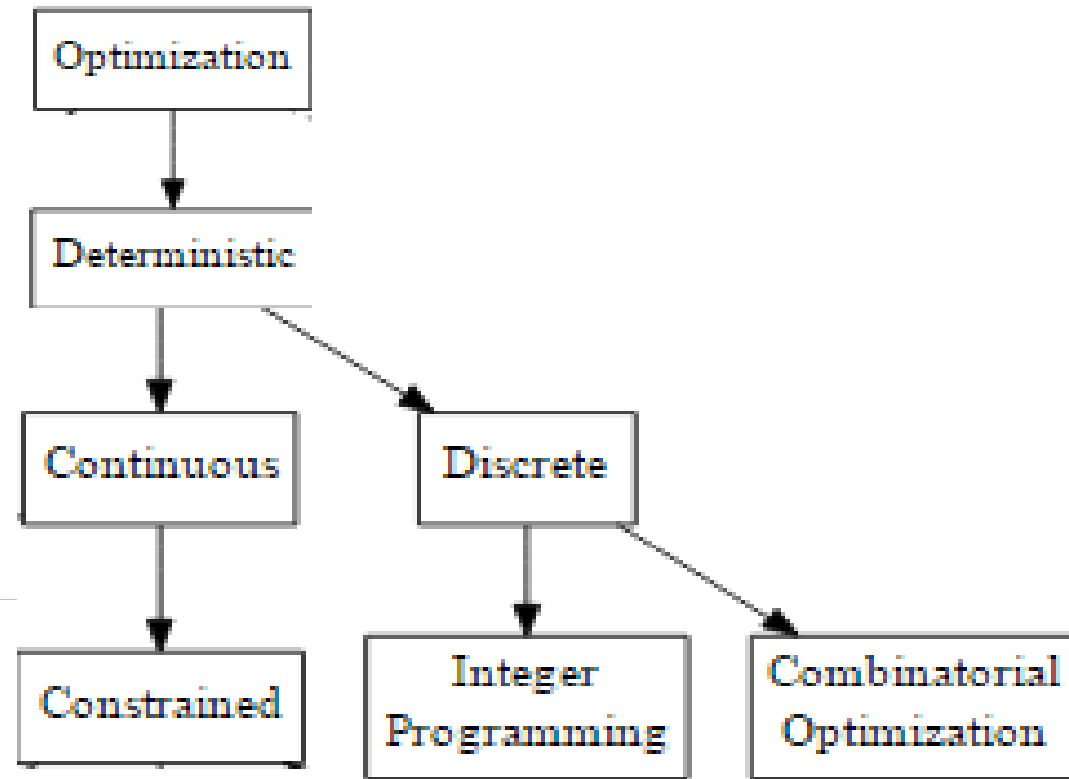
- Approximation Algorithms
- Branch and Bound/ Branch and Cut
- Cutting Plane Methods
 - Mixed Integer Chvatal-Gomory Cuts
 - Mixed Integer Rounding Cuts
 - Disjunctive Cuts
- Decomposition Methods
 - Benders Decomposition
- Group Theoretic Approach

Summary of today

- Focused on **Linear** objective functions and a **finite** set of **linear** constraints

Variables	Classification		Solution Methods
Continuous	Continuous Programming		Simplex (Primal/Dual), Column Generation, Ellipsoid Method, Interior Point Methods
Binary	Combinatorial	Easy	Polynomial time Algorithms, LP methods with separation oracles
		Hard	Implicit Enumeration, Cutting Planes, Group Theoretic Approach, Decomposition Methods
Integer	Integer Programming		
Continuous & Integer	Mixed Integer Programming		

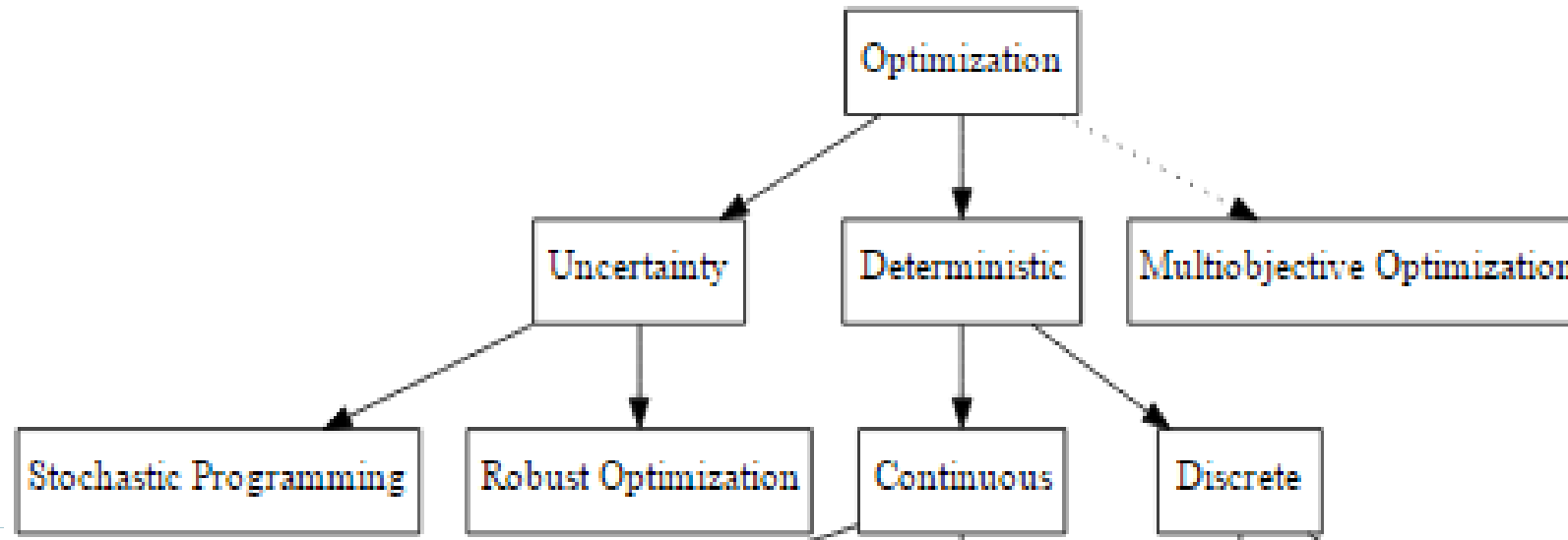
Summary of today



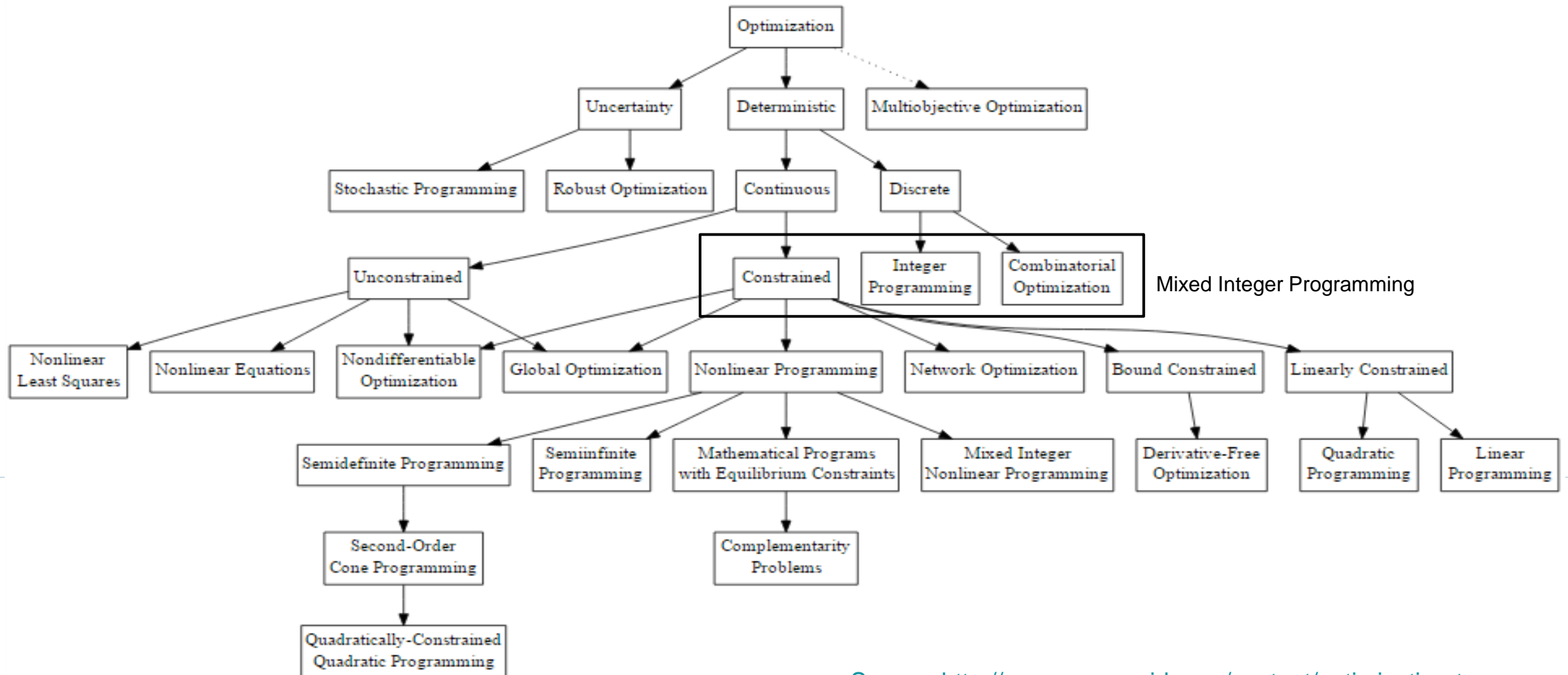
But there's a lot more ...

- ▶ **Multiple** Objective Functions
- ▶ **Convex** and **Non Convex** objective functions
- ▶ **Convex** and **Non Convex** constraints
- ▶ **Infinite** number of constraints
- ▶ **Uncertain** parameter data

An Approximate Taxonomy (by the NEOS Guide)



An Approximate Taxonomy (by the NEOS Guide)



The NEOS Server

- ▶ The NEOS Server is a free internet-based service for solving numerical optimization problems.
- ▶ Hosted by the Wisconsin Institutes of Discovery at the University of Wisconsin in Madison.
- ▶ Provides access to more than 60 state-of-the-art solvers, both commercial and open source, in more than a dozen optimization categories.
- ▶ Offers a variety of interfaces for accessing the solvers, and jobs run on distributed high-performance machines enabled by the HTCondor software.

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Thank you!