

MAEG4070 Engineering Optimization

Lecture 1 Introduction: What is Optimization?

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Course Setup

Welcome to the course on Engineering Optimization, with an introduction of its application in energy systems!

Basic administrative details:

- **Instructor:**

- Prof. Yue CHEN yuechen@mae.cuhk.edu.hk (FYB 604C)
- Office hour: 13:00-14:00, every Friday (online)
- English, Cantonese, Mandarin

- **Teaching assistants:**

- DENG Zhiyu zydeng@mae.cuhk.edu.hk (ERB113)
- INNERO Gino ginnero@mae.cuhk.edu.hk (AB1 205)
- JIN Liuchao lcjin@mae.cuhk.edu.hk (ERB 201)
- LIU Jingjun jingjunliu@mae.cuhk.edu.hk (AB1 2F)
- TANG Yunxi yxtang@mae.cuhk.edu.hk (AB1 2F)

Time for tutorial?

Posted on: Thursday, September 1, 2022 10:42:27 AM HKT

Dear MAEG4070 students,

Please select your time available for tutorial via the following link **before Sep 7.**

<https://forms.gle/zseCDZk6qdcqJFWFA>

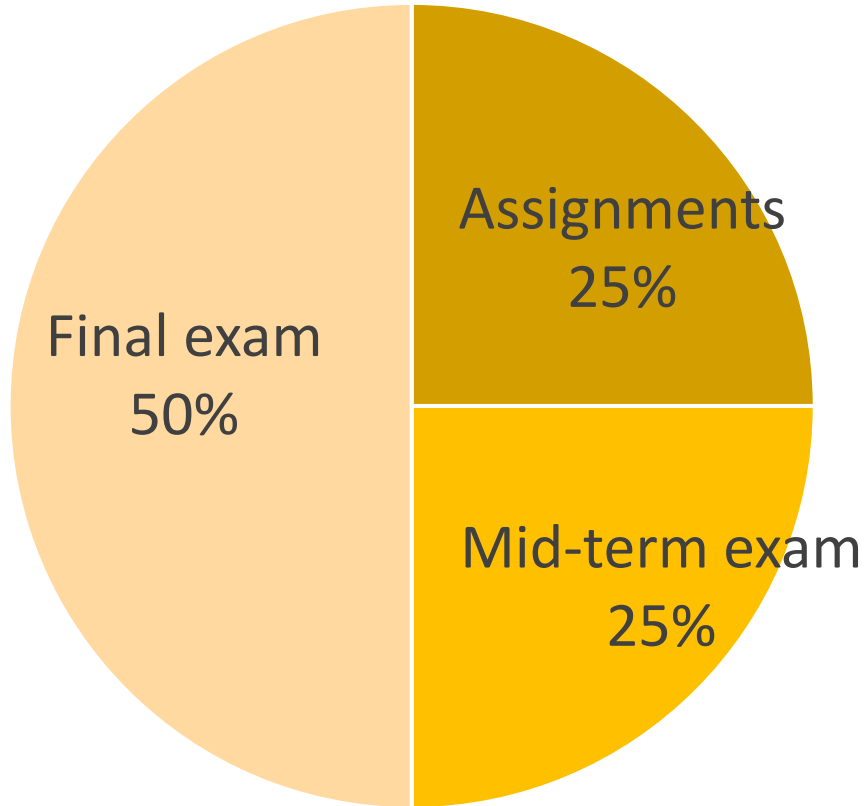
The tutorial will be given by TAs, starting from week 2.

Thanks!

Your time available for tutorial

- ☐ Tuesday 13:30 - 14:15
- ☐ Wednesday 10:30 - 11:15
- ☐ Wednesday 12:30 - 13:15
- ☐ Thursday 14:30 - 15:15
- ☐ Friday 11:30 - 12:15

Course Grading Scheme



- Due days for assignments will be specified.
- Assignments will carry a **50 % penalty** if handed in late.
- No credit will be given to assignments which are more than **three days late**.
- *Copying is **strictly prohibited**.*
- No make-up exam is given unless you get approval from the Director of Registry Services for permission for absence.
- If not permitted, a zero grade in that exam will be given.

Perquisite and reference

Assuming work with knowledge of:

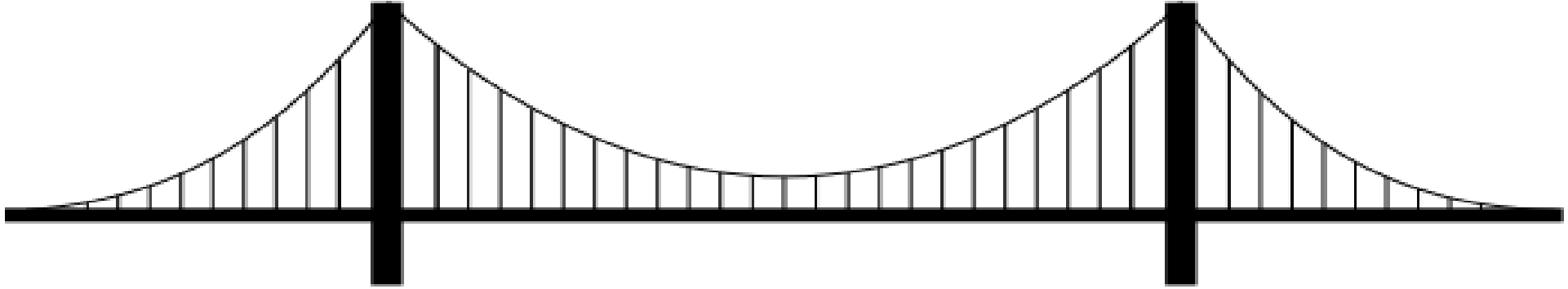
- Calculus, Linear Algebra
- Formal mathematical thinking
- Programming (Matlab, Python, ...)

If you fall short on any one of these things, **don't worry!**

Reference:

- S. Boyd, L. Vandenberghe. Convex optimization. Cambridge university press, 2004.
- R. Sioshansi, A. J. Conejo. Optimization in Engineering: Models and Algorithms. Springer, 2017.
- S. S. Rao. Engineering optimization: theory and practice. John Wiley & Sons, 2019.

Orientation of this course



Basic models:

- Linear programming
- Convex optimization
- Integer programming
-

Algorithms & Solvers:

- Lagrange / Dual Methods
- Linearization approaches
- CPLEX, MOSEK, ...

Engineering problems:

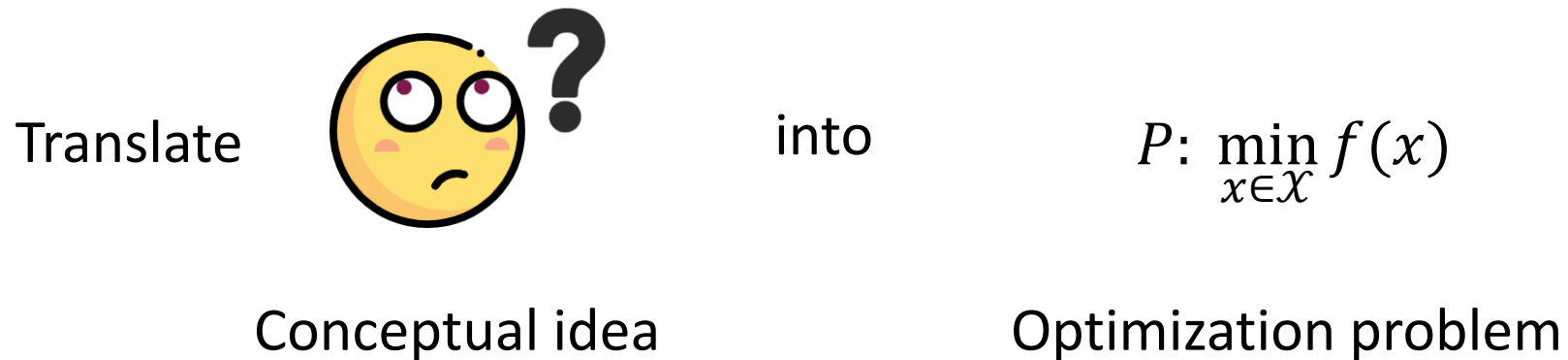
- Scheduling
- Machine Learning
- Market Analysis
-

A course bridges *mathematical models* and *engineering applications*
A course combining *math* and *programming*

What's optimization?

Different people may have different understanding about *optimization*

- Listing all possibilities and pick up the best?
- qualitative suggestions that lead to a better product design?
- trial and error?

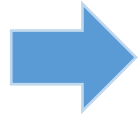


A **quantitative** and systematic methodology to search for the **best design** among numerous possibilities while **satisfying given constraints**.

Where can we see optimization?

As a matter of fact, any rational human behavior could be modelled as an optimization problem (intentionally or subconsciously) almost all the time.

Demand & supply
of goods



Minimize
Travel time

warehouse placement

Location of warehouses

Where can we see optimization?

Parameters, Plan



bridge construction



Detailed Design



**Maximize
Load Bearing**

Historical stock prices,
economy



stock market



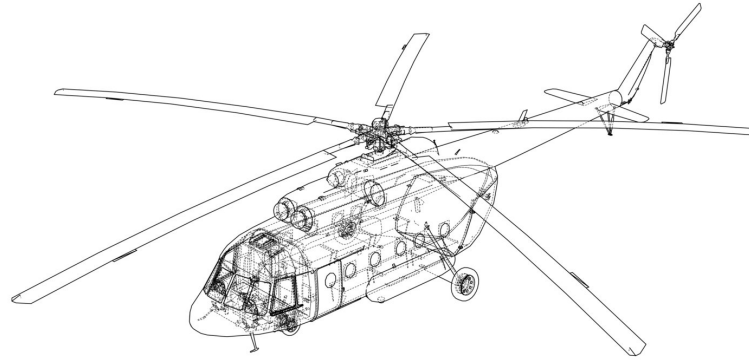
Stock Portfolio



**Maximize
Returns**

Where can we see optimization?

Parameters, Use plan

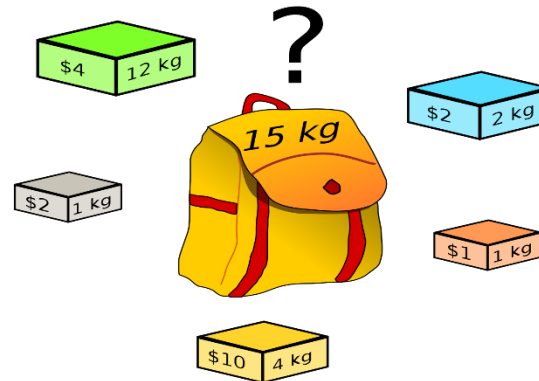


Minimize
Weight

Airplane design

Design

List of items



Maximize
Total value

knapsack problem

Number of items

Successful Applications in Real-world

Organization	Application	Cost Saving
AT&T	Location planning of telephone selling centers	\$ 406 million
79 electric utilities	Purchasing and energy management	\$ 125 million
Delta Air Line	Aircraft scheduling	\$ 100 million
SNCF	Train scheduling	\$ 15 million

- Not all engineering problems can be quantitatively modelled as an optimization and solved with current technologies.
- With the development of more advanced mathematics and computational tools, we can model and simulate more sophisticated process, behaviors, etc.
- **The application of optimization is increasingly practical, significant, and worthwhile!**

History of optimization

Greek mathematicians considers geometrical optimization problems.

Euclid

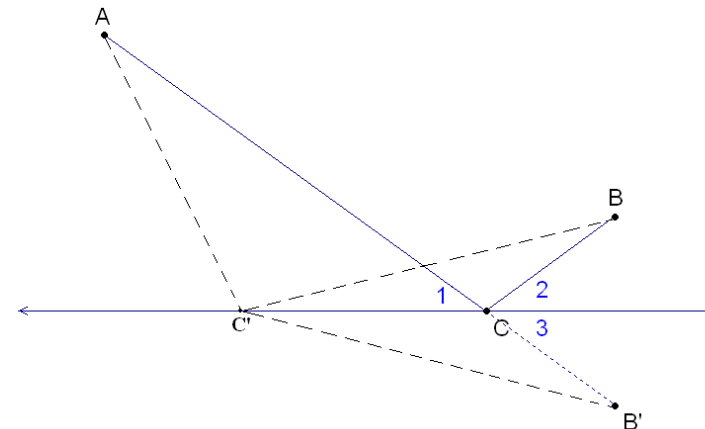
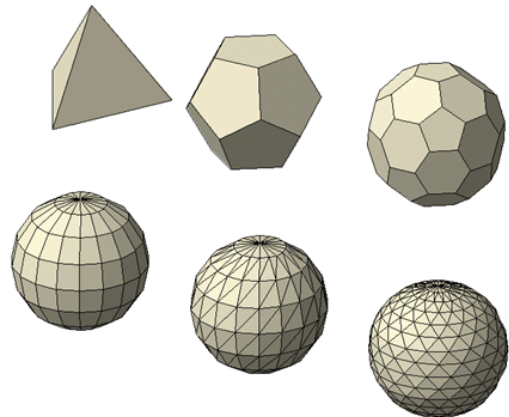
- the minimal distance between a point and a line.
- the greatest area among the rectangles with given total length of edges

Zenodorus

- A sphere encloses the greatest volume for a given surface area

Heron

- light travels between two points through the path with shortest traveling time when reflected at or refracted through a boundary



History of optimization

The Earliest Optimization Approach: Calculus

- where $\frac{df(x)}{dx} = 0$ gives a maximum or minimum.
- Pierre De Fermat & Joseph-Louis Lagrange: calculus-based formulae for identifying optima
- Isaac Newton & Johann C.F. Gauss: iterative methods to search for an optimum.

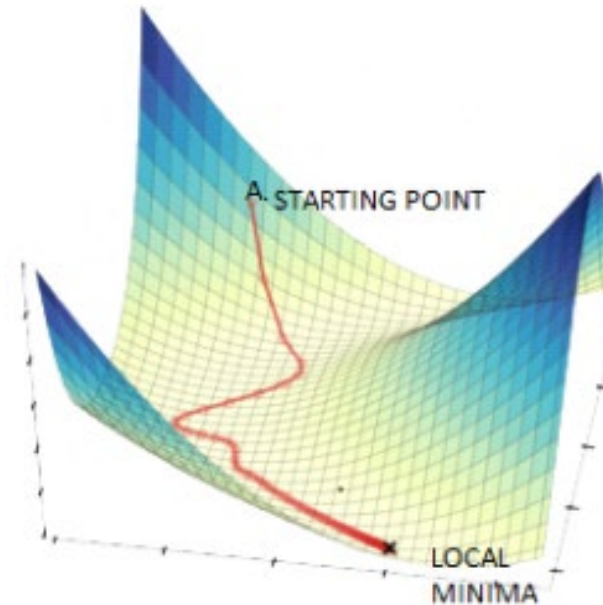
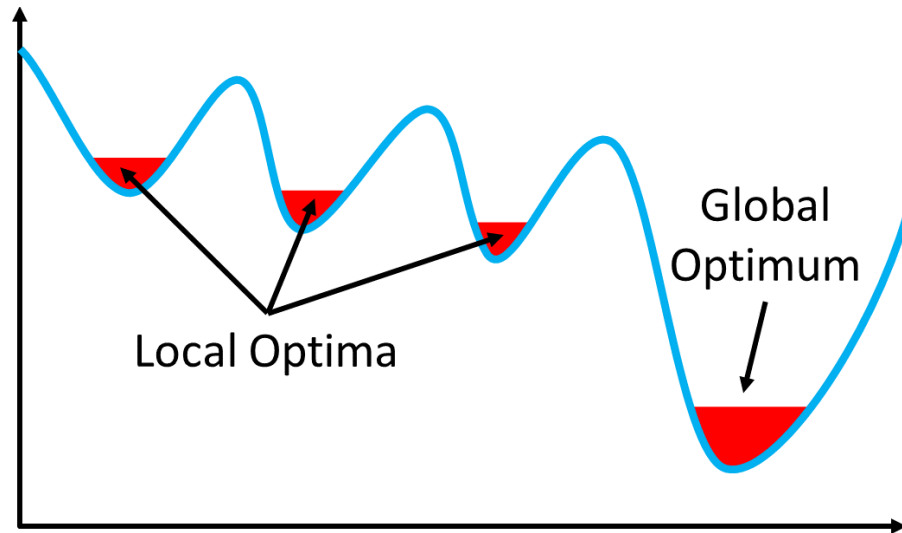
Classic Optimization approaches

- Leonid Kantorovich: Linear Programming, 1939
- George Dantzig: the Simplex Method, 1947
- John von Neumann: **the Theory of Duality**, 1947
- The **Karush-Kuhn-Tucker (KKT) condition**, 1939 and 1951 by two separate groups
- Models: Unconstrained/Constrained optimization, single-/multi-objective optimization, etc.
- Algorithms: the steepest descent method, Newton's method, the penalty method, etc.

History of optimization

First Generation Optimization: Local, Iterative, and Gradient-based

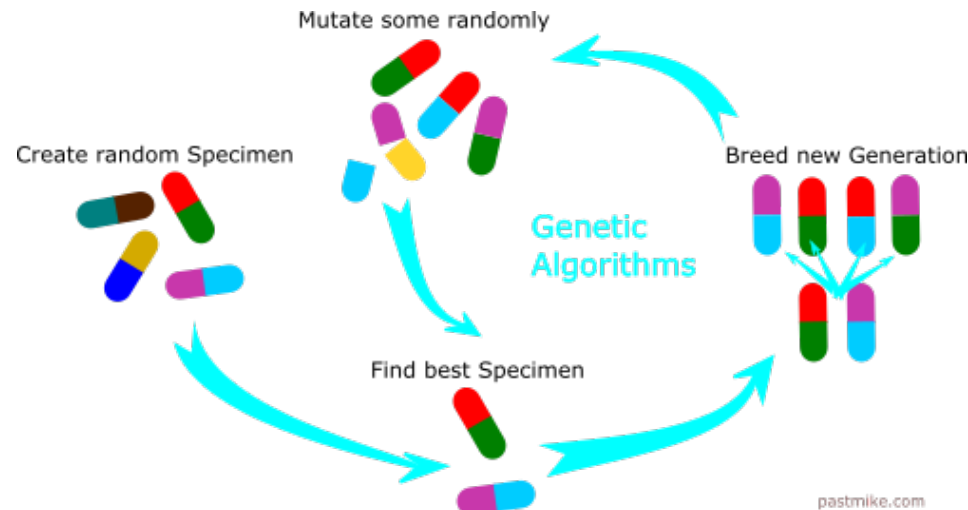
- Considers a *local optimal*
- Iterative methods: based on the location of the previously explored point
- Reliance on gradients or higher order derivatives
- Cons: hard to explain why optimal is optimal, limited computing power



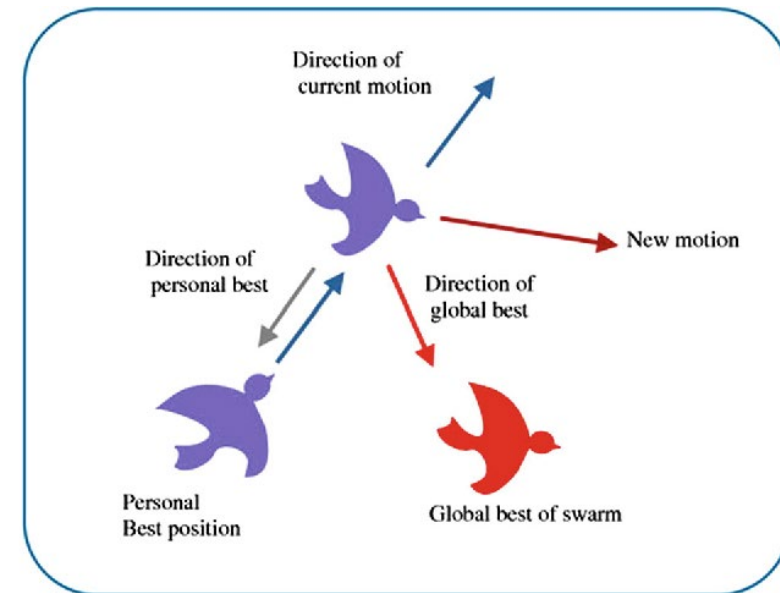
History of optimization

Second Generation Optimization: The Metaheuristic Approach

- Genetic Algorithms, “survival of the fittest”; Particle Swarm Optimization
- Pros: global optimization approaches; do not require gradients; support parallel computation.
- Cons: an enormous amount of trial points; the computation time could be hours or days.



Genetic algorithms

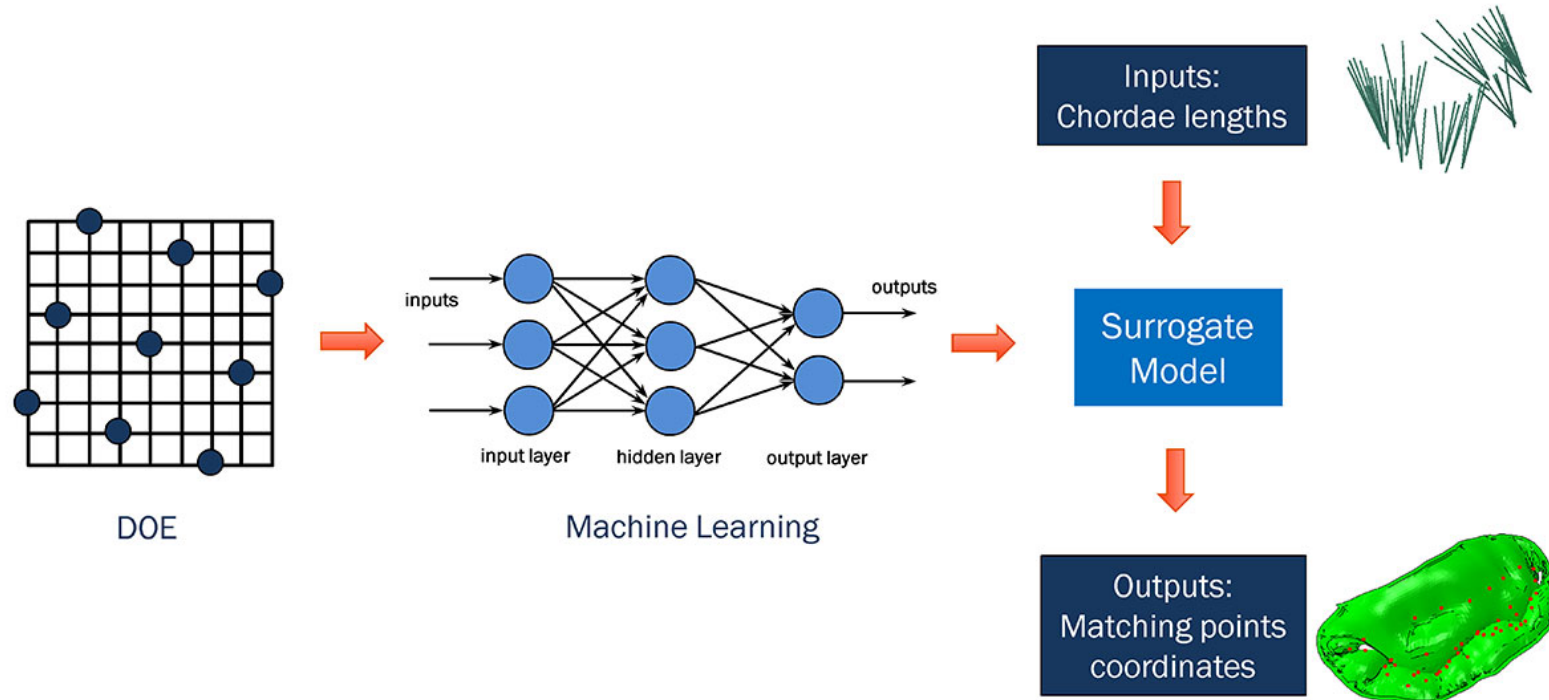


Particle swarm optimization

History of optimization

Third Generation Optimization: The AI-Based Approach

- Also called surrogate-based optimization
- Pros: support parallel computation, do not need gradients, use fewer design trials than before, offer insight and knowledge about the design problem
- Cons: curse-of-dimensionality (Richard E. Bellman)



Basic concept

$$P: \min_{x \in \mathcal{X}} f(x)$$

- **Variable:** x - entities and parameters that a designer can change
- **Objective:** $f(x)$ - the goals that a designer wants to achieve
- **Constraints:** \mathcal{X} – technical restrictions that a product or process must satisfy; or can be called *feasible region*; x is a feasible point if $x \in \mathcal{X}$.

An optimization is either:

- **Infeasible**, where $\mathcal{X} = \Phi$
- **Unbounded**, where $\mathcal{X} \neq \Phi$, but $f(x)$ can go to infinitely negative (unbounded below, also called "optimum/minimum not attained") or infinitely positive (unbounded above, usually treated as an infeasible point) when x varies in \mathcal{X}
- **Feasible**, where $\mathcal{X} \neq \Phi$, and the value $f(x)$ is finite.

Basic concept

Global optimum. Let $f(x)$ be the objective function, \mathcal{X} be the feasible region, and $x_0 \in \mathcal{X}$. Then x_0 is the global optimum if and only if $f(x) \geq f(x_0), \forall x \in \mathcal{X}$.

Local optimum. Let $f(x)$ be the objective function, \mathcal{X} be the feasible region, and $x_0 \in \mathcal{X}$. If there is a neighborhood of x_0 with radius $\varepsilon > 0$:

$$\mathcal{N}_\varepsilon(x_0) = \{x \mid ||x - x_0|| < \varepsilon\}$$

Such that $\forall x \in \mathcal{X} \cap \mathcal{N}_\varepsilon(x_0)$, we have $f(x) \geq f(x_0)$. Then x_0 is a local optimum.



Classification of optimization problems

Problem:

- Constrained v.s. unconstrained
- Single-objective v.s. multi-objective
- Single-level v.s. multi-level
- Deterministic v.s. uncertain

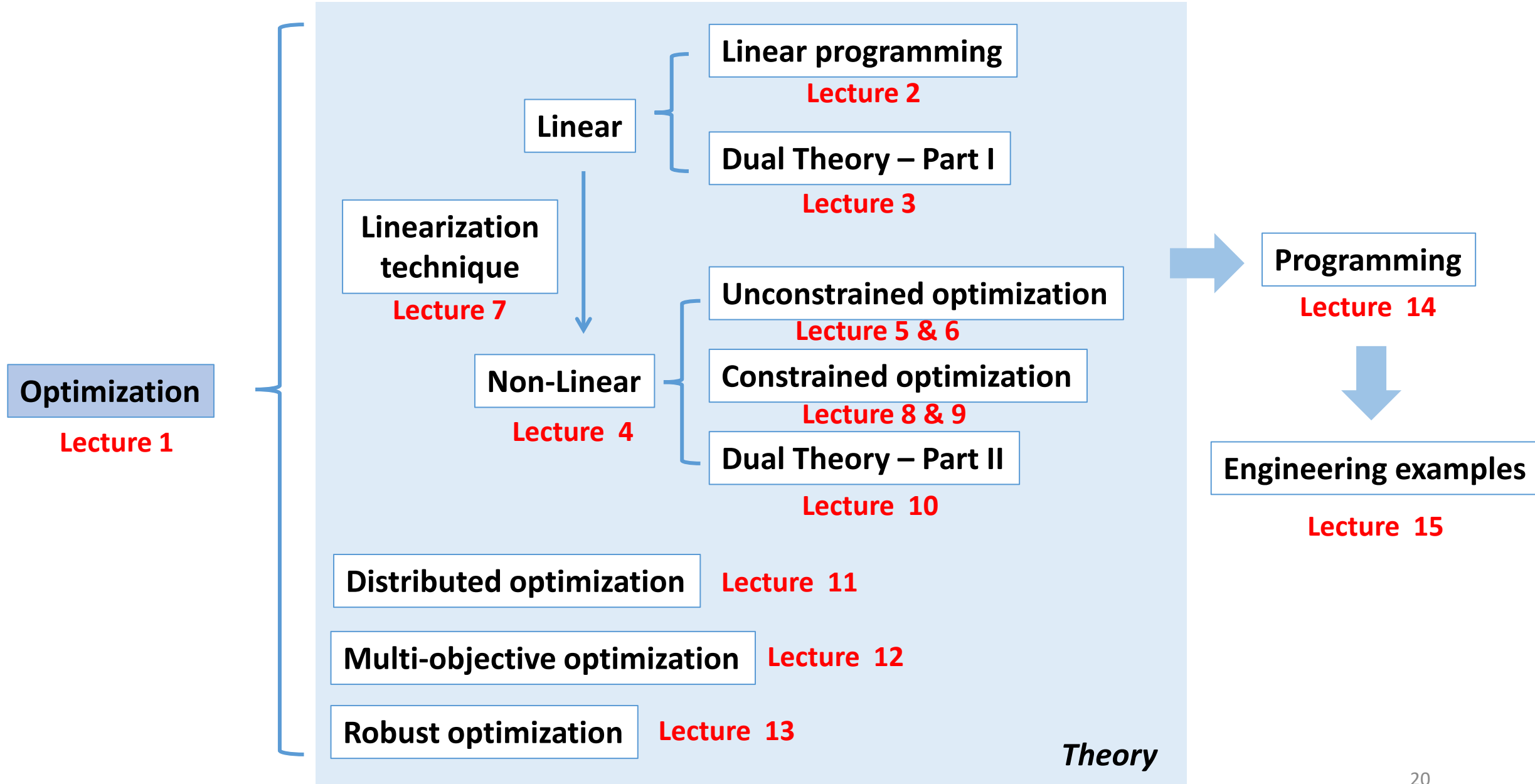
Response:

- Linear v.s. nonlinear
- Convex v.s. nonconvex
- Smooth v.s. nonsmooth

Variable:

- Continuous v.s. discrete (integer/binary)

Content of this course (tentative)



Procedure of applying optimization in engineering

In general, applying optimization in engineering follows five steps:

Step 1: Propose optimization problems, collect relevant data and information

Step 2: Establish mathematical model: determine the variables, the objective function and constraints

Step 3: Analyze the model and select the appropriate optimization method

Step 4: Solve: obtain the optimal solution via programming

Step 5: Test and implementation of optimal solution



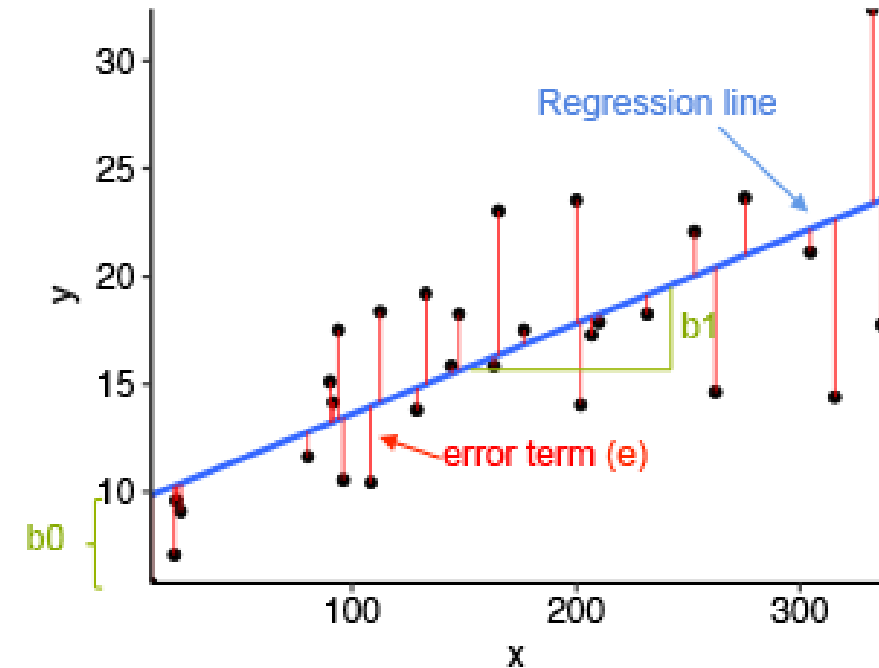
Example-1 Parametric Regression

Given a data set $\{y_i, x_i\}, \forall i = 1, \dots, N$
we assume that the relationship between the dependent variable y and the regressor x is linear.

$$y = b_0 + b_1x + \varepsilon$$

We want to minimize the sum of square error.

$$\min_{b_0, b_1} \sum_{i=1}^N (y_i - b_0 - b_1x_i)^2$$



Example-2 Production planning

A company has some resources to produce three products (denoted as A, B, C). Each product consumes a different mix of resources, and there will be a profit from selling the product. The endowment of resources and its relationship with products are:

	A	B	C	Endowment
Steel	3	4	2	600
Wood	2	1	2	400
Label	1	3	3	300
Machine	1	4	4	200
Profit	2	4	3	

Question: How to maximize the total profit?

Example-2 Production planning

Variables: Denote x_1, x_2, x_3 be the production of products A, B, C, respectively.

Objective: How to maximize the total profit?

Constraints: do not violate the resource endowment

$$\max_{x_1, x_2, x_3} 2x_1 + 4x_2 + 3x_3$$

$$\text{s.t. } 3x_1 + 4x_2 + 2x_3 \leq 600$$

$$2x_1 + x_2 + 3x_3 \leq 400$$

$$x_1 + 3x_2 + 3x_3 \leq 300$$

$$x_1 + 4x_2 + 4x_3 \leq 200$$

$$x_1, x_2, x_3 \geq 0$$

Endowment limits



Production must larger than 0



Example-3 Transportation

A building materials company has three cement factories A_1, A_2, A_3 and four dealers B_1, B_2, B_3, B_4 . Its output, sales volume and freight are shown in the table below

<div></div>	B_1	B_2	B_3	B_4	Production
A_1	8	7	3	2	2000
A_2	4	7	5	1	10000
A_3	2	4	9	6	4000
Sales	3000	2000	4000	5000	

Question: How to minimize the freight?

Example-3 Transportation

Variables: Denote x_{ij} as the quantity from factory A_i to dealer B_j

Constraints: Production ability limits; selling requirement

Objective: Minimize the total freight

$$\begin{aligned} \min_{x_{ij}, \forall i, j} \quad & 8x_{11} + 7x_{12} + 3x_{13} + 2x_{14} + 4x_{21} + 7x_{22} \\ & + 5x_{23} + x_{24} + 2x_{31} + 4x_{32} + 9x_{33} + 6x_{34} \end{aligned}$$

$$\text{s.t. } x_{11} + x_{12} + x_{13} + x_{14} \leq 2000$$

$$x_{21} + x_{22} + x_{23} + x_{24} \leq 10000$$

$$x_{31} + x_{32} + x_{33} + x_{34} \leq 4000$$

$$x_{11} + x_{21} + x_{31} \geq 3000$$

$$x_{12} + x_{22} + x_{32} \geq 2000$$

$$x_{13} + x_{23} + x_{33} \geq 4000$$

$$x_{14} + x_{24} + x_{34} \geq 5000$$

$$x_{ij} \geq 0, i = 1, 2, 3; j = 1, 2, 3, 4$$

Production ability

Sells requirement

Quantity must larger than 0

Example-4 Location problem

Suppose there are $j = 1, \dots, n$ markets whose location is (a_j, b_j) . Market j needs q_j product. We plan to build m warehouse whose capacities are $c_i, i = 1, \dots, m$. How to choose the location of these warehouses so that the total cost is minimized?

$$\begin{aligned} \min_{x_i, y_i, w_{ij}} \quad & \sum_{j=1}^n \sum_{i=1}^m w_{ij} \sqrt{(x_i - a_j)^2 + (y_i - b_j)^2} \\ \text{s.t.} \quad & \sum_{j=1}^n w_{ij} \leq c_i, \forall i = 1, \dots, m \\ & \sum_{i=1}^m w_{ij} = q_j, \forall j = 1, \dots, n \\ & w_{ij} \geq 0, i = 1, \dots, m, j = 1, \dots, n \end{aligned}$$

Thanks!