

# Introduction

Dabeen Lee

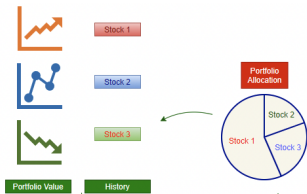
Industrial and Systems Engineering, KAIST

IE 539: Convex Optimization

August 28, 2023

# What is "Optimization"?

## Portfolio optimization

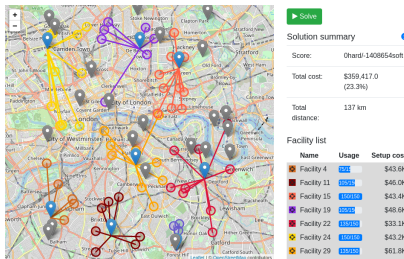


- $d$  financial assets (stocks, bonds, etc).
- Asset  $i$  that has return  $\mu_i$ .
- $\sigma_{ij}$  is the covariance of assets  $i$  and  $j$ .
- We allocate  $x_i$  fraction of our budget to asset  $i$ .

Goal: find a portfolio (allocation) maximizing return while minimizing risk (measured as a function of the covariance).

# What is “Optimization”?

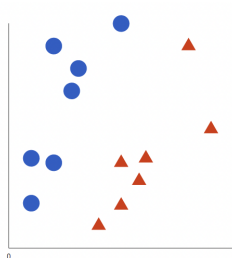
## Facility location



Goal: build “fire stations” covering all households while minimizing the longest distance to a household.

# What is “Optimization”?

## Support vector machine



- $n$  data  $(x_1, y_1), \dots, (x_n, y_n)$  where  $y_i \in \{-1, 1\}$  are labels.
- We want to find a separating hyperplane

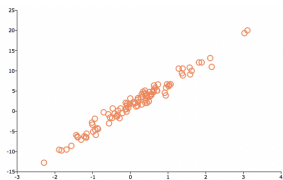
$$w^\top x = b$$

to classify data with  $+1$  and data with  $-1$ .

Goal: find a separating hyperplane  $w^\top x = b$  with the “gap” ( $1/\|w\|$ ) being maximized.

# What is "Optimization"?

## Linear regression



- $n$  data points  $(x_1, y_1), \dots, (x_n, y_n)$ .
- We want to find a linear rule

$$y = \beta^\top x$$

that best represents the relationship between  $x$  and  $y$ .

Goal: find  $\beta$  minimizing

$$\underbrace{\frac{1}{n} \sum_{i=1}^n (y_i - \beta^\top x_i)^2}_{\text{mean squared error}} + \underbrace{R(\beta)}_{\text{regularization}} .$$

# What is “Optimization”?

## Policy optimization for Markov decision process

- Compute an optimal policy  $\pi$  maximizing the value function:

$$\max_{\pi} \mathbb{E}_{s \sim \rho} [V_r^{\pi}(s)]$$

where

- $\rho$  is the initial distribution of states,
- $r$  is the reward function,
- $V_r^{\pi}(s) = \mathbb{E} [\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \mid s_0 = s, \pi]$

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# Who is Dabeen?



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Office hours: Tuesday 2:00 - 3:00 pm

Research interests:

- Optimization Theory (discrete, continuous, stochastic, online).
- Optimization for Machine Learning.
- Algorithm Design for Operations Research (resource allocation, scheduling, dynamic routing).



## About this course

The following is a tentative list of topics covered in this course.

| Theory  | Algorithms   | Applications   |
|---|--|--|
| Convex Analysis<br>(sets, functions,<br>operations) | Gradient Descent (GD)<br>Proximal, Projected, Online,<br>Stochastic GD     | Machine Learning (SVM,<br>LASSO, Ridge Regression,<br>Policy Gradient, etc.)                       |
| Optimality<br>Conditions                            | Frank-Wolfe  | Statistics (Uncertainty<br>Quantification, Inverse<br>Covariance Selection)                        |
| Semidefinite<br>Programming                         | Proximal Point Algorithm and<br>Augmented Lagrangian Method                | Operations Research<br>(Advertisement Allocation,<br>Facility Location, Portfolio<br>Optimization) |
| Quadratic<br>Programming                            | Operator Splitting and ADMM<br>Newton's method and Quasi<br>Newton methods |  |

- Many more applications will be discussed on the way.
- We might also cover other algorithms such as Mirror descent, and Interior Point Methods.

# Logistics

Class times: Monday and Wednesday 4:00 - 5:15 pm.

Assessment:

- 5 assignments (50%)
- Course project (20%)
- Take-home final (30%)

No attendance check (but be responsible!)

# Assignment

- Being comfortable with making mathematical arguments, writing proofs and programming is required throughout this course.
- **Typesetting in LaTeX is required for any submission.**
- Easiest option: **Overleaf** (<https://www.overleaf.com>)

```
1 \documentclass[arXiv]{article}
2 \usepackage{graphics} % Required for inserting images
3
4 \title{IE331 Assignment 1}
5 \author{Dabeen Lee}
6 \date{2023}
7
8 \usepackage{amsmath,amsymb}
9
10 \begin{document}
11
12 \maketitle
13
14 \begin{enumerate}
15
16 \item My answer to question 1 to ...
17
18 \end{itemize}
19
20 \item My answer to question 2(a) to ...
21
22 \begin{equation}
23 \text{let } f(x) = \dots
24 \text{let } g(x) = \dots
25 \text{let } h(x) = \dots
26 \end{equation}
27
28 \item My answer to question 2(b) to ...
29
30 \begin{equation}
31 d(x) = \sum_{i \in [m]} \|x - v^i\|_{\infty}
32 \end{equation}
33
34 \item My answer to question 2(c) to ...
35
36 \begin{equation}
37 d(x) = \sum_{i \in [n]} \|x - v^i\|_1
38 \end{equation}
39
40 \item My answer to question 2(d) to ...
```

## IE331 Assignment 1

Dabeen Lee

March 14, 2023

1. My answer to question 1 is ...

$$\text{epi}(f) = \{(x, t) \in \mathbb{R}^d \times \mathbb{R} : \exists y \in \mathbb{R}^p \text{ s.t. } Ax + Dy + ht \leq r\}$$

2. (a) My answer to question 2(a) is ...

$$\begin{aligned} \min_x & f(x) \\ \text{s.t. } & g_i(x) \leq b_i, \quad i \in [m], \\ & x \in \mathbb{R}^d. \end{aligned}$$

(b) My answer to question 2(b) is ...

$$d(x) = \sum_{i \in [n]} \|x - v^i\|_{\infty}.$$

(c) My answer to question 2(c) is ...

$$d(x) = \sum_{i \in [n]} \|x - v^i\|_1.$$

(d) My answer to question 2(d) is ...

# Project

There are two options.

1. Review of a research paper related to convex optimization.
  - Choose a paper published in a journal or announced at a conference.
2. Formulation and implementation of algorithms or methods for certain optimization problem.
  - Numerical implementation is required.

Submit (1) a proposal and (2) a final report.

## Objectives

We formulate a decision-making problem as an optimization model

$$P : \min_{x \in D} f(x).$$

Then

- We have to study the structure of the problem,  $f$  and  $D$ .
  - Is  $P$  convex? a linear program (LP)? a quadratic program (QP)? a semidefinite program (SDP)?
  - Is  $f$  smooth? strongly convex? both?
  - Is  $D$  convex? an affine subspace?
- We have to figure out and test candidate algorithms for solving  $P$ .
  - Gradient Descent, simply? Proximal Gradient Descent? Newton's method?

For this task, we need comprehensive knowledge in convex optimization.

Later, this knowledge will help you create a new optimization problem.

## Example: dual methods

Consider

$$\begin{aligned} \min \quad & f(x) + g(y) \\ \text{s.t.} \quad & Ax + By = c \end{aligned}$$

where  $f, g$  are convex and  $A, B, c$  are matrices of appropriate dimension.

How do we solve the problem?

- If  $f$  and  $g$  are both strongly convex, then Gradient Ascent in the dual.
- If only  $f$  is strongly convex while  $g$  has an easy Prox, then Proximal Gradient in the dual.
- If neither  $f$  nor  $g$  is strongly convex, then Proximal Point Algorithm in the dual or ADMM.