

# Optimization Theory and Algorithms

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# Outline

- Syllabus
- Background information
- Mathematical optimization
- Optimization problems
- Examples

# Syllabus

- Reference textbook: *Convex Optimization* by Stephen Boyd and Lieven Vandenberghe  
Available at [https://web.stanford.edu/~boyd/cvxbook/bv\\_cvxbook.pdf](https://web.stanford.edu/~boyd/cvxbook/bv_cvxbook.pdf)
- Grading scheme: 40% homework (4 times) + 60% exam

# Course Information

- Application driven: manufacturing; transportation; scheduling; investment...
- Decision problem
- Mathematical modeling
- Topics: introduction to optimization; convex optimization; duality theory; convex optimization algorithms.


# Mathematical Optimization

$$\begin{array}{ll}\text{minimize} & f(x) \\ \text{subject to} & g_i(x) \leq 0, i = 1, \dots, m \\ & h_i(x) = 0, i = 1, \dots, l \\ & x \in X\end{array}$$

- $x = (x_1, \dots, x_n)$ : optimization/decision variables
- $f(\cdot): \mathbb{R}^n \rightarrow \mathbb{R}$ : objective function
- $g_i(x), i = 1, \dots, m$ : inequality constrain functions
- $h_i(x), i = 1, \dots, l$ : equality constrain functions
- $X \subseteq \mathbb{R}^n$ : feasible region

**Global minimizer**  $x^*$ : has the smallest value of  $f$  for all  $x \in X$ , i.e.,  $f(x^*) \leq f(x)$ .

**Local minimizer**  $x'$ : there exist an  $\varepsilon$  such that  $f(x') \leq f(x)$  for all  $x \in X \cap B(x', \varepsilon)$ .


$$\{x \in \mathbb{R}^n: ||x - x'||_2 \leq \varepsilon\}$$

Euclidean ball of radius  $\varepsilon > 0$  centered at  $x'$

# Linear Programming

$$\begin{array}{ll}\text{minimize} & c^T x \\ \text{subject to} & Ax = b \\ & Gx \preceq h\end{array}$$

Component-wise inequality

- $x \in \mathbb{R}^n, c \in \mathbb{R}^n$
- $A \in \mathbb{R}^{p \times n}, b \in \mathbb{R}^p, G \in \mathbb{R}^{m \times n}, h \in \mathbb{R}^m$
- Linear objective function, linear equality constraint, and linear inequality constraint.

# Example of Linear Programming

Diet problem: To find the cheapest combination of foods that satisfies some nutritional requirements.

$$\begin{array}{ll}\text{minimize} & c^T x \\ \text{subject to} & Gx \geq h \\ & x \geq 0\end{array}$$

- $x \in \mathbb{R}^n, c \in \mathbb{R}^n, G \in \mathbb{R}^{m \times n}, h \in \mathbb{R}^m$
- $x_j$ : units of food  $j$ ;  $c_j$ : per-unit price of food  $j$
- $G_{ij}$ : content of nutrient  $i$  in per unit of food  $j$
- $h_i$ : minimum required intake of nutrient  $i$

# Example of Linear Programming

Air traffic control problem

- There are  $n$  airplanes: airplane  $i$  arrival interval  $[a_i, b_i]$ .
- Assume airplane arrive in the order  $1, 2, \dots, n$ .
- Control objective: maximize the minimum over all inter-arrival times between two consecutive planes.

$$\begin{array}{ll} \text{maximize} & \min_{1 \leq j \leq n-1} (t_{j+1} - t_j) \\ \text{subject to} & a_i \leq t_i \leq b_i, \quad i = 1, \dots, n \\ & t_i \leq t_{i+1}, \quad i = 1, \dots, n-1 \end{array}$$



Introduce a new decision variable

$$\begin{array}{ll} \text{maximize} & z \\ \text{subject to} & t_{j+1} - t_j \geq z, \quad i = 1, \dots, n-1 \\ & a_i \leq t_i \leq b_i, \quad i = 1, \dots, n \\ & t_i \leq t_{i+1}, \quad i = 1, \dots, n-1 \end{array}$$

decision variables:  $z, t_i, i = 1, \dots, n,$



# Quadratic Programming

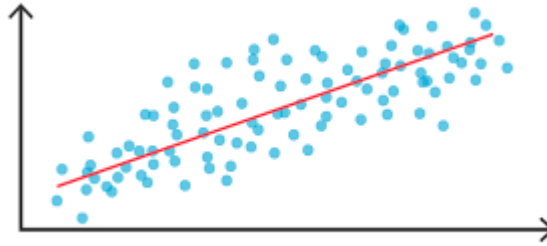
$$\begin{array}{ll}\text{minimize} & \frac{1}{2}x^T Qx + q^T x \\ \text{subject to} & Ax = b \\ & Gx \preceq h\end{array}$$

- $Q = [Q_{ij}] \in \mathbb{R}^{n \times n}$ ,  $x^T Qx \equiv \sum_{i=1}^n \sum_{j=1}^n Q_{ij} x_i x_j$
- Assume  $Q$  is symmetric.

$$x^T Qx = x^T \left( \frac{Q + Q^T}{2} \right) x$$

# Example of Quadratic Programming

Data fitting problem



$$\underset{x}{\text{minimize}} \ ||Ax - b||_2^2 = (Ax - b)^T (Ax - b) = x^T A^T Ax - 2b^T Ax + b^T b$$

- $A \in \mathbb{R}^{m \times n}$ : each row  $i$  represents a data point with  $n$  features.
- $b \in \mathbb{R}^m$ : each component  $i$  represents a prediction.
- To find the parameter  $x$  that minimized the squared L2-norm of the error.

$p$ -norm of a vector  $x$  ( $p \geq 1$ ):

$$\|x\|_p \triangleq \left( \sum_{i=1}^n |x_i|^p \right)^{1/p}$$

# Example of Quadratic Programming

Portfolio optimization:

- There  $n$  assets or stocks. Let  $x_i$  denote the amount of asset  $i$  invested.
- Constraint: a minimum return, budget feasibility, and non-negative investment.
- Objective: minimizing overall risk.

$$\begin{aligned} & \text{minimize} && x^T \Sigma x \\ & \text{subject to} && R^T x \geq r_{\min} \\ & && \mathbf{1}^T x = B \\ & && x \geq 0 \end{aligned}$$

- $R \in \mathbb{R}^n$ : expected return for each invested asset;  $r_{\min} \in \mathbb{R}$ : minimum return.
- $\mathbf{1} \in \mathbb{R}^n$ : every component is 1;  $B$ : budget.
- $\Sigma \in \mathbb{R}^{n \times n}$ : covariance matrix for the prices of all assets; indicates investment risk.

# Semidefinite Programming

Positive semidefinite matrix ( $Q \succcurlyeq \mathbf{0}$  or  $Q \in \mathbf{S}_+^n$ ):

An  $n \times n$  symmetric matrix  $Q$  is **positive semidefinite** if

$$x^T Q x \geq 0 \text{ for all } x \in \mathbb{R}^n.$$

positive definite ( $Q \succ \mathbf{0}$  or  $Q \in \mathbf{S}_{++}^n$ )  $\Rightarrow$   
 $x^T Q x > 0$  for all  $x \neq \mathbf{0}$

$$\begin{aligned} & \text{minimize } C \bullet X \\ & \text{subject to } A_i \bullet X = b_i, \quad \text{for } i = 1, \dots, m \\ & \quad X \succcurlyeq \mathbf{0} \end{aligned}$$

- $C \in \mathbf{S}_+^n$ :  $n \times n$  symmetric matrix.
- $C \bullet X \triangleq \sum_{i=1}^n \sum_{j=1}^n C_{ij} X_{ij}$ .



$\text{tr}(Z)$ : sum of matrix  $Z$  diagonal elements  
 $\text{tr}(CX) = \sum_{i=1}^n \sum_{j=1}^n C_{ij} X_{ij}$

# Example of Semidefinite Programming

Minimize the largest eigenvalue:

- Consider  $k$   $n \times n$  symmetric matrix  $A_1, \dots, A_k$ .
- Consider a function  $A: R^k \rightarrow R^{n \times n}$

$$A(x) = \sum_{i=1}^k x_i A_i$$

eigenvalue

$$\text{minimize } \max_i \lambda_i(A(x))$$



Introduce an auxiliary valuable  $t$

$$\begin{aligned} &\text{minimize } t \\ &\text{subject to } tI - A(x) \succcurlyeq \mathbf{0} \end{aligned}$$

Proposition

Let  $Z$  be an arbitrary  $n \times n$  symmetric matrix, and let  $\lambda_{\max}(Z)$  be the largest eigenvalue of  $Z$ . Then, we have  $t \geq \lambda_{\max}(Z)$  if and only if  $tI - Z \succcurlyeq \mathbf{0}$ .

# What's Next

- Basic concepts of convexity
- Convex optimization
- Optimality condition and duality theory
- Optimization algorithms
- Applications