

## Lecture 7: Optimization

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Mathematics for Machine Learning  
<https://yung-web.github.io/home/courses/mathml.html>  
KAIST EE

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- (1) Optimization Using Gradient Descent
- (2) Constrained Optimization and Lagrange Multipliers
- (3) Convex Sets and Functions
- (4) Convex Optimization
- (5) Convex Conjugate

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## Summary

- Training machine learning models = finding a good set of parameters
- A good set of parameters = Solution (or close to solution) to some optimization problem
- Directions: Unconstrained optimization, Constrained optimization, Convex optimization
- High-school math: A necessary condition for the optimal point:  $f'(x) = 0$  (stationary point)
  - Gradient will play an important role

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- Goal

$$\min f(\mathbf{x}), \quad f(\mathbf{x}) : \mathbb{R}^n \mapsto \mathbb{R}, \quad f \in C^1$$

- Gradient-type algorithms

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \gamma_k \mathbf{d}_k, \quad k = 0, 1, 2, \dots$$

- **Lemma.** Any direction  $\mathbf{d} \in \mathbb{R}^{n \times 1}$  that satisfies  $\nabla f(\mathbf{x}) \cdot \mathbf{d} < 0$  is a descent direction of  $f$  at  $\mathbf{x}$ . That is, if we let  $\mathbf{x}_\alpha = \mathbf{x} + \alpha \mathbf{d}$ ,  $\exists \bar{\alpha} > 0$ , such that for all  $\alpha \in (0, \bar{\alpha}]$ ,  $f(\mathbf{x}_\alpha) < f(\mathbf{x})$ .
- **Steepest gradient descent**<sup>1</sup>.  $\mathbf{d}_k = -\nabla f(\mathbf{x}_k)^\top$ .
- Finding a local optimum  $f(\mathbf{x}_*)$ , if the step-size  $\gamma_k$  is suitably chosen.
- **Question.** How do we choose  $\mathbf{d}_k$  for a constrained optimization?

<sup>1</sup>In some cases, just gradient descent often means this steepest gradient descent.

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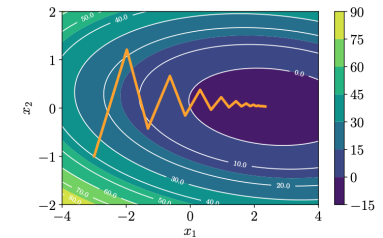
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- A quadratic function  $f : \mathbb{R}^2 \mapsto \mathbb{R}$ .

$$f\left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}\right) = \frac{1}{2} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}^\top \begin{pmatrix} 2 & 1 \\ 1 & 20 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} 5 \\ 3 \end{pmatrix}^\top \begin{pmatrix} x_1 \\ x_2 \end{pmatrix},$$

$$\text{whose gradient is } \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}^\top \begin{pmatrix} 2 & 1 \\ 1 & 20 \end{pmatrix} - \begin{pmatrix} 5 \\ 3 \end{pmatrix}^\top$$

- $\mathbf{x}_0 = (-3 - 1)^\top$
- constant step size  $\alpha = 0.085$
- Zigzag pattern



- Goal:  $\min L(\theta)$  for  $n$  training data
- Based on the **amount of training data** used for **each** iteration
  - Batch gradient descent (the entire  $n$ )
  - Mini-batch gradient descent ( $k < n$  data)
  - Stochastic gradient descent (one sampled data)
- Based on the adaptive method of update
  - Momentum, NAG, Adagrad, RMSprop, Adam, etc
- <https://ruder.io/optimizing-gradient-descent/>

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- Assume  $L(\theta) = \sum_{i=1}^n L_n(\theta)$  (which happens in many cases in machine learning, e.g., negative log-likelihood in regression)

- Gradient update

$$\theta_{k+1} = \theta_k - \gamma_k \nabla L(\theta_k)^\top = \theta_k - \gamma_k \sum_{n=1}^N \nabla L_n(\theta_k)^\top$$

- Batch gradient:  $\sum_{n=1}^N \nabla L_n(\theta_k)^\top$
- Mini-batch gradient:  $\sum_{n \in \mathcal{K}} \nabla L_n(\theta_k)^\top$  for a suitable choice of  $\mathcal{K}$ ,  $|\mathcal{K}| < n$
- Stochastic gradient:  $\nabla L_n(\theta_i)^\top$  for some (randomly chosen)  $i$ . Noisy approximation to the real gradient.
- Tradeoff: computation burden vs. exactness

- Step size.
  - Too small: slow update, Too big: overshoot, zig-zag, often fail to converge
- Adaptive update: smooth out the erratic behavior and dampens oscillations
- Gradient descent with **momentum**

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \gamma_i \nabla f(\mathbf{x}_k)^\top + \alpha \Delta \mathbf{x}_k, \quad \alpha \in [0, 1]$$

$$\Delta \mathbf{x}_k = \mathbf{x}_k - \mathbf{x}_{k-1}$$
  - Memory term:  $\alpha \Delta \mathbf{x}_k$ , where  $\alpha$  is the degree of how much we remember the past
  - Next update = a linear combination of current and previous updates

- (1) Optimization Using Gradient Descent
- (2) **Constrained Optimization and Lagrange Multipliers**
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- An optimization problem in standard form:
 
$$\begin{aligned} &\text{minimize } f(\mathbf{x}) \\ &\text{subject to } g_i(\mathbf{x}) \leq 0, \quad i = 1, 2, \dots, m \quad (\text{Inequality constraints}) \\ &\quad \quad \quad h_j(\mathbf{x}) = 0, \quad j = 1, 2, \dots, p \quad (\text{Equality constraints}) \end{aligned}$$
- Variables:  $\mathbf{x} \in \mathbb{R}^n$ . Assume nonempty feasible set
- Optimal value:  $p^*$ . Optimizer:  $\mathbf{x}^*$

- Duality Mentality
  - **Bound** or **solve** an optimization problem via a **different** optimization problem!
  - We'll develop the basic Lagrange duality theory for a **general** optimization problem, then specialize for convex optimization
- Idea: augment the objective with a weighted sum of constraints
  - **Lagrangian**:

$$\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu}) = f(\mathbf{x}) + \sum_{i=1}^m \lambda_i g_i(\mathbf{x}) + \sum_{i=1}^p \nu_i h_i(\mathbf{x})$$

- **Lagrange multipliers (dual variables)**:  $\boldsymbol{\lambda} = (\lambda_i : i = 1, \dots, m) \succeq 0, \boldsymbol{\nu} = (\nu_1, \dots, \nu_p)$
- **Lagrange dual function**:

$$\mathcal{D}(\boldsymbol{\lambda}, \boldsymbol{\nu}) = \inf_{\mathbf{x}} \mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu})$$

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- The dual function  $\mathcal{D}(\lambda, \nu)$  is the **lower bound** on the optimal value  $p^*$ .

- Theorem.**  $\mathcal{D}(\lambda, \nu) \leq p^*, \forall \lambda \succeq 0, \nu$

- Proof.** Consider feasible  $\tilde{\mathbf{x}}$ . Then,

$$\mathcal{L}(\tilde{\mathbf{x}}, \lambda, \nu) = f(\tilde{\mathbf{x}}) + \sum_{i=1}^m \lambda_i g_i(\tilde{\mathbf{x}}) + \sum_{i=1}^p \nu_i h_i(\tilde{\mathbf{x}}) \leq f(\tilde{\mathbf{x}})$$

since  $f_i(\tilde{\mathbf{x}}) \leq 0$  and  $\lambda_i \geq 0$ .

Hence,  $\mathcal{D}(\lambda, \nu) \leq \mathcal{L}(\tilde{\mathbf{x}}, \lambda, \nu) \leq f(\tilde{\mathbf{x}})$  for all feasible  $\tilde{\mathbf{x}}$ . Therefore,  $\mathcal{D}(\lambda, \nu) \leq p^*$ .

- Lower bound from Lagrange dual function depends on  $(\lambda, \nu)$ .

- Question.** What's the best lower bound?

$$\begin{array}{ll} \text{Lagrangian dual problem} & \text{maximize } \mathcal{D}(\lambda, \nu) \\ & \text{subject to } \lambda \succeq 0 \end{array}$$

- Dual variables:  $(\lambda, \nu)$
- Always a convex optimization**, because  $\mathcal{D}(\lambda, \nu)$  is always concave over  $\lambda, \nu$ .
  - Infimum over  $\mathbf{x}$  of a family of affine functions in  $(\lambda, \nu)$  (we will see this later)
- Denote the optimal value of Lagrange dual problem by  $d^*$ .

- What's the relationship between  $d^*$  and  $p^*$ ?

#### Weak Duality

$$d^* \leq p^*$$

- Weak duality **always** hold (even if the primal problem is not convex):
- Optimal duality gap:  $p^* - d^*$
- Efficient generation of the lower bounds through the dual problem

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- Convex optimization problem

minimize  $f(\mathbf{x})$

subject to  $\mathbf{x} \in \mathcal{X}$ ,

where  $f(\mathbf{x}) : \mathbb{R}^n \mapsto \mathbb{R}$  is a convex function, and  $\mathcal{X}$  is a convex set.

- The watershed between easily solvable problem and intractable ones is not 'linearity', but 'convexity'
- Let's overview the background of convex functions, convex sets, and their basic properties.

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- Set  $\mathcal{C}$  is a **convex set** if the line segment between any two points in  $\mathcal{C}$  lies in  $\mathcal{C}$ , i.e., if for any  $x_1, x_2 \in \mathcal{C}$  and any  $\theta \in [0, 1]$ , we have  $\theta x_1 + (1 - \theta)x_2 \in \mathcal{C}$

- Convex hull** of  $\mathcal{C}$  is the set of all **convex combinations** of points in  $\mathcal{C}$ :

$$\left\{ \sum_{i=1}^k \theta_i x_i \mid x_i \in \mathcal{C}, \theta_i \geq 0, i = 1, 2, \dots, k, \sum_{i=1}^k \theta_i = 1 \right\}$$

- What is  $k$ ? For all  $k$ ? For some  $k$ ?

- Generalize to infinite sums and integrals:

$$\sum_{i=1}^{\infty} \theta_i x_i \in \mathcal{C}, \quad \int_{\mathcal{C}} p(x) x dx \in \mathcal{C},$$

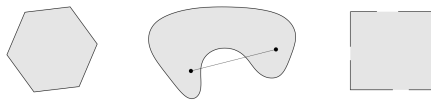
where  $\sum_{i=1}^{\infty} \theta_i = 1$  and  $p(x)$  is a pdf of some random variable.

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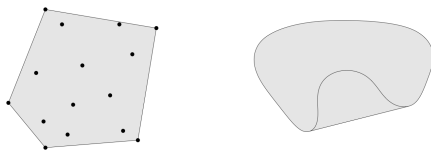
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## Examples

- Convex and Non-convex sets



- Convex hulls



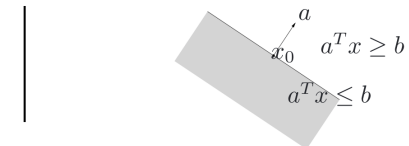
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## Examples of Convex Sets

- Hyperplane** in  $\mathbb{R}^n$  is a set:  $\{x \mid a^T x = b\}$  where  $a \in \mathbb{R}^n, a \neq 0, b \in \mathbb{R}$   
In other words,  $\{x \mid a^T(x - x_0) = 0\}$ , where  $x_0$  is any point in the hyperplane, i.e.,  $a^T x_0 = b$ .

- Divides  $\mathbb{R}^n$  into two **halfspaces**:  
 $\{x \mid a^T x \leq b\}$  and  $\{x \mid a^T x > b\}$



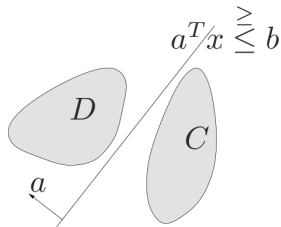
- Polyhedron** is the solution set of a finite number of linear equalities and inequalities (intersection of finite number of halfspaces and hyperplanes)

$$\mathcal{P} = \{x \mid a_j^T x \leq b_j, j = 1, \dots, m, c_j^T x = d_j, j = 1, \dots, p\} = \{x \mid Ax \leq b, Cx = d\}$$

- Polytope**: a bounded polyhedron

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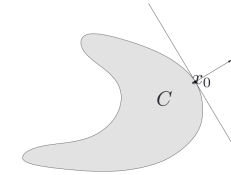
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- $\mathcal{C}$  and  $\mathcal{D}$ : non-intersecting convex sets, i.e.,  $\mathcal{C} \cap \mathcal{D} = \emptyset$ .
- Then, there exist  $a \neq 0$  and  $b$  such that  $a^T x \leq b$  for all  $x \in \mathcal{C}$  and  $a^T x \geq b$  for all  $x \in \mathcal{D}$ .

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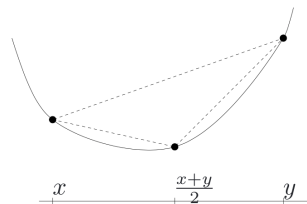


- Given a set  $\mathcal{C} \in \mathbb{R}^n$  and a point  $x_0$  on its boundary, if  $a \neq 0$  satisfies  $a^T x \leq a^T x_0$  for all  $x \in \mathcal{C}$ , then  $\{x | a^T x = a^T x_0\}$  is called a **supporting hyperplane** to  $\mathcal{C}$  at  $x_0$ .
- For any nonempty convex set  $\mathcal{C}$  and **any**  $x_0$  on boundary of  $\mathcal{C}$ , there exists a supporting hyperplane to  $\mathcal{C}$  at  $x_0$ .
- What happens if  $\mathcal{C}$  is non-convex?

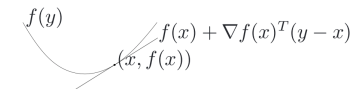
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- $f : \mathbb{R}^n \mapsto \mathbb{R}$  is a **convex function** if  $\text{dom } f$  is a convex set and for all  $x, y \in \text{dom } f$  and  $\theta \in [0, 1]$ , we have
 
$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$$
- $f$  is **strictly convex** if the strict inequality in the above holds for all  $x \neq y$  and  $0 < \theta < 1$ .
- $f$  is **concave** if  $-f$  is convex
- Affine functions are convex and concave
- **Jensen's inequality**. For a rv  $X$ ,  $f(\mathbb{E}[X]) \leq \mathbb{E}[f(X)]$ .



- **First-order condition**. For differentiable functions,  $f$  is convex iff
 
$$f(y) - f(x) \geq \nabla f(x)^T (y - x), \quad \forall x, y \in \text{dom } f, \text{ and } \text{dom } f \text{ is convex}$$



- **Example**.  $f(y) = y^2$ .
- $f(y) \geq \tilde{f}_x(y)$  where  $\tilde{f}_x(y)$  is the first order Taylor expansion of  $f(y)$  at  $x$ .
- **Local** information (first order Taylor approximation) about a convex function provides **global** information (global underestimator).
- If  $\nabla f(x) = 0$ , then  $f(y) \geq f(x)$ ,  $\forall y$ . Thus,  $x$  is a global minimizer of  $f$ .

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- **Second-order condition.** For twice differentiable functions,  $f$  is convex iff  $\nabla^2 f(x) \succeq 0$  for all  $x \in \text{dom } f$  (upward slope) and  $\text{dom } f$  is convex
- Example:  $f(x) = x^2$ .
- Meaning: The graph of the function have positive (upward) curvature at  $x$ .

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- $e^{ax}$  is convex on  $\mathbb{R}$ , for any  $a \in \mathbb{R}$
- $x^a$  is convex on  $\mathbb{R}_{++}$  when  $a \geq 1$  or  $a \leq 0$ , and concave for  $0 \leq a \leq 1$
- $|x|^p$  is convex on  $\mathbb{R}$  for  $p \geq 1$
- $\log x$  is concave on  $\mathbb{R}_{++}$
- $x \log x$  is strictly convex on  $\mathbb{R}_{++}$
- Every norm on  $\mathbb{R}^n$  is convex
- $f(x) = \max\{x_1, \dots, x_n\}$  is convex on  $\mathbb{R}^n$
- $f(x) = \log \sum_{i=1}^n e^{x_i}$  is convex on  $\mathbb{R}^n$
- $f(x) = (\prod_{i=1}^n x_i)^{\frac{1}{n}}$  is concave on  $\mathbb{R}_{++}^n$

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- $f = \sum_{i=1}^n w_i f_i$  convex if  $f_i$  are all convex and  $w_i \geq 0$
- $g(x) = f(Ax + b)$  is convex iff  $f(x)$  is convex
- $f(x) = \max\{f_1(x), f_2(x)\}$  convex if  $f_i$  convex, e.g., sum of  $r$  largest components is convex
- $f(x) = h(g(x))$ , where  $h: \mathbb{R}^k \mapsto \mathbb{R}$  and  $g: \mathbb{R}^n \mapsto \mathbb{R}^k$ .  
If  $k = 1$ :  $f''(x) = h''(g(x))g'(x)^2 + h'(g(x))g''(x)$ . So,  $f$  is convex if  $h$  is convex and nondecreasing and  $g$  is convex, or if  $h$  is convex and nonincreasing and  $g$  is concave ...
- $g(x) = \inf_{y \in \mathcal{C}} f(x, y)$  is convex if  $f$  is convex in  $(x, y)$  and  $\mathcal{C}$  is convex

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- If  $f(x, y)$  is convex in  $x$  for each  $y \in \mathcal{A}$ , then

$$g(x) = \sup_{y \in \mathcal{A}} f(x, y)$$

is **convex**. Similarly, if  $f(x, y)$  is concave in  $x$  for each  $y \in \mathcal{A}$ , then

$$g(x) = \inf_{y \in \mathcal{A}} f(x, y)$$

is **concave**.

- **Example.** distance to farthest point in a set  $\mathcal{C}$ :  $f(x) = \sup_{y \in \mathcal{C}} \|x - y\|$  is **convex**.
- **Example.** Lagrange dual function

$$\mathcal{D}(\lambda, \nu) = \inf_x \mathcal{L}(x, \lambda, \nu)$$

is **concave**.

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- (1) Optimization Using Gradient Descent
- (2) Constrained Optimization and Lagrange Multipliers
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- A **standard convex optimization** problem with variables  $\mathbf{x}$ :

$$\begin{aligned} &\text{minimize} && f(\mathbf{x}) \\ &\text{subject to} && g_i(\mathbf{x}) \leq 0, \quad i = 1, 2, \dots, m \\ &&& a_i^T \mathbf{x} = b_i, \quad i = 1, 2, \dots, p \end{aligned}$$

where  $f, f_1, \dots, f_m$  are convex functions.

- Minimize convex** objective function (or maximize concave objective function)
- Upper bound inequality** constraints on **convex** functions ( $\Rightarrow$  Constraint set is convex)
- Equality** constraints must be **affine** (Only affine functions leads to a convex set for the equality constraints)

- Local optimality implies global optimality.**
  - Given  $\mathbf{x}$  is **locally optimal** for a convex optimization problem, i.e.,  $\mathbf{x}$  is feasible and for some  $R > 0$ ,
$$f(\mathbf{x}) = \inf\{f(\mathbf{z}) \mid \mathbf{z} \text{ is feasible, } \|\mathbf{z} - \mathbf{x}\|_2 \leq R\}$$
  - Theorem.** if  $\mathbf{x}$  is locally optimal in convex program, then globally optimal.
- Optimal condition for differentiable  $f$** 
  - $\mathbf{x}$  is optimal for a convex optimization problem iff  $\mathbf{x}$  is feasible and for all feasible  $\mathbf{y}$ :
$$\nabla f(\mathbf{x})^T (\mathbf{y} - \mathbf{x}) \geq 0$$
  - $-\nabla f(\mathbf{x})$  defines a supporting hyperplane to the feasible set  $(\{\mathbf{y} \mid -\nabla f(\mathbf{x})^T \mathbf{y} \leq -\nabla f(\mathbf{x})^T \mathbf{x}\})$ .
  - (Note) Unconstrained convex optimization: condition reduces to:  $\nabla f(\mathbf{x}) = 0$

- Strong duality** (zero optimal duality gap):

$$d^* = p^*$$

- If strong duality holds, solving dual is 'equivalent' to solving primal. But strong duality does **not** always hold
- Convexity and **constraint qualifications**  $\Rightarrow$  Strong duality
- A simple constraint qualification: **Slater's condition** (there exists strictly feasible primal variables  $f_i(\mathbf{x}) < 0$  for non-affine  $f_i$ ) (see Section 5.3.2 of Boyd's book).
- Another reason why convex optimization is 'easy'



- Assume **strong duality** holds. Then,

$$\begin{aligned} f(\mathbf{x}^*) = \mathcal{D}(\boldsymbol{\lambda}^*, \boldsymbol{\nu}^*) &= \inf_{\mathbf{x}} \left( f(\mathbf{x}) + \sum_{i=1}^m \lambda_i^* f_i(\mathbf{x}) + \sum_{i=1}^p \nu_i^* h_i(\mathbf{x}) \right) \\ &\leq f(\mathbf{x}^*) + \sum_{i=1}^m \lambda_i^* f_i(\mathbf{x}^*) + \sum_{i=1}^p \nu_i^* h_i(\mathbf{x}^*) \leq f(\mathbf{x}^*) \end{aligned}$$

- Thus, the two inequalities must hold with equality, implying:  $\lambda_i^* f_i(\mathbf{x}^*) = 0, \forall i$

- Complementary slackness** condition:

$$\begin{aligned} \lambda_i^* > 0 &\implies f_i(\mathbf{x}^*) = 0 \\ f_i(\mathbf{x}^*) < 0 &\implies \lambda_i^* = 0 \end{aligned}$$

- $i$ -th optimal Lagrange multiplier is zero unless the  $i$ th constraint is active at the optimum.

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- Since  $\mathbf{x}^*$  minimizes  $\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}^*, \boldsymbol{\nu}^*)$  over  $\mathbf{x}$ ,

$$\nabla f(\mathbf{x}^*) + \sum_{i=1}^m \lambda_i^* \nabla f_i(\mathbf{x}^*) + \sum_{i=1}^p \nu_i^* \nabla h_i(\mathbf{x}^*) = 0$$

Karush-Kuhn-Tucker optimality condition

$$f_i(\mathbf{x}^*) \leq 0, \quad h_i(\mathbf{x}^*) = 0, \quad \lambda_i^* \succeq 0$$

$$\lambda_i^* f_i(\mathbf{x}^*) = 0$$

$$\nabla f(\mathbf{x}^*) + \sum_{i=1}^m \lambda_i^* \nabla f_i(\mathbf{x}^*) + \sum_{i=1}^p \nu_i^* \nabla h_i(\mathbf{x}^*) = 0$$

- Any** optimization with strong duality, KKT condition is necessary for primal-dual optimality
- Convex** optimization with Slater's condition, KKT is also **sufficient** for primal-dual optimality.

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- Minimization problem (**min-min-max** rule)

- Problem:  $\min f(\mathbf{x})$  s.t.  $f_i(\mathbf{x}) \leq 0, \quad g_i(\mathbf{x}) = 0, \quad \mathbf{x}$
- $f(\mathbf{x})$ : convex,  $f_i(\mathbf{x})$ : convex,  $g_i(\mathbf{x})$ : affine
- $L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = f(\mathbf{x}) + \sum_i \lambda_i f_i(\mathbf{x}) + \sum_i \mu_i g_i(\mathbf{x})$
- $\inf_{\mathbf{x}} L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \mathcal{D}(\boldsymbol{\lambda}, \boldsymbol{\mu})$
- $\max_{\boldsymbol{\lambda} \geq 0} \mathcal{D}(\boldsymbol{\lambda}, \boldsymbol{\mu})$

- Maximization problem (**max-max-min** rule)

- Problem:  $\max f(\mathbf{x})$  s.t.  $f_i(\mathbf{x}) \geq 0, \quad g_i(\mathbf{x}) = 0, \quad \mathbf{x}$
- $f(\mathbf{x})$ : concave,  $f_i(\mathbf{x})$ : concave,  $g_i(\mathbf{x})$ : affine
- $L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = f(\mathbf{x}) + \sum_i \lambda_i f_i(\mathbf{x}) + \sum_i \mu_i g_i(\mathbf{x})$
- $\sup_{\mathbf{x}} L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \mathcal{D}(\boldsymbol{\lambda}, \boldsymbol{\mu})$
- $\min_{\boldsymbol{\lambda} \geq 0} \mathcal{D}(\boldsymbol{\lambda}, \boldsymbol{\mu})$

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- Primal problem

$$\begin{aligned} \min_{\mathbf{x} \in \mathbb{R}^d} \quad & \mathbf{c}^T \mathbf{x} \\ \text{subject to} \quad & \mathbf{A} \mathbf{x} \preceq \mathbf{b}, \end{aligned}$$

where  $\mathbf{A} \in \mathbb{R}^{m \times d}$  and  $\mathbf{b} \in \mathbb{R}^m$ .

- Dual problem

$$\begin{aligned} \max_{\boldsymbol{\lambda} \in \mathbb{R}^m} \quad & -\mathbf{b}^T \boldsymbol{\lambda} \\ \text{subject to} \quad & \mathbf{c} + \mathbf{A}^T \boldsymbol{\lambda} = 0, \quad \boldsymbol{\lambda} \succeq 0, \end{aligned}$$

where  $\boldsymbol{\lambda} \in \mathbb{R}^m$ .

- The Lagrangian:  $\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}) = (\mathbf{c} + \mathbf{A}^T \boldsymbol{\lambda})^T \mathbf{x} - \boldsymbol{\lambda}^T \mathbf{b}$ , whose derivative w.r.t.  $\mathbf{x}$  becomes zero, when  $\mathbf{c} + \mathbf{A}^T \boldsymbol{\lambda} = 0$ .
- The dual function:  $\mathcal{D}(\boldsymbol{\lambda}) = -\boldsymbol{\lambda}^T \mathbf{b}$

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- Primal problem

$$\begin{aligned} \min_{\mathbf{x} \in \mathbb{R}^d} \quad & \frac{1}{2} \mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{c}^T \mathbf{x} \\ \text{subject to} \quad & \mathbf{A} \mathbf{x} \preceq \mathbf{b}, \end{aligned}$$

where  $\mathbf{A} \in \mathbb{R}^{m \times d}$ ,  $\mathbf{b} \in \mathbb{R}^m$ ,  $\mathbf{c} \in \mathbb{R}^d$ , the square matrix  $\mathbf{Q}$  is symmetric, positive definite.

- Dual problem

$$\begin{aligned} \max_{\boldsymbol{\lambda} \in \mathbb{R}^m} \quad & \left( -\frac{1}{2} (\mathbf{c} + \mathbf{A}^T \boldsymbol{\lambda})^T \mathbf{A} \mathbf{Q}^{-1} (\mathbf{c} + \mathbf{A}^T \boldsymbol{\lambda}) - \boldsymbol{\lambda}^T \mathbf{b} \right) \\ \text{subject to} \quad & \boldsymbol{\lambda} \succeq 0, \end{aligned}$$

where  $\boldsymbol{\lambda} \in \mathbb{R}^m$ .

- (1) Optimization Using Gradient Descent
- (2) Constrained Optimization and Lagrange Multipliers
- (3) Convex Sets and Functions
- (4) Convex Optimization
- (5) **Convex Conjugate**

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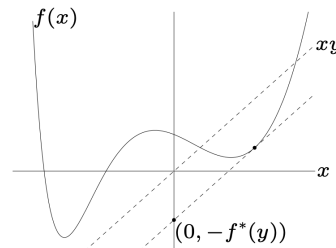
## Conjugate Function: Definition and Meaning

- Given  $f : \mathbb{R}^n \mapsto \mathbb{R}$ , the **conjugate function**  $f^* : \mathbb{R}^n \mapsto \mathbb{R}$  defined as:

$$f^*(\mathbf{y}) = \sup_{\mathbf{x} \in \text{dom } f} (\mathbf{y}^T \mathbf{x} - f(\mathbf{x}))$$

with domain consisting of  $\mathbf{y} \in \mathbb{R}^n$  for which the supremum is finite

- Assume  $\mathbb{R}^1$ .
- For a given slope of  $y$ ,  $yx - f(x)$  is the vertical distance between the line  $yx$  and  $f(x)$ .
- Thus,  $f^*(y)$  is the maximum distance



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## Conjugate Function: Properties

- Given  $f : \mathbb{R}^n \mapsto \mathbb{R}$ , the conjugate function  $f^* : \mathbb{R}^n \mapsto \mathbb{R}$  defined as:

$$f^*(\mathbf{y}) = \sup_{\mathbf{x} \in \text{dom } f} (\mathbf{y}^T \mathbf{x} - f(\mathbf{x}))$$

with domain consisting of  $\mathbf{y} \in \mathbb{R}^n$  for which the supremum is finite

- $f^*(\mathbf{y})$ : **always convex** (the pointwise supremum of a family of affine functions of  $\mathbf{y}$ )
- $f^* = f$  if  $f$  is convex and closed
- Fenchel's inequality**:  $f(\mathbf{x}) + f^*(\mathbf{y}) \geq \mathbf{x}^T \mathbf{y}$  for all  $\mathbf{x}, \mathbf{y}$  (by definition)
  - Example**.  $f(x) = |x|^2/2$ . Then,  $f^*(y) = |y|^2/2$ . Thus, F-inequality tells us:

$$\frac{1}{2}(|x|^2 + |y|^2) \geq xy$$

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- $f(x) = ax + b$ ,  $f^*(a) = -b$
- $f(x) = -\log x$ ,  $f^*(y) = -\log(-y) - 1$  for  $y < 0$
- $f(x) = e^x$ ,  $f^*(y) = y \log y - y$
- $f(x) = x \log x$ ,  $f^*(y) = e^{y-1}$
- $f(x) = \frac{1}{2}x^T Q x$ ,  $f^*(y) = \frac{1}{2}y^T Q^{-1}y$  ( $Q$  is positive definite)
- $f(x) = \log \sum_{i=1}^n e^{x_i}$ ,  

$$f^*(y) = \begin{cases} \sum_{i=1}^n y_i \log y_i & \text{if } y \succeq 0 \text{ and } \sum_{i=1}^n y_i = 1, \\ \infty & \text{otherwise} \end{cases}$$

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- They are closely related. Consider the following problem:

$$\begin{aligned} &\text{minimize} && f(\mathbf{x}) \\ &\text{subject to} && \mathbf{Ax} \preceq \mathbf{b}, \\ &&& \mathbf{Cx} = \mathbf{d} \end{aligned}$$

- Using the conjugate of  $f$ , we can write the dual function as:

$$\begin{aligned} \mathcal{D}(\boldsymbol{\lambda}, \boldsymbol{\nu}) &= \inf_{\mathbf{x}} \left( f(\mathbf{x}) + \boldsymbol{\lambda}^T (\mathbf{Ax} - \mathbf{b}) + \boldsymbol{\nu}^T (\mathbf{Cx} - \mathbf{d}) \right) \\ &= -\mathbf{b}^T \boldsymbol{\lambda} - \mathbf{d}^T \boldsymbol{\nu} + \inf_{\mathbf{x}} \left( f(\mathbf{x}) + (\mathbf{A}^T \boldsymbol{\lambda} + \mathbf{C}^T \boldsymbol{\nu})^T \mathbf{x} \right) \\ &= -\mathbf{b}^T \boldsymbol{\lambda} - \mathbf{d}^T \boldsymbol{\nu} - f^* \left( -\mathbf{A}^T \boldsymbol{\lambda} - \mathbf{C}^T \boldsymbol{\nu} \right) \end{aligned}$$

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Questions?

1)

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