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# OUT LINE

- The Lagrangian Dual Problem
  - Primal and Dual Problems
- Geometric Interpretation of the Lagrangian Dual
- Weak Duality
- Strong Duality
  - ≻Example

2021/12/10

# LAGRANGIAN DUALITY

### **Primal Problem P**

Minimize f(x)Subject to:  $g_i(x) \le 0, i = 1, ..., m$  $h_i(x) = 0, i = 1, ..., \ell$ Variables:  $x \in \mathcal{X}$ 

#### Lagrangian Dual Problem D

grangian Dual Problem D Maximize  $\theta(\mathbf{u}, \mathbf{v}) = \inf_{x \in \mathcal{X}} \{ f(x) + \sum_{i=1}^{m} u_j g_i(x) + \sum_{i=1}^{\ell} v_j h_i(x) \}$ Subject to:  $u_i \ge 0, i = 1, ..., m$ Variables:  $\mathbf{u} \in \mathbb{R}^m$ ,  $\mathbf{v} \in \mathbb{R}^\ell$ 

Lagrange multipliers

- > Inequality constraints  $g_i(x) \le 0$  corresponds to nonnegative Lagrange multipliers  $u_i$ .
- $\succ$  Equality constraints  $h_i(x) = 0$  corresponds to unrestricted Lagrange multipliers  $v_i$ .

#### Duality theorem: (Informal statement)

Under certain convexity assumptions and suitable constraint qualifications, the primal and dual problems have equal optimal objective values.

### **Primal Problem P** Minimize f(x)Subject to: $g(x) \le 0$

Variables:  $x \in \mathcal{X}$ 



#### Primal minimum $z^*$













Primal minimum  $z^*$  = Dual maximum  $\theta(u^*)$ 



### WEAK DUALITY

#### **Primal Problem P**

Minimize f(x)Subject to:  $g_i(x) \le 0, i = 1, ..., m$  $h_i(x) = 0, i = 1, ..., \ell$ Variables:  $x \in X$ 

### Lagrangian Dual Problem D

Maximize  $\theta(\mathbf{u}, \mathbf{v}) = \inf_{x \in \mathcal{X}} \{ f(x) + \sum_{i=1}^{m} u_i g_i(x) + \sum_{i=1}^{\ell} v_i h_i(x) \}$ Subject to:  $u_i \ge 0, i = 1, ..., m$ Variables:  $\mathbf{u} \in \mathbb{R}^m, \mathbf{v} \in \mathbb{R}^{\ell}$ 

Duality gap: Difference between primal minimum and dual maximum

### Weak Duality Theorem:

For arbitrary primal feasible solution x and dual feasible solution  $(\mathbf{u}, \mathbf{v})$ , one has  $f(x) \ge \theta(\mathbf{u}, \mathbf{v})$ 

#### Proof:

$$\theta(\mathbf{u}, \mathbf{v}) = \inf_{\tilde{x} \in \mathcal{X}} \left\{ f(\tilde{x}) + \sum_{i=1}^{m} u_i g_i(\tilde{x}) + \sum_{i=1}^{\ell} v_i h_i(\tilde{x}) \right\}$$
$$\leq f(x) + \sum_{i=1}^{m} u_i g_i(x) + \sum_{i=1}^{\ell} v_i h_i(x) \leq f(x)$$



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# STRONG DUALITY

**Primal Problem P** Minimize f(x)Subject to:  $g_i(x) \le 0, i = 1, ..., m$   $h_i(x) = 0, i = 1, ..., \ell$ Variables:  $x \in X$ 

Lagrangian Dual Problem D Maximize  $\theta(\mathbf{u}, \mathbf{v}) = \inf_{x \in \mathcal{X}} \{ f(x) + \sum_{i=1}^{m} u_i g_i(x) + \sum_{i=1}^{\ell} v_i h_i(x) \}$ Subject to:  $u_i \ge 0, i = 1, ..., m$ Variables:  $\mathbf{u} \in \mathbb{R}^m, \mathbf{v} \in \mathbb{R}^{\ell}$ 

#### Theorem (Strong Duality Theorem)

Let X be a nonempty convex set in  $\mathbb{R}^n$ . Let  $f : \mathbb{R}^n \to \mathbb{R}$  and  $g : \mathbb{R}^n \to \mathbb{R}^m$  be convex, and  $h : \mathbb{R}^n \to \mathbb{R}^\ell$  be affine. Suppose that the following constraint qualification is satisfied. There exists an  $\hat{x} \in X$  such that  $g(\hat{x}) < 0$  and  $h(\hat{x}) = 0$ , and  $0 \in int h(X)$ , where  $h(X) = \{h(x) : x \in X\}$ . Then,

$$\inf\{f(x): x \in X, g(x) \le 0, h(x) = 0\} = \sup\{\theta(u, v): u \ge 0\}, \quad (5)$$

where  $\theta(u, v) = \inf\{f(x) + u^{\mathsf{T}}g(x) + v^{\mathsf{T}}h(x) : x \in X\}$ . Furthermore, if the inf is finite, then  $\sup\{\theta(u, v) : u \ge 0\}$  is achieved at  $(\overline{u}, \overline{v})$  with  $\overline{u} \ge 0$ . If the inf is achieved at  $\overline{x}$ , then  $\overline{u^{\mathsf{T}}}g(\overline{x}) = 0$ .

