

## Strong Lagrange Duality

Let  $f : R^n \rightarrow R$  and  $g : R^n \rightarrow R^m$  are **convex** functions,

$X$  is a closed convex set over  $R^n$

there exists  $\hat{x} \in X : g(\hat{x}) < 0$ .

Then:

if  $x^*$  **minimizes**  $f(x)$  subject to  $g(x) \leq 0, x \in X$

$\lambda^*$  **maximizes**  $L(\lambda)$  subject to  $\lambda \geq 0$

↖ primal program

← dual program

then  $f(x^*) = L(\lambda^*)$

$$L(\lambda) = \min_{x \in X} \underbrace{\{f(x) + \langle \lambda, g(x) \rangle\}}_{\ell(\lambda, x)}$$

vector  $\lambda$ : so called Lagrange multipliers

## Strong Lagrange Duality (with equality constraints)

Let  $f : R^n \rightarrow R$  and  $g : R^n \rightarrow R^m$  are **convex** functions,

$h : R^n \rightarrow R^k$  is **affine**

$X$  is a closed convex set over  $R^n$

there exists  $\hat{x} \in X : g(\hat{x}) < 0$  and  $h(\hat{x}) = 0$ .

Then:

if  $x^*$  **minimizes**  $f(x)$  subject to  $g(x) \leq 0$ ,  $h(x) = 0$ ,  $x \in X$

$(\lambda_g^*, \lambda_h^*)$  **maximizes**  $L(\lambda_g, \lambda_h)$  subject to  $\lambda_g \geq 0$

↖ primal program

← dual program

then  $f(x^*) = L(\lambda_g^*, \lambda_h^*)$

$$L(\lambda_g, \lambda_h) = \min_{x \in X} \underbrace{\{f(x) + \langle \lambda_g, g(x) \rangle + \langle \lambda_h, h(x) \rangle\}}_{\ell(\lambda_g, \lambda_h, x)}$$

vectors  $\lambda_g, \lambda_h$ : so called Lagrange multipliers