

$$L = -b^T v + \langle y, x \rangle.$$

$$\inf_x L(v, x) = -b^T v + \inf_x \langle y, x \rangle.$$

$$\inf_x \langle y, x \rangle = 0 \quad \text{if } y = 0.$$

$$\text{If } y \neq 0. \quad \inf_x \langle y, x \rangle = -\infty.$$

$$x = y \quad \langle y, x \rangle = \|y\|^2$$

$$x = -1000y \quad \langle y, x \rangle = -1000 \|y\|^2.$$

$$x = a \cdot y \quad \langle y, x \rangle = a \|y\|^2.$$

$$a \rightarrow -\infty. \quad \langle y, x \rangle \rightarrow -\infty.$$

For  $\lambda \geq 0$ , any  $v$ .  $g(\lambda, v) \leq p^*$ .

The Lagrange dual problem associated with (1) is defined as

$$\begin{array}{ll} \text{maximize} & g(\lambda, v) \\ \text{subject to} & \lambda \geq 0. \end{array}$$

— Find the best lower bound on  $p^*$  that can be obtained from the dual function.

— Let  $d^*$  to denote the optimal value of the dual problem.

—  $\lambda, v$  are dual feasible if  $\lambda \geq 0$   
and  $\lambda, v \in \text{dom } g = \{(\lambda, v) : g(\lambda, v) > -\infty\}$ .

—  $(\lambda^*, v^*)$  are dual optimal if they are optimal for the problem  
 $g(\lambda^*, v^*) = d^*$ .

# Lagrange dual of LP.

Standard form

$$\begin{aligned} \text{minimize} \quad & c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0. \end{aligned}$$

Inequality form

$$\begin{aligned} \text{minimize} \quad & c^T x \\ \text{s.t.} \quad & Ax \leq b. \end{aligned}$$

— dual function

$$g(\lambda, v) = \begin{cases} -b^T v, & \text{if } c + A^T v - \lambda = 0. \\ -\infty, & \text{otherwise.} \end{cases}$$

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— dual problem

$$\begin{aligned} \text{maximize} \quad & -b^T v \\ \text{s.t.} \quad & \begin{cases} c + A^T v - \lambda = 0 \\ \lambda \geq 0 \end{cases} \end{aligned}$$

$$\begin{aligned} \text{maximize} \quad & -b^T \lambda \\ \text{s.t.} \quad & \begin{cases} c + A^T \lambda = 0 \\ \lambda \geq 0. \end{cases} \end{aligned}$$

$$c + A^T v = \lambda \geq 0.$$

also a LP.

$$\Leftrightarrow \boxed{\begin{aligned} \text{maximize} \quad & -b^T v \\ \text{s.t.} \quad & c + A^T v \geq 0. \\ & \text{also a LP} \end{aligned}}$$

compare

Weak duality :  $d^* \leq p^*$   
always holds (for convex and non convex problems).

— The difference  $p^* - d^*$  ( $\geq 0$ ) is called  
the optimal duality gap of the original problem.

— The dual problem is always convex  
 $\Rightarrow$  a nontrivial lower bound for a  
difficult problem.

Example.

$$\begin{array}{ll} \text{minimize} & x^T W x. \\ \text{st.} & x_i^2 = 1, i=1, \dots, n. \end{array} \quad \begin{array}{l} W \in S^n \\ x \in \mathbb{R}^n. \end{array}$$

$$x_i \in \{+1, -1\}.$$

The feasible set is  $x \in \{+1, -1\}^n$ .  $\leftarrow$  discrete.  
ex.  $x = (+1, +1, +1, \dots, (-1), +1)$ .  
of  $2^n$  points

— This problem is not convex.

- The Lagrangian is

$$\begin{aligned}
 \mathcal{L}(x, v) &= x^T W x + \sum_i v_i (x_i^2 - 1) \\
 &= x^T W x - \sum_i v_i + (x_1 \ x_2 \ \dots \ x_n) \begin{pmatrix} v_1 & & \\ & v_2 & \\ & & \ddots \\ & & & v_n \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \\
 &= x^T (W + \text{diag}(v)) x - \mathbf{1}^T v
 \end{aligned}$$

$\uparrow$  this is the all-1 vector.

-  $g(v) = \inf_x \mathcal{L}(x, v)$

$$= -\mathbf{1}^T v + \inf_x x^T (W + \text{diag}(v)) x$$

This is not necessarily optimal simply a lower bound for  $p^*$

$$\sum_i \lambda_i \|x_i^T y_i\|_2^2$$

$$\text{if } \lambda_j < \infty, \quad x = -y_j : \alpha$$

$$= \begin{cases} -\mathbf{1}^T v, & \text{if } W + \text{diag}(v) \geq 0 \\ -\infty, & \text{otherwise.} \end{cases}$$

choose  $x=0$  in the  $\inf(\quad)$

- The dual problem is (SDP)

$$\begin{aligned}
 &\text{maximize } -\mathbf{1}^T v = -\sum_i v_i \\
 &\text{s.t. } W + \text{diag}(v) \geq 0.
 \end{aligned}$$

minimize  $\sum_i v_i$

$$v_i \geq -\pi_{\min}$$

Choose  $\text{diag } v = -\pi_{\min} \cdot \mathbf{1}$

$$\rightarrow p^* \geq n \pi_{\min}$$

$$W = \bigcup \begin{pmatrix} \pi_1 & & \\ & \pi_2 & \\ & & \ddots \\ & & & \pi_n \end{pmatrix} \bigcup^T$$

$$W + \text{diag}(v) = \bigcup \begin{pmatrix} \pi_1 + v_1 & & \\ & \pi_2 + v_2 & \\ & & \ddots \\ & & & \pi_n + v_n \end{pmatrix} \bigcup^T \geq 0$$

Strong duality  $d^* = p^*$ .

— does not hold in general.

— It usually holds for convex problems.

— Slater's constraint qualification.

The strong duality holds for the convex problem (i). if there exists an  $x^*$  such that.

$$f_i(x) < 0 \quad i=1, \dots, m.$$

$$Ax = b$$

(The problem is strictly feasible.).

Then  $\exists$  a dual feasible  $(\lambda^*, \nu^*)$  with  $g(\lambda^*, \nu^*) = d^* = p^*$  if  $d^* \neq -\infty$ .

(See P. 234).