

# Lec17-mwf

Thursday, February 24, 2011 10:07 PM

# Partial Lagrangian

Wednesday, February 04, 2009 10:27 AM

- We also have the flexibility to relax some constraint (by Lagrange multipliers) but not others

$$\begin{aligned} \min \quad & f_0(x) \\ \text{sub to} \quad & f_1(x) \leq 0 \quad \lambda \\ & f_2(x) \leq 0 \quad \Leftarrow \text{do not want to relax} \end{aligned}$$

$$L(x, \lambda) = f_0(x) + \lambda f_1(x)$$

$$\begin{aligned} g(\lambda) = \min \quad & L(x, \lambda) \\ \text{sub to} \quad & f_2(x) \leq 0 \end{aligned}$$

$$\begin{aligned} \text{Dual:} \quad & \max \quad g(\lambda) \\ \text{sub to} \quad & \lambda \geq 0 \end{aligned}$$

- Reason this is okay?

- Think of the objective func. as

$$f_0'(x) = \begin{cases} f_0(x) & \text{if } f_2(x) \leq 0 \\ +\infty & \text{o/w.} \end{cases}$$

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This is useful when some constraints are "easy" or not coupled.

-  $x_i \geq 0$

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# Linear program

Sunday, February 01, 2009 2:00 PM

$$\begin{array}{ll} \min & c^T x \\ \text{sub to} & Ax = b \\ & x \geq 0 \end{array} \quad \begin{array}{l} \nu \\ \lambda \end{array}$$

$\Rightarrow -x \leq 0$

$$\begin{aligned} L(x, \lambda, \nu) &= c^T x - \lambda^T x + \nu^T (Ax - b) \\ &= (c^T - \lambda^T + \nu^T A)x - \nu^T b \end{aligned}$$

$$\begin{aligned} g(\lambda, \nu) &= \min_x L(x, \lambda, \nu) \\ &= \begin{cases} -\nu^T b & \text{if } c - \lambda + A^T \nu = 0 \\ -\infty & \text{otherwise} \end{cases} \end{aligned}$$

Note that  $g(\lambda, \nu)$  is linear on a convex set

$$\Rightarrow \max g(\lambda, \nu)$$

$$\Leftrightarrow \begin{array}{ll} \max & -b^T \nu \\ \lambda \geq 0 & \\ \text{sub to} & c - \lambda + A^T \nu = 0 \end{array}$$

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Alternatively, only use one Lagrange multiplier  $\nu$

$$\begin{aligned} L(x, \nu) &= c^T x + \nu^T (Ax - b) \\ &= (c^T + \nu^T A)x - \nu^T b. \end{aligned}$$

Now we should

$$\begin{aligned} \min \quad & L(x, v) \\ \text{sub to} \quad & x \geq 0 \end{aligned}$$

$$\Rightarrow \text{If } (C^T + v^T A)_i \geq 0 \Rightarrow x_i = 0$$

$$(C^T + v^T A)_i < 0 \Rightarrow x_i \rightarrow +\infty$$

$$\Rightarrow g(v) = \min_{x \geq 0} L(x, v)$$

$$= \begin{cases} -v^T b & \text{if } (C^T + v^T A)_i \geq 0 \text{ for all } i \\ -\infty & \text{o/w.} \end{cases}$$

Therefore, the dual problem is

$$\begin{aligned} \max \quad & -v^T b \\ \text{sub to} \quad & C^T + v^T A \geq 0 \end{aligned}$$

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## Weak and strong duality

Wednesday, February 04, 2009 10:31 AM

We have seen that:

①  $g(\lambda, \nu)$  is always concave

②  $d^* = \max_{\lambda \geq 0} g(\lambda, \nu) \leq p^* \Leftarrow$  optimal value of the primal problem

—  $d^* - p^*$  is referred to as the "duality gap"

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③ When is the duality gap zero?

— under fairly general assumptions, the duality gap will be zero if the primal problem is convex.

— Recall  $D \triangleq \text{dom} f_0 \cap \text{dom} f_1 \cap \text{dom} h_1$

Roughly speaking, we just need a feasible point in the "interior" of the constraints ("strictly inside")

— However, the "interior" of  $D$  or  $C$  may be  $\emptyset!$   
(due to linear/equality constraints  $\rightarrow$  hyperplane)

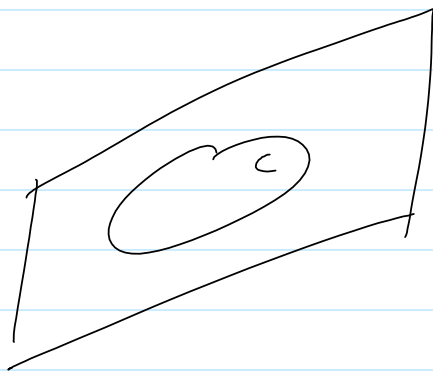
$\Rightarrow$  relative interior.

## Relative Interior: (Boyd P23)

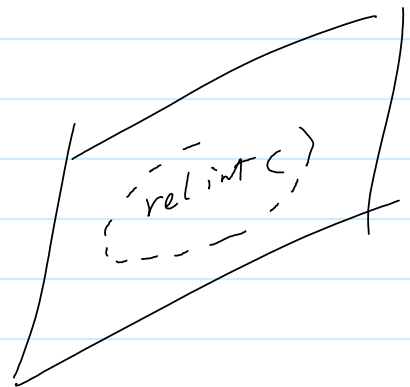
$$\text{rel int } C = \left\{ x \in C \mid B(x, r) \cap \text{aff } C \subseteq C \text{ for some } r > 0 \right\}$$

- Compare with the definition of interior

$$\text{int } C = \left\{ x \in C \mid B(x, r) \subseteq C \text{ for some } r > 0 \right\}$$



$$\text{- int } C = \emptyset$$



$$\text{- rel int } C \neq \emptyset$$

Slater Condition: There exists an  $x \in \text{rel int } D$

$$\text{such that } \begin{cases} f_i(x) < 0 & \forall i \\ Ax = b \end{cases}$$

Theorem: (Boyd P 227) If the Slater condition holds, and in addition,  $\text{rank } A = p$ , where  $p$  is the number of equality constraints, then the duality gap is zero for the convex program  $(*)$ .

$\Rightarrow$  "strong duality"

Note: The Slater condition is very mild.

- It only requires at least one feasible point in the relative interior of  $C$
- Often the existence of such a point is trivial

Example: Rate control

$$\max_{x, \mu} \sum_s \mu_s(x_s)$$

$$\text{sub to } \sum_s H_s^l x_s \leq R^l \quad \forall l.$$

- need  $R_l > 0$  for Slater condition to hold.

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# Graphical interpretation

Sunday, February 01, 2009 1:44 PM

- Consider the case with only inequality constraints

- Boyd p234.

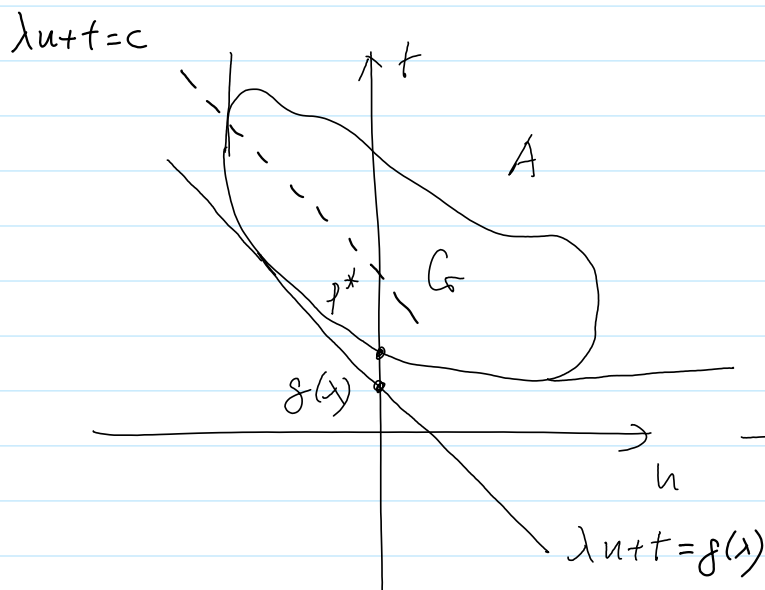
- Let  $G = \{ \underbrace{f_1(x), \dots, f_m(x)}_{u'}, \underbrace{f_0(x)}_{t'} \mid x \in D \}$

- Let  $A = \{ (u, t) \mid \exists x \in D, f_i(x) \leq u_i, f_0(x) \leq t \}$

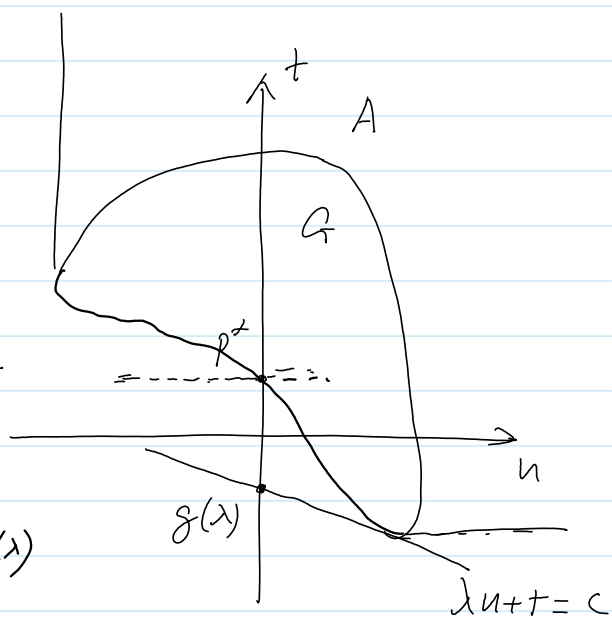
- Like an epigraph, but without the variable  $x$ .

- If the problem is convex, then  $A$  is a convex set. ( $G$  may not be convex.)

- Further, the lower boundary must be non-increasing in  $u$ .



convex problems



non-convex problems

- Let  $p^*$  denote the optimal value of

the primal problem:

$$\begin{aligned} \text{Then } p^* &= \inf \{t' \mid (u', t') \in G, u' \leq 0\} \\ &= \inf \{t \mid (u, t) \in A, u = 0\} \end{aligned}$$

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## The Dual

- Let

$$\begin{aligned} g(\lambda) &= \inf \{ \lambda u' + t' \mid (u', t') \in G \} \\ &= \inf \{ \lambda u + t \mid (u, t) \in A \}, \lambda \geq 0 \end{aligned}$$

- It is the intersection <sup>with</sup> the vertical-axis at the highest line below A.

- Clearly  $p^* \geq g(\lambda)$

- If there is a hyperplane that supports A at the point  $(0, p^*)$

Then  $p^* = g(\lambda^*)$

- The Slater condition ensures that there is some part of A on the left of the vertical axis  $\Rightarrow$  supporting hyperplane must exist.

- If the Slater condition does not hold:



- To argue about this, we need an important result for convex sets, called separation theorem.
- It is quite technical, so we will focus on the implication of strong duality first, and return to separation theorem later.

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