

# Reduction

Sunday, February 9, 2025

10:08 AM

MEM  
 $MEM_K(y) - \text{YES if } y \in K \text{ NO otherwise}$   
 $SEP_K(y) - \text{vector } c \text{ s.t. } c^T x \leq c^T y \forall x \in K$

$OPT_K(c) - \text{vector } y \text{ s.t. } c^T x \leq c^T y \forall x \in K$   
 or "K is empty".

$VAL_K(c) - \max_{x \in K} c^T x \text{ or "K is empty".}$

<u>Examples</u>	<u>K</u>	<u>Easy Oracle</u>
	$\{x: Ax \leq b\}$	SEP/MEM
	$\text{conv}\{v_1, \dots, v_m\}$	OPT
	$\{x: x \geq 0\}$	SEP/MEM
	Spanning tree polytope	SEP
	Matching polytope	SEP

Q. Are these oracles equivalent?

e.g. Does MEM suffice for OPT?

## Function oracles

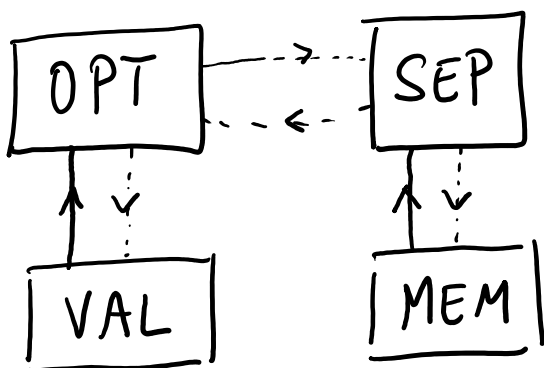
$\text{EVAL}_f(y)$  : outputs  $f(y)$

$\text{GRAD}_f(y)$  :  $f(y), g$  s.t.  $\forall x$   
 $f(x) \geq f(y) + \langle g, x-y \rangle$

$$f = \delta_K$$

$$\text{EVAL}_{\delta_K} \equiv \text{MEM}_K$$

$$\text{GRAD}_{\delta_K} \equiv \text{SEP}_K.$$



Dual (Polar) of a convex set  $K$ .

$$K^* = \{ \theta \mid \langle \theta, x \rangle \leq 1 \quad \forall x \in K \}$$

Thm.  $(K^*)^* = K$  iff  $0 \in K$

$$\text{SEP}_K(y) = \begin{cases} \text{YES} \end{cases}$$

$$y \in K$$

$$\langle \theta, x \rangle \leq \langle \theta, y \rangle \quad \forall x \in K$$

$$\text{SEP}_K(y) = \left\{ \theta : \langle \theta, x \rangle \leq \langle \theta, y \rangle \quad \forall x \in K \right.$$

i.e.  $\exists \theta$  s.t.  $\langle \theta, y \rangle \geq 1$   
 $\theta \in K^* \quad \langle \theta, x \rangle \leq 1 \quad \forall x \in K$  ) by scaling  $\theta$

This is  $\text{OPT}_{K^*}(y) = \arg\max_{\theta \in K^*} \langle \theta, y \rangle$

$$\text{SEP}_{K^*}(\theta) = \begin{cases} \text{YES} & \theta \in K^* \\ y \in K \text{ s.t. } \langle \theta, y \rangle > 1. \end{cases}$$

$$\begin{aligned} \text{OPT}_K(\theta) &= y \text{ s.t. } \langle \theta, x \rangle \leq \langle \theta, y \rangle \quad \forall x \in K. \\ &= \arg\max_{y \in K} \langle \theta, y \rangle \end{aligned}$$

What about the dual of a convex function?

Fenchel dual:

$$f^*(\theta) = \sup_x \theta^T x - f(x)$$

Lemma.  $f^*$  is convex.  $f^*(0) = - \inf_x f(x)$ .

Note:  $f = \delta_K$  then  $f^* = \delta_K^* = \sup_{x \in K} \theta^T x$   
 $= \begin{cases} 0 & x \in K \end{cases}$  - EVAL( $\delta_K^*$ ).

$$= \begin{cases} 0 & x \in K \\ \infty & x \notin K \end{cases}$$

$$VAL_K \equiv EVAL(\delta_K^*)$$

Lemma.  $f$  continuous.

$$\nabla f^*(\theta) = \underset{x}{\operatorname{argmax}} \theta^T x - f(x)$$

Pf. Need to show sup is achieved.

$$x_\theta = \underset{x}{\operatorname{argmax}} \theta^T x - f(x)$$

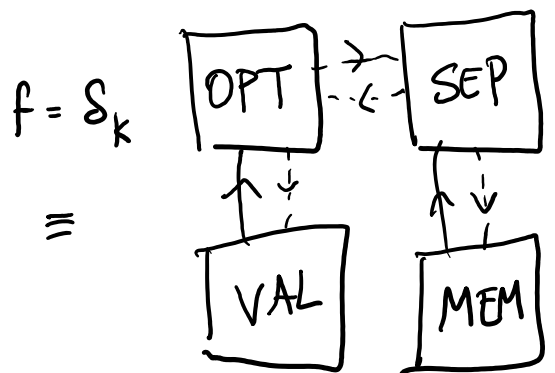
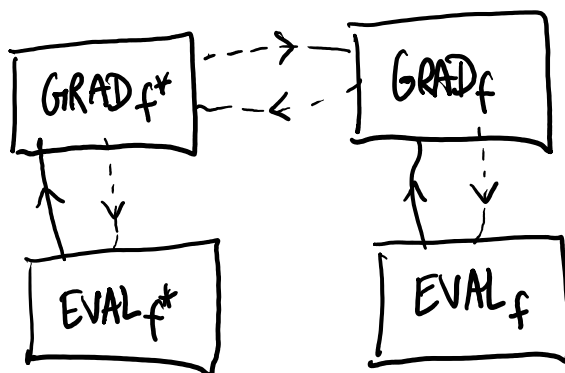
$$f^*(\theta) = \theta^T x_\theta - f(x_\theta)$$

$$\forall \eta \quad f^*(\eta) \geq \eta^T x_\theta - f(x_\theta)$$

$$\Rightarrow f^*(\eta) - f^*(\theta) \geq \langle x_\theta, \eta - \theta \rangle$$

$$\therefore x_\theta \in \nabla f^*(\theta).$$

$$\operatorname{GRAD} \delta_K^* = \operatorname{OPT}_K$$



Example 1.  $f(x) = a^T x - b$

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$$f(x) = a^T x - b$$

$$f^*(\theta) = \sup_x \theta^T x - (a^T x - b)$$

$$= \max_x \langle (\theta - a), x \rangle + b = \begin{cases} b & \text{if } \theta = a \\ \infty & \text{o.w.} \end{cases}$$

$$(f^*)^*(x) = \sup_{\theta} \theta^T x - f^*(\theta) = a^T x - b.$$

Ex. 2.

$$f(x) = \frac{1}{p} \|x\|_p^p = \frac{1}{p} \sum_i x_i^p \quad p \geq 1.$$

$$\begin{aligned} f^*(\theta) &= \max_x \theta^T x - \frac{1}{p} \|x\|_p^p \\ &= \sum_i \theta_i^{1+\frac{1}{p-1}} - \frac{1}{p} \sum_i \theta_i^{\frac{p}{p-1}} \\ &= \frac{p-1}{p} \sum_i \theta_i^{\frac{p}{p-1}} \\ &= \frac{1}{q} \|\theta\|_q^q \end{aligned}$$

Setting  $\nabla = 0$

$$\theta = \begin{pmatrix} x_i^{p-1} \end{pmatrix} \quad x_i = \theta_i^{\frac{1}{p-1}}$$

$$\frac{1}{p} + \frac{1}{q} = 1 \quad \frac{1}{q} = 1 - \frac{1}{p}$$

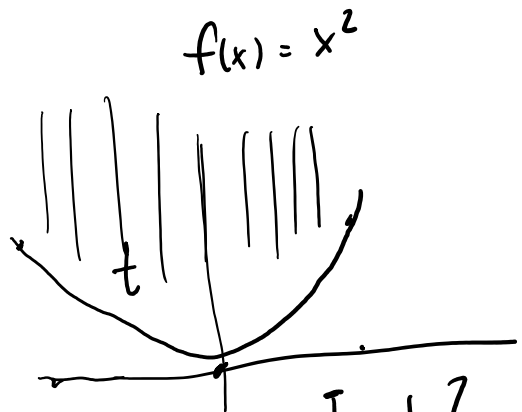
$$\text{Epi}(f) = \{(x, t) : f(x) \leq t\}$$

Thm.  $\text{Epi}(f)$  is closed  
 $\Rightarrow (f^*)^* = f.$

Pf. By convexity  $\text{Epi}(f) = \bigcap \{(x, t) : t \geq \theta^T x - b\}$   
 $\mathcal{H} = \{(\theta, b) : f(x) \geq \theta^T x - b\}$

$$f(x) = \sup_{\theta} \theta^T x - b$$

1. let  $\mathcal{H}$  supporting halfspaces



$$f(x) = \sup_{\theta, b} \theta^T x - b$$

$\mathcal{H} = \{(\theta, b) : \dots\}$        $\mathcal{H}$ : set of supporting halfspaces of  $\text{Epi}(f)$ .

Fix  $\theta$ . Then  $b \geq \theta^T x - f(x) \quad \forall x$

$$b_\theta^* = \sup_x \theta^T x - f(x) = f^*(\theta)$$

$$\therefore f(x) = \sup_{\theta} \theta^T x - f^*(\theta) = (f^*)^*(x).$$


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Ex 3.       $f(x) = \sum_i e^{x_i}$

$$f^*(\theta) = \max_x \theta^T x - \sum_i e^{x_i}$$

$$= \begin{cases} 0 & \text{if } \theta_i = 0 \quad \forall i \\ \infty & \text{if } \exists i \quad \theta_i < 0 \\ \sum_i \theta_i \ln \theta_i - \theta_i & \text{o.w.} \end{cases}$$


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Duality helps in many ways.

Efficiency.

$$\begin{array}{cc|c} \max C^T x & (P) & \min b^T y \quad (D) \\ \hline \text{A} & & \sum y_i A_i \preceq C \end{array}$$

$A_i \cdot X = b_i \quad i=1..m$ $X \succeq 0$	$\sum y_i A_i \preceq C$
$n^2 (Z + n^4) \quad \#var = n^2$	$m (Z + n^m + m^2) \quad \#var = m$

if  $m < n^2$ , faster to solve dual.

But how to recover primal solution from dual?

We use duality!

Suppose we solve (D) using CPM  
and obtain  $y$  :

$$b^T y \leq \min_{\substack{\sum y_i A_i \preceq C \\ y_i \geq 0}} b^T y + \epsilon$$

$$= \min_{\substack{\sum y_i A_i \preceq C \\ y_i \geq 0}} b^T y$$

$$v^T \left( \sum_i y_i A_i - C \right) v \geq 0 \quad \forall v, \|v\| = 1.$$

By CPM, with cutting planes  $S$

By CPTM, with cutting planes  $S$

$$\min_{\substack{b^T y \\ v^T (\sum y_i A_i - C) v \geq 0 \\ v \in S}} \leq \text{OPT} + \epsilon$$

Now take dual of LHS.

$$\min_{\substack{b^T y \\ v^T (\sum y_i A_i - C) v \geq 0 \\ v \in S}} = \min_y \max_{\substack{\lambda_r \geq 0 \\ v \in S}} b^T y - \sum_v \lambda_r v^T (\sum_i y_i A_i - C) v$$

$$= \max_{\lambda_r \geq 0} \min_y b^T y + C \cdot \sum_v \lambda_r v v^T - \sum_i y_i \sum_v \lambda_r v^T A_i v$$

$$= \max_{\lambda_r \geq 0} \min_y C \cdot X + \sum_i y_i (\lambda_i \cdot X - b_i)$$

$X = \sum \lambda_r v v^T$

$$= \max_{\substack{X = \sum_{r \in S} \lambda_r v v^T \\ A_i \cdot X = b_i \\ \lambda_r \geq 0}} C \cdot X$$

$$\geq \text{OPT} - \epsilon.$$



LP!

$$\max \sum_r \lambda_r v^T C v$$

$$\sum_r \lambda_r (v^T A_i v) = b_i \quad i=1 \dots m$$

$$\lambda_r \geq 0$$