# CS599: Convex and Combinatorial Optimization Fall 2013

Lecture 7: Duality of Convex Sets and Functions

Instructor: Shaddin Dughmi

# **Announcements**

- Today: Duality of Convex Sets and Functions
  - Read all of B&V Chapter 3.
  - Some material not in book. Will post references.

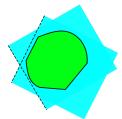
# Outline

Convexity and Duality

2 Duality of Convex Sets

3 Duality of Convex Functions

# **Duality Correspondances**

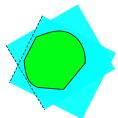


There are two equivalent ways to represent a convex set

- The family of points in the set (standard representation)
- The set of halfspaces containing the set ("dual" representation)

Convexity and Duality 1/14

# **Duality Correspondances**



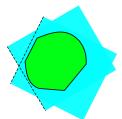
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This equivalence between the two representations gives rise to a variety of "duality" relationships among convex sets, cones, and functions.

Convexity and Duality 1/14

# **Duality Correspondances**



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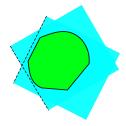
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This equivalence between the two representations gives rise to a variety of "duality" relationships among convex sets, cones, and functions.

#### **Definition**

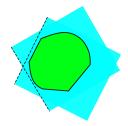
"Duality" is a woefully overloaded mathematical term for a relation that groups elements of a set into "dual" pairs.

Convexity and Duality 1/14



A closed convex set S is the intersection of all closed halfspaces  ${\cal H}$  containing it.

Convexity and Duality 2/14



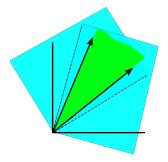
A closed convex set S is the intersection of all closed halfspaces  $\mathcal{H}$ containing it.

#### **Proof**

- Clearly,  $S \subseteq \bigcap_{H \in \mathcal{H}} H$
- To prove equality, consider  $x \notin S$
- By the separating hyperplane theorem, there is a hyperplane separating S from x
- Therefore there is  $H \in \mathcal{H}$  with  $x \notin H$ , hence  $x \notin \bigcap_{H \in \mathcal{H}} H$

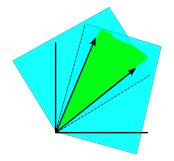
Convexity and Duality

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A closed convex cone K is the intersection of all closed homogeneous halfspaces  $\mathcal H$  containing it.

Convexity and Duality 3/14

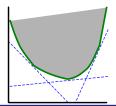


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#### **Proof**

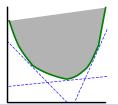
- For every non-homogeneous halfspace  $a^{T}x \leq b$  containing K, the smaller homogeneous halfspace  $a^{T}x \leq 0$  contains K as well.
- Therefore, can discard non-homogeneous halfspaces when taking the intersection

Convexity and Duality 3/14



A convex function is the point-wise supremum of all affine functions under-estimating it everywhere.

Convexity and Duality 4/14



A convex function is the point-wise supremum of all affine functions under-estimating it everywhere.

#### Proof

- epi f is convex
- Therefore  $\mathbf{epi}\ f$  is the intersection of a family of halfspaces of the form  $a^{\mathsf{T}}x t \leq b$ , for some  $a \in \mathbb{R}^n$  and  $b \in \mathbb{R}$ .
- Each such halfspace constrains  $(x,t) \in \operatorname{epi} f$  to  $a^{\mathsf{T}}x b \leq t$
- f(x) is the lowest t s.t.  $(x,t) \in \operatorname{epi} f$
- Therefore, f(x) is the point-wise maximum of  $a^{\rm T}x-b$  over all halfspaces

Convexity and Duality 4/1

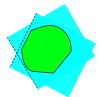
# Outline

Convexity and Duality

Duality of Convex Sets

3 Duality of Convex Functions

# Polar Duality of Convex Sets





One way of representing the all halfspaces containing a convex set.

#### Polar

Let  $S \subseteq \mathbb{R}^n$  be a closed convex set containing the origin. The polar of S is defined as follows:

$$S^{\circ} = \{ y : y^{\mathsf{T}} x \le 1 \text{ for all } x \in S \}$$

#### Note

- Every halfspace  $a^{\intercal}x \leq b$  with  $b \neq 0$  can be written as a "normalized" inequality  $y^{\intercal}x \leq 1$ , by dividing by b.
- S° can be thought of as the normalized representations of halfspaces containing S.

Duality of Convex Sets 5.

$$S^{\circ} = \{ y : y^{\mathsf{T}} x \le 1 \text{ for all } x \in S \}$$

- ${\bf 2} \ S^{\circ}$  is a closed convex set containing the origin
- **3** When 0 is in the interior of S, then  $S^{\circ}$  is bounded.

6/14

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- Follows from representation as intersection of halfspaces
- § S contains an  $\epsilon$ -ball centered at the origin, so  $||y|| \leq 1/\epsilon$  for all  $y \in S^{\circ}$ .

Duality of Convex Sets 6/14

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- **3** When 0 is in the interior of S, then  $S^{\circ}$  is bounded.

- Easy to see that  $S \subseteq S^{\circ \circ}$ 
  - Take  $x_{\circ} \notin S$ , by SHT and  $0 \in S$ , there is a halfspace  $z^{\intercal}x \leq 1$  containing S but not  $x_{\circ}$  (i.e.  $z^{\intercal}x_{\circ} > 1$ )
  - $z \in S^{\circ}$ , therefore  $x \not \in S^{\circ \circ}$

Duality of Convex Sets 6/14

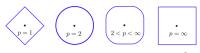
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- ${f 2}$   $S^{\circ}$  is a closed convex set containing the origin
- **3** When 0 is in the interior of S, then  $S^{\circ}$  is bounded.

#### Note

When S is non-convex,  $S^{\circ} = (convexhull(S))^{\circ}$ , and  $S^{\circ \circ} = convexhull(S)$ .

# Examples



The unit sphere for different metrics:  $||x||_{l_p} = 1$  in  $\mathbb{R}^2$ .

#### Norm Balls

- The polar of the Euclidean unit ball is itself (we say it is self-dual)
- ullet The polar of the 1-norm ball is the  $\infty$ -norm ball
- More generally, the p-norm ball is dual to the q-norm ball, where  $\frac{1}{2} + \frac{1}{2} = 1$

Duality of Convex Sets 7/14

# Examples



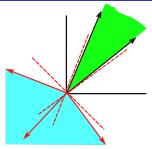
# **Polytopes**

Given a polytope P represented as  $Ax \leq \vec{1}$ , the polar  $P^{\circ}$  is the convex hull of the rows of A.

- Facets of P correspond to vertices of  $P^{\circ}$ .
- Dually, vertices of P correspond to facets of  $P^{\circ}$ .

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# Polar Duality of Convex Cones



Polar duality takes a simplified form when applied to cones

#### Polar

The polar of a closed convex cone K is given by

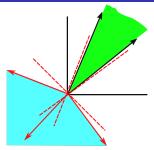
$$K^{\circ} = \{ y : y^{\mathsf{T}} x \le 0 \text{ for all } x \in K \}$$

#### Note

- If halfspace  $y^{\mathsf{T}}x \leq b$  contains K, then so does smaller  $y^{\mathsf{T}}x \leq 0$ .
- $K^{\circ}$  represents all homogeneous halfspaces containing K.

Duality of Convex Sets 8/

# Polar Duality of Convex Cones



Polar duality takes a simplified form when applied to cones

#### Polar

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#### **Dual Cone**

By convention,  $K^* = -K^{\circ}$  is referred to as the dual cone of K.  $K^* = \{y : y^{\mathsf{T}}x \geq 0 \text{ for all } x \in K\}$ 

Duality of Convex Sets 8/14

$$K^{\circ} = \{y : y^{\mathsf{T}}x \leq 0 \text{ for all } x \in K\}$$

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- Same as before
- Intersection of homogeneous halfspaces

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# Examples

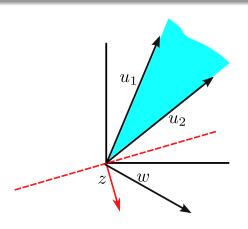
- The polar of a subspace is its orthogonal complement
- The polar cone of the nonnegative orthant is the nonpositive orthant
  - Self-dual
- The polar of a polyhedral cone  $Ax \le 0$  is the conic hull of the rows of A
- The polar of the cone of positive semi-definite matrices is the cone of negative semi-definite matrices

Self-dual

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## Recall: Farkas' Lemma

Let K be a closed convex cone and let  $w \notin K$ . There is  $z \in \mathbb{R}^n$  such that  $z^{\mathsf{T}}x \leq 0$  for all  $x \in K$ , and  $z^{\mathsf{T}}w > 0$ .



Equivalently: there is  $z \in K^{\circ}$  with  $z^{\mathsf{T}}w > 0$ .

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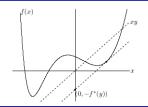
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# Conjugation of Convex Functions



# Conjugate

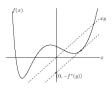
Duality of Convex Functions

Let  $f:\mathbb{R}^n \to \mathbb{R} \bigcup \{\infty\}$  be a convex function. The conjugate of f is

$$f^*(y) = \sup_{x} (y^{\mathsf{T}}x - f(x))$$

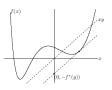
## Note

- $f^*(y)$  is the minimal value of  $\beta$  such that the affine function  $y^Tx \beta$  underestimates f(x) everywhere.
- Equivalently, the distance we need to lower the hyperplane  $y^{\mathsf{T}}x t = 0$  in order to get a supporting hyperplane to  $\mathbf{epi}\ f$ .
- $y^{\mathsf{T}}x t = f^*(y)$  are the supporting hyperplanes of  $\mathbf{epi}\,f$



$$f^*(y) = \sup_{x} (y^{\mathsf{T}}x - f(x))$$

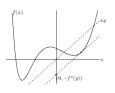
- $f^{**} = f$



$$f^*(y) = \sup_{x} (y^{\mathsf{T}}x - f(x))$$

- $f^{**} = f$
- 2  $f^*$  is a convex function

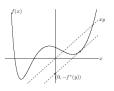
2 Supremum of affine functions of y



$$f^*(y) = \sup_{x} (y^{\mathsf{T}}x - f(x))$$

- $f^{**} = f$
- 2  $f^*$  is a convex function

- $f^{**}(x) = \max_{y} y^{\mathsf{T}} x f^{*}(y)$  when f is convex
  - For fixed y,  $f^*(y)$  is minimal  $\beta$  such that  $y^{\mathsf{T}}x \beta$  underestimates f.
  - Therefore  $f^{**}(x)$  is the maximum, over all y, of affine underestimates  $y^{\mathsf{T}}x \beta$  of f
  - By our characterization early in this lecture, this is equal to f.



$$f^*(y) = \sup_{x} (y^{\mathsf{T}}x - f(x))$$

- $f^{**} = f$

#### Note

When f is non-convex,  $f^* = (convexhull(f))^*$ , and  $f^{**} = convexhull(f)$ .

# Examples

- Affine function: f(x) = ax + b. Conjugate has  $f^*(a) = b$ , and  $\infty$  elsewhere
- $f(x) = x^2/2$  is self-conjugate
- Exponential:  $f(x) = e^x$ . Conjugate has  $f^*(y) = y \log y y$  for  $y \in \mathbb{R}_+$ , and  $\infty$  elsewhere.
- Quadratic:  $f(x) = \frac{1}{2}x^{\mathsf{T}}Qx$  with  $Q \succeq 0$ . Self conjugate.
- Log-sum-exp:  $f(x) = \log(\sum_i e^{x_i})$ . Conjugate has  $f^*(y) = \sum_i y_i \log y_i$  for  $y \succeq 0$  and  $1^\intercal y = 1$ ,  $\infty$  otherwise.