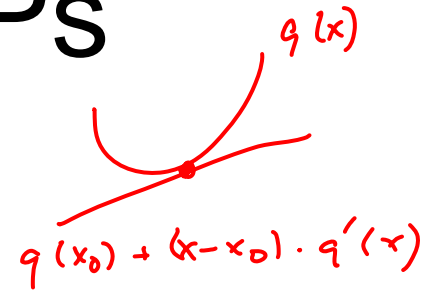


Solving convex programs

- Linear programs: *Simplex, subgradient, ellipsoid, interior point*
- General CP: *"simplex," subgradient, ellipsoid, interior point*
- Interesting special cases: QP, SOCP, SDP

Separation oracle: QPs

- $\min_x \underbrace{q(x)}_{\text{quadratic}} \text{ st } \underbrace{Ax = b}_{\text{linear}}, \underbrace{x \geq 0}_{\text{non-negativity}}$



$$\min_{z, x} z \quad \text{st.} \quad \underline{Ax = b} \quad \underline{x \geq 0} \quad \underline{z \geq q(x)}$$

$$\begin{aligned} x_0, z_0 \quad \text{s.t.} \quad & z_0 < q(x_0) \quad \leftarrow \text{violated by } x_0 \\ & z_0 < q(x_0) + (x - x_0) \cdot q'(x_0) \quad \leftarrow \text{violated by } x_0 \\ & z \geq q(x_0) + \underline{(x - x_0) \cdot q'(x_0)} \quad \leftarrow \text{sat. by all feasible } x, z \end{aligned}$$

Separation oracle: SOCPs

- SOC constraint: $\|Ax + b\| \leq c^T x + d$
- Given x_0 that fails:

$$u = \frac{Ax_0 + b}{\|Ax_0 + b\|} \quad \text{or} \quad u = e_1 \quad \text{if} \quad \underline{Ax_0 + b = 0}$$

$$\text{new constr: } u^T (Ax + b) \leq c^T x + d$$

$$\begin{aligned} \text{plug in } x_0: \underbrace{u^T (Ax_0 + b)}_{= \frac{(Ax_0 + b)^T (Ax_0 + b)}{\|Ax_0 + b\|}} &\stackrel{?}{\leq} c^T x_0 + d \Rightarrow \|Ax_0 + b\| \stackrel{?}{\leq} c^T x_0 + d \\ &\Rightarrow \text{violated} \end{aligned}$$

$$\text{for any feasible } x: u^T (Ax + b) \leq \cancel{\|u\|} \|Ax + b\| \leq c^T x + d$$

Separation oracle: SDPs

- SDP constraint: $A_i \in \mathbb{R}^{n \times n}$ $A_i = A_i^T$
 $x_i \in \mathbb{R}$

$$A = \underline{x_1} A_1 + x_2 \underline{\underline{A_2}} + \dots$$

$$\underline{A \in S_+}$$

given x_0, A_0 w/ $A_0 \not\geq 0$ but $A = \sum_i x_i A_i$

$\Rightarrow \exists u \neq 0. u^T A_0 u < 0 \Rightarrow A_0$ violates $u^T A u \geq 0$

Convex duality

- Several new types of duality
 - convex cones
 - convex sets
 - convex functions
 - convex programs
- Generalize LP/QP duality
- Generalize norm duality (e.g., L_1 v. L_∞)

Cone duality

- Cone K (not necessarily convex)

$$x \in K \Rightarrow \lambda x \in K \quad \lambda \geq 0$$

$$\rightarrow K^* = \{ y \mid x \cdot y \geq 0 \quad \forall x \in K \}$$

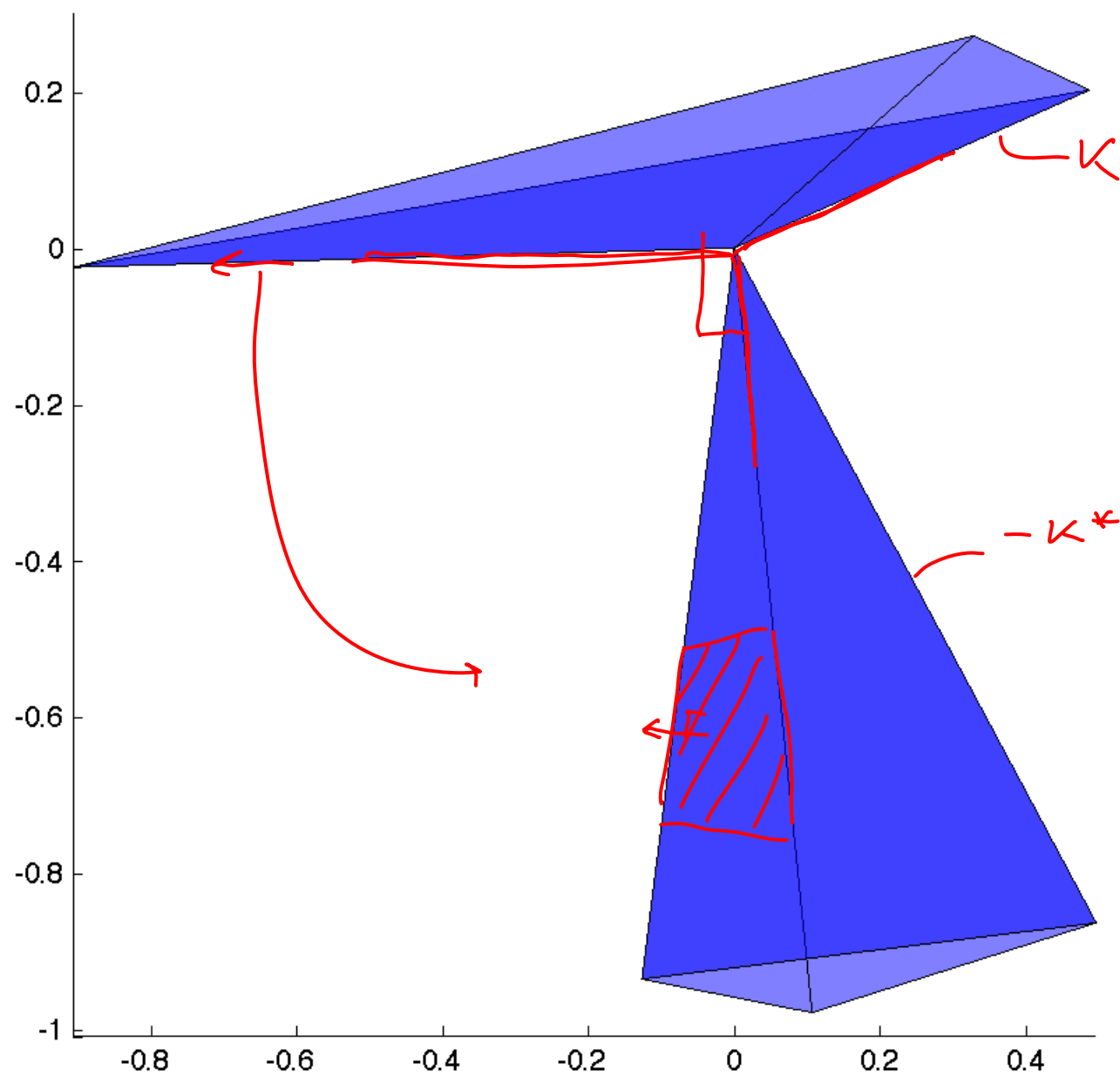
K^* = dual cone, polar cone

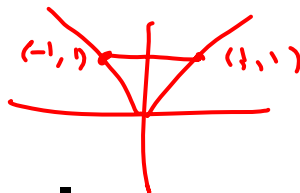
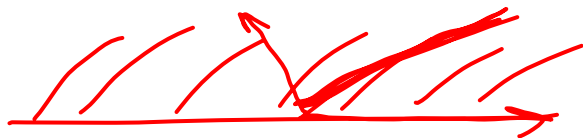


Some books define K^*
 $= \{ y \mid x \cdot y \leq 0 \quad \forall x \in K \}$
 \sim
 $K^* = -K^*$



$\Leftrightarrow -y$ normal of halfspace
 containing K
 $x \cdot (-y) \leq 0$



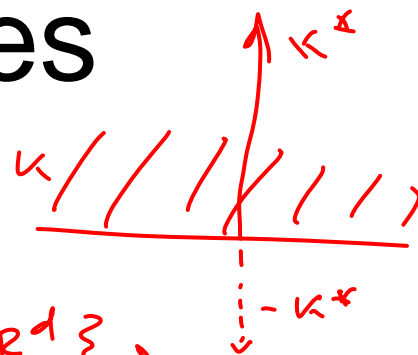


Examples of dual cones

$$\{0\} \Rightarrow \mathbb{R}^n$$

- Halfspace $a^T x \geq 0$

$$\{ \lambda a \mid \lambda \geq 0 \}$$



- Subspace $\{ x \mid Ax = 0 \}$

$$\{ A^T y \mid y \in \mathbb{R}^d \}$$

$$(\mathbb{R}_+^n)^* = \mathbb{R}_+^n$$

$$x \geq 0, y \geq 0 \Rightarrow x^T y \geq 0$$

$$x = (3, -1, 2) \quad y = (0, 1, 0) \quad x^T y = -1$$

- SOC: $\{ (\underline{x}, \underline{s}) \mid \|\underline{x}\|_2 \leq \underline{s} \}$

$$soc^* = soc$$

$$\begin{pmatrix} x \\ s \end{pmatrix} \cdot \begin{pmatrix} y \\ t \end{pmatrix} = x \cdot y + st \geq -\|x\| \|y\| + st \geq 0 \Leftrightarrow (\|x\| \|y\| \leq st)$$

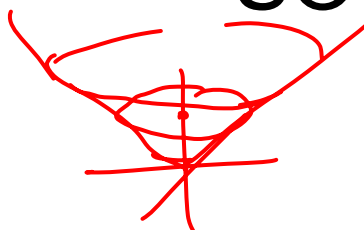
$$\text{if } x = y, s = t = \|x\| \Rightarrow -s \cdot s + s \cdot s = 0$$

since
 x, s, y, t
 $\in soc$

- norm cone: $\{ (x, s) \mid \|x\| \leq s \}$

$$\text{dual} = \{ (y, t) \mid \|y\|_* \leq t \}$$

not necessarily $\|\cdot\|_2$



1D norm

$$\|y\|_* = \max_{\{x \mid \|x\| \leq 1\}} x \cdot y$$

definition — e.g.

$$\|x\| = \max_i |x_i|$$

$$\|y\|_* = \max_x x \cdot y \mid -1 \leq x_i \leq 1 = \sum_i |y_i|$$

S_+ is self-dual

- $S_+ : \{ A \mid A=A^T, x^T A x \geq 0 \text{ for all } x \}$

$$S_+^* \subseteq S_+ \quad \text{Suppose } Y \neq 0 \Rightarrow u^T Y u < 0$$

$$\Rightarrow \text{tr}(u^T Y u) < 0 \Rightarrow \text{tr}(\underline{u u^T} Y) < 0$$

$$\Rightarrow Y \notin S_+^*$$

$$S_+^* \supseteq S_+ \quad \text{given } X \succeq 0 \text{ show } \text{tr}(X^T Y) \geq 0 \text{ for all } Y \succeq 0$$

$$X = \sum_i \lambda_i v_i v_i^T \quad \lambda_i \geq 0$$

$$\text{tr}(Y^T X) = \sum_i \lambda_i \text{tr}(Y^T v_i v_i^T) = \sum_i \lambda_i \underline{\text{tr}(v_i^T Y^T v_i)} \geq 0$$

Ex: Euclidean distance matrices

- Given points $x_i \in \mathbb{R}^n$
- Matrix D : $D_{ij} = \|x_i - x_j\|^2$

$$\mathcal{K} = \{D\}$$

$$\mathcal{K}^* = \{P + Q \mid P \geq 0, P = P^T, \sum_{ij} P_{ij} = 0, Q \text{ diagonal}\}$$

$$\text{show } \text{tr}(D^T(P+Q)) \geq 0 \quad \text{show } \text{tr}(D^T(uu^T + Q)) \geq 0$$

$$1^T u = 0$$

$$\text{tr}(D^T Q) = 0 \quad \text{since } D_{ii} = 0 \quad \forall i$$

$$\text{tr}(D^T uu^T) = \text{tr}(u^T D u) = \sum_{ij} u_i u_j (x_i^T x_i - 2x_i^T x_j + x_j^T x_j)$$

$$= 2 \sum_{ij} u_i u_j x_i^T x_i - 2 \sum_{ij} u_i u_j x_i^T x_j$$

$$= 2 \sum_i u_i x_i^T x_i \underbrace{\sum_j u_j}_{=0} - 2 \left(\sum_i u_i x_i \right)^T \left(\sum_j u_j x_j \right) \leq 0$$

Properties of dual cones

- K^* is closed and convex

given y_1, y_2 s.t. $y_1^T x \geq 0 \quad y_2^T x \geq 0 \quad \forall x \in K$

$$\Rightarrow (\alpha y_1 + (1-\alpha)y_2)^T x \geq 0 \Rightarrow \alpha y_1 + (1-\alpha)y_2 \in K^*$$

given y_1, y_2, \dots, y_t s.t. $y_t^T x \geq 0 \quad \left(\lim_{t \rightarrow \infty} y_t \right) \cdot x = \lim_{t \rightarrow \infty} y_t \cdot x \geq 0$

- $K^{**} = \text{cl conv } K$

$$K^{**} \supseteq \text{cl conv } K \quad \forall x \in K \quad x^T y \geq 0 \quad \forall y \in K^* \Rightarrow x \in K^{**}$$

by closedness & convexity, $\lim x_t \in K^{**}$


$$\alpha x_1 + (1-\alpha)x_2 \in K^{**}$$

$K^{**} \subseteq \text{cl conv } K$: take $v \notin \text{cl conv } K \Rightarrow \exists y. \underbrace{y^T v < 0}_{v \notin K^{**}} \quad \underbrace{y^T x \geq 0}_{\substack{\forall x \in \\ \text{cl conv } K \\ y \in K^*}}$

- If K closed and convex, $K^{**} = K$

Properties of dual cones

- $K_1 \subseteq K_2 \Rightarrow \underline{K_2^*} \subseteq \underline{K_1^*}$



- $K_1 \supseteq K_2 \quad K_2^* \supseteq K_1^*$

- If K_1 , K_2 are closed and convex:

$$K_1 \subseteq K_2 \iff K_1^* \supseteq K_2^*$$

$$K_1 \subset K_2 \iff K_1^* \supset K_2^*$$