

## Examples

Def. 2  $K_1 \subseteq \mathbb{R}^m, K_2 \subseteq \mathbb{R}^n$  Convex cones. Direct product  
 $K_1 \times K_2 = \{ (x, y) \in \mathbb{R}^{m+n} : x \in K_1, y \in K_2 \}$ .

Proposition 3 a) If  $K_1, K_2$  are both proper convex cones,  
then so is  $K_1 \times K_2$ .

b)  $(K_1 \times K_2)^* = K_1^* \times K_2^*$ .

Proof easy verification.

(A) Linear programming (LP)

$K = \mathbb{R}_{\geq 0}^n$   $p^* = \sup \{ c^T x : x \in \mathbb{R}^n, Ax = b, \underbrace{x \geq 0}_{\text{Component-wise}} \}$   
 $d^* = \inf \{ b^T y : A^T y - c \in \mathbb{R}_{\geq 0}^n \}$ .

(B) Conic quadratic programming (CQP)

$K = \mathcal{L}^{n_1+1} \times \mathcal{L}^{n_2+1} \times \dots \times \mathcal{L}^{n_r+1}$

$p^* = \sup (c_1, \theta_1), \dots, (c_r, \theta_r)^T (x_1, t_1), \dots, (x_r, t_r)$   
 $((x_1, t_1), \dots, (x_r, t_r)) \in \mathcal{L}^{n_1+1} \times \dots \times \mathcal{L}^{n_r+1}$   
 $(a_{j1}, d_{j1}), \dots, (a_{jr}, d_{jr})^T (x_1, t_1), \dots, (x_r, t_r) = b_j,$   
 $j \in [m].$

$$d^* = \inf b^T y$$

$$(*) \quad \begin{array}{l} y \in \mathbb{R}^m \\ \sum_{j=1}^m y_j \left( (a_{j1}, \alpha_{j1}), \dots, (a_{j\tau}, \alpha_{j\tau}) \right) - \left( (c_1, \beta_1), \dots, (c_\tau, \beta_\tau) \right) \\ \in \mathcal{L}^{n_1+1} \times \dots \times \mathcal{L}^{n_\tau+1} \end{array}$$

More intuitively: Define matrices

$$A_i = \begin{bmatrix} a_{i1} & \dots & a_{im} \end{bmatrix} \in \mathbb{R}^{n_i \times m}, \quad i = 1, \dots, \tau,$$

and vectors  $d_i = (\alpha_{i1}, \dots, \alpha_{im})^T, \quad i = 1, \dots, \tau.$

Then,  $(*) \Leftrightarrow \|A_i y - c_i\| \leq d_i^T y - \beta_i, \quad i = 1, \dots, \tau.$

In particular, one recognises that LP is a special case of

CQP: set  $A_i = 0, c_i = 0.$

### (c) Semidefinite programming (SDP)

$$K = S_{\geq 0}^m.$$

$$p^* = \sup \langle C, X \rangle$$

$$X \in S_{\geq 0}^m$$

$$\langle A_j, X \rangle = b_j, \quad j \in [m].$$

$$d^* = \inf b^T y$$

$$y \in \mathbb{R}^m$$

$$\sum_{j=1}^m y_j A_j - C \in S_{\geq 0}^n$$

Inequalities of the form  $\sum_{j=1}^m y_j A_j - C \geq 0$  are called  
linear matrix inequalities (LMIs)

- LP is a special case of SDP:  $X$  is diagonal matrix
- QP is a special case of SDP:

Lemma 4  $\mathcal{L}^{n+1} = \{ (x, t) \in \mathbb{R}^{n+1} : \|x\| \leq t \}$   
 $= \{ (x, t) \in \mathbb{R}^{n+1} : \begin{bmatrix} tI_n & x \\ x^T & t \end{bmatrix} \geq 0 \}$ .

Proof If  $t = 0$ , then  $x = 0$ .

If  $t > 0$ , then  $tI_n > 0$ .

Consider the Schur complement of  $tI_n$  in  $\begin{bmatrix} tI_n & x \\ x^T & t \end{bmatrix}$ :

Using Proposition 2.8:  $\begin{bmatrix} tI_n & x \\ x^T & t \end{bmatrix}$  is positive semidefinite

if and only if  $t - x^T \frac{1}{t} I_n x \geq 0 \iff t^2 \geq x^T x$   
 $\iff t \geq \|x\|$ . □

## §4 Theorem of alternatives

Recall: Farkas Lemma from OR.

Lemma 1 For  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$  exactly one of the following two alternatives holds:

(i)  $\exists x \geq 0 : Ax = b$

(ii)  $\exists y \in \mathbb{R}^m : A^T y \geq 0, b^T y < 0.$

Goal: Generalise to conic programs; replace " $\geq 0$ " by cone condition.

First try: Let  $K \subseteq \mathbb{R}^n$  be a proper convex cone. For  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$  exactly one of the following two alternatives holds:

(i)  $\exists x \in K : Ax = b$

(ii)  $\exists y \in \mathbb{R}^m : A^T y \in K^*, b^T y < 0.$

"Proof" (i)  $\Rightarrow$   $\neg$  (ii) Suppose  $x$  is feasible for (i) and  $y$  is feasible for (ii). Then,

$$0 \leq (A^T y)^T x = y^T A x = y^T b < 0. \quad \text{Contradiction!}$$