

67731 | Convex Optimization and Applications | Ex 2

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1.

Recall that LP is written as:

$$\min_x x^\top x$$

$$\text{s.t } Gx \preceq h, Ax = b$$

And the linear conic programming formulation:

$$K = \mathbb{R}^d$$

$$f_1(x) = h - Gx$$

$$h_1(x) = b - Ax$$

Notice that \mathbb{R}^d is a cone, and that both f_1, h_1 are affine, and so:

$$Ax = b \Leftrightarrow h_1(x) = 0, \quad Gx \preceq h \Leftrightarrow f_1(x) \in K$$

As for SOCP:

$$c = f$$

$$h_1(x) = Cx - d$$

$$f_i(x) = \begin{bmatrix} A_i \\ c^\top \end{bmatrix} x + \begin{bmatrix} b_i \\ d_i \end{bmatrix}.$$

As we can see both f_i, h_1 are affine and so:

$$\|A_i x + b_i\| \leq c_i^\top x + d_i \Leftrightarrow$$

$$\begin{bmatrix} A_i x + b_i \\ c_i^\top x + d_i \end{bmatrix} \in K \Leftrightarrow$$

$$\begin{bmatrix} A_i \\ c^\top \end{bmatrix} x + \begin{bmatrix} b_i \\ d_i \end{bmatrix} \in K$$

2.

1.

Lets look at each row of the problem:

$$\min_x c^\top x$$

$$\text{s.t } A_i x \leq b_i \forall A \in \mathcal{A}$$

And for each scalar we get:

$$\min_x c^\top x$$

$$\max_{A \in \mathcal{A}} A_i x \leq b_i$$

Notice that :

$$A_{i,j} \leq \hat{A}_{i,j} x_j + V_{i,j} x_j$$

and that inequality holds for each coordinate.

In fact we get that :

$$\max_{A \in \mathcal{A}} A_i x = \hat{A}_i + V_i |x|$$

Lets denote $z = |x|$ and write the problem as:

$$\hat{A}x + Vz \leq b$$

$$s.t \quad -z \leq x \leq z$$

2.

We can say that

$$P_i = U D_i^1 U^\top$$

$$G = U D_i^2 U^\top$$

And so:

$$\sum_i x_i U D_i^1 U^\top + U D_i^2 U^\top \preceq 0$$

And getting U, U^\top to the sides we get:

$$U \sum (x_i D_i^1 + D^2) U^\top \leq 0 \rightarrow \sum (x_i D_i^1 + D^2) \leq 0$$

Since D^1, D^2 are both diagonal we can fit their values in 1d vectors
and so we get that we can rearrange the problem:

$$\hat{D}^1 x \leq -D^2$$

Which is LP.

3.

set $z = \begin{bmatrix} R(x) \\ I(x) \end{bmatrix}$
for $p = 1$:

$$\min_x \|x\|_1 \quad s.t \quad Ax = b$$

$$= \min_{z \in \mathbb{R}^{2n}} \sum_{i=1}^n \|z_i \dots z_{i+n}\|_2$$

$$s.t : \begin{bmatrix} R(A) & -I(A) \\ I(A) & R(A) \end{bmatrix}, z = \begin{bmatrix} R(b) \\ I(b) \end{bmatrix}$$

$$= \min_{z \in \mathbb{R}^{2n}, t \in \mathbb{R}} 1^\top t$$

$$s.t : \begin{bmatrix} R(A) & -I(A) \\ I(A) & R(A) \end{bmatrix}, z = \begin{bmatrix} R(b) \\ I(b) \end{bmatrix}, \|z_i \dots z_{i+n}\|_2 \leq t$$

for $p = 2$:

$$\begin{aligned}
& \min_x \|x\| \quad s.t \quad Ax = b \\
& = \min_{z \in \mathbb{R}^{2n}} \|z\|_2 \\
& s.t : \begin{bmatrix} R(A) & -I(A) \\ I(A) & R(A) \end{bmatrix}, z = \begin{bmatrix} R(b) \\ I(b) \end{bmatrix} \\
& = \min_{z \in \mathbb{R}^{2n}, t \in \mathbb{R}} t \\
& s.t : \begin{bmatrix} R(A) & -I(A) \\ I(A) & R(A) \end{bmatrix}, z = \begin{bmatrix} R(b) \\ I(b) \end{bmatrix}, \|z\|_2 \leq t
\end{aligned}$$

for $p = \infty$:

$$\begin{aligned}
& \min_x \|x\|_\infty \quad s.t \quad Ax = b \\
& = \min_{z \in \mathbb{R}^{2n}} \|z\|_2 \\
& = \min_{z \in \mathbb{R}^{2n}} \max \|z_i \dots z_{i+n}\|_2 \\
& s.t : \begin{bmatrix} R(A) & -I(A) \\ I(A) & R(A) \end{bmatrix}, z = \begin{bmatrix} R(b) \\ I(b) \end{bmatrix} \\
& = \min_{z \in \mathbb{R}^{2n}, t \in \mathbb{R}} t \\
& s.t : \begin{bmatrix} R(A) & -I(A) \\ I(A) & R(A) \end{bmatrix}, z = \begin{bmatrix} R(b) \\ I(b) \end{bmatrix}, \|z_i \dots z_{i+n}\|_2 \leq t
\end{aligned}$$

4.

1.

$$\|A^*q\| = \left\| \frac{uq^\top}{\|u\| \cdot \|q\|} q \right\| = \|q\|$$

also:

$$\|Aq\| \leq \|A\|_F \cdot \|q\| \leq \|q\| \rightarrow \max_{\|A\|_F \leq 1} \|Aq\| \leq \|q\|$$

And together with $\|A^*q\| = \|q\|$ we get that $\max_{\|A\|_F \leq 1} \|Aq\| = \|q\|$

2.