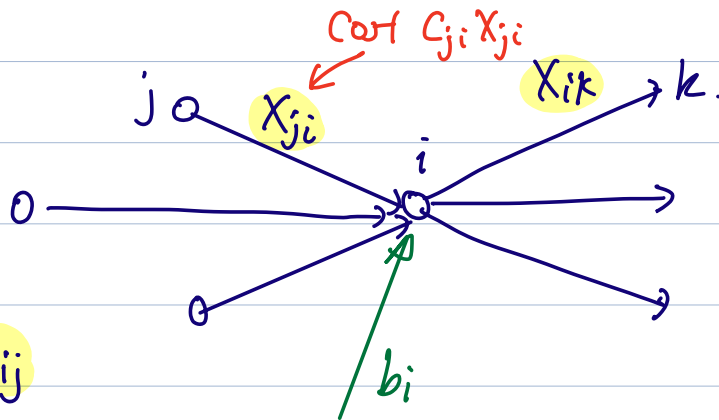


Tutorial 7.

BV 4.12

$$\min_{\lambda} X = \{x_{ij}\}$$

$$C = \sum_{i,j} c_{ij} x_{ij}$$



$$\underline{l}_{ij} \leq x_{ij} \leq u_{ij} \quad \forall i, j$$

Conservation of flow

$$\forall i \in [n], \quad \text{in} = \text{out}$$

$$b_i + \sum_{j=1}^n x_{ji} = \sum_{k=1}^n x_{ik} \quad (\text{affine/linear})$$

BV 4.23

ℓ_4 -norm approximation

$$\min_x \|Ax - b\|_4 = \left(\sum_{i=1}^m ((Ax)_i - b_i)^4 \right)^{1/4}$$

$$x \in \mathbb{R}^n$$

$$A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$$

$$= \left(\sum_{i=1}^m (a_i^T x - b_i)^4 \right)^{1/4}$$

Formulate this as a QCP

$$P_i \in S_+^n, i=0,1,\dots,m.$$

$$\min_x \quad \frac{1}{2} x^T P_0 x + q_0^T x + r_0$$

$$\text{s.t.} \quad \frac{1}{2} x^T P_i x + q_i^T x + r_i \leq 0 \quad \forall i=1,\dots,m.$$

$$Ax = b.$$

$$\min_{x \in \mathbb{R}^n} \sum_{i=1}^m (a_i^T x - b_i)^2$$

$$\text{Let } y_i = a_i^T x - b_i \quad i=1,\dots,m$$

$$y_i^2 \leq z_i \quad i=1,\dots,m.$$

$$\min_{\substack{x \in \mathbb{R}^n \\ y \in \mathbb{R}^m, z \in \mathbb{R}^m}} \sum_{i=1}^m z_i = z^T z$$

$$y_i = a_i^T x - b_i \quad i=1,\dots,m$$

$$y_i^2 \leq z_i \quad i=1,\dots,m.$$

$$w = \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^{n+2m}$$

Objective:

$$\min_{w \in \mathbb{R}^{n+2m}}$$

$$\frac{1}{2} \begin{bmatrix} x \\ y \\ z \end{bmatrix}^T \overbrace{\begin{bmatrix} 0_{n \times n} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & I_{m \times m} \end{bmatrix}}^{P_0} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Equality :

Constraint

$$y_i = a_i^T x - b_i \Rightarrow A w = b.$$

$$\Leftarrow i=1, \dots, m$$

$$\Downarrow$$

$$-a_i^T x + y_i = -b_i$$

$$\begin{bmatrix} -A & I & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} -b \end{bmatrix}$$

Inequality constraint:

$$\begin{array}{l} y_i^2 \leq z_i \\ i=1, \dots, m. \end{array}$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix}^T p_i \begin{bmatrix} x \\ y \\ z \end{bmatrix} + q_i^T \begin{bmatrix} x \\ y \\ z \end{bmatrix} + r_i \leq 0.$$

$$\underbrace{\begin{bmatrix} x \\ y \\ z \end{bmatrix}^T}_w \begin{bmatrix} 0 & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & 0 \end{bmatrix} \underbrace{\begin{bmatrix} x \\ y \\ z \end{bmatrix}}_w - \underbrace{\begin{bmatrix} 0_n \\ 0_m \\ 1_m \end{bmatrix}^T}_w \underbrace{\begin{bmatrix} x \\ y \\ z \end{bmatrix}}_w \leq 0.$$

BV 4.28

$$\min_x \frac{1}{2} x^T P x + q^T x + r \text{ s.t. } Ax \leq b$$

$$\min_x \sup_{p \in \mathcal{E}} \left\{ \frac{1}{2} x^T P x + q^T x + r \right\} \text{ s.t. } Ax \leq b$$

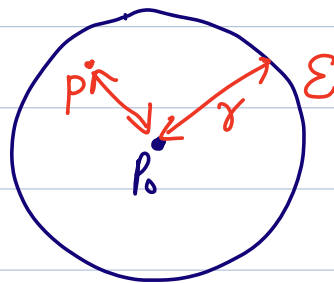
$$a) \quad \Sigma = \{P_1, \dots, P_K\}, \quad P_i \in S_+^n$$

$$\min_{x \in \mathbb{R}^n} \max_{i=1, \dots, K} \left\{ \frac{1}{2} x^T P_i x + q^T x + r \right\} \quad \text{s.t.} \quad Ax \leq b$$

$$\equiv \min_{x \in \mathbb{R}^n, t \in \mathbb{R}} t \quad \text{s.t.} \quad \frac{1}{2} x^T P_i x + q^T x + r \leq t \quad \forall i=1, \dots, K \\ Ax \leq b.$$

$$\text{QCQP} \quad \begin{pmatrix} x \\ t \end{pmatrix} \in \mathbb{R}^{n+1}$$

$$b) \quad \Sigma = \{P \in S_+^n : -\gamma I \leq P - P_0 \leq \gamma I\}$$



\Downarrow

$$\lambda_{\max}(P - P_0) \leq \gamma$$

$$\min_x \sup_{P \in \Sigma} \left\{ \frac{1}{2} x^T P x + q^T x + r \right\} \quad \text{s.t.} \quad Ax \leq b$$

$$\sup_{P \in \Sigma} \left\{ \frac{1}{2} x^T P x \right\} = \sup_{-\gamma I \leq Q \leq \gamma I} \left\{ \frac{1}{2} x^T (P_0 + Q) x \right\}$$

$$= \frac{1}{2} (x^T P_0 x + \sup_{-\gamma I \leq Q \leq \gamma I} x^T Q x)$$

$$\boxed{\sup_{x \neq 0} \frac{x^T Q x}{x^T x} = \lambda_1(Q)}$$

$$= \frac{1}{2} (x^T P_0 x + x^T \gamma I x)$$

$$= \frac{1}{2} x^T P_0 x + \gamma x^T x.$$

$$\min_x \quad \frac{1}{2} x^T (P_0 + \gamma I) x + q^T x + r \quad \text{s.t. } Ax \leq b.$$

$$c) \quad \Sigma = \left\{ P_0 + \sum_{i=1}^K P_i u_i : \|u\|_2 \leq 1 \right\}.$$

Objective writes

$$\min_x \sup_{P \in \Sigma} \frac{1}{2} x^T P x$$

$$\equiv \min_x \sup_{u: \|u\|_2 \leq 1} \frac{1}{2} x^T \left(P_0 + \sum_{i=1}^K P_i u_i \right) x$$

$$\equiv \min_x \frac{1}{2} \left(x^T P_0 x + \sup_{u: \|u\|_2 \leq 1} \sum_{i=1}^K \underbrace{(x^T P_i x)}_{w_i} u_i \right).$$

$$\sup_{u: \|u\|_2 \leq 1} \sum_{i=1}^K w_i u_i = \sup_{u: \|u\| \leq 1} u^T w = \|w\|_2$$

$$\equiv \min_x \frac{1}{2} \left(\underbrace{x^T P_0 x}_{\checkmark} + \underbrace{\left(\sum_{i=1}^K (x^T P_i x)^2 \right)^{\frac{1}{2}}}_{\text{Convex}} \right) + q^T x + r \quad \checkmark$$

We know that the function $g_i(x) \triangleq x^T P_i x$ is convex in x , since $P_i \geq 0$.

The second term $\left(\sum_i \underbrace{(x^T P_i x)^2}_{\text{convex in } x} \right)^{\frac{1}{2}}$ is

$$h(y) = \|y\|_2 \cdot \underbrace{h(g_1(x), g_2(x), \dots, g_K(x))}_{\text{nonnegative}}$$

$|y|$

h is convex & when the arguments are nonnegative, h is non-decreasing in its arguments. Hence, the 2nd term is convex.

$$\equiv \min_{x, y, u, t} \underbrace{\frac{1}{2} x^T P_0 x}_u + \underbrace{\|y\|_2}_t + q^T x + r$$

$$\frac{1}{2} x^T P_i x \leq y_i \quad i=1, \dots, K$$

$$Ax \leq b$$

$$\frac{1}{2} x^T P_0 x \leq u$$

$$\|y\| \leq t \quad \text{SOCP}$$

\Downarrow SOCP

$$\left\| \begin{bmatrix} P_0^{1/2} x \\ 2u - \frac{1}{4} \end{bmatrix} \right\| \leq 2u + \frac{1}{4}$$

$$\|Ax + b\| \leq c^T x + d$$

$$\left\| \begin{bmatrix} P_i^{1/2} x \\ 2y_i - \frac{1}{4} \end{bmatrix} \right\| \leq 2y_i + \frac{1}{4}$$

$$\|P_0^{1/2} x\|^2 + (2u - \frac{1}{4})^2 \leq (2u + \frac{1}{4})^2$$

$$x^T P_0 x + -u \leq u$$

$$\frac{1}{2} x^T P_0 x \leq u.$$

