

Consider

$$(Q) \quad \begin{aligned} & \inf \quad x^T C x \\ & \text{s.t.} \quad x^T Q_i x \geq b_i, \quad i=1, \dots, m. \end{aligned} \quad \text{Data: } \begin{aligned} & C, Q_1, \dots, Q_m \in S^n \\ & b_1, \dots, b_m \in \mathbb{R} \end{aligned}$$

(quadratically constrained quadratic optimization (QCQP))

Remarks:

- ① No convexity assumption is made
- ② Problem (Q) can model a wide range of problems, e.g.

$$\begin{aligned} \inf \quad x^T C x \quad & \longleftrightarrow \quad \inf \quad x^T C x \\ \text{s.t.} \quad x_i \in \{-1, 1\} \quad & \text{s.t.} \quad \begin{aligned} x_i^2 &\leq 1 \\ -x_i^2 &\leq -1 \end{aligned} \end{aligned}$$

Semidefinite relaxation (SDR) technique for (Q):

Observe

$$x^T C x = \text{tr}(x^T C x) = \text{tr}(C x x^T) = \langle C, x x^T \rangle$$

$\xrightarrow{\text{tr}}$        $\xrightarrow{\text{tr}}$        $\xrightarrow{\text{tr}}$

Hence, (Q) is equivalent to

$$\begin{aligned} & \inf \quad \langle C, x x^T \rangle \\ & \text{s.t.} \quad \langle Q_i, x x^T \rangle \geq b_i, \quad \forall i. \end{aligned}$$

Observe that (Q) is linear in  $X$ . Moreover,

$$X = x x^T \iff X \in S_+^n, \quad \text{rank}(X) \leq 1$$

$\parallel$   
 # of non-zero eigenvalues of  $X$

$$\begin{aligned} x(x^T u) & \text{ eigenvalue} \\ \parallel & \\ (x x^T) u & = \lambda u \\ \uparrow & \\ & \text{eigenvector} \\ & (\|u\|_2 = 1) \end{aligned}$$

Hence, (Q) is equivalent to

$$\inf \langle C, X \rangle \quad \text{— linear}$$

Take  $u = \frac{x}{\|x\|_2}$ . Then,

$$x x^T u = \|x\|_2 x$$

$$\begin{aligned} & \inf \langle C, X \rangle \quad \text{— linear} \\ \text{(Q)} \quad & \text{s.t. } \langle Q_i, X \rangle \geq b_i, \quad \text{— linear} \\ & X \in S_+^n, \quad \text{rank}(X) \leq 1 \\ & \quad \quad \quad \underbrace{\hspace{10em}}_{\text{non-convex}} \\ & \quad \quad \quad \underbrace{\hspace{5em}}_{\text{psd}} \end{aligned}$$

take  $u = \frac{x}{\|x\|_2}$ , then

$$x x^T u = \|x\|_2 x$$

↙

$$\text{eigenvector} = \|x\|_2^2 \cdot u$$

largest eigenvalue

The SDR of (Q) is

$$\begin{aligned} \text{(SDR)} \quad & \inf \langle C, X \rangle \\ & \text{s.t. } \langle Q_i, X \rangle \geq b_i, \quad \leftarrow \text{SDP} \\ & X \in S_+^n \end{aligned}$$

Q: Given an optimal solution  $X^*$  to (SDR), how do we extract from it a feasible solution to (Q)?

Remark - Idea of SDR:  $X = x x^T \rightarrow X \in S_+^n$

In essence,

$$\begin{array}{ccc} x^T C x & \rightarrow & \langle C, X \rangle \\ \parallel & & \parallel \\ \sum_{i,j} C_{ij} x_i x_j & & \sum_{i,j} C_{ij} X_{ij} \end{array}$$

(Note:  $x_i x_j$  and  $X_{ij}$  are circled in red in the original image)

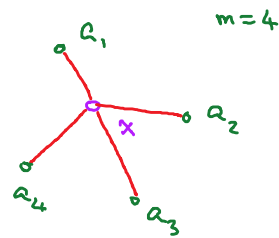
$$g_i^2 = g_i g_i \rightarrow G_{ii}$$

Example: Single-source localization

$x \in \mathbb{R}^n$ : source with unknown position

$a_i \in \mathbb{R}^n$ : anchor with known position

( $i=1, \dots, m$ )



Measurement model:

$$d_i = \|x - a_i\|_2 + \epsilon_i, \quad i=1, \dots, m.$$

measurement (under  $d_i$ )      noise (under  $\epsilon_i$ )

Goal: Recover  $x$  from  $d_1, \dots, d_m$ .

Least-squares formulation

$$\min_{x \in \mathbb{R}^n} \sum_{i=1}^m (d_i - \|x - a_i\|_2)^2$$

$$\begin{aligned}
 \text{(LS)} \quad & \min_{\substack{x \in \mathbb{R}^n \\ g \in \mathbb{R}^m}} \sum_{i=1}^m (d_i - g_i)^2 = \sum_{i=1}^m \frac{(d_i - g_i)^2}{1} = \|d - g\|_2^2 = \underbrace{\begin{bmatrix} g^T & 1 \end{bmatrix}}_{\text{data}} \underbrace{\begin{bmatrix} I & -d \\ -d & \|d\|_2^2 \end{bmatrix}}_{D} \begin{bmatrix} g \\ 1 \end{bmatrix} \\
 \Leftrightarrow & \quad \text{s.t.} \quad g_i^2 = \|x - a_i\|_2^2, \quad i=1, \dots, m, \\
 & \quad \quad \quad g_i \geq 0 \quad \Leftrightarrow \quad g_i^2 = \underbrace{\begin{bmatrix} x^T & 1 \end{bmatrix}}_{\text{data}} \underbrace{\begin{bmatrix} I & -a_i \\ -a_i^T & \|a_i\|_2^2 \end{bmatrix}}_{A_i} \begin{bmatrix} x \\ 1 \end{bmatrix}
 \end{aligned}$$

Note:

$$\begin{aligned}
 \begin{bmatrix} g^T & 1 \end{bmatrix} D \begin{bmatrix} g \\ 1 \end{bmatrix} &= \text{tr} \left( \begin{bmatrix} g^T & 1 \end{bmatrix} D \begin{bmatrix} g \\ 1 \end{bmatrix} \right) = \langle D, \begin{bmatrix} g \\ 1 \end{bmatrix} \begin{bmatrix} g^T & 1 \end{bmatrix} \rangle \\
 &= \langle D, \begin{bmatrix} g & g \\ g^T & 1 \end{bmatrix} \rangle
 \end{aligned}$$

Similarly,

$$\begin{bmatrix} x^T & 1 \end{bmatrix} A_i \begin{bmatrix} x \\ 1 \end{bmatrix} = \langle A_i, \begin{bmatrix} x & x \\ x^T & 1 \end{bmatrix} \rangle$$

Hence, the SDR of (LS) is

$$\begin{aligned}
 \min_{\substack{G, g \\ X, x}} & \langle D, \begin{bmatrix} G & g \\ g^T & 1 \end{bmatrix} \rangle \\
 \text{s.t.} & \quad G_{ii} = \langle A_i, \begin{bmatrix} x & x \\ x^T & 1 \end{bmatrix} \rangle, \\
 & \quad \quad \quad g_i \geq 0, \\
 & \quad \quad \quad X \in S_+^n, \quad G \in S_+^m.
 \end{aligned}$$