

Q1. (a) Equivalent to the LP: minimize  $1^T y$   
subject to  $-y \leq Ax - b \leq y$   
 $-1 \leq x \leq 1$  ( $x \in \mathbb{R}^n$  and  $y \in \mathbb{R}^m$ )

(b) Equivalent to the LP: minimize  $1^T y$   
subject to  $-y \leq x \leq y$   
 $-1 \leq Ax - b \leq 1$  ( $x \in \mathbb{R}^n$  and  $y \in \mathbb{R}^n$ )

(c) Equivalent to the LP: minimize  $1^T y + t$   
subject to  $-y \leq Ax - b \leq y$   
 $-t \leq x \leq t$  ( $x \in \mathbb{R}^n$ ,  $y \in \mathbb{R}^m$ ,  $t \in \mathbb{R}$ )

Q2. Adding slack variables  $t_i$  for  $i=1, \dots, m$ , the problem can be converted to

$$\min_{x, t} \sum_{i=1}^m t_i^2$$

$$\text{s.t. } (a_i^T x - b_i)^2 \leq t_i, \quad i=1, \dots, m.$$

which is a convex QCAP

Q3.  $a_i^T x + b_i \geq 0 \quad i=1, 2, \dots, m$   
 $c_i^T x + d_i \leq 0, \quad i=1, 2, \dots, k$   $\Rightarrow$   $a_i^T x + b_i \leq 0$  &  $a_i^T x + b_i \geq 0 \quad i=1, \dots, m$   
 $c_i^T x + d_i \leq 0 \quad i=1, \dots, k$

To transform it into SDP,  $[A_0 \ A_1 \ \dots \ A_n] \begin{bmatrix} 1 \\ x_1 \\ \vdots \\ x_n \end{bmatrix} \leq 0$

We have  $A_t = \begin{cases} \begin{bmatrix} b_i \\ d_i \\ -b_i \end{bmatrix} & (t=0) \\ \begin{bmatrix} a_i^T \\ c_i^T \\ -a_i^T \end{bmatrix} & (t=1, 2, \dots, n) \end{cases}$

Q4. Since  $f(x)$  is convex, consider FOC:  $f(x) \geq f(x^*) + \nabla f(x^*)^T (x - x^*)$

$$\Rightarrow f(x) \geq f(x^*) + \nabla f(x^*)^T x - \nabla f(x^*)^T x^*$$

$$\because [\nabla f(x^*)]^T x^* = 0 \quad \therefore f(x) \geq f(x^*) + \nabla f(x^*)^T x$$

$$\because x \geq 0, \nabla f(x^*) \geq 0 \quad \therefore \nabla f(x^*)^T x \geq 0$$

$$\therefore f(x^*) + \nabla f(x^*)^T x \geq f(x^*) \quad \therefore f(x) \geq f(x^*) \quad \therefore x^* \text{ is optimal solution}$$