

### Problem 4.1: Necessary Conditions for Least Squares

Consider the following unconstrained optimization problem  $P$ :

$$(P) : \min. \|Ax - b\|_2^2 \quad (1)$$

where  $A$  is a matrix in  $\mathbb{R}^{m \times n}$  and  $b$  is a vector in  $\mathbb{R}^m$ . This problem is typically called a *least-squares* problem when using the Euclidean norm, and it has several applications in regression analysis, optimal control, parameter estimation, data fitting, etc.

An extension of the problem  $P$  involves minimizing  $\|x\|_2^2$  on top of the original objective. To solve this problem, we can use *regularization* which is a common scalarization technique to find solutions to bi-criterion problems. We will consider the following *regularized* least-squares problem

$$(RP) : \min. \|Ax - b\|_2^2 + \delta \|x\|_2^2 \quad (2)$$

where the penalty term  $\delta > 0$  controls the trade-off between the two objectives.

- (a) Give brief interpretations of the problems (1) and (2).
- (b) Find solutions for the problems (1) and (2) by writing the first-order necessary optimality conditions. Justify why these conditions are also sufficient.

### Problem 4.2: Optimality of Points in a Convex Problem

Consider the following convex optimization problem  $P$ :

$$(P) : \min. (x_1 - 3)^2 + (x_2 - 2)^2 \quad (3)$$

$$\text{subject to: } x_1^2 + x_2^2 \leq 5 \quad (4)$$

$$x_1 + x_2 \leq 3 \quad (5)$$

$$x_1 \geq 0 \quad (6)$$

$$x_2 \geq 0 \quad (7)$$

Let  $S$  denote the feasible set defined by the constraints (4) – (7), and let  $f : \mathbb{R}^2 \rightarrow \mathbb{R}$  with  $f(x) = (x_1 - 3)^2 + (x_2 - 2)^2$  denote the objective function (3). Notice that both  $S$  and  $f$  are convex. Recall the following optimality condition for convex optimization problems presented in Lecture 4 (Corollary 4):

Let  $S \subseteq \mathbb{R}^n$  be a convex set and  $f : S \rightarrow \mathbb{R}$  a differentiable convex function on  $S$ . Then  $\bar{x} \in S$  is optimal if and only if

$$\nabla f(\bar{x})^\top (x - \bar{x}) \geq 0, \text{ for all } x \in S \quad (8)$$

Using the condition (8), examine graphically if the following points are optimal for problem  $P$ :

- (a)  $\bar{x}_1 = (1, 2)$
- (b)  $\bar{x}_2 = (2, 1)$

### Problem 4.3: Optimal Point of a Nonsmooth Convex Problem

Consider the following nonsmooth optimization problem  $P$ :

$$(P) : \min. f(x) = \begin{cases} -\frac{3}{2}x + 6, & \text{if } 0 < x \leq 2 \\ -\frac{1}{2}x + 4, & \text{if } 2 \leq x \leq 4 \\ \frac{1}{4}x + 1 & \text{if } 4 \leq x \leq 8 \\ x - 5 & \text{if } x \geq 8 \end{cases} \quad (9)$$

$$\text{subject to: } x \in \mathbb{R}^+. \quad (10)$$

Let  $S$  denote the feasible set defined by the constraint (10), and let  $f : \mathbb{R}^+ \rightarrow \mathbb{R}$  with  $f(x)$  denote the objective function (9). Notice that both  $S$  and  $f$  are convex.

Characterize the subdifferential sets of  $f$  at points  $\bar{x}_1 = 2$ ,  $\bar{x}_2 = 4$ , and  $\bar{x}_3 = 8$ . Use Corollary 3 from Lecture 4 to show that  $\bar{x}_2 = 4$  is the unique optimal solution to the problem  $P$ . Corollary 3 states that a point  $\bar{x} \in S$  is an optimal solution to  $P$  if and only if  $0 \in \partial f(\bar{x})$ , that is,  $f$  has a subgradient  $\xi = 0$  at  $\bar{x}$  that belongs to the subdifferential set  $\partial f(\bar{x})$ .