

## SOLUTIONS HW 2

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### 1 Problem 1

- Let us consider  $f(x) = -x^2$  and  $\alpha = -1$ , then  $\mathcal{S} = (-\infty, -1] \cup [1, +\infty)$ . The  $\mathcal{S}$  is not convex, because although  $-1, 1 \in \mathcal{S}$ , we have  $(-1 + 1)/2 = 0 \notin \mathcal{S}$ .
- By triangle inequality, we have  $\|tx + (1-t)y\|_p \leq \|tx\|_p + \|(1-t)y\|_p = t\|x\|_p + (1-t)\|y\|_p$ . Hence the  $\ell_p$  norm  $\|\cdot\|_p$  is a convex function, and its sublevel set is convex.
- We observe that  $f$  can be rewritten as  $f(x) = \frac{1}{2}x^T Qx + p^T x + r$  with  $Q$  being given as

$$Q = \begin{bmatrix} 4 & 0 & 2 \\ 0 & 4 & 3 \\ 2 & 3 & 1 \end{bmatrix}$$

Therefore, we can directly get

$$\nabla^2 f = \begin{bmatrix} 4 & 0 & 2 \\ 0 & 4 & 3 \\ 2 & 3 & 1 \end{bmatrix}, \quad \forall x$$

Since  $\det([4]) = 4 > 0$ ,  $\det \begin{pmatrix} 4 & 0 \\ 0 & 4 \end{pmatrix} = 16 > 0$  and  $\det(\nabla^2 f) = -36 < 0$ , we know  $\nabla^2 f$  is not PSD.

Since  $\det(-[4]) = -4 < 0$ ,  $\det \begin{pmatrix} -4 & 0 \\ 0 & -4 \end{pmatrix} = 16 > 0$  and  $\det(-\nabla^2 f) = 36 > 0$ , we know  $\nabla^2 f$  is not NSD. Therefore,  $\nabla^2 f$  is indefinite. We can conclude that  $f$  is neither convex nor concave.

- Yes. The function  $f(x) = x \log(x)$ ,  $x > 0$  is convex since  $f''(x) = \frac{1}{x} > 0$ . We also prove that the function  $g(x, y) = x \log(x) + y \log(y)$  is convex. Indeed, let us fix  $x_1, x_2, y_1, y_2 \in \mathbb{R}^+$  and  $a \in [0, 1]$ , then

$$\begin{aligned} g(ax_1 + (1-a)x_2, ay_1 + (1-a)y_2) &= f(ax_1 + (1-a)x_2) + f(ay_1 + (1-a)y_2) \\ &\leq af(x_1) + (1-a)f(x_2) + af(y_1) + (1-a)f(y_2) \\ &= ag(x_1, y_1) + (1-a)g(x_2, y_2) \end{aligned} \quad (1)$$

As a result the set  $\mathcal{S} \equiv \{(x_1, x_2) : x_1, x_2 > 0, \quad g(x_1, x_2) \leq 4\}$  is convex.

- Let us fix  $x_1, x_2 \in \mathbb{R}^n$  and  $a \in [0, 1]$ . By concavity of  $g$  it holds  $g(ax_1 + (1-a)x_2) \geq ag(x_1) + (1-a)g(x_2)$ . In order to prove that  $f \circ g$  is concave, we proceed as follows

$$\begin{aligned} f(g(ax_1 + (1-a)x_2)) &\geq f(ag(x_1) + (1-a)g(x_2)), \quad \text{by concavity of } g, \text{ \& the fact } f \text{ is increasing} \\ &\geq af(g(x_1)) + (1-a)f(g(x_2)), \quad \text{by concavity of } f \end{aligned} \quad (2)$$

Hence,  $f \circ g$  is concave.

### 2 Problem 2

- The function  $f$  does not have maximum over  $\mathbb{R}^3$  because  $f(x_1, 0, 0) = 2x_1^2 - 2x_1 + 5$  is not bounded. The function  $f$  has a unique minimum. Indeed,

$$\nabla f = [4x_1 - 2, 4x_2 + 2x_3 - 2, 2x_3 + 2x_2 - 2]^T \quad (3)$$

and  $\nabla f(x) = 0 \Rightarrow (x_1, x_2, x_3) = (0.5, 0, 1)$ . Since,

$$\nabla^2 f = \begin{pmatrix} 4 & 0 & 0 \\ 0 & 4 & 2 \\ 0 & 2 & 2 \end{pmatrix} = \begin{pmatrix} 4 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & 2 & 2 \\ 0 & 2 & 2 \end{pmatrix} \quad (4)$$

is PD, we conclude the result.

2. Since  $Q$  is PD we have  $\nabla f(x) = Qx$ . We consider  $g(a_k) = f(x_k - a_k Q x_k)$  and we minimize  $g$

$$g(a_k) = f((I - a_k Q) x_k) = \frac{1}{2} x_k^T Q x_k - (x_k^T Q^2 x_k) a_k + \frac{1}{2} (x_k^T Q^3 x_k) a_k^2 \quad (5)$$

Hence  $g(a_k)$  is minimized when  $a_k = \frac{x_k^T Q^2 x_k}{x_k^T Q^3 x_k}$

3. Let us consider matrix  $A$  whose  $i^{\text{th}}$  row is  $a_i$  and the column vector  $b = (b_1, \dots, b_n)^T$ , then

$$\begin{aligned} f(x) &= \frac{1}{n} (Ax - b)^T (Ax - b) + \frac{\lambda}{2} x^T I x \\ &= \frac{1}{n} (x^T A^T A x + b^T b - b^T A x - x^T A^T b) + \frac{\lambda}{2} x^T I x \end{aligned} \quad (6)$$

We have

$$\nabla f = \frac{1}{n} (2A^T A x - 2A^T b) + \lambda x = \left( \frac{2}{n} A^T A + \lambda I \right) x - \frac{2}{n} A^T b \quad (7)$$

and  $\nabla f = 0 \Rightarrow x^* = (A^T A + \frac{n}{2} \lambda I)^{-1} A^T b$ . Also,  $\nabla^2 f = \frac{2}{n} A^T A + \lambda I$  is PD because  $x^T \nabla^2 x = \frac{2}{n} (Ax)^T (Ax) + \lambda x^T x > 0$  for all  $x \neq 0$ . Hence, the optimal solution  $x^*$  is unique. It is worth mentioning that  $A^T A = \sum_{i=1}^n a_i a_i^T$  and  $A^T b = \sum_{i=1}^n a_i^T b_i$ .

### 3 Problem 3

We must find the minimum  $m$  such that

$$f(x_k + \beta^m \tilde{\alpha} d_k) \leq f(x_k) + \sigma \beta^m \tilde{\alpha} \nabla f^T d_k \quad (8)$$

where  $\nabla f = [4x_1, 8x_2^3]^T$ , and since we apply steepest decent we choose  $d_k = -\nabla f$ . Hence, by substitution we obtain

$$f(1 - 0.5^m 4, 0) = 2(1 - 0.5^m 4)^2 \leq 2 - 0.80 \cdot 5^m \quad (9)$$

and the minimum  $m$  that satisfies the inequality is  $m = 2$ , which implies that  $a_k = \tilde{\alpha} \beta^m = 1 \cdot 0.5^2 = 0.25$ .

### 4 Problem 4

We have

$$\begin{aligned} f(x_k) - f(x_{k+1}) &\geq (\nabla f(x_k))^T \alpha D \nabla f(x_k) - \frac{L}{2} \|\alpha D \nabla f(x_k)\|_2^2 \\ &\geq \alpha \left( \lambda_{\min} - \frac{L}{2} \alpha \lambda_{\max}^2 \right) \|\nabla f(x_k)\|^2 \end{aligned} \quad (10)$$

We know  $\lambda_{\min} - \frac{L}{2} \alpha \lambda_{\max}^2 > 0$ . We observe that

$$\alpha \left( \lambda_{\min} - \frac{L}{2} \alpha \lambda_{\max}^2 \right) \sum_{k=0}^n \|\nabla f(x_k)\|^2 \leq f(x_0) - f(x_{n+1}) \leq f(x_0) - f_{\min} \quad (11)$$

As a result for all  $n \in \mathbb{N}$

$$\sum_{k=0}^n \|\nabla f(x_k)\|^2 \leq \frac{f(x_0) - f_{\min}}{\alpha \left( \lambda_{\min} - \frac{L}{2} \alpha \lambda_{\max}^2 \right)} \quad (12)$$

which implies that as  $n \rightarrow \infty$  the series converges and as a result  $\lim_{n \rightarrow \infty} \nabla f(x_n) = 0$ .