Class-in exam: 02:30-4:25 pm 25th.

Name: Number:

- 1. [16] Prove or disprove the convexity or concavity of the following problem explicitly
 - (a) [4] Consider two convex sets S_1 and S_2 . Show whether a new set $S=S_1-S_2$ is convex or not
 - (b) [4] Show whether the function $f(x_1, x_2) = 10 3(x_2 x_1^2)^2$ over $S = \{(x_1, x_2) | -1 \le x_2 \le 1, -1 \le x_2 \le 1\}$ is convex or concave.
 - (c) [4] $f(x) = ||x||^p$ for $p \ge 1$
 - (d) [4] Let x be a real-valued random variable which takes values in a_1, \ldots, a_n , whereas $a_1 < \cdots < a_n$ and $\Pr(x = a_i) = p_i$. Show whether the variance of x is convex or not.
 - (a) Suppose $x_1, x_2 \in S_1$ and $y_1, y_2 \in S_2$. Then, S can have $x_1 y_1$ and $x_2 y_2$. For S to be convex, $\alpha(x_1 y_1) + (1 \alpha)(x_2 y_2)$ must belong to S. To see this,

$$\underbrace{\alpha(x_1 - y_1) + (1 - \alpha)(x_2 - y_2)}_{\in S_1} = \underbrace{\alpha x_1 + (1 - \alpha)x_2}_{\in S_2} - \underbrace{[\alpha y_1 + (1 - \alpha)y_2]}_{\in S_2}$$

Thus, S is convex.

(b) Hessian of f is

$$6\begin{bmatrix} -6x_1^2 + 2x_2 & 2x_1 \\ 2x_1 & -1 \end{bmatrix}$$

whose determinant is $6(6x_1^2 - 2x_2 - 4x_1^2) = 12(x_1^2 - x_2)$. Thus, it is neither convex, nor concave

- (c) f(x) is viewed as a composition of two functions, f(x) = g(h(x)) with $g(t) = t^p$ and h(x) = ||x||. Note that $g(t) = t^p$ is convex for $p \ge 1$ and $t \ge 0$, whereas h(x) = ||x|| is convex. Thus, f(x) is convex.
- (d)

$$\operatorname{var} \boldsymbol{x} = \sum_{i=1}^n p_i a_i^2 - \left(\sum_{i=1}^n p_i a_i\right)^2$$

which is a concave quadratic function of p_i

2. [10] Using the steepest descent method for the problem

minimize
$$f(x_1, x_2) = 4x_1^2 + x_2^2$$

- (a) [6] If $x_1^{(0)}=1, x_2^{(0)}=4$, find the expression for $x_1^{(k)}, x_2^{(k)}$ explicitly.
- (b) [4] What is the rate of convergence of the sequence $f(x^{(k)}) f(x^*)$?
- (a) Gradient and Hessian of f is

$$\nabla f(\boldsymbol{x}) = \begin{bmatrix} 8x_1 \\ 2x_2 \end{bmatrix} \quad \text{and} \quad \nabla^2 f(\boldsymbol{x}) = \begin{bmatrix} 8 & 0 \\ 0 & 2 \end{bmatrix}$$

Thus, $oldsymbol{x}^{(k)}$ is updated as

$$\boldsymbol{x}^{(k+1)} = \boldsymbol{x}^{(k)} - \frac{64x_1^2 + 4x_2^2}{8(64x_1^2 + x_2^2)} \begin{bmatrix} 8x_1 \\ 2x_2 \end{bmatrix} = \boldsymbol{x}^{(k)} - \frac{16x_1^2 + x_2^2}{64x_1^2 + x_2^2} \begin{bmatrix} 4x_1 \\ x_2 \end{bmatrix}$$

By induction, we have

$$\boldsymbol{x}^{(k)} = (0.6)^k \begin{bmatrix} (-1)^k \\ 4 \end{bmatrix}$$

(b) Note that the optimal value is 0. To get the rate of convergence, we write

$$\frac{4(-1)^{2k+2}(0.6)^{2k+2} + (0.6)^{2k+2}16}{4(-1)^{2k}(0.6)^{2k} + (0.6)^{2k}16} = 0.36$$

3. [12] Using KKT conditions, solve

$$\label{eq:continuous_subject} \begin{aligned} & \underset{x_1,x_2}{\text{minimize}} & \quad x_1^2 - x_1x_2 + 2x_2^2 - 4x_1 - 5x_2 \\ & \text{subject to} & \quad x_1 + 2x_2 \leq 6 \\ & \quad x_1 \leq 2 \\ & \quad x_1,x_2 \geq 0 \end{aligned}$$

Confirm that your solution is a global minimizer with the second-order KKT condition.

The objective function is

$$\frac{1}{2} \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 2 & -1 \\ -1 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - \begin{bmatrix} 4 & 5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Its minimum without constraints is obtained as

$$\begin{bmatrix} 2 & -1 \\ -1 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 \\ 5 \end{bmatrix} \Rightarrow \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \frac{1}{7} \begin{bmatrix} 4 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 4 \\ 5 \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \end{bmatrix}$$

Thus, it is highly likely that the objective function hits the constraint $x_1 \leq 2$ at its minimum. Now, consider dual feasibility is

$$\begin{bmatrix} 2 & -1 \\ -1 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - \begin{bmatrix} 4 \\ 5 \end{bmatrix} + \lambda_1 \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \lambda_2 \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \lambda_3 \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \lambda_4 \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

If the second is active; $\lambda_1=\lambda_3=\lambda_4=0.$ Then, we have

$$\begin{bmatrix} 2 & -1 \\ -1 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 - \lambda_2 \\ 5 \end{bmatrix} \Rightarrow \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \frac{1}{7} \begin{bmatrix} 4 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 4 - \lambda_2 \\ 5 \end{bmatrix} = \frac{1}{7} \begin{bmatrix} 21 - 4\lambda_2 \\ 14 - \lambda_2 \end{bmatrix}$$

Since we assume that $x_1=2$, we obtain $\lambda_2=7/4$, with which we also have $x_2=7/4$. The basis of the null space for the gradient of the second constraint is $[0\ 1]^T$, while Hessian of Lagrangian is $\begin{bmatrix} 2 & -1 \\ -1 & 4 \end{bmatrix}$. We can check

$$\begin{bmatrix} 0 \ 1 \end{bmatrix} \begin{bmatrix} 2 & -1 \\ -1 & 4 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 4 > 0$$

Thus, it is the global minimizer

4. [12] Solve the following problem with the feasible direction method

$$\begin{array}{ll} \underset{\boldsymbol{x}}{\text{minimize}} & 2x_1^2 + 2x_2^2 - 2x_1x_2 - 4x_1 - 6x_2 \\ \text{subject to} & x_1 + x_2 \leq 2 \\ & x_1 + 5x_2 \leq 5 \\ & -x_1 < 0, -x_2 < 0 \end{array}$$

Use the initial point, $x_1^{(0)}=0$ and $x_2^{(0)}=0$. At each step, specify d_1 , d_2 , optimal step size α , $x_1^{(k)}$ and $x_2^{(k)}$.

$$\bullet$$
 At iteration 1, since $\nabla f(x)=\begin{bmatrix} 4x_1-2x_2-4\\ 4x_2-2x_1-6 \end{bmatrix}$, we solve
$$\min_{d} \min = -4d_1-6d_2$$
 subject to $-d_1\leq 0$

$$-d_2 \le 0$$

- $1 \le d_1 \le 1, -1 \le d_2 \le 1$

We have $d_1=1$ and $d_2=1$, while $\alpha_{\rm max}=5/6$

The step size is determined by finding the minimum of $f(\alpha)=2\alpha^2-10\alpha$ for $0\leq\alpha\leq5/6$. The step size is $\alpha=2/5$ so that we have $x_1^{(1)}=5/6$ and $x_2^{(1)}=5/6$

• At iteration 2, we need to solve

$$\begin{array}{ll} \text{minimize} & -\frac{7}{3}d_1-\frac{13}{3}d_2\\ \\ \text{subject to} & d_1+5d_2\leq 0\\ & -1\leq d_1\leq 1, -1\leq d_2\leq 1 \end{array}$$

We have $d_1=1$ and $d_2=-1/5$. Furthermore, we find α of minimizing $f(\alpha)=\frac{62}{25}\alpha^2-\frac{22}{15}\alpha-\frac{125}{8}$ for $0\leq\alpha\leq5/12$; $\alpha=55/186$. Thus, $x_1^{(2)}=\frac{5}{6}-\frac{55}{186}1=\frac{35}{31}$ and $x_2^{(2)}=\frac{5}{6}+\frac{55}{186}\frac{1}{5}=\frac{24}{31}$

• At iteration 3, we solve

$$\label{eq:definition} \begin{aligned} & \min_{\boldsymbol{d}} & & -\frac{32}{31}d_1 - \frac{160}{31}d_2\\ & \text{subject to} & & d_1 + 5d_2 \leq 0\\ & & -1 \leq d_1 \leq 1, -1 \leq d_2 \leq 1 \end{aligned}$$

which yields $d_1=1$ and $d_2=-1/5$. So this is a KKT point.

5. [10] Consider the bound-contrainted problem $(l_i < u_i)$

$$\begin{array}{ll} \text{minimize} & \sum_{i=1}^n c_i x_i \\ \\ \text{subject to} & l_i \leq x_i \leq u_i \ \ \text{for} \ \ i=1,2,\dots,n \end{array}$$

Using the first-order KKT conditions, find the minimizer x_i^* and the minimum.

Lagrangian is

$$\sum_{i=1}^{n} (c_i + \lambda_i(-x_i + l_i) + \mu_i(x_i - u_i)) = 0$$

whereas dual feasibility condition is

$$c_i - \lambda_i + \mu_i = 0$$

- ullet If $x_i^*=u_i$, then $\lambda_i=0$, such that we have $\mu_i=-c_i>0$. Thus, c_i must be negative.
- If $x_i^* = l_i$, then $\mu_i = 0$, such that we have $\lambda_i = c_i > 0$. Thus, c_i must be positive.
- If $c_i = 0$, then we can see $l_i < x_i < \mu_i$. Thus, the optimium value is

$$\sum_{i=1}^{n} (l_i \max(c_i, 0) + u_i \max(-c_i, 0))$$