

**Indian Institute of Information Technology Allahabad**  
**Convex Optimization (SMAT430C)**  
**Quiz 02: Tentative Marking Scheme**

Maximum marks is **25**. If you get more than 25, the extra mark(s) will be added to your total marks out of 150 as a **bonus**.

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1. Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  be a continuous function. Let  $c \in \mathbb{R}$  be a point such that for  $t \leq c$ ,  $f$  is decreasing, and for  $t \geq c$ ,  $f$  is increasing. Prove that  $f$  is quasiconvex. (Note:  $f$  need not be convex). [4]

**Solution.** Let  $x, y \in S_\alpha = \{x : f(x) \leq \alpha\}$  such that  $x < y$ . Then  $f(x) \leq \alpha$ ,  $f(y) \leq \alpha$ . [1]

Let  $z = \lambda x + (1 - \lambda)y$ , for  $\lambda \in (0, 1)$ . We have  $x < z < y$ . We want to show that  $S_\alpha$  is convex, i.e.,  $z \in S_\alpha$  or  $f(z) \leq \alpha$ . [1]

If  $z \leq c$ , then  $f(z) \leq f(x) \leq \alpha$  ( $\because f$  is decreasing for  $t \leq c$ ). [1]

If  $z \geq c$ , then  $f(z) \leq f(y) \leq \alpha$  ( $\because f$  is increasing for  $t \geq c$ ). [1]

2. Find  $\sup\{a^T x : \|x\|_2 \leq 5\}$ , where  $a$  is a nonzero vector in  $\mathbb{R}^n$ . [5]

**Solution.** Let  $S = \{a^T x : \|x\|_2 \leq 5\}$ . Then

$$\langle a, x \rangle = a^T x \leq \|a\|_2 \|x\|_2 \leq 5\|a\|_2, \text{ (by Cauchy-Schwartz inequality).} \quad [2]$$

Let  $x_0 = \frac{5a}{\|a\|_2}$ . Then  $\|x_0\|_2 = 5$  and, [1]

$$a^T x_0 = \frac{a^T (5a)}{\|a\|_2} = \frac{5\|a\|_2^2}{\|a\|_2} = 5\|a\|_2. \quad [1]$$

$$\therefore \sup S = 5\|a\|_2. \quad [1]$$

3. Let the pair  $x$  and  $(\lambda, \nu)$  be primal and dual feasible respectively. If the duality gap associated with this pair is zero, prove that  $x$  is primal optimal and  $(\lambda, \nu)$  is dual optimal. [7]

**Solution.** If  $x$  is primal feasible, and  $(\lambda, \nu)$  is dual feasible, then

$$f_0(x) - p^* \leq f_0(x) - g(\lambda, \nu). \quad [1]$$

Given that the duality gap is zero, i.e.,  $f_0(x) - g(\lambda, \nu) = 0$  or  $f_0(x) = g(\lambda, \nu)$ . [1]

$$\therefore f_0(x) - p^* \leq 0 \implies f_0(x) = p^*, \text{ by definition of } p^*. \quad [1]$$

$\therefore x$  is primal optimal. [1]

Now, we know that  $g(\lambda, \nu) \leq d^* \leq p^*$ . [1]

$$\text{But } f_0(x) = g(\lambda, \nu) \leq d^* \leq p^* = f_0(x) \implies g(\lambda, \nu) = d^*. \quad [1]$$

$\therefore (\lambda, \nu)$  is dual optimal. [1]

4. Find the local extreme values of  $f(x, y) = 3y^2 - 2y^3 - 3x^2 + 6xy$ . [10]

Since  $f$  is differentiable everywhere, it can assume extreme values only where

$$f_x = 6y - 6x = 0, \text{ and } f_y = 6y - 6y^2 + 6x = 0. \quad [1+1]$$

Therefore, the two critical points are  $(0, 0)$  and  $(2, 2)$ . [1+1]

To classify the critical points, we calculate the second derivatives:

$$f_{xx} = -6, f_{yy} = 6 - 12y, f_{xy} = 6. \quad [1+1+1]$$

The discriminant is given by

$$f_{xx}f_{yy} - f_{xy}^2 = 72(y - 1). \quad [1]$$

At  $(0, 0)$ , the discriminant is negative, so the function has a saddle point at the origin. [1]

At  $(2, 2)$  the discriminant is positive, and  $f_{xx} < 0$ , so  $(2, 2)$  is a point of local maximum. [1]

5. A vector  $g \in \mathbb{R}^n$  is a *subgradient* of  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  at  $x \in \text{dom } f$  if for all  $y \in \text{dom } f$  we have  $f(y) \geq f(x) + g^T(y - x)$ . If  $f$  is convex and differentiable, then its gradient at  $x$  is a subgradient.

A function  $f$  is called *subdifferentiable* at  $x$  if there exists at least one subgradient at  $x$ . The set of subgradients of  $f$  at the point  $x$  is called the *subdifferential* of  $f$  at  $x$ , and is denoted by  $\delta f(x)$ .

Consider the absolute value function  $f(x) = |x|$ ,  $x \in \mathbb{R}$ . Find  $\delta|x|$ . [10]

**Solution.**  $|x|$  is convex  $\forall x \in \mathbb{R}$ , and differentiable  $\forall x \in \mathbb{R} \setminus \{0\}$ . Hence, subgradient is unique. [1]

$$\delta|x| = 1 \text{ for } x > 0, \text{ and } \delta|x| = -1 \text{ for } x < 0. \quad [2+2]$$

At  $x = 0$ , the subdifferential is defined by the inequality  $|y| \geq gy$  for all  $y \in \mathbb{R}$ . [2]

This is satisfied if and only if  $g \in [-1, 1]$ . [3]

Thus,

$$\delta|x| = \begin{cases} +1 & x > 0, \\ [-1, 1] & x = 0, \\ -1 & x < 0. \end{cases}$$

6. Consider the problem

$$\begin{aligned} &\text{minimize} && -xy \\ &\text{subject to} && x + y^2 \leq 2, \\ &&& x, y \geq 0. \end{aligned}$$

Find the Lagrangian associated with the above problem. Derive the KKT conditions. [12]

**Solution.** The Lagrangian is given by

$$L(x, y, \lambda_1, \lambda_2, \lambda_3) = -xy + \lambda_1(x + y^2 - 2) + \lambda_2(-x) + \lambda_3(-y). \quad [1]$$

The KKT conditions are given by

[11]

$$\begin{aligned}x + y^2 - 2 &\leq 0, \\-x &\leq 0, \\-y &\leq 0, \\\lambda_1 &\geq 0, \\\lambda_2 &\geq 0, \\\lambda_3 &\geq 0, \\\lambda_1(x + y^2 - 2) &= 0, \\\lambda_2 x &= 0, \\\lambda_3 y &= 0, \\-y + \lambda_1 - \lambda_2 &= 0, \\-x + 2\lambda_1 y - \lambda_3 &= 0.\end{aligned}$$