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Problem 1. [P: 15pts, S: 20pts] Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a differentiable function. For some $\mu \in \mathbb{R}$, suppose that $f(x) - \frac{\mu}{2}\|x\|^2$ is a convex function. Show that the following inequality holds:

$$\langle \nabla f(x) - \nabla f(y), x - y \rangle \geq \mu \|x - y\|^2, \quad \forall x, y \in \mathbb{R}^n.$$

Remark: For $x, y \in \mathbb{R}^n$, $\langle x | y \rangle$ denotes the inner product between the two vectors, i.e., $\langle x | y \rangle = x^T y$.

$$\therefore g(x) = f(x) - \frac{\mu}{2}\|x\|^2 \text{ is convex}$$

$$\therefore g(x) \geq g(y) + \nabla g(y)^T (x - y) \quad \forall x, y \in \mathbb{R}^n$$

$$f(x) - \frac{\mu}{2}\|x\|^2 \geq f(y) - \frac{\mu}{2}\|y\|^2 + [\nabla f(y) - \mu y]^T (x - y) \quad (1)$$

$$f(y) - \frac{\mu}{2}\|y\|^2 \geq f(x) - \frac{\mu}{2}\|x\|^2 + [\nabla f(x) - \mu x]^T (y - x) \quad (2)$$

$$\therefore (1) + (2): \cancel{f(x)} + \cancel{f(y)} - \frac{\mu}{2}(\|x\|^2 + \|y\|^2) \geq \cancel{f(y)} + \cancel{f(x)} - \frac{\mu}{2}(\|y\|^2 + \|x\|^2) + [\nabla f(x) - \mu x - \nabla f(y) + \mu y]^T (y - x)$$

$$0 \geq [\nabla f(x) - \nabla f(y)]^T (y - x) + (\mu y - \mu x)^T (y - x)$$

$$\therefore [\nabla f(x) - \nabla f(y)]^T (x - y) \geq \mu \|x - y\|^2$$

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Problem 2. [P: 20pts, S: 30pts] Consider the following polyhedral set:

$$X = \left\{ x \in \mathbb{R}^4 : \begin{array}{l} x_1 - x_2 - x_3 \leq 1 \\ x_2 - x_4 \leq 2 \\ x_1, x_2, x_3, x_4 \geq 0 \end{array} \right\}$$

(a) Find **all** the extreme/corner points of X , and justify why they are extreme/corner points.

(b) Consider the following **linear integer program**:

$$\begin{array}{ll} \max_{x_1, x_2, x_3, x_4} & x_1 + 2x_2 + 3x_3 + 4x_4 \\ \text{s.t.} & x_1 - x_2 - x_3 \leq 1 \\ & x_2 - x_4 \leq 2 \\ & x_1, x_2, x_3, x_4 \geq 0 \\ & x_1, x_2, x_3, x_4 \in \mathbb{Z} \end{array}$$

Find an **optimal solution** to the above integer program. Justify your answer.

(a) Matrix of the constraints

$$\begin{array}{cccc|c} x_1 & x_2 & x_3 & x_4 & b \\ 1 & -1 & -1 & 0 & 1 \\ 0 & 1 & 0 & -1 & 2 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{array}$$

Take ① ② ③ ④, can be simplified to

$$\begin{array}{cccc|c} 0 & 0 & 1 & 0 & -1 \\ 0 & 0 & 0 & 1 & -2 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{array} \rightarrow x = (0, 0, -1, -2)$$

not satisfy ⑤, ⑥

Take ① ② ⑤ ⑥,

$$\begin{array}{cccc|c} 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 1 & -2 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{array} \rightarrow x = (0, -1, 0, -3)$$

not satisfy

Take ① ② ③ ⑤

$$\begin{array}{cccc|c} 0 & 0 & 1 & 0 & -1 \\ 0 & 1 & 0 & 0 & 2 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{array}$$

$\rightarrow x = (0, 2, -3, 0)$
not satisfy ⑥

Take ① ② ④ ⑤

$$\begin{array}{cccc|c} 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 2 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{array}$$

$\rightarrow x = (1, 0, 0, -2)$
not satisfy

Take ① ② ④ ⑥

not linear independent

Take ③ ④ ⑤ ⑥

$$(0, 0, 0, 0) \checkmark$$

$$\textcircled{1} \textcircled{4} \textcircled{5} \textcircled{6} : x = (1, 0, 0, 0) \checkmark$$

$$\textcircled{2} \textcircled{4} \textcircled{5} \textcircled{6} : x = (0, 2, 0, 0) \checkmark$$

Take ① ② ⑤ ⑥

$$\begin{array}{cccc|c} 1 & 0 & 0 & 0 & 3 \\ 0 & 1 & 0 & 0 & 2 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{array} \rightarrow x = (3, 2, 0, 0)$$

\checkmark

另一个思路是,

x_1, x_2, x_3, x_4 至少 2个为0,

代入看是否为合法解

(b) \therefore The LP have BFS (vertex),

\therefore either optimal value is $+\infty$, or exists a BFS optimal sol

We can specify $x_3 \rightarrow +\infty, x_4 \rightarrow +\infty \therefore$ The optimal value is $+\infty$

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Problem 3. [P: 30pts, S: 15pts] Let $f : \mathbb{R} \rightarrow \mathbb{R}$ be a differentiable, increasing function with $f(0) = 0$. Consider

$$F(x) = \int_0^x f(a) da.$$

- (a) Let $F^*(y) = \sup_u \{uy - F(u)\}$ be the conjugate function of $F(x)$. Show the following inequality:

$$xy \leq F(x) + F^*(y), \quad \forall x, y \in \mathbb{R}.$$

- (b) Let $g = f^{-1}$ such that g is an inverse function and suppose that it is differentiable. Show that the conjugate function of $F(x)$ can be written as

$$G(y) = F^*(y) = \int_0^y g(b) db.$$

Remark: You may prove either using a graphical method by drawing the integration region; or apply the change of variable and integration-by-part, respectively, whose formulas are provided as follows for your convenience:

$$\int_a^b h(\phi(x))\phi'(x) dx = \int_{\phi(a)}^{\phi(b)} h(u) du, \quad \int_a^b u(x)v'(x) dx = [u(x)v(x)]_a^b - \int_a^b u'(x)v(x) dx.$$

(a) $F^*(y) = \sup_u \{uy - F(u)\}$

take $x = u$, $\therefore F^*(y) = \sup_x \{xy - F(x)\}$

$$\therefore F^*(y) \geq xy - F(x) \rightarrow xy \leq F^*(y) + F(x)$$

(b) $\because g = f^{-1} \therefore$ take $g(y) = u$ $y = f(u)$

$$G(y) = \int_0^y g(b) db = \int_{f(0)}^{f(u)} g(b) db$$

$$= \int_0^u g(f(x)) f'(x) dx = \int_0^u x f'(x) dx$$

$$= x f(x) \Big|_0^u - \int_0^u f(x) dx$$

$$= u f(u) - \int_0^u f(x) dx$$

$$= uy - \int_0^u f(x) dx = F^*(y)$$

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Problem 6. [S: 20pts] Consider the constraint set $\mathcal{C} = \{x \in \mathbb{R}^n : x^\top e \geq 0\}$, where $e \in \mathbb{R}^n$ is an all-one n -dimensional vector. Define the operator:

$$\mathcal{P}(x) = \begin{cases} y - \frac{1}{n}(y^\top e)e, & \text{if } y^\top e \leq 0 \\ y, & \text{if } y^\top e > 0. \end{cases}$$

Show that for any $x \in \mathbb{R}^n$, $\mathcal{P}(x)$ is the projection of x onto \mathcal{C} .

① Verify $\mathcal{P}(x) \in \mathcal{C}$

if $x^\top e > 0$, obviously $\mathcal{P}(x) = x \in \mathcal{C}$

if $x^\top e \leq 0$, $\mathcal{P}(x) = x - \frac{1}{n}(x^\top e)e$

$$\mathcal{P}(x)^\top e = x^\top e - \frac{1}{n}(x^\top e)e^\top e = 0$$

$\therefore \mathcal{P}(x) \in \mathcal{C}$

② for $\forall z \in \mathcal{C}$ verify $(z - \mathcal{P}(x))^\top (x - \mathcal{P}(x)) \leq 0$
 $z \in \mathcal{C}, x \in \mathbb{R}^n$

if $x^\top e > 0$,

$$\begin{aligned} & (z - \mathcal{P}(x))^\top (x - \mathcal{P}(x)) \\ &= (z - x)^\top (x - x) = 0, \end{aligned}$$

if $x^\top e \leq 0$

$$\begin{aligned} & (z - \mathcal{P}(x))^\top (x - \mathcal{P}(x)) \\ &= (z - x + \frac{1}{n}(x^\top e)e)^\top (\frac{1}{n}(x^\top e)e) \\ &= z^\top (\frac{1}{n}(x^\top e)e) - \mathcal{P}(x)^\top (\frac{1}{n}(x^\top e)e) \\ &= \underbrace{\frac{1}{n}(x^\top e)}_{\leq 0} \underbrace{z^\top e}_{\geq 0} - \underbrace{\frac{1}{n}(x^\top e)}_{=0} \underbrace{\mathcal{P}(x)^\top e}_{=0} \leq 0 \end{aligned}$$

$\therefore (z - \mathcal{P}(x))^\top (x - \mathcal{P}(x)) \leq 0$, i.e. $\mathcal{P}(x) = \Pi_{\mathcal{C}}(x)$

OR20 Problem 7. [S: 15pts] Consider a non-differentiable, convex function $f: \mathbb{R}^n \rightarrow \mathbb{R}$.

(a) Consider a point $\bar{x} \in \mathbb{R}^n$ such that $0 \in \partial f(\bar{x})$. Show that \bar{x} is a global optimal solution to the optimization problem $\min_{x \in \mathbb{R}^n} f(x)$.

(b) Let $y \in \mathbb{R}^n$ and $\lambda > 0$ be fixed constant vector/scalar. Consider the optimization problem:

$$\min_{x \in \mathbb{R}^n} \frac{1}{2} \|x - y\|_2^2 + \lambda \|x\|_1 \quad \|x\|_1 = \sum_{i=1}^n |x_i|$$

Using the result from (a), find an optimal solution $\bar{x} \in \mathbb{R}^n$ to the above problem. Express your solution in terms of y and λ .

(a) $\partial f(\bar{x}) = \{s \in \mathbb{R}^n : f(x) \geq f(\bar{x}) + s^T (x - \bar{x}), \forall x \in \mathbb{R}^n\}$

$\because 0 \in \partial f(\bar{x}) \quad \therefore f(x) \geq f(\bar{x}) + 0^T (x - \bar{x}), \text{ for } \forall x \in \mathbb{R}^n$
i.e. $f(x) \geq f(\bar{x}) \text{ for } \forall x \in \mathbb{R}^n$

(b) Take $f_1(x) = \frac{1}{2} \|x - y\|_2^2$, f_1 is convex and differentiable

$f_2(x) = \lambda \|x\|_1$, f_2 is convex but non-differentiable

$\therefore \partial f(x) = \partial f_1(x) + \partial f_2(x)$

where, $\partial f_1(x) = \nabla f_1(x) = x - y$

$$\partial f_2(x) = \left\{ \frac{\partial f_2}{\partial x_i} \right\} \quad \frac{\partial f_2}{\partial x_i} = \begin{cases} \lambda & \text{if } x_i > 0 \\ [-\lambda, \lambda] & \text{if } x_i = 0 \\ -\lambda & \text{if } x_i < 0 \end{cases}$$

Suppose \bar{x} is an optimal solution, we have $0 \in \partial f(\bar{x})$

i.e. we can find $\bar{x} - y + \partial f_2(\bar{x}) = 0$

$$\bar{x} = y - \partial f_2(\bar{x})$$

where $\bar{x}_i = \begin{cases} y_i - \lambda & \text{if } y_i > \lambda \\ 0 & \text{if } y_i \in [-\lambda, \lambda] \\ y_i + \lambda & \text{if } y_i < -\lambda \end{cases}$