EE367000



Introduction to Mathematics for Communications: Convex Analysis and Optimization

Homework 3

Due: 06 June 2019 (12:05 PM)

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NOTE

- You can hand in your hard-copy in the class or at our lab located in ECE building, room 706.
- Submissions later than the due date will be accepted with a point deduction (5% for each hour).
- As a NTHU student, strong academic ethics is assumed and punished otherwise by deducting the whole homework score.

Name:	
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Total points: 100 11 Questions

Q1(total: 9 Points)

- (a) The set C_1 is a convex set with non-empty interior. Let C_2 be a non-empty convex set that $C_2 \cap \operatorname{int} C_1 = \emptyset$. Show that there exists a hyperplane, \mathcal{H} , such that \mathcal{H}_+ (or \mathcal{H}_-) contains C_2 , and does not intersect with the interior of C_1 .
- (b) By a counter example, disprove similar statement as part (a) but instead of $C_2 \cap (4_{pt})$ int $C_1 = \emptyset$, consider $C_2 \cap \operatorname{relint} C_1 = \emptyset$.

$$(P1) a_1 \ge a_2 \ge \dots \ge a_n, \quad b_1 \ge b_2 \ge \dots \ge b_n,$$

(P2)
$$\sum_{i=1}^{r} a_i \ge \sum_{i=1}^{r} b_i \quad (\forall r < n),$$

(P3)
$$\sum_{i=1}^{n} a_i = \sum_{i=1}^{n} b_i .$$

Prove the below inequality,

$$\sum_{i=1}^{n} f(a_i) \ge \sum_{i=1}^{n} f(b_i).$$

Q3(total: 4 Points)

Suppose $f: \mathbb{R}^n \to \mathbb{R}$ be a convex and continuous function. Prove,

$$\mathcal{G}_f(\mathbf{x}) = \{\overline{\nabla}f(\mathbf{x})\} \neq \emptyset, \quad \forall \mathbf{x} \in \mathbb{R}^n,$$

where $\mathcal{G}_f(\mathbf{x})$ denotes the set of all the subgradients of $f(\mathbf{x})$ at \mathbf{x} .

Consider $\mathbf{x} = [x_1, x_2, \dots, x_n]^T$. Show that the function $f : \mathbb{R}^n \to \mathbb{R}$,

$$f(\mathbf{x}) = \begin{cases} -(x_1 x_2 \dots x_n)^{\frac{1}{n}}, & \text{if } x_i > 0, i = 1, 2, \dots, n \\ \infty, & \text{otherwise} \end{cases},$$

is convex.

- **Q5**(total: 10 Points) A function f is called log-convex if $f(\mathbf{x}) > 0$, $\forall \mathbf{x} \in \mathbf{dom} \ f$ and $\ln (f(\mathbf{x}))$ be convex.
- $(5_{pt.})$ (a) Show that if f is log-convex, then f is convex.
- $(5_{pt.})$ (b) Show that f is log-convex if and only if

$$f(\theta \mathbf{x} + (1 - \theta)\mathbf{y}) \le f(\mathbf{x})^{\theta} f(\mathbf{y})^{1-\theta}, \quad \forall \mathbf{x}, \mathbf{y} \in \mathbf{dom} f,$$

where $\forall \theta \in [0, 1]$.

Q6(total: 7 Points) Let q be a convex function. Consider the function f given by

$$f(x) = \int_{-\infty}^{\infty} g(t) \exp^{-\left(\frac{x-t}{\sigma}\right)^2} dt,$$

where $x \in \mathbb{R}$ and σ are scalar. Show that f is a convex function.

- **Q7**(total: 11 Points)
- (a) Consider f as a strictly quasiconvex function on the convex set P. Show that, $(3_{pt.})$

$$\forall p_1, p_2 \in P, \quad f(p_1) < f\left(\frac{p_1 + p_2}{2}\right) \Rightarrow f\left(\frac{p_1 + p_2}{2}\right) < f(p_2).$$

- $(8_{pt.})$ (b) Suppose Q be a compact set and P be a convex set and let f(q,p) be defined on $Q \times P$ such that:
 - 1. $\forall q \in Q$, the function f(q, p) is strictly quasiconvex on P,
 - 2. $\forall p \in P$, the function f(q,p) is continuous function on Q.

Consider the function $g(p) = \max_{q \in \mathcal{Q}} f(q, p)$, prove g is strictly quasiconvex on P (You may use the result in part (a) to prove this statement).

Q8(total: 11 Points)

Let $K \subseteq \mathbb{R}^m$ be a proper convex cone with associated generalized inequality \preceq_K , and let $\mathbf{f} : \mathbb{R}^n \to \mathbb{R}^m$. For $\boldsymbol{\alpha} \in \mathbb{R}^m$, the $\boldsymbol{\alpha}$ -sublevel set of \mathbf{f} (with respect to \preceq_K) is defined as

$$S_{\alpha} = \{ \mathbf{x} \in \mathbb{R}^n \mid \mathbf{f}(\mathbf{x}) \leq_K \alpha \}.$$

The epigraph of \mathbf{f} , with respect to \leq_K , is defined as the set

$$\mathbf{epi}_K \mathbf{f} = \{ (\mathbf{x}, \mathbf{t}) \in \mathbb{R}^{n+m} \mid \mathbf{f}(\mathbf{x}) \leq_K \mathbf{t} \}.$$

Show the followings:

- (a) If **f** is K-convex, then its sublevel sets S_{α} are convex for all α . (4 pt.)
- (b) The function \mathbf{f} is K-convex if and only if $\mathbf{epi}_K \mathbf{f}$ is a convex set. (7 $_{pt}$.)

Q9(total: 12 Points)

- (a) Consider the function $f(\mathbf{X}, t) = nt(\log t) t \log \det \mathbf{X}$, with **dom** $f = \mathbb{S}^n_{++} \times \mathbb{R}_{++}$. (6 pt.) Show that $f(\mathbf{X}, t)$ is convex.
- (b) Use the result obtained in (a) to show that (6_{pt})

$$g(\mathbf{X}) = n(\text{Tr}(\mathbf{X})) \log(\text{Tr}(\mathbf{X})) - (\text{Tr}(\mathbf{X})) \log \det \mathbf{X},$$

is convex on \mathbb{S}^n_{++} .

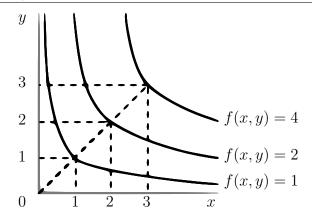
Q10 (total: 16 Points)

(a) Consider the function $f: \mathbb{R} \to \mathbb{R}$ with parameters a, b, c and d defined as $f(x) = ax^3 + bx^2 + cx + d$. Find the range of parameters a, b, c and d for the function f to be quasiconcave.

Hint

The [1, Fact 3.3, page 129] may help you solve this question.

- (b) Consider two quasiconcave function $f_1 : \mathbb{R} \to \mathbb{R}$ and $f_2 : \mathbb{R} \to \mathbb{R}$. Provide an example which $f_1 + f_2$ is not quasiconcave.
- (c) Discuss the part (b) but this time consider f_1 to be concave. (4_{pt})
- (d) Figure below depicts the level set representation of the function $f: \mathbb{R}^2 \to \mathbb{R}$. Using information provided in the figure, discuss if the curves are consistent with a notion of concavity and quasiconcavity of f. Note that we do not know the complete information about the function f (e.g. other levels not depicted here). However, you need to discuss the (in)consistency of the limited information provided here regarding (quasi)concavity of function f.



$$f(\mathbf{X}, \mathbf{y}) = \mathbf{y}^T \mathbf{X}^{-1} \mathbf{y}, \quad \mathbf{dom} \, f = \big\{ (\mathbf{X}, \mathbf{y}) \, \big| \, \mathbf{X} + \mathbf{X}^T \succ 0 \big\}.$$

The f is convex or not? If it's convex, prove it, and if not, disproves it by a counter example.

References

- [1] C.-Y. Chi, W.-C. Li, and C.-H. Lin, Convex optimization for signal processing and communications: from fundamentals to applications. CRC Press, 2017.
- [2] S. Boyd and L. Vandenberghe, Convex optimization. Cambridge university press, 2004.