Optimization Theory

Optimization Theory Tutorial 7

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Optimization Theory

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Existence of Optimal Solutions

The set of **minima** of a real-valued function *f* over a nonempty set X , call is X^* , is equal to the intersection of X and the level sets of *f* that have a common points with *X* :

 $X^* = \bigcap_{k=0}^{\infty} \{x \in X | f(x) \leq \gamma_k\},\$

where $\{\gamma_k\}$ is any scalar sequence with $\gamma_k \downarrow inf_{x \in X} f(x)$ *.*

Existence of Optimal Solutions

Theorem

Weierstrass' Theorem *Consider a closed proper function*

f → (*−∞, ∞*]*,*

and assume that any one of the following three conditions holds:

(1) *dom*(*f*) *is bounded.*

(2) *There exists a scalar γ*¯ *such that the level set*

 ${x|f(x) \leq \overline{\gamma}}$

is nonempty and bounded.

(3) *f is coercive.*

Then the set of minima of f *over* \mathbb{R}^n *is nonempty and compact.*

Partial Minimization of convex functions

Theorem

Consider a function $F: \mathbb{R}^{n+m} \to (-\infty, \infty]$ *and the function* $f: \Re^n \to [-\infty, \infty]$ defined by

$$
f(x) = inf_{z \in \mathbb{R}^m F(x,z)}.
$$

Then:

- (a) *If F is convex, then f is also convex.*
- (b) *We have*

$$
P(epi(F)) \subset epi(f) \subset cl(P(epi(F))),
$$

where P(*·*) *denotes projection on the space of* (*x, w*)*, i.e., for any subset S* of \Re^{n+m+1} , $P(S) = (x, w) | (x, z, w) \in S$.

Saddle Point and Minimax Theory

Theorem

Saddle Point: A pair of vectors $x^* \in X$ and $z^* \in Z$ is called a *saddle point of ϕ if*

 $\phi(x^*, z) \leq \phi(x^*, z^*) \leq \phi(x, z^*), \forall x \in X, \forall z \in Z.$

minimax equality:

 $sup_{z \in \mathbb{Z}} inf_{x \in \mathbb{X}} \phi(x, z) = inf_{x \in \mathbb{X}} sup_{z \in \mathbb{Z}} \phi(x, z)$.

Saddle Point and Minimax Theory

Theorem

A pair (*x ∗ , z∗*) *is a saddle point of ϕ if and only if the minimax equality holds, and x ∗ is an optimal solution of the problem:*

minimize $\sup_{z \in Z} \phi(x, z)$ *, subject to* $x \in X$ *,*

while z ∗ is an optimal solution of the problem

*maximize inf*_{*x*∈*X*} ϕ (*x*, *z*)*, subject to z* ∈ *Z*

Saddle Point and Minimax Theory

Lemma 2.6.1: Let X be a nonempty convex subset of \mathbb{R}^n , let Z be a nonempty subset of \Re^m , and let $\phi: X \times Z \mapsto \Re$ be a function. Assume that for each $z \in Z$, the function $\phi(\cdot, z) : X \mapsto \Re$ is convex. Then the function p of Eq. (2.33) is convex.

Saddle Point and Minimax Theory

Lemma 2.6.2: Let X be a nonempty subset of \mathbb{R}^n , let Z be a nonempty convex subset of \Re^m , and let $\phi: X \times Z \mapsto \Re$ be a function. Assume that for each $x \in X$, the function $-\phi(x, \cdot) : Z \mapsto \Re$ is closed and convex. Then the function $q : \Re^m \mapsto [-\infty, \infty]$ given by

$$
q(\mu)=\inf_{(u,w)\in {\operatorname{epi}}(p)}\bigl\{w+u'\mu\bigr\},\qquad \mu\in \Re^m,
$$

where p is given by Eq. (2.33) , satisfies

 \bar{z}

$$
q(\mu) = \begin{cases} \inf_{x \in X} \phi(x, \mu) & \text{if } \mu \in Z, \\ -\infty & \text{if } \mu \notin Z. \end{cases}
$$
 (2.36)

Furthermore, we have $q^* = w^*$ if and only if the minimax equality (2.26) holds.

 $\ddot{\cdot}$

Saddle Point and Minimax Theory

Proposition 2.6.2: (Minimax Theorem I) Let X and Z be nonempty convex subsets of \real^n and $\real^m,$ respectively, and let $\phi:X\times Z\mapsto \real$ be a function. Assume that for each $z \in Z$, the function $\phi(\cdot, z) : X \mapsto$ \Re is convex, and for each $x \in X$, the function $-\phi(x, \cdot) : Z \mapsto \Re$ is closed and convex. Assume further that

$$
\inf_{x\in X}\sup_{z\in Z}\phi(x,z)<\infty.
$$

Then, the minimax equality holds, i.e.,

$$
\sup_{z \in Z} \inf_{x \in X} \phi(x, z) = \inf_{x \in X} \sup_{z \in Z} \phi(x, z)
$$

if and only if the function p of Eq. (2.33) is lower semicontinuous at $u = 0$, i.e., $p(0) \leq \liminf_{k \to \infty} p(u_k)$ for all sequences $\{u_k\}$ with $u_k \rightarrow 0.$

Saddle Point and Minimax Theory

Proposition 2.6.3: (Minimax Theorem II) Let X and Z be nonempty convex subsets of \Re^n and $\Re^m,$ respectively, and let ϕ : $X \times Z \mapsto \Re$ be a function. Assume that for each $z \in Z$, the function $\phi(\cdot, z) : X \mapsto \Re$ is convex, and for each $x \in X$, the function $-\phi(x,\cdot):Z\mapsto\Re$ is closed and convex. Assume further that

 $\label{eq:3.1} -\infty < \inf_{x \in X} \sup_{z \in Z} \phi(x,z),$

Saddle Point and Minimax Theory

and that 0 lies in the relative interior of the effective domain of $% \mathcal{N}$ the function p of Eq. (2.33). Then, the minimax equality holds, i.e., ģ.

$$
\sup_{z\in Z}\inf_{x\in X}\phi(x,z)=\inf_{x\in X}\sup_{z\in Z}\phi(x,z),
$$

and the supremum over Z in the left-hand side is finite and is attained. Furthermore, the set of $z \in Z$ attaining this supremum is compact if and only if 0 lies in the interior of the effective domain of p .

Optimization Theory Exexcise

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EX 1 **Saddle Points in Two Dimensions**

> Consider a function *ϕ* of two real variables *x* and *z* taking values in compact intervals of *X* and *Z*, respectively. Assume that for each $z \in Z$, the function $\phi(\cdot, z)$ is minimized over X at a unique point denoted $\hat{x}(z)$. Similarly, assume that for each $x \in X$, the function $\phi(x, \cdot)$ is maximized over *Z* at a unique point denoted $\hat{z}(x)$. Assume further that the functions $\hat{x}(z)$ and $\hat{z}(x)$ are continuous over Z and X , respectively. Show that ϕ has a saddle point (*x ∗ , z∗*). Use this to investigate the existence of saddle points of $\phi(x, z) = x^2 + z^2$ over $X = [0, 1]$ and $Z = [0, 1]$.

We consider a function ϕ of two real variables x and z taking values in compact intervals X and Z, respectively. We assume that for each $z \in Z$, the function $\phi(\cdot, z)$ is minimized over X at a unique point denoted $\hat{x}(z)$, and for each $x \in X$, the function $\phi(x, \cdot)$ is maximized over Z at a unique point denoted $\hat{z}(x)$,

$$
\hat{x}(z) = \arg\min_{x \in X} \phi(x, z), \qquad \hat{z}(x) = \arg\max_{z \in Z} \phi(x, z).
$$

Consider the composite function $f: X \mapsto X$ given by

$$
f(x) = \hat{x}(\hat{z}(x)),
$$

which is a continuous function in view of the assumption that the functions $\hat{x}(z)$ and $\hat{z}(x)$ are continuous over Z and X, respectively. Assume that the compact interval X is given by $[a, b]$. We now show that the function f has a fixed point, i.e., there exists some $x^* \in [a,b]$ such that

$$
f(x^*)=x^*.
$$

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Solution 1

Define the function $g:X\mapsto X$ by

$$
g(x) = f(x) - x.
$$

Assume that $f(a) > a$ and $f(b) < b$, since otherwise we are done. We have

$$
g(a) = f(a) - a > 0,
$$

$$
g(b) = f(b) - b < 0.
$$

Since g is a continuous function, the preceding relations imply that there exists some $x^* \in (a, b)$ such that $g(x^*) = 0$, i.e., $f(x^*) = x^*$. Hence, we have

$$
\hat{x}(\hat{z}(x^*))=x^*.
$$

Denoting $\hat{z}(x^*)$ by z^* , we get

$$
x^* = \hat{x}(z^*), \qquad z^* = \hat{z}(x^*). \tag{2.24}
$$

By definition, a pair $(\overline{x}, \overline{z})$ is a saddle point if and only if

$$
\max_{z \in Z} \phi(\overline{x}, z) = \phi(\overline{x}, \overline{z}) = \min_{x \in X} \phi(x, \overline{z}),
$$

or equivalently, if $\overline{x} = \hat{x}(\overline{z})$ and $\overline{z} = \hat{z}(\overline{x})$. Therefore, from Eq. (2.24), we see that (x^*, z^*) is a saddle point of ϕ .

We now consider the function $\phi(x, z) = x^2 + z^2$ over $X = [0, 1]$ and $Z =$ [0,1]. For each $z \in [0,1]$, the function $\phi(\cdot, z)$ is minimized over [0,1] at a unique point $\hat{x}(z) = 0$, and for each $x \in [0,1]$, the function $\phi(x, \cdot)$ is maximized over [0,1] at a unique point $\hat{z}(x) = 1$. These two curves intersect at $(x^*, z^*) = (0, 1)$, which is the unique saddle point of ϕ .

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Ex 2 **Saddle Points of Quadratic Functions**

Consider a quadratic function $\phi: X \times Z \to \Re$ of the form

$$
\phi(x, z) = x'Qx + x'Dz - z'Rz,
$$

where Q and R are symmetric positive semidefinite $n \times n$ and $m \times m$ matrices, respectively, *D* is some $n \times m$ matrix, and *X* and *Z* are subsets of *ℜ n* and *ℜ ^m*, respectively. Derive conditions under which *ϕ* has at least one saddle point.

Let X and Z be closed and convex sets. Then, for each $z \in Z$, the function $t_z : \Re^n \mapsto (-\infty, \infty]$ defined by

$$
t_z(x) = \begin{cases} \phi(x, z) & \text{if } x \in X, \\ \infty & \text{otherwise,} \end{cases}
$$

is closed and convex in view of the assumption that Q is a positive semidefinite symmetric matrix. Similarly, for each $x \in X$, the function $r_x : \mathbb{R}^m \mapsto (-\infty, \infty]$ defined by

$$
r_x(z) = \begin{cases} -\phi(x, z) & \text{if } z \in Z, \\ \infty & \text{otherwise,} \end{cases}
$$

is closed and convex in view of the assumption that R is a positive semidefinite symmetric matrix. Hence, Assumption 2.6.1 is satisfied. Let also Assumptions $2.6.2$ and $2.6.3$ hold, i.e,

$$
\inf_{x \in X} \sup_{z \in Z} \phi(x, z) < \infty
$$

and

$$
-\infty < \sup_{z \in Z} \inf_{x \in X} \phi(x, z).
$$

By the positive semidefiniteness of Q , it can be seen that, for each $z \in Z$, the recession cone of the function t_z is given by

$$
R_{t_z} = R_X \cap N(Q) \cap \{y \mid y'Dz \le 0\},\
$$

where R_X is the recession cone of the convex set X and $N(Q)$ is the null space of the matrix Q. Similarly, for each $z \in Z$, the constancy space of the function t_z is given by

$$
L_{t_z}=L_X\cap N(Q)\cap \{y\mid y'Dz=0\},\
$$

where L_X is the lineality space of the set X. By the positive semidefiniteness of R, for each $x \in X$, it can be seen that the recession cone of the function r_x is given by

$$
R_{rx} = R_Z \cap N(R) \cap \{y \mid x'Dy \ge 0\},\
$$

where R_Z is the recession cone of the convex set Z and $N(R)$ is the null space of the matrix R. Similarly, for each $x \in X$, the constancy space of the function r_x is given by

$$
L_{r_x} = L_Z \cap N(R) \cap \{y \mid x'Dy = 0\},\
$$

where ${\cal L}_Z$ is the lineality space of the set $Z.$ If

$$
\bigcap_{z\in Z} R_{t_z} = \{0\}, \quad \text{and} \quad \bigcap_{x\in X} R_{r_x} = \{0\},\tag{2.25}
$$

then it follows from the Saddle Point Theorem part (a), that the set of saddle points of ϕ is nonempty and compact. [In particular, the condition given in Eq. (2.25) holds when Q and R are positive definite matrices, or if X and Z are compact.]

Similarly, if

$$
\bigcap_{z \in Z} R_{t_z} = \bigcap_{z \in Z} L_{t_z}, \quad \text{and} \quad \bigcap_{x \in X} R_{r_x} = \bigcap_{x \in X} L_{r_x},
$$

then it follows from the Saddle Point Theorem part (b), that the set of saddle points of ϕ is nonempty.

Ex 3

Convex-concave functions and saddle points

 \forall Me say the function $f : \Re^n \times \Re^m \to \Re$ is convex-concave if $f(x,z)$ is a concave function of *z*, for each fixed *x*, and a convex function of *x*, for each fixed *z*. We also require its domain to have the product form $\textbf{dom} f = A \times B$, where $A \subset \Re^n$ and $B \subset \Re^m$ are convex.

- (a) Give a second-order condition for a twice differentiable function $f: \Re^n \times \Re^m \to \Re$ to be convex-concave, interms of its Hessian $\nabla^2 f(x, z)$.
- (b) Suppose that $f : \Re^n \times \Re^m \to \Re$ is convex-concave and differentiable, with $\nabla f(\hat{x}, \hat{z}) = 0$. Show that the saddle point property holds: for all *x, z*, we have

$$
f(\hat{x}, z \le f(\hat{x}, \hat{z})) \le f(x, \hat{z}).
$$

Show that this implies that *f* satisfies the strong max-min property:

$$
sup_z inf_x f(x, z) = inf_x sup_z f(x, z)
$$

(and their common value is $f(\hat{x}, \hat{z})$).

(c) Now suppose that $f : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}$ is differentiable, but not necessarily convex-concave, and the saddle-point property holds at \hat{x} , \hat{z} :

$$
f(\hat{x}, z \le f(\hat{x}, \hat{z})) \le f(x, \hat{z}).
$$

for all *x*, *z*. Show that $\nabla f(\hat{x}, \hat{z}) = 0$.

(a) The condition follows directly from the second-order conditions for convexity and concavity: it is

$$
\nabla_{xx}^2 f(x,z) \succeq 0, \qquad \nabla_{zz}^2 f(x,z) \preceq 0,
$$

for all x, z . In terms of $\nabla^2 f$, this means that its 1, 1 block is positive semidefinite, and its 2, 2 block is negative semidefinite.

(b) Let us fix \tilde{z} . Since $\nabla_x f(\tilde{x}, \tilde{z}) = 0$ and $f(x, \tilde{z})$ is convex in x, we conclude that \tilde{x} minimizes $f(x, \tilde{z})$ over x, *i.e.*, for all z, we have

$$
f(\tilde{x}, \tilde{z}) \le f(x, \tilde{z}).
$$

This is one of the inequalities in the saddle-point condition. We can argue in the same way about \tilde{z} . Fix \tilde{x} , and note that $\nabla_z f(\tilde{x}, \tilde{z}) = 0$, together with concavity of this function in z, means that \tilde{z} maximizes the function, *i.e.*, for any x we have

$$
f(\tilde{x},\tilde{z}) \ge f(\tilde{x},z)
$$

(c) To establish this we argue the same way. If the saddle-point condition holds, then \tilde{x} minimizes $f(x, \tilde{z})$ over all x . Therefore we have $\nabla f_x(\tilde{x}, \tilde{z}) = 0$. Similarly, since \tilde{z} maximizes $f(\tilde{x}, z)$ over all z , we have $\nabla f_z(\tilde{x}, \tilde{z}) = 0$.