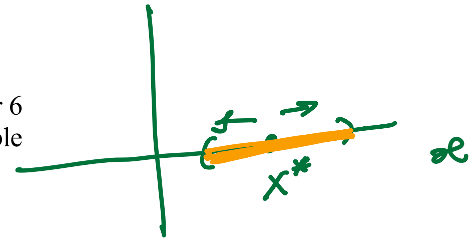


Chapter 6
Multivariable Optimization without Constraints

6.1 Definitions of Extreme Points

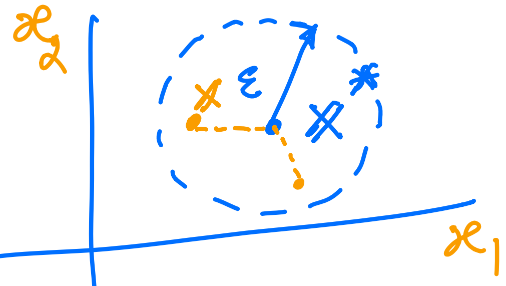
Similar to the definitions of extreme points of single-variable functions, we have

Definition 6.1 A point $\mathbf{x}^*$ is a ***local maximum point*** of $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, if

$$f(\mathbf{x}^*) \geq f(\mathbf{x}),$$

for any $\mathbf{x} \in \boldsymbol{S}$ such that $\|\mathbf{x} - \mathbf{x}^*\| < \varepsilon$ for some $\varepsilon > 0$.

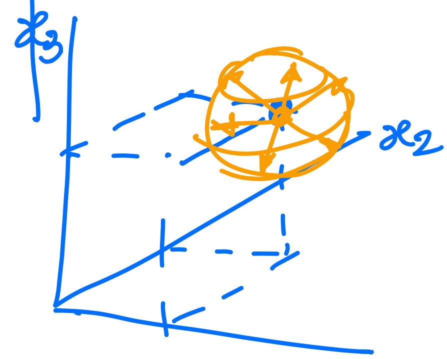
$|x - x^*| < \varepsilon$.
$\Leftrightarrow x^* - \varepsilon < x < x^* + \varepsilon$
$\|x - x^*\|$ – distance between x & x^*
$= \sqrt{(x - x^*)^T (x - x^*)}$



Definition 6.2 A point $\mathbf{x}^*$ is a ***local strict maximum point*** of $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, if

$$f(\mathbf{x}^*) > f(\mathbf{x}),$$

for any $\mathbf{x} \in \boldsymbol{S}$, $\mathbf{x} \neq \mathbf{x}^*$, such that $\|\mathbf{x} - \mathbf{x}^*\| < \varepsilon$ for some $\varepsilon > 0$.



$\|x - x^*\| < \varepsilon$.

Definition 6.3 A point $\mathbf{x}^*$ is a ***global maximum point*** of $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, if

$$f(\mathbf{x}^*) \geq f(\mathbf{x}),$$

for any $\mathbf{x} \in \boldsymbol{S}$.

Definition 6.4 A point $\mathbf{x}^*$ is a ***global strict maximum point*** of $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, if

$$f(\mathbf{x}^*) > f(\mathbf{x}),$$

for any $\mathbf{x} \in \boldsymbol{S}$, $\mathbf{x} \neq \mathbf{x}^*$.

6.2 2-Variable Optimization

A 2-variable differentiable function and its total differential are given by

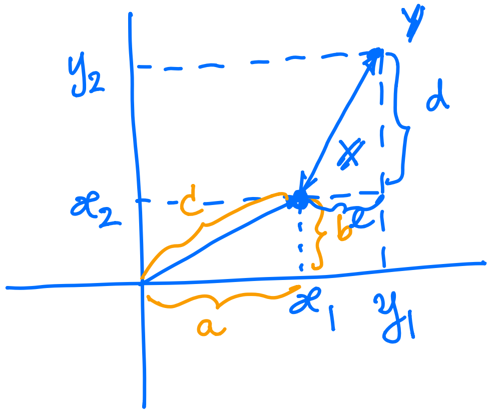
$$y = f(x_1, x_2)$$
$$dy = f_1(x_1, x_2)dx_1 + f_2(x_1, x_2)dx_2.$$

At extreme point (x_1^*, x_2^*), minimum or maximum, for any arbitrarily small changes in x_1 and x_2, in terms of dx_1 and dx_2, there is no change in y, i.e.,

$$dy = f_1(x_1^*, x_2^*)dx_1 + f_2(x_1^*, x_2^*)dx_2. = 0.$$

6.3 First-Order Necessary Condition

From the last equation, we can conclude that



$$\|\mathbf{x}\| = \sqrt{x_1^2 + x_2^2}$$

$$\|\mathbf{x}-\mathbf{y}\| = \sqrt{e^2+d^2}$$

$$= \sqrt{(y_1-x_1)^2 + (y_2-x_2)^2}$$

$$= \sqrt{\begin{bmatrix}(x_1-y_1) & (x_2-y_2)\end{bmatrix}\begin{bmatrix}(x_1-y_1)\\ x_2-y_2\end{bmatrix}}$$

x^* local max of f, $f \in C^1$

$\Rightarrow \nabla f(x^*) = 0$

Theorem 6.1 If (x_1^*, x_2^*) is an extreme point of a differentiable function $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^2$, then $f_1(x_1^*, x_2^*) = 0$ and $f_2(x_1^*, x_2^*) = 0$.

Proof See Theorem 6.6 for the case of n variables case. ∎

At maximum point (x_1^*, x_2^*), the change of the change must be non-positive, i.e.,

$$dy^2 \leq 0,$$

where for any dx_1 and dx_2, with the argument (x_1^*, x_2^*) is suppressed for brevity and legibility,

$$\begin{aligned}
dy^2 &= d(\underbrace{f_1(x_1^*, x_2^*)dx_1 + f_2(x_1^*, x_2^*)dx_2}_{dy}.) \\
&= (f_{11}dx_1 + f_{12}dx_2)dx_1 + (f_{21}dx_1 + f_{22}dx_2)dx_2 \\
&= f_{11}dx_1^2 + 2f_{12}dx_1dx_2 + f_{22}dx_2^2 \\
&= [dx_1 \quad dx_2]\begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}\begin{bmatrix} dx_1 \\ dx_2 \end{bmatrix} \\
&= \mathbf{dx}^{\mathrm{T}}\mathbf{H}(x_1^*, x_2^*)\mathbf{dx} \leq 0.
\end{aligned}$$

Hessian.

The quadratic form $\mathbf{dx}^{\mathrm{T}}\mathbf{H}(x_1^*, x_2^*)\mathbf{dx} \leq 0$ for any vector $\mathbf{dx}$ means that the symmetric matrix $\mathbf{H}$ is negative semi-definite. We have the second-order necessary condition as follows.

6.4 Second-Order Necessary Condition

Theorem 6.2 If (x_1^*, x_2^*) is a ***maximum point*** of a twice-differentiable function $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^2$, then $\mathbf{H}(x_1^*, x_2^*)$ is ***negative semi-definite***. That means,

a) $f_{11}(x_1^*, x_2^*) \leq 0, f_{22}(x_1^*, x_2^*) \leq 0$, and
b) $f_{11}(x_1^*, x_2^*)f_{22}(x_1^*, x_2^*) - [f_{12}(x_1^*, x_2^*)]^2 \geq 0$.

Proof See Theorem 6.6 for the case of n variables case. ∎

Theorem 6.3 If (x_1^*, x_2^*) is a ***minimum point*** of a twice-differentiable function $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^2$, then $\mathbf{H}(x_1^*, x_2^*)$ is ***positive semi-definite***. That means,

a) $f_{11}(x_1^*, x_2^*) \geq 0, f_{22}(x_1^*, x_2^*) \geq 0$, and
b) $f_{11}(x_1^*, x_2^*)f_{22}(x_1^*, x_2^*) - [f_{12}(x_1^*, x_2^*)]^2 \geq 0$.

Proof See Theorem 6.6 and for the case of n variables case. ∎

Example *Profit Maximization*. Let the production function be given by

$$q = f(L, K)$$

each finished good is sold at p bahts. The price of capital and labor is fixed at p_L and p_K, respectively. The profit function is thus a function of both labor L and capital K,

$$\pi(L, K) = pf(L, K) - (p_L L + p_K K).$$

If (L^*, K^*) is the profit maximizing (locally) point, by the first order necessary condition,

$$\pi_L(L^*, K^*) = pf_L(L^*, K^*) - p_L = 0$$
$$\pi_K(L^*, K^*) = pf_K(L^*, K^*) - p_K = 0.$$

Thus, at the maximum point, the ***value of the marginal product*** of each input must equal its price. Since $p_L, p_K > 0$, this is equivalent to

$$\frac{f_L(L^*, K^*)}{f_K(L^*, K^*)} = \frac{p_L}{p_k}.$$

By the second-order necessary condition,

$$pf_{LL}(L^*, K^*) \leq 0$$
$$pf_{KK}(L^*, K^*) \leq 0$$
$$p^2 f_{LL}(L^*, K^*) f_{KK}(L^*, K^*) - (pf_{LK}(L^*, K^*))^2 \geq 0.$$

6.5 Sufficient Conditions

These are the conditions that, when satisfied, guarantee that a point is a maximum or minimum point of a twice-differentiable function. However, these conditions may not identify every maximum and minimum points.

Theorem 6.4 For a twice-differentiable function , $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^2$, if
a) $f_1(x_1^*, x_2^*) = 0, f_2(x_1^*, x_2^*) = 0$
b) $f_{11}(x_1^*, x_2^*) < 0$ and
$f_{11}(x_1^*, x_2^*) f_{22}(x_1^*, x_2^*) - [f_{12}(x_1^*, x_2^*)]^2 > 0,$
then (x_1^*, x_2^*) is a ***local maximum point***.

Proof See Theorem 6.6 and Theorem 6.8 for the case of n variables case. ■

- Both conditions must be satisfied.
- Part (b) means the Hessian is negative definite.
- The sufficient conditions actually find a local ***strict*** maximum point.

Theorem 6.5 For a twice-differentiable function $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^2$, if

a) $f_1(x_1^*, x_2^*) = 0, f_2(x_1^*, x_2^*) = 0$
b) $f_{11}(x_1^*, x_2^*) < 0$ and $f_{11}(x_1^*, x_2^*)f_{22}(x_1^*, x_2^*) - [f_{12}(x_1^*, x_2^*)]^2 > 0,$

then (x_1^*, x_2^*) is a ***local minimum point***.

Proof See Theorem 6.6 and Theorem 6.8 for the case of n variables case. ■

Example Use the sufficient conditions to find the point of maximum profit, when the production function is $q = f(L, K) = 5L^{\frac{1}{5}}K^{\frac{2}{5}}$, and $p_L = 4, p_K = 3$. The output price p is assumed to be 1. The profit function is then given by

$$\pi(L, K) = 5L^{\frac{1}{5}}K^{\frac{2}{5}} - 4L - 3K.$$

The partial derivatives with respect to each input at the maximum point are given by

$$L_0^{-\frac{4}{5}}K_0^{\frac{2}{5}} - 4 = 0$$
$$2L_0^{\frac{1}{5}}K_0^{-\frac{3}{5}} - 3 = 0$$

The ***critical point*** is $(L_0, K_0) = (\frac{1}{12}, \frac{2}{9})$. Verify that the second-order sufficient conditions

$$-\frac{4}{5}L_0^{-\frac{9}{5}}K_0^{\frac{2}{5}} < 0, \text{and}$$
$$\left(-\frac{4}{5}L_0^{-\frac{9}{5}}K_0^{\frac{2}{5}}\right)\left(-\frac{6}{5}L_0^{\frac{1}{5}}K_0^{-\frac{8}{5}}\right) - \left(\frac{2}{5}L_0^{\frac{4}{5}}K_0^{-\frac{3}{5}}\right)^2 > 0$$

are satisfied. Then conclude that the point $(L_0, K_0) = (\frac{1}{12}, \frac{2}{9})$ is a local maximum point.

- If all the prices p, p_L and p_K are increased by 5%, will the point $(L_0, K_0) = (\frac{1}{12}, \frac{2}{9})$ still be a local maximum point?

Problem With production function $q = f(L, K) = 5LK^2$, recalculate the maximum point.

Example Find the input levels that maximize the profit when the production function is given by

$$q = f(L, K) = 5L + L^{\frac{3}{4}}K^{\frac{1}{2}},$$

and $p = 2$, $p_L = 16$, and $p_K = 4$. The profit function is then given by

$$\pi(L, K) = 2\left(5L + L^{\frac{3}{4}}K^{\frac{1}{2}}\right) - 16L - 4K,$$

The partial derivatives with respect to each input at the maximum point are given by

$$10 + \frac{3}{2}L_0^{-\frac{1}{4}}K_0^{\frac{1}{2}} - 16 = 0$$
$$L_0^{\frac{3}{4}}K_0^{-\frac{1}{2}} - 4 = 0.$$

The ***critical point*** is $(L_0, K_0) = (256,256)$. However, the second-order sufficient conditions are not satisfied because

$$\pi_{LL}(L_0, K_0) = -\frac{3}{16}L_0^{-\frac{5}{4}}K_0^{\frac{1}{2}} < 0$$
$$\pi_{LL}(L_0, K_0)\pi_{KK}(L_0, K_0) - [\pi_{LK}(L_0, K_0)]^2$$
$$= \left(-\frac{3}{8}L_0^{-\frac{5}{4}}K_0^{\frac{1}{2}}\right)\left(-\frac{1}{2}L_0^{\frac{3}{4}}K_0^{-\frac{3}{2}}\right) - \left(\frac{3}{4}L_0^{-\frac{1}{4}}K_0^{-\frac{1}{2}}\right)^2$$
$$= \left(\frac{3}{16}L_0^{-\frac{1}{2}}K_0^{-1}\right) - \left(\frac{9}{16}L_0^{-\frac{1}{2}}K_0^{-1}\right)$$
$$= -\frac{6}{16}L_0^{-\frac{1}{2}}K_0^{-1} < 0.$$

We cannot conclude that the critical point found is a maximum point.

Problem Baldani, p. 193, #7.1 (a,b,c), 7.2 (a,b,c)

6.6 Multivariable Optimization without Constraints

With the same exposition as in the 2-variable case, we can discuss the necessary and sufficient conditions of the extreme points of functions with *n* variables as follows. A differentiable function with *n* variables and its differential is given by

$$y = f(\mathbf{x}) = f(x_1, x_2, \dots, x_n)$$

At extreme point $\mathbf{x}^* = (x_1^*, x_2^*, \dots, x_n^*)$ minimum or maximum, similar to the case of two variables that for any arbitrarily small changes in terms of **dx** there is no change in *y*, i.e.,

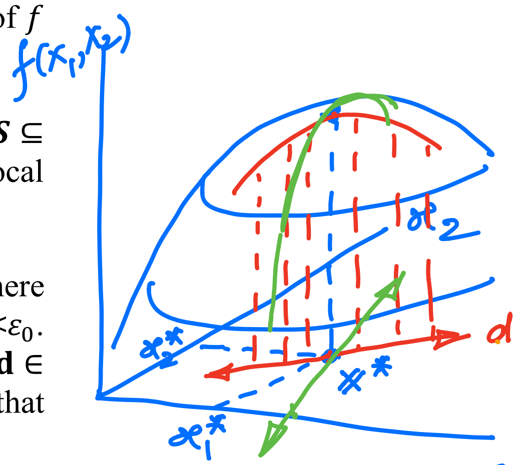
$$dy = \nabla f(\mathbf{x}^*)^{\mathrm{T}}\mathbf{dx} = \sum_{i=1}^{n} f_j(\mathbf{x}^*)dx_j = 0,$$

and

$$
\begin{aligned}
dy^2 = d(\nabla f(\mathbf{x}^*)^{\mathrm{T}}\mathbf{dx}) &= d\left(\sum_{i=1}^{n} f_j(\mathbf{x}^*)dx_j\right) \\
&= (f_{11}dx_1 + f_{12}dx_2 + \cdots + f_{1n}dx_n)dx_1 \\
&\quad +(f_{21}dx_1 + f_{22}dx_2 + \cdots + f_{2n}dx_n)dx_2 \\
&\quad + \cdots + (f_{n1}dx_1 + f_{n2}dx_2 + \cdots + f_{nn}dx_n)dx_n \\
&= \mathbf{dx}^{\mathrm{T}}\mathbf{H}(\mathbf{x}^*)\mathbf{dx} \le 0.
\end{aligned}
$$

Concave curvature.

The necessary and sufficient conditions can be found by defining a composite function $g_{\mathbf{d}}: \mathbb{R} \to \mathbb{R}$, $g_{\mathbf{d}}(t) = f(\mathbf{x}^* + t\mathbf{d})$, where $\mathbf{d} \in \mathbb{R}^n$, and find its first- and second-order directional derivatives. The following establishes that the maximum point of f is closely related to the maximum point of $g_{\mathbf{d}}$.



Theorem 6.6 A point $\mathbf{x}^*$ is a local maximum point of $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, if, and only if, $g_{\mathbf{d}}: \mathbb{R} \to \mathbb{R}$, $g_{\mathbf{d}}(t) = f(\mathbf{x}^* + t\mathbf{d})$, has a local maximum point at $t = 0$ for any $\mathbf{d} \in \mathbb{R}^n$.

Proof If $\mathbf{x}^*$ is a local maximum point of $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, there exists some $\varepsilon_0 > 0$, such that $f(\mathbf{x}^*) \ge f(\mathbf{x})$, for any $\|\mathbf{x} - \mathbf{x}^*\| < \varepsilon_0$. Suppose $t = 0$ is not a local maximum point for $g_{\mathbf{d}}$ for some $\mathbf{d} \in \mathbb{R}^n$. Then, for any $\varepsilon > 0$, there exists some $\hat{t}, -\varepsilon < \hat{t} < \varepsilon$, such that

$$
\begin{gathered}
g_{\mathbf{d}}(\hat{t}) > g_{\mathbf{d}}(0) \\
f(\mathbf{x}^* + \hat{t}\mathbf{d}) > f(\mathbf{x}^*),
\end{gathered}
$$

$g_d(t) = f(x^* + td)$
$g_d(0) = f(x^*)$
$t=0$ – max point of $g_d(t)$

Note that $\|\mathbf{x}^* + \hat{t}\mathbf{d} - \mathbf{x}^*\| = |\hat{t}|\|\mathbf{d}\|$. We then need to show that $|\hat{t}|\|\mathbf{d}\| < \varepsilon_0$. This can be easily done by choosing ε such that $\hat{t} < \varepsilon < \frac{\varepsilon_0}{\|\mathbf{d}\|}$ so that we have a contradiction.

g''

If $t = 0$ is a local maximum point for $g_{\mathbf{d}}$ for any $\mathbf{d} \in \mathbb{R}^n$, there exists some $\varepsilon_0 > 0$, such that $g_{\mathbf{d}}(0) \ge g_{\mathbf{d}}(t)$, for any $t, -\varepsilon_0 < t < \varepsilon_0$. Suppose that $\mathbf{x}^*$ is not a local maximum point of $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$. Then, for any $\varepsilon > 0$, there exists some $\hat{\mathbf{x}}$ such that $f(\mathbf{x}^*) < f(\hat{\mathbf{x}})$, $\|\hat{\mathbf{x}} - \mathbf{x}^*\| < \varepsilon$. Write $\mathbf{x}(\hat{t}) = \hat{\mathbf{x}} = \mathbf{x}^* + \hat{t}\mathbf{d}$, for some $\mathbf{d}$ such that $|\hat{t}| < \varepsilon_0$ so that we have a contradiction.

Choose $\mathbf{d} = z(\hat{\mathbf{x}} - \mathbf{x}^*)$, $z > \frac{\varepsilon}{\varepsilon_0\|\hat{\mathbf{x}} - \mathbf{x}^*\|}$. Then,

$$
\begin{gathered}
\|\hat{\mathbf{x}} - \mathbf{x}^*\| = \|\mathbf{x}^* + \hat{t}\mathbf{d} - \mathbf{x}^*\| = |\hat{t}|\|\mathbf{d}\| = |\hat{t}|z\|\hat{\mathbf{x}} - \mathbf{x}^*\| < \varepsilon \\
|\hat{t}| < \frac{\varepsilon}{z\|\hat{\mathbf{x}} - \mathbf{x}^*\|} < \varepsilon_0 \blacksquare
\end{gathered}
$$

As a result of Theorem 6.5, we can apply the Necessary and Sufficient Conditions of single-variable function to obtain those of multi-variable functions.

6.7 First-Order and Second-Order Necessary Condition

x^* local max of f

$\Longleftrightarrow$ $g_{d}(t)$ has local max at $t=0$

single var. fn

Necessary Conditions.

Theorem 6.7 If $\mathbf{x}^*$ is an extreme point of a twice-differentiable function $f: \boldsymbol{S} \to \mathbb{R}, \boldsymbol{S} \subseteq \mathbb{R}^n$, then

1) $\nabla f(\mathbf{x}^*) = \mathbf{0}$,
2) $\mathbf{d}^{\mathrm{T}}\, \mathbf{H}(\mathbf{x}^*)\mathbf{d} \le 0$, for any $\mathbf{d} \in \mathbb{R}^n$.

Proof Define composite function $g_{\mathbf{d}}: \mathbb{R} \to \mathbb{R}$, $g_{\mathbf{d}}(t) = f(\mathbf{x}^* + t\mathbf{d})$, where $\mathbf{d} \in \mathbb{R}^n$. The function $g_{\mathbf{d}}$ attains local maximum value at $t = 0$ for each direction $\mathbf{d} \in \mathbb{R}^n$. By Theorem 2.5, for any $\mathbf{d} \in \mathbb{R}^n$

$g'_{d}(0) = 0$, $g''_{d}(0) < 0$ } for any $d \in \mathbb{R}^n$.

1) $g'_{\mathbf{d}}(0) = \nabla f(\mathbf{x}^*)^{\mathrm{T}}\mathbf{d} = 0 \Leftrightarrow \nabla f(\mathbf{x}^*) = \mathbf{0}$.
2) $g''_{\mathbf{d}}(0) = \mathbf{d}^{\mathrm{T}}\nabla^2 f(\mathbf{x}^*)\mathbf{d} = \boxed{\mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x}^*)\mathbf{d}} \le 0.$ ■

$H(x^*)$ is neg semidef.

$f(x) = x^T A x$

$= a_{11}x_1^2 + a_{12}x_1x_2 + \dots$

$- - - -$ $a_{nn}x_n^2$

This means that when $\mathbf{x}^*$ is a local maximum point, moving away from it in any direction $\mathbf{d}$ infinitestimally will not increase the value of f, and the curvature of the graph is concave, which means the Hessian is negative semi-definite according to the following definition.

Definition 6.5 A square matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$ is ***negative (positive) semi-definite*** if for any $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d}^{\mathrm{T}}\mathbf{A}\mathbf{d} \le (\ge) 0$.

For the Sufficient Conditions, we will need the following definiteness definition.

Definition 6.6 A square matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$ is ***negative (positive) definite*** if for any $\mathbf{d} \in \mathbb{R}^n, \mathbf{d} \ne \mathbf{0}$, $\mathbf{d}^{\mathrm{T}}\mathbf{A}\mathbf{d} < (>) 0$.

6.9 Sufficient Conditions

These are the conditions that, when satisfied, guarantee that a point is a maximum or minimum point of a twice-differentiable function of multivariable. However, these conditions may not identify every maximum and minimum points.

Theorem 6.8 For a twice-differentiable function $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, if at any $\mathbf{x}^* \in \boldsymbol{S}$,

$g'_{d}(0) = 0$, $g''_{d}(0) < 0$ } for any d

1) $\nabla f(\mathbf{x}^*) = \mathbf{0}$, and
2) $\mathbf{H}(\mathbf{x}^*)$ is negative (positive) definite,

$d^T H(x^*) d < 0$

$\Longrightarrow$ x^* local max.

$\Updownarrow$ $g_{d}(t)$ has local max at $t=0$ for any $d \in \mathbb{R}^n$

then $\mathbf{x}^*$ is a ***local maximum (minimum) point*** of f.

Proof Since $\mathbf{x}^*$ is a local maximum (minimum) point of f if, and only if, the composite function $g_{\mathbf{d}}: \mathbb{R} \to \mathbb{R}$, $g_{\mathbf{d}}(t) = f(\mathbf{x}^* + t\mathbf{d})$, has a local maximum (minimum) at $t = 0$, for any $\mathbf{d} \in \mathbb{R}^n$. By Theorem 2.6, the function $g_{\mathbf{d}}$ has a local maximum at $t = 0$, if

1) $g'_{\mathbf{d}}(0) = \nabla f(\mathbf{x}^*)^{\mathrm{T}}\mathbf{d} = 0 \Leftrightarrow \nabla f(\mathbf{x}^*) = \mathbf{0}$, and
2) $g''_{\mathbf{d}}(0) = \mathbf{d}^{\mathrm{T}}\nabla^2 f(\mathbf{x}^*)\mathbf{d} = \mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x}^*)\mathbf{d} < 0$.

For local minimum, the inequality in (2) is of the reverse direction.■

- Both conditions must be satisfied.
- The sufficient conditions actually find a local ***strict*** maximum (minimum) point.

MA217 Test.

$H(x_1,x_2) = \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}$

1) $f_{11} < 0$
2) $f_{11}f_{22} - (f_{12})^2 > 0$.

6.10 Test of Definiteness of the Hessian

See Simon and Blume [1994] Theorem 16.2, page 383, for the test of semi-definiteness of a square matrix. Only the test for definiteness is discussed here.

$H = \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}$

Definition 6.7 The submatrix $\mathbf{H}_k$ of $\mathbf{H}(\mathbf{x}^*)$ is called the ***leading principal submatrix*** of order k if it is the matrix $\mathbf{H}(\mathbf{x}^*)$ with the last $n-k$ rows and columns deleted.

Definition 6.8 $|\mathbf{H}_k|$ is called the ***leading principal minor*** of order k.

$f_{21}\cdot f_{12} = (f_{12})^2$

Theorem 6.9 $\mathbf{H}(\mathbf{x}^*)$ is ***positive*** definite if $|\mathbf{H}_k| > 0$, $k = 1,2,\ldots,n$.
Theorem $\mathbf{H}(\mathbf{x}^*)$ is ***negative*** definite if , $(-1)^k|\mathbf{H}_k| > 0$, $k = 1,2,\ldots,n$.

k-odd <0

$f_{12} = f_{21}$

HW Baldani, p. 194, #7.4 (a,b,c,d)

$H = \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix}$ $n=3$ 3x3

last $\underbrace{n-1}_{2}$ row+col.

$H_1 = f_{11}$

6.11 Concavity, Convexity and Optimization

The sufficient conditions can only guarantee that a point is a local maximum or minimum. We need additional assumption to obtain a global extreme point. One of such assumptions is the concavity or convexity of the function. This is similar to the concavity and convexity of the single-variable functions as discussed in Chapter 2.

$n-k=3-2=1$ | $k=2$ $H_2 = \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}$

Definition 6.9 A function $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, is a ***concave*** (convex) function, if

convex combination of x_1, x_2

$n-k=3-3=0$ | $k=3$ $H_3 = H$

$$f(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) \geq \lambda f(\mathbf{x}_1) + (1-\lambda)f(\mathbf{x}_2)$$

for any $\mathbf{x}_1, \mathbf{x}_2 \in \boldsymbol{S}$, and $0 \leq \lambda \leq 1$.

$\lambda x_1 + (1-\lambda)x_2$

Definition 6.10 A function $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S} \subseteq \mathbb{R}^n$, is a ***strictly concave*** (convex) function, if

$$f(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) > \lambda f(\mathbf{x}_1) + (1-\lambda)f(\mathbf{x}_2)$$

$\lambda \mathbf{x}_1 + (1-\lambda)\mathbf{x}_2$

$\lambda \begin{bmatrix} x_1^1 \\ \vdots \\ x_n^1 \end{bmatrix} + (1-\lambda) \begin{bmatrix} x_1^2 \\ \vdots \\ x_n^2 \end{bmatrix}$

$\max f(x)$, $f \in C^2$

Necessary Conditions.

$d \in \mathbb{R}^n$

$g_d(t) = f(x^* + td)$

$\underbrace{\nabla f(x^*)}_{=0}{}^T d = g_d'(0) \leq 0 \;\forall d$

x^* local max of $f \implies$ 1) $\nabla f(x^*) = 0$

2) $H(x^*)$ neg semi def.

$g_d''(0) \leq 0 \quad \forall d.$

$d^T \nabla^2 f(x^*) d = \underbrace{d^T H(x^*) d \leq 0}_{H(x^*) \text{ neg semi-definite.}} \quad \forall d \in \mathbb{R}^n$

Sufficient Conditions.

1) $\nabla f(x^*) = 0.$

2) $\left.\begin{array}{l} d^T \nabla^2 f(x^*) d < 0 \\ d^T H(x^*) d < 0 \end{array}\right\} \begin{array}{l} \forall d \in \mathbb{R}^n \\ d \neq 0. \end{array}$

– $H(x^*)$ neg definite.

all leading principle minors $\gtrless 0$

$\left.\begin{array}{l} |H(x^*)| > 0 \\ \text{or} < 0 \end{array}\right\} \implies H(x^*)$ is nonsing.

if x^* was found by Suff conditions to be a local max (min), we have $|H(x^*)| \neq 0.$

for any $\mathbf{x}_1, \mathbf{x}_2 \in \boldsymbol{S}$, $\mathbf{x}_1 \neq \mathbf{x}_2$, and $0 < \lambda < 1$.

We will have the following results similar to the case of single variable in Chapter 2. We can extend the results of Chapter 2 to multivariable concave (convex) function by first proving the following Theorem.

Definition 6.11 Given a function $f: \boldsymbol{S} \to \mathbb{R}^n$, $\boldsymbol{S} \subseteq \mathbb{R}$, for any $\mathbf{x}, \mathbf{y} \in \boldsymbol{S}$, define $g_{\mathbf{xy}}: [0,1] \to \mathbb{R}$, where

$$g_{\mathbf{xy}}(t) = f(t\mathbf{x} + (1-t)\mathbf{y}).$$

Theorem 6.10 (Simon & Blume, Theorem 21.1) A function $f: \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S}$ is a convex set, $\boldsymbol{S} \subseteq \mathbb{R}^n$, is concave (convex) if, and only if, for any $\mathbf{x}, \mathbf{y} \in \boldsymbol{S}$, $g_{\mathbf{xy}}$ is.

Proof First, assume that $g_{\mathbf{xy}}$ is concave for any $\mathbf{x}, \mathbf{y} \in \boldsymbol{S}$. Note that

$g_{\mathbf{xy}}(0) = f(\mathbf{y})$,
$g_{\mathbf{xy}}(1) = f(\mathbf{x})$, and
$g_{\mathbf{xy}}(\lambda) = f(\mathbf{x} + (1-\lambda)(\mathbf{y} - \mathbf{x})) = f(\lambda\mathbf{x} + (1-\lambda)\mathbf{y})$.

Thus,

$$\begin{aligned} f(\lambda\mathbf{x} + (1-\lambda)\mathbf{y}) = g_{\mathbf{xy}}(\lambda) &= g_{\mathbf{xy}}(\lambda 1 + (1-\lambda)0) \\ &\geq \lambda g_{\mathbf{xy}}(1) + (1-\lambda) g_{\mathbf{xy}}(0) \\ &= \lambda f(\mathbf{x}) + (1-\lambda) f(\mathbf{y}). \end{aligned}$$

Now, if f is concave, we have to show that $g_{\mathbf{xy}}$ is concave for any $\mathbf{x}, \mathbf{y} \in \boldsymbol{S}$. For any $s_1, s_2, \lambda \in [0,1]$,

$$\begin{aligned} &g_{\mathbf{xy}}(\lambda s_1 + (1-\lambda)s_2) \\ &= f((\lambda s_1 + (1-\lambda)s_2)\mathbf{x} + \big(1 - (\lambda s_1 + (1-\lambda)s_2)\big)\mathbf{y}) \\ &= f((\lambda s_1 + (1-\lambda)s_2)\mathbf{x} + \big(\lambda + (1-\lambda) - (\lambda s_1 + (1-\lambda)s_2)\big)\mathbf{y}) \\ &= f((\lambda s_1 + (1-\lambda)s_2)\mathbf{x} + (\lambda(1-s_1) + (1-\lambda) - (1-\lambda)s_2)\mathbf{y}) \\ &= f((\lambda s_1 + (1-\lambda)s_2)\mathbf{x} + (\lambda(1-s_1) + (1-\lambda)(1-s_2))\mathbf{y}) \\ &= f(\lambda(s_1\mathbf{x} + (1-s_1))\mathbf{y}) + (1-\lambda)(s_2\mathbf{x} + (1-s_2)\mathbf{y})) \\ &\geq \lambda f(s_1\mathbf{x} + (1-s_1))\mathbf{y}) + (1-\lambda) f(s_2\mathbf{x} + (1-s_2)\mathbf{y}) \\ &= \lambda g_{\mathbf{xy}}(s_1) + (1-\lambda) g_{\mathbf{xy}}(s_2). \end{aligned}$$

Thus, $g_{\mathbf{xy}}$ is concave.■

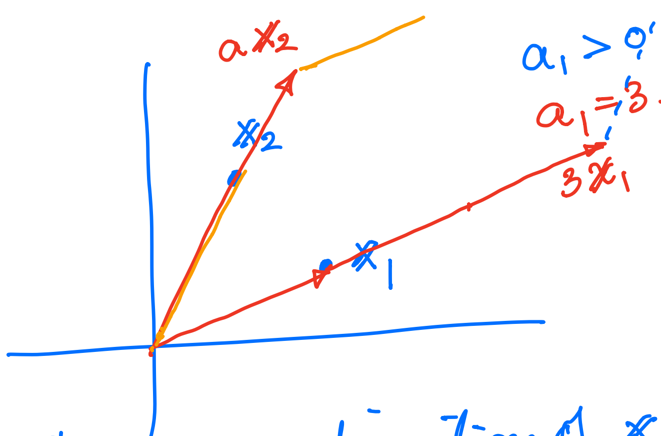
We can now use results from Chapter 2 to obtain the analogous results for the multivariable function.

Theorem 6.11 Let $f: \boldsymbol{S} \to \mathbb{R}^n$, $\boldsymbol{S} \subseteq \mathbb{R}$, be a differentiable function. The function f is concave (convex) if, and only if,

Linear Combination of x_1, x_2 | $x_1, x_2, \dots, x_k$

$\boxed{a_1 x_1 + a_2 x_2}$ $\quad a x_1 + a_2 x_2$ | $a_1 x_1 + a_2 x_2 + \dots + a_k x_k$

a_1, a_2 are scalars. (numbers) | $a_1, \dots, a_k$ numbers.

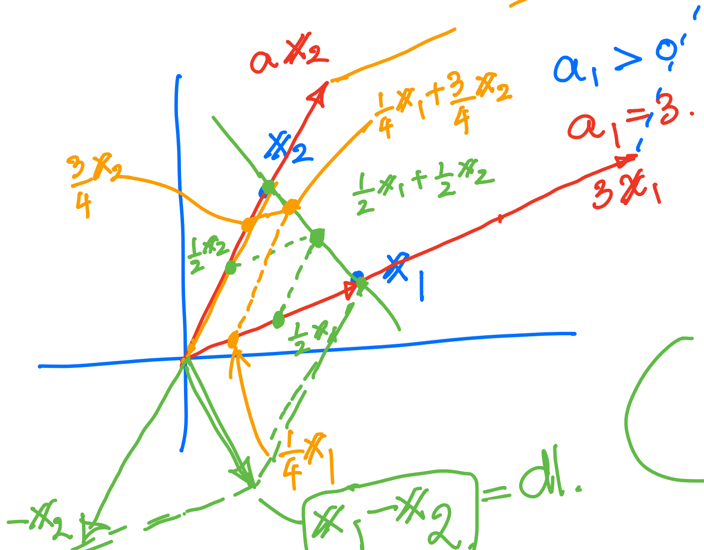


Convex combination of x_1, x_2

$x_\lambda = \boxed{\lambda x_1 + (1-\lambda) x_2}$, $0 \le \lambda \le 1$

$\left[\begin{array}{l} \lambda = \frac{1}{2}. \\ (1-\lambda) = \frac{1}{2} \end{array}\right.$

$\left[\begin{array}{l} \lambda = \frac{1}{4}. \\ (1-\lambda) = \frac{3}{4}. \end{array}\right.$



$\boxed{x_1 - x_2} = d.$

$\lambda x_1 + (1-\lambda) x_2 = x_2 + \lambda (x_1 - x_2)$

$= x_2 + \lambda d.$

$\lambda = 1 \quad x_\lambda = x_1$ ✓

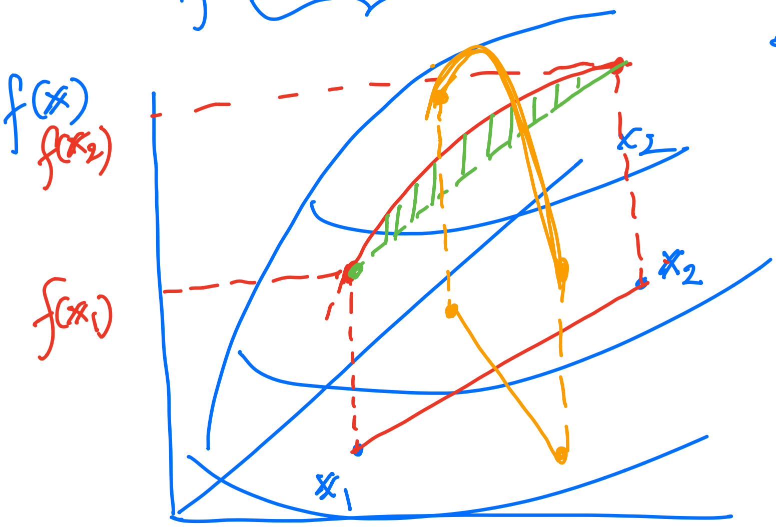
$\lambda = \frac{1}{2} \quad x_\lambda =$

$f: S \to \mathbb{R}$, $S \subseteq \mathbb{R}^n$

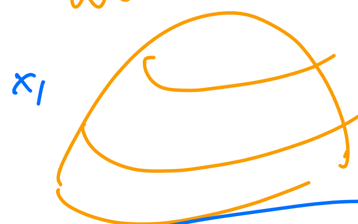
f concave if for any $x_1, x_2 \in S$, then

$$f(\underbrace{\lambda x_1 + (1-\lambda) x_2}) \geq \lambda f(x_1) + (1-\lambda) f(x_2)$$

for any $0 \leq \lambda \leq 1$



wok.



$$\boxed{g(\lambda) = f(x_2 + \lambda(x_1 - x_2))}$$

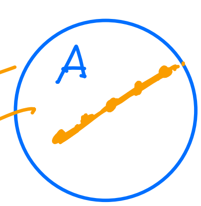
$$g(t) = f(x_0 + td)$$

convex combination

Convex set. $A \subseteq \mathbb{R}^2$, if for any $x_1, x_2 \in A$

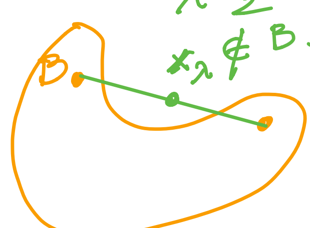
$$\underbrace{\lambda x_1 + (1-\lambda) x_2} \in \underline{A}$$

a convex set

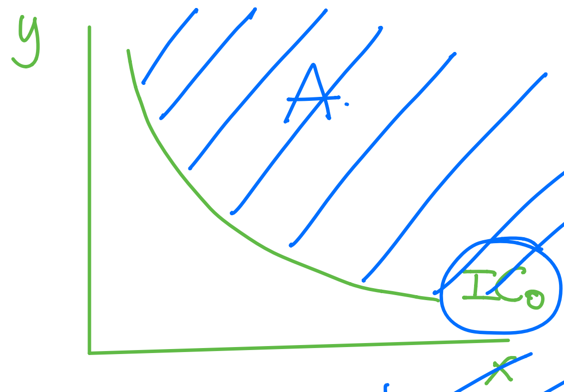


$\lambda = \frac{1}{2}$

$x_\lambda \notin B$.

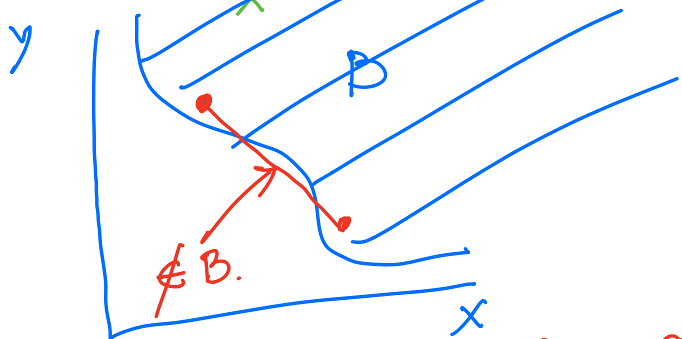


not a convex set.



$A = \{(x,y) \mid u(x,y) \geq \bar{u}\}$

A convex set.



This is needed to show that $u(x)$ is quasi-concave

$$f(\lambda x_1 + (1-\lambda) x_2) \geq \min\{f(x_1), f(x_2)\}.$$

$f \in C^1$

$$f(\mathbf{y}) - f(\mathbf{x}) \le \nabla f(\mathbf{x})^{\mathrm{T}}(\mathbf{y} - \mathbf{x}),$$
$$(\ge)$$

(concave)

convex.

for any $\mathbf{x}, \mathbf{y} \in \boldsymbol{S}$.

$f(y) - f(x) \le f'(x)(y - x)$

$f \to g_{xy}$
$y = 1,\ x = 0.$

Proof We show only for the case of concave function. If we define function $g_{\mathbf{xy}}$ slightly different from the previous theorem, namely

$$g_{\mathbf{xy}}(t) = f\big((1-t)\mathbf{x} + t\mathbf{y}\big) = f\big(\mathbf{x} + t(\mathbf{y} - \mathbf{x})\big).$$

$g_{xy}(1) - g_{xy}(0) \le g'_{xy}(0)(1-0)$

then by the previous theorem, $f\colon \boldsymbol{S} \to \mathbb{R}^n$, $\boldsymbol{S} \subseteq \mathbb{R}$, is a differentiable and concave if, and only if $g_{\mathbf{xy}}$ is, and by Theorem 2.8,

$$\Leftrightarrow g_{\mathbf{xy}}(1) - g_{\mathbf{xy}}(0) \le g'_{\mathbf{xy}}(0)(1-0)$$
$$\Leftrightarrow f(\mathbf{y}) - f(\mathbf{x}) \le \nabla f(\mathbf{x})^{\mathrm{T}}(\mathbf{y} - \mathbf{x}) \blacksquare$$

$\nabla f(x^*) = 0.$
x^* global max.

Similarly, with the same argument we can write for strict concavity and convexity

$f \in C^1$

Theorem 6.12 Let $f\colon \boldsymbol{S} \to \mathbb{R}^n$, $\boldsymbol{S} \subseteq \mathbb{R}$, be a differentiable function. The function f is strictly concave (convex) if, and only if,

$$f(\mathbf{y}) - f(\mathbf{x}) < \nabla f(\mathbf{x})^{\mathrm{T}}(\mathbf{y} - \mathbf{x}),$$
$$(>)$$

for any $\mathbf{x}, \mathbf{y} \in \boldsymbol{S}, \mathbf{x} \ne \mathbf{y}$.

Problem. Prove this Theorem 6.11. The proof is similar to that of Theorem 6.10 but with strict inequality.

$f \in C^2$

Theorem 6.13 (Simon & Blume, Theorem 21.5 page 513) If $f\colon \boldsymbol{S} \to \mathbb{R}$, $\boldsymbol{S}$ is a convex set, $\boldsymbol{S} \subseteq \mathbb{R}^n$, is twice differentiable, then

a) f is concave $\Leftrightarrow$ For any $\mathbf{x} \in \boldsymbol{S}$, $\mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x})\mathbf{d} \le 0$, $\mathbf{d} \in \mathbb{R}^n$, – neg semidef.
b) For any $\mathbf{x} \in \boldsymbol{S}$, $\mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x})\mathbf{d} < 0$, $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \ne \mathbf{0} \Rightarrow f$ is strictly concave

neg def

Proof (a) ($\Longrightarrow$) Let f be concave over a convex set $\boldsymbol{S}$. We have to show that $\mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x})\mathbf{d} \le 0$, $\mathbf{d} \in \mathbb{R}^n$. For any $\mathbf{x} \in \boldsymbol{S}$, since f is differentiable at $\mathbf{x}$, there exists some sufficiently small $t_0 > 0$, such that $\mathbf{y_d} = \mathbf{x} + t_0\mathbf{d} \in \boldsymbol{S}$, for any $\mathbf{d} \in \mathbb{R}^n$. Since f is concave, $g_{\mathbf{xy_d}}$ is concave and $g''_{\mathbf{xy_d}}(0) \le 0$. Thus

$$\left.\begin{aligned} 0 \ge g''_{\mathbf{xy_d}}(0) &= (\mathbf{y_d} - \mathbf{x})^{\mathrm{T}}\mathbf{H}(\mathbf{x})(\mathbf{y_d} - \mathbf{x}) \\ &= t_0\mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x})t_0\mathbf{d} \\ &= t_0^2\mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x})\mathbf{d} \end{aligned}\right\}$$

Thus, we have $\mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x})\mathbf{d} \le 0$, for any $\mathbf{x} \in \boldsymbol{S}$.

$f(x)$ concave
if $f''(x) \le 0 \ \forall x$

($\Longleftarrow$) If, for any $\mathbf{x}, \mathbf{y} \in \boldsymbol{S}$, $\mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x})\mathbf{d} \leq 0$, $\mathbf{d} \in \mathbb{R}^n$. Since, $g''_{\mathbf{xy}}(0) = \mathbf{d}^{\mathrm{T}}\mathbf{H}(\mathbf{x})\mathbf{d} \leq 0$, then $g_{\mathbf{xy}}(t)$ is concave and so is f. ■

Problem Prove (b) of Theorem 6.~~12~~ 13 above. Note that the arrow is only in one direction.

This means that if the function f is twice differentiable, it is concave if and only if the Hessian is negative semi-definite everywhere. And the function is strictly concave if the Hessian is negative definite everywhere.

Test Definiteness

$|H_k| \gtrless 0$

$(|H_n| = |H|) \gtrless 0$

nonzero.

Theorem 6.14 If a matrix is positive (negative) definite, it is nonsingular.

Problem Prove Theorem 6.~~13~~ 14

Problem Baldani, p. 194, #7.6, 7.7, 7.8

Theorem 6.15 Let $f: \boldsymbol{S} \to \mathbb{R}, \boldsymbol{S} \subseteq \mathbb{R}^n$,

a)If f is concave, a local maximum point $\mathbf{x}^*$ is also a global one.

b)If f is strictly concave, a local maximum point $\mathbf{x}^*$ is also a strictly global one.

Proof Similar to the proof of Theorem 2.12.

Theorem 6.16 Let $f: \boldsymbol{S} \to \mathbb{R}, \boldsymbol{S} \subseteq \mathbb{R}^n$, be differentiable.

a) If f is concave and $\boxed{\nabla f(\mathbf{x}^*) = \mathbf{0}}$, $\mathbf{x}^* \in \boldsymbol{S}$, then $\mathbf{x}^*$is a global maximum of f.

b) If f is strictly concave and $\nabla f(\mathbf{x}^*) = \mathbf{0}, \mathbf{x}^* \in \boldsymbol{S}$, then $\mathbf{x}^*$is a strict global maximum of f.

Proof We prove only for (a). By Theorem…, for any $\mathbf{y} \in \boldsymbol{S}$

$$f(\mathbf{y}) - f(\mathbf{x}^*) \leq \underbrace{\nabla f(\mathbf{x}^*)^{\mathrm{T}}}_{=0}(\mathbf{y} - \mathbf{x}) = \mathbf{0}.$$

$f(y) - f(x^*) \leq 0.$

$f(y) \leq f(x^*)$ $y \in S$

Thus, $f(\mathbf{x}^*) \geq f(\mathbf{y})$, and $\mathbf{x}^*$is a global maximum of f.■

6.12 Comparative Statics Analysis

$f: \mathbb{R}^{n+k} \to \mathbb{R}^n$

Consider $y = f(\mathbf{x}; \mathbf{c})$, with $\mathbf{c}$ being a vector of parameters $\mathbf{c} \in \mathbb{R}^k$. Suppose that the optimal solution is found by the first-order sufficient condition at some specific value of $\mathbf{c}_0$

$$f(x^*; c_0) = \nabla_{\mathbf{x}} f(\mathbf{x}^*; \mathbf{c}_0) = \mathbf{0}. \Big\} = \begin{bmatrix} f_1(x^*; c_0) \\ \vdots \\ f_n(x^*; c_0) \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \Big\} \; n \text{ implicit fns}$$

endog.

x endog.

$x \in \mathbb{R}^n$

This can be considered as a system of n implicit functions with n endogeneous variables $\mathbf{x}$ and k exogeneous variables $\mathbf{c}$.

c_0 - exog.

$k \geq 1$

how each of c_0 exog variables affect each of endog variables x

Yes if x^* was found by $1^{st}+2^{nd}$ order suff. cond!

If the optimal solution is found by the sufficient conditions, $\mathbf{H}(\mathbf{x}^*;\mathbf{c}_0)$ is either positive or negative definite and thus nonsingular. Thus the Implicit Function Theorem applies because

$$\nabla_{\mathbf{x}}\big(\nabla_{\mathbf{x}} f(\mathbf{x}^*;\mathbf{c}_0)\big) = \nabla_{\mathbf{x}}^2 f(\mathbf{x}^*;\mathbf{c}_0) = \mathbf{H}(\mathbf{x}^*;\mathbf{c}_0).$$

— nonsingular.

.

$\nabla_x f(x^*, c_0) =$

By the Implicit Function Theorem (Theorem 4.8), there exists a differentiable function $\mathbf{x} = \mathbf{x}(\mathbf{c})$ and $\varepsilon > 0$ such that

a) $\nabla_{\mathbf{x}} f(\mathbf{x}(\mathbf{c});\mathbf{c}) = \mathbf{0}$, for $\|\mathbf{c}-\mathbf{c}_0\| < \varepsilon$,
b) $\mathbf{x}(\mathbf{c}_0) = \mathbf{x}^*$, and
c) the gradient

$$\begin{aligned}\nabla_{\mathbf{c}}\mathbf{x}(\mathbf{c}_0) &= -\big[\nabla_{\mathbf{x}}\big(\nabla_{\mathbf{x}} f(\mathbf{x}^*;\mathbf{c}_0)\big)\big]^{-1}\nabla_{\mathbf{c}}\big(\nabla_{\mathbf{x}} f(\mathbf{x}^*;\mathbf{c}_0)\big)\\ &= -[\nabla_{\mathbf{x}}^2 f(\mathbf{x}^*;\mathbf{c}_0)]^{-1}\nabla_{\mathbf{c}}\big(\nabla_{\mathbf{x}} f(\mathbf{x}^*;\mathbf{c}_0)\big)\\ &= -[\mathbf{H}(\mathbf{x}^*;\mathbf{c}_0)]^{-1}\nabla_{\mathbf{c}}\big(\nabla_{\mathbf{x}} f(\mathbf{x}^*;\mathbf{c}_0)\big).\end{aligned}$$

endog. exog.

Example Suppose $y = f(x_1, x_2, x_3; c)$ is a function of three decision variables and one parameter c. By the first-order condition at $(x_1^*, x_2^*, x_3^*; c_0)$ as the system of implicit functions

$$\begin{cases} f_1(x_1^*, x_2^*, x_3^*; c_0) = 0\\ f_2(x_1^*, x_2^*, x_3^*; c_0) = 0\\ f_3(x_1^*, x_2^*, x_3^*; c_0) = 0\end{cases}$$

imp functions 3. if H is nonsing.

There exists a function $\mathbf{x} = \mathbf{x}(c)$ such that $\nabla_{\mathbf{x}} f(\mathbf{x}(c);c) = \mathbf{0}$ for, $|c - c_0| < \varepsilon, \mathbf{x}^* = \mathbf{x}(c_0)$ and

$$\mathbf{x}'(c_0) = -[\mathbf{H}(\mathbf{x}^*;c_0)]^{-1}\nabla_c\big(\nabla_{\mathbf{x}} f(\mathbf{x}^*;c_0)\big)$$

$$\begin{bmatrix} x_1'(c_0)\\ x_2'(c_0)\\ x_3'(c_0)\end{bmatrix} = -\underbrace{\begin{bmatrix} f_{11} & f_{12} & f_{13}\\ f_{21} & f_{22} & f_{23}\\ f_{31} & f_{32} & f_{33}\end{bmatrix}}_{\text{Hessian.}}{}^{-1}\begin{bmatrix} f_{1c}\\ f_{2c}\\ f_{3c}\end{bmatrix}$$

where all second-order and cross-partial derivatives are evaluated at $(x_1^*, x_2^*, x_3^*; c_0)$.

By Cramer's Rule,

$$x_3'(c_0) = -\frac{\begin{vmatrix} f_{11} & f_{12} & f_{1c}\\ f_{21} & f_{22} & f_{2c}\\ f_{31} & f_{32} & f_{3c}\end{vmatrix}}{\begin{vmatrix} f_{11} & f_{12} & f_{13}\\ f_{21} & f_{22} & f_{23}\\ f_{31} & f_{32} & f_{33}\end{vmatrix}},$$

whose sign is difficult to determine without explicit computation.

If f_1 and f_2 does not involve c so that $f_{1c} = f_{2c} = 0$ and then

$$x_3'(c_0) = -\frac{\begin{vmatrix} f_{11} & f_{12} & 0 \\ f_{21} & f_{22} & 0 \\ f_{31} & f_{32} & f_{3c} \end{vmatrix}}{\begin{vmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{vmatrix}} = \boxed{-\frac{f_{3c}|\mathbf{H}_2|}{|\mathbf{H}|}}.$$

Thus if $\mathbf{x}^*$ is determined to be a local maximum point by the 1st and 2nd-order sufficient conditions, $-\frac{|\mathbf{H}_2|}{|\mathbf{H}|} > 0$ and thus $sign[x_3'(c_0)] = sign[f_{3c}]$.

Problem Baldani, p. 194, #7.9 (a,b,c)