

Constrained Optimization: F.O.C.

經濟學是蝦密? Optimal allocation of scarce resources

$$\text{Max } \underbrace{f(x_1, \dots, x_n)}_{\text{Objective function}} \quad \text{s.t.} \quad \begin{cases} g_1(x_1, \dots, x_n) \leq b_1 \\ \vdots \\ g_k(x_1, \dots, x_n) \leq b_k \end{cases} \quad \begin{matrix} \text{(inequality} \\ \text{constraints)} \end{matrix}$$

$k_n: x_1 > 0, x_2 > 0$

$$\begin{cases} h_1(x_1, \dots, x_n) = c_1 \\ \vdots \\ h_m(x_1, \dots, x_n) = c_m \end{cases} \quad \begin{matrix} \text{(equality} \\ \text{constraints)} \end{matrix}$$

EX: 1. 廠商問題: (Profit Maximization of a competitive firm)

$$\text{Max } \Pi(x_1, \dots, x_n) = \underbrace{p \cdot f(x_1, \dots, x_n)}_{\text{Total Revenue}} - \underbrace{(w_1 x_1 + w_2 x_2 + \dots + w_n x_n)}_{\text{Total Cost}}$$

s.t. $p f(x_1, \dots, x_n) - (w_1 x_1 + w_2 x_2 + \dots + w_n x_n) \geq 0$ (nonnegative profits)

$g_1(x_1, \dots, x_n) \leq b_1, \dots, g_k(x_1, \dots, x_n) \leq b_k$ (availability of inputs)

$x_1 \geq 0, x_2 \geq 0, \dots, x_n \geq 0$

2. 消費者問題: (Utility Maximization)

$$\text{Max } U(x_1, \dots, x_n)$$

$$\text{s.t. } p_1 x_1 + p_2 x_2 + \dots + p_n x_n \leq I \quad (\text{budget constraint})$$

$$x_1 \geq 0, x_2 \geq 0, \dots, x_n \geq 0 \quad (\text{nonnegative constraints})$$

3. 加時間限制式的消費者問題: (Utility Maximization with Labor/Leisure)

$$\text{Max } U(x_1, \dots, x_n, l_1)$$

$$\text{s.t. } p_1 x_1 + p_2 x_2 + \dots + p_n x_n \leq I = I' + w l_0, \quad l_0 + l_1 = 24$$

$$x_1 \geq 0, x_2 \geq 0, \dots, x_n \geq 0, \quad l_0 \geq 0, l_1 \geq 0$$

(time constraint)

Homework: Exercise 18.4, 18.9, 18.13, 18.14, 18.15, 18.20, 18.21

Equality Constraints: $h(x_1, x_2) = c$

消費者問題:

$$\text{Max } f(x_1, x_2)$$

x_1, x_2

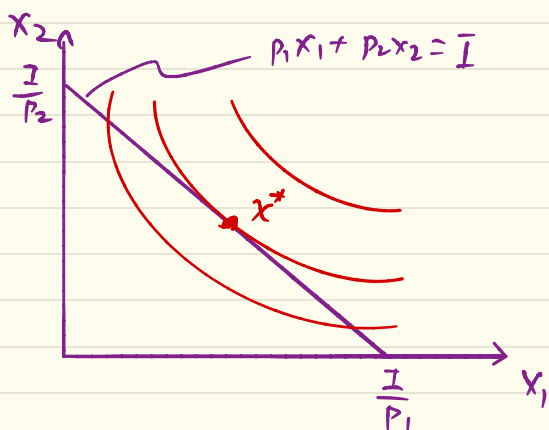
$$\text{s.t. } p_1 x_1 + p_2 x_2 = I$$

兩變數、一條限制等式。

($x_1 \geq 0, x_2 \geq 0$ 先忽略)

$$h(x_1, x_2) = p_1 x_1 + p_2 x_2 = I = c$$

圖形解法:



找 indifference curve (無異曲線) 和 budget constraint (預算限制式) 的切點

$$\text{相切} \Rightarrow \frac{-\frac{\partial f}{\partial x_1}(x^*)}{\frac{\partial f}{\partial x_2}(x^*)} = \frac{-\frac{\partial h}{\partial x_1}(x^*)}{\frac{\partial h}{\partial x_2}(x^*)}$$

$$\frac{-\frac{\partial f}{\partial x_1}(x^*)}{\frac{\partial f}{\partial x_2}(x^*)} = \frac{-\frac{\partial h}{\partial x_1}(x^*)}{\frac{\partial h}{\partial x_2}(x^*)} \Rightarrow \frac{\frac{\partial f}{\partial x_1}(x^*)}{\frac{\partial h}{\partial x_1}(x^*)} = \frac{\frac{\partial f}{\partial x_2}(x^*)}{\frac{\partial h}{\partial x_2}(x^*)} = \mu$$

$$\Rightarrow \begin{cases} \frac{\partial f}{\partial x_1}(x^*) - \mu \frac{\partial h}{\partial x_1}(x^*) = 0 & \text{--- ①} \\ \frac{\partial f}{\partial x_2}(x^*) - \mu \frac{\partial h}{\partial x_2}(x^*) = 0 & \text{--- ②} \end{cases} \quad \text{加上 } h(x_1, x_2) = c \text{ --- ③ 共三條方程式}$$

可解 x_1, x_2, μ

其實 ①, ②, ③ 就是 Lagrangian Function 的 F.O.C., μ 是 Lagrange Multiplier.

$$\mathcal{L}(x_1, x_2, \mu) = f(x_1, x_2) - \mu [h(x_1, x_2) - c]$$

$$\text{FOC: } \begin{aligned} \frac{\partial \mathcal{L}}{\partial x_1} &= \frac{\partial f}{\partial x_1}(x^*) - \mu \frac{\partial h}{\partial x_1}(x^*) = 0 & \text{--- ①} & \quad \frac{\partial \mathcal{L}}{\partial \mu} = h(x_1, x_2) - c = 0 & \text{--- ③} \\ \frac{\partial \mathcal{L}}{\partial x_2} &= \frac{\partial f}{\partial x_2}(x^*) - \mu \frac{\partial h}{\partial x_2}(x^*) = 0 & \text{--- ②} \end{aligned}$$

也就是說：兩變數、一條限制等式的 Constrained optimization
(變成) " = " 三變數的 Unconstrained optimization

但書：需要 $\frac{\partial h}{\partial x_1}, \frac{\partial h}{\partial x_2}$ 不同時為 0!! \Rightarrow Constraint Qualification (CQ)

EX: 前面幾個例子 $h(x_1, x_2)$ 都是線性函數，故 CQ 自動成立。

故，我們有下面這個定理：

Thm 18.1 Let f, h be C^1 functions of two variables.

Suppose $x^* = (x_1^*, x_2^*)$ is a solution of the problem

$$\text{Max}_{x_1, x_2} \left\{ f(x_1, x_2) \mid h(x_1, x_2) = c \right\}.$$

If x^* is not a critical point of h , then $\exists \mu^* \in \mathbb{R}$ s.t.

$$\frac{\partial \mathcal{L}}{\partial x_1} = 0, \quad \frac{\partial \mathcal{L}}{\partial x_2} = 0, \quad \frac{\partial \mathcal{L}}{\partial \mu} = 0 \quad \text{at } (x_1^*, x_2^*, \mu^*) \quad \text{for}$$

$$\mathcal{L}(x_1, x_2, \mu) \equiv f(x_1, x_2) - \mu [h(x_1, x_2) - c].$$

更一般地來說, 考慮 gradient (梯度) $\nabla f(x) = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{pmatrix}$, $\nabla h(x) = \begin{pmatrix} \frac{\partial h}{\partial x_1} \\ \frac{\partial h}{\partial x_2} \end{pmatrix}$,

也就是和 Level set 垂直的向量, 則 "f, h 在 x^* 相切" 也就代表兩 gradient 平行:

$$\nabla f(x^*) = \mu^* \nabla h(x^*) \quad , \text{ multiplier } \mu^* \in \mathbb{R}$$

$\equiv \textcircled{1} \ \& \ \textcircled{2}$

Remarks: 極大 or 極小要看 SOC (在 19.3), Thm 的證明在 19.6.

EX: 消費者問題: $\boxed{\begin{array}{l} \text{Max } f(x_1, x_2) = x_1 x_2 \\ x_1, x_2 \\ \text{s.t. } p_1 x_1 + p_2 x_2 = I \end{array}} \equiv x_1 + 4x_2 = 16$

(Sol) $\nabla h(x) = \begin{pmatrix} 1 \\ 4 \end{pmatrix} \neq 0$ at all x . \Rightarrow CQ satisfied.

$$\mathcal{L}(x_1, x_2, \mu) = x_1 x_2 - \mu [x_1 + 4x_2 - 16]$$

$$\text{FOC: } \begin{cases} \frac{\partial \mathcal{L}}{\partial x_1} = x_2 - \mu = 0 & \Rightarrow \mu = x_2 = \frac{1}{4} x_1 \\ \frac{\partial \mathcal{L}}{\partial x_2} = x_1 - 4\mu = 0 & \text{wavy line} \\ \frac{\partial \mathcal{L}}{\partial \mu} = -x_1 - 4x_2 + 16 = 0 & \Rightarrow x_1 + 4\left(\frac{1}{4} x_1\right) - 16 = 2x_1 - 16 = 0 \Rightarrow \begin{cases} x_1 = 8 \\ x_2 = 2 = \mu \end{cases} \end{cases} \quad (\text{唯一可能})$$

EX: ~~消費者問題~~: $\text{Max } f(x_1, x_2) = x_1^2 x_2$

$$x_1, x_2 \text{ s.t. } (x_1, x_2) \in C^h = \{(x_1, x_2) \mid 2x_1^2 + x_2^2 = 3\}$$

(Sol) $\frac{\partial h}{\partial x_1} = 4x_1, \frac{\partial h}{\partial x_2} = 2x_2 \Rightarrow CQ$ satisfied for all $(x_1, x_2) \neq (0, 0)$

$$\mathcal{L}(x_1, x_2, \mu) = x_1^2 x_2 - \mu [2x_1^2 + x_2^2 - 3]$$

$$\text{FOC: } \begin{cases} \frac{\partial \mathcal{L}}{\partial x_1} = 2x_1 x_2 - 4\mu x_1 = 0 = 2x_1(x_2 - 2\mu) \Rightarrow x_1 = 0 \text{ or } x_2 = 2\mu \\ \frac{\partial \mathcal{L}}{\partial x_2} = x_1^2 - 2\mu x_2 = 0 \Rightarrow x_1^2 = 2\mu x_2 \\ \frac{\partial \mathcal{L}}{\partial \mu} = -2x_1^2 - x_2^2 + 3 = 0 \Rightarrow 2x_1^2 + x_2^2 = 3 \end{cases}$$

(i) $x_1 \neq 0$: $x_2 = 2\mu, x_1^2 = (2\mu)^2 = x_2^2 \Rightarrow 3x_1^2 = 3$ or $x_1 = \pm 1, x_2 = \pm 1$

$$\Rightarrow (1, 1, 0.5), (-1, 1, 0.5), (1, -1, -0.5), (-1, -1, -0.5)$$

(ii) $x_1 = 0$: $\Rightarrow x_2^2 = 3 \Rightarrow x_2 = \pm\sqrt{3}, \mu = \frac{x_1^2}{2x_2} = 0 \Rightarrow (0, \pm\sqrt{3}, 0)$

$$f(\underline{1, 1}) = f(\underline{-1, 1}) = 1 > f(0, \pm\sqrt{3}) = 0 > f(1, -1) = f(-1, -1) = -1 \Rightarrow \underline{(\pm 1, 1)}$$

小結: 如何解 Constrained Optimization (兩變數, 一個限制等式)

1. 先檢查 CQ: $\frac{\partial h}{\partial x_1} = 0$ & $\frac{\partial h}{\partial x_2} = 0$ 為 critical point.

如果有, 則列入可能的候選人.

2. CQ ok, 則列式 \mathcal{L}

用 FOC 指出所有可能是 optimal 的 critical point

3. 比較所有候選人那一個讓 $f(x^*)$ 最大(最小).

Exercise: 用 Thm 18.2 證明算幾不等式:

(1) Maximize $x^2 y^2 z^2$ subject to $x^2 + y^2 + z^2 = c^2$, c is constant.

What is this maximum value?

(2) Show that $x^2 y^2 z^2 \leq \left[\frac{1}{3}(x^2 + y^2 + z^2) \right]^3$, or $\sqrt[3]{x^2 y^2 z^2} \leq \frac{x^2 + y^2 + z^2}{3}$.

(3) Extend your results to any $n \in \mathbb{N}$:

$$(x_1^2 \cdot x_2^2 \cdots x_n^2)^{\frac{1}{n}} \leq \frac{1}{n} [x_1^2 + x_2^2 + \cdots + x_n^2]$$

with equality iff $x_1^2 = x_2^2 = \cdots = x_n^2$.

Several Equality Constraints:

Max $f(x_1, \dots, x_n)$

s.t. $C_h = \{x = (x_1, \dots, x_n) \mid \underline{h_1(x) = a_1}, \underline{h_2(x) = a_2}, \dots, \underline{h_m(x) = a_m}\}$

How can we extend CQ in the simple case? $\left(\frac{\partial h}{\partial x_1}, \frac{\partial h}{\partial x_2} \right) \neq (0, 0)$

Consider Jacobian $Dh(\hat{x}) = \begin{pmatrix} \frac{\partial h_1}{\partial x_1}(\hat{x}) & \dots & \frac{\partial h_1}{\partial x_n}(\hat{x}) \\ \frac{\partial h_2}{\partial x_1}(\hat{x}) & \dots & \frac{\partial h_2}{\partial x_n}(\hat{x}) \\ \vdots & & \vdots \\ \frac{\partial h_m}{\partial x_1}(\hat{x}) & \dots & \frac{\partial h_m}{\partial x_n}(\hat{x}) \end{pmatrix} = \begin{pmatrix} Dh_1 \\ Dh_2 \\ \vdots \\ Dh_m \end{pmatrix}$

$\Rightarrow x$ is a **critical point** if $\text{rank}(Dh(\hat{x})) < m$.

$h = (h_1, \dots, h_m)$ satisfies **NDCQ** (Non-Degenerate Constraint Qualification) at \hat{x} if $\text{rank}(Dh(\hat{x})) = m$.

i.e. Vectors $\frac{\partial h_1}{\partial x}, \frac{\partial h_2}{\partial x}, \dots, \frac{\partial h_m}{\partial x}$ are linearly independent
 $\parallel Dh_1, Dh_2, \dots, Dh_m = \left(\frac{\partial h_m}{\partial x_1}, \dots, \frac{\partial h_m}{\partial x_n} \right)$

s.t. $H = \{v = a_1(Dh_1) + a_2(Dh_2) + \dots + a_m(Dh_m) : a_i \in \mathbb{R}\}$ has dimension = m .

Linear dependence vs. Linear independence:

Vectors $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_m \in \mathbb{R}^n$ are linearly dependent if

$$\exists a_1, \dots, a_m \in \mathbb{R} \text{ such that } a_1 \vec{v}_1 + a_2 \vec{v}_2 + \dots + a_m \vec{v}_m = \vec{0}$$

If no such a_i exists, $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ are linearly independent.

\Rightarrow If $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ are linearly independent, the space it spans

$$H = \{v = a_1 \vec{v}_1 + a_2 \vec{v}_2 + \dots + a_m \vec{v}_m : a_1, \dots, a_m \in \mathbb{R}\} \text{ has dimension} = m.$$

$h = (h_1, \dots, h_m)$ satisfies **NDCQ** (Non-Degenerate Constraint Qualification) at \hat{x} if $\text{rank}(Dh(\hat{x})) = m$ (or Dh_1, \dots, Dh_m are linearly independent). Then, we have

Thm 18.2 Let $f, h_1, \dots, h_m \in C^1$, consider

$$\text{Max } f(x_1, \dots, x_n)$$

$$\text{s.t. } C_h = \{x = (x_1, \dots, x_n) \mid h_1(x) = a_1, h_2(x) = a_2, \dots, h_m(x) = a_m\}$$

Suppose $x^* = (x_1^*, \dots, x_n^*) \in C_h$ and satisfies NDCQ.

If x^* is a (local) max or min of f on C_h , then there exists

$\mu^* = (\mu_1^*, \dots, \mu_m^*)$ such that (x^*, μ^*) is a critical point of

$$\mathcal{L}(x, \mu) = f(x) - \mu_1 [h_1(x) - a_1] - \mu_2 [h_2(x) - a_2] - \dots - \mu_m [h_m(x) - a_m]$$

$$\text{i.e. } \frac{\partial \mathcal{L}}{\partial x_i}(x^*, \mu^*) = 0, \dots, \frac{\partial \mathcal{L}}{\partial x_n}(x^*, \mu^*) = 0; \quad \frac{\partial \mathcal{L}}{\partial \mu_1}(x^*, \mu^*) = 0, \dots, \frac{\partial \mathcal{L}}{\partial \mu_m}(x^*, \mu^*) = 0$$

Example (18.6):

$$\text{Max } xyz$$

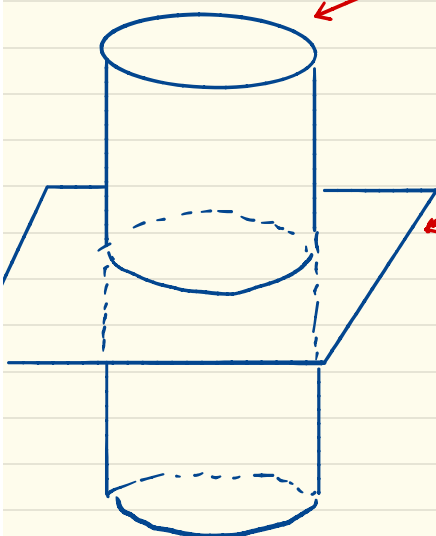
$$\text{s.t. } h_1(x, y, z) = x^2 + y^2 = 1$$

$$h_2(x, y, z) = x + z = 1$$

$$\Rightarrow Dh(x, y, z) = \begin{pmatrix} 2x & 2y & 0 \\ 1 & 0 & 1 \end{pmatrix}$$

$$\Rightarrow \text{rank} = 2 \text{ unless } x=y=0 \text{ (But this violates } h_1)$$

$$\therefore \text{NDCQ satisfied for all } (x, y, z) \in C_h$$



$$\mathcal{L} = xyz - \mu_1(x^2 + y^2 - 1) - \mu_2(x + y - 1)$$

$$\text{FOC: } \frac{\partial \mathcal{L}}{\partial x} = yz - 2\mu_1 x - \mu_2 = 0$$

$$\frac{\partial \mathcal{L}}{\partial y} = xz - 2\mu_1 y = 0 \Rightarrow \mu_1 = \frac{xz}{2y}$$

$$\frac{\partial \mathcal{L}}{\partial z} = xy - \mu_2 = 0 \Rightarrow \mu_2 = xy$$

$$\frac{\partial \mathcal{L}}{\partial \mu_1} = x^2 + y^2 - 1 = 0 \Rightarrow y^2 = 1 - x^2$$

$$\frac{\partial \mathcal{L}}{\partial \mu_2} = x + y - 1 = 0 \Rightarrow y = 1 - x$$

$$\Rightarrow yz - \frac{xz}{y} = xy \Rightarrow \underline{(y^2 - x^2)z = xy^2}$$

$$(1 - 2x^2)(1 - x) = x(1 - x^2)$$

$$\Rightarrow 1 - x = 0 \text{ or } 1 - 2x^2 = x + x^2 \Rightarrow 3x^2 + x - 1 = 0$$

$$\Rightarrow x^* = \frac{1}{6}(-1 \pm \sqrt{13}) \approx \begin{cases} +0.4343 \\ -0.7676 \end{cases}, y^* = 1 - x^2 = \begin{cases} \pm 0.9008 \\ \pm 0.6409 \end{cases}, z^* = 1 - x^* = \begin{cases} 0.5657 \\ 1.7676 \end{cases}$$

Check to see xyz maximized at $x^* = -0.7676, y^* = -0.6409, z^* = 1.7676$

Inequality Constraints: $g(x_1, x_2) \leq b$

消費者問題:

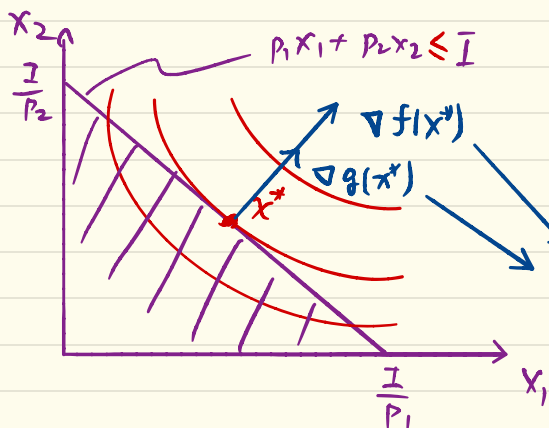
$$\begin{cases} \text{Max } f(x_1, x_2) \\ x_1, x_2 \text{ s.t. } p_1 x_1 + p_2 x_2 \leq I \end{cases}$$

兩變數、一條限制不等式。

($x_1 \geq 0, x_2 \geq 0$ 先忽略)

$$g(x_1, x_2) = p_1 x_1 + p_2 x_2 \leq I = b$$

圖形解法:



$$\begin{cases} g \\ b \text{ for inequality,} \\ \lambda \end{cases} \begin{cases} h \\ c \text{ for equality} \\ m \end{cases}$$

$$\nabla f(x^*) = \lambda \nabla g(x^*) \text{ if binding ("=")}$$

而且 $\lambda \geq 0$, 因為 $\nabla f(x^*)$ 指向 f 增加最大的方向, 如果指向 $g(x^*) \leq b$ (即 $\lambda < 0$) 則可

往該方向移動、增加 $f(x_1, x_2)$ 但又保持 $g(x_1, x_2) \leq b$, 跟 x^* 是 Max 矛盾!

因此設 $\mathcal{L}(x_1, x_2, \mu) = f(x_1, x_2) - \lambda [g(x_1, x_2) - b]$ (而且仍要符合 CQ)

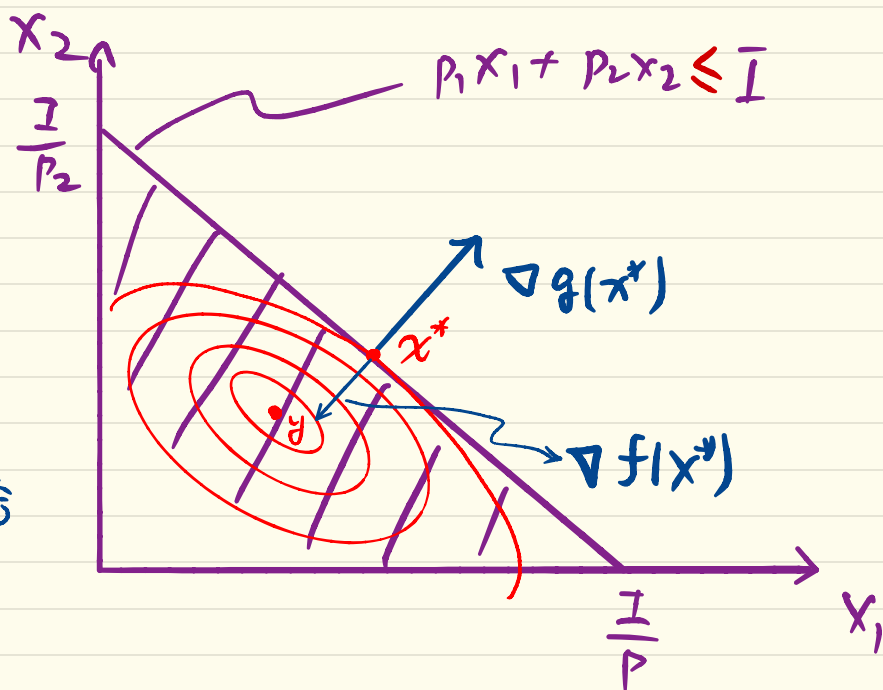
$$\text{FOC: } \frac{\partial \mathcal{L}}{\partial x_1} = \frac{\partial f}{\partial x_1}(x^*) - \lambda \frac{\partial g}{\partial x_1}(x^*) = 0, \quad \frac{\partial \mathcal{L}}{\partial x_2} = \frac{\partial f}{\partial x_2}(x^*) - \lambda \frac{\partial g}{\partial x_2}(x^*) = 0$$

但是等一下: 如果 constraint not binding 怎麼辦??

圖形解法:

若 y 才是 Max, 則 constraint 是 not binding (" $<$ "), 表示 y 也是 local (unconstraint) max.

(的確, $\nabla f(x^*)$ 指向 $g(x_1, x_2) \leq b$, 故可往該方向增加 f , 但又符合 $g(x_1, x_2) \leq b$.)



若 y 才是 Max, 則 constraint 是 not binding (" $<$ "), 表示 y 也是 local max.

因此設 $\mathcal{L}(x_1, x_2, \mu) = f(x_1, x_2) - \lambda [g(x_1, x_2) - b]$ 亦可, 只要 $\lambda = 0$!!

$$\text{FOC: } \begin{cases} \frac{\partial \mathcal{L}}{\partial x_1} = \frac{\partial f}{\partial x_1}(x^*) - \lambda \frac{\partial g}{\partial x_1}(x^*) = 0 \\ \frac{\partial \mathcal{L}}{\partial x_2} = \frac{\partial f}{\partial x_2}(x^*) - \lambda \frac{\partial g}{\partial x_2}(x^*) = 0 \end{cases} \quad \text{即 } \begin{cases} \frac{\partial f}{\partial x_1} = 0 \\ \frac{\partial f}{\partial x_2} = 0 \end{cases}$$

也就是說, 我們需要 $\lambda \cdot [g(x_1, x_2) - b] = 0$
(即 $\lambda = 0$ or $g(x_1, x_2) - b = 0$)

因此設 $\mathcal{L}(x_1, x_2, \mu) = f(x_1, x_2) - \lambda [g(x_1, x_2) - b]$, 則:

$$\text{FOC: } \frac{\partial \mathcal{L}}{\partial x_1} = \frac{\partial f}{\partial x_1}(x^*) - \lambda \frac{\partial g}{\partial x_1}(x^*) = 0 \quad \text{--- (1)} \quad \lambda \cdot [g(x_1, x_2) - b] = 0 \quad \text{--- (2)}$$

$$\frac{\partial \mathcal{L}}{\partial x_2} = \frac{\partial f}{\partial x_2}(x^*) - \lambda \frac{\partial g}{\partial x_2}(x^*) = 0 \quad \text{--- (3)}$$

故, 我們有下面這個定理:

Thm 18.3 Let f, g be C^1 functions of two variables.

Suppose $x^* = (x_1^*, x_2^*)$ is a solution of the problem

$$\text{Max}_{x_1, x_2} \left\{ f(x_1, x_2) \mid g(x_1, x_2) \leq b \right\}.$$

If $g(x^*) = b$, then x^* is not a critical point of g .

$$\text{(i.e. } \frac{\partial g}{\partial x_1}(x^*) \neq 0 \text{ or } \frac{\partial g}{\partial x_2}(x^*) \neq 0)$$

Then for $\mathcal{L}(x_1, x_2, \mu) \equiv f(x_1, x_2) - \lambda [g(x_1, x_2) - b]$

$$\exists \lambda^* \in \mathbb{R} \text{ s.t. } \overset{(a)}{\frac{\partial \mathcal{L}}{\partial x_1}} = 0, \overset{(b)}{\frac{\partial \mathcal{L}}{\partial x_2}} = 0 \text{ at } (x_1^*, x_2^*, \mu^*)$$

$$\text{and } \overset{(c)}{\lambda^* \cdot [g(x^*) - b]} = 0$$

$$\overset{(d)}{\lambda^*} \geq 0$$

$$\overset{(e)}{\frac{\partial \mathcal{L}}{\partial \lambda}} = g(x^*) - b \leq 0$$

Remark: 比較 Thm 18.1 (" $=$ ") 和 Thm 18.3 (" \leq "):

1. 兩者都要求 $\frac{\partial \mathcal{L}}{\partial x_1} = 0, \frac{\partial \mathcal{L}}{\partial x_2} = 0$

2. $\frac{\partial \mathcal{L}}{\partial \mu} = h(x^*) - c = 0 \rightarrow \frac{\partial \mathcal{L}}{\partial \lambda} = g(x^*) - b \leq 0 \ \& \ \lambda [g(x^*) - b] = 0$

3. CQ \rightarrow 當 constraint bind 時才要求 CQ.

4. $\mu^* \in \mathbb{R} \rightarrow \lambda^* \geq 0$

5. min 做法 $\bar{\cup}$ max $\rightarrow \lambda^* \geq 0$ for max, $\lambda^* \leq 0$ for min
(見 18.5)

但其實 $\lambda \cdot [g(x^*) - b] = 0$ 可被看作

If $\lambda > 0$, then $g(x^*) = b$ (binding). 而簡化為 equality 條件

Example: $\text{Max } U(x_1, x_2)$ (Assume $U(x_1, x_2) \in C^1$)
s.t. $p_1 x_1 + p_2 x_2 \leq I$ $\left(\frac{\partial U}{\partial x_1} > 0, \frac{\partial U}{\partial x_2} > 0 \right)$

$$\mathcal{L} = U(x_1, x_2) - \lambda [p_1 x_1 + p_2 x_2 - I], \text{ CQ ok.}$$

$$\text{FOC: } \frac{\partial U}{\partial x_1} - \lambda p_1 = 0 \Rightarrow \lambda = \frac{\frac{\partial U}{\partial x_1}}{p_1} > 0 \therefore p_1 x_1 + p_2 x_2 - I = 0$$

$$\frac{\partial U}{\partial x_2} - \lambda p_2 = 0$$

(equality case!!)

$$\lambda \cdot [p_1 x_1 + p_2 x_2 - I] = 0$$