

Lecture 7-10

Nonlinear Programming . (inequality constraints)

$$\max f(x, y) \quad \text{s.t. } g(x, y) \leq c$$

The Kuhn-Tucker method.

- The Kuhn-Tucker conditions. If I have $g(x, y) > c$
Then $L = \dots - \lambda(c - g(x, y))$
- i) $L(x, y) = f(x, y) - \lambda [g(x, y) - c]$ ≤ 0
 - ii) $L'_1(x, y) = f'_1(x, y) - \lambda g'_1(x, y) = 0$
 - iii) $L'_2(x, y) = f'_2(x, y) - \lambda g'_2(x, y) = 0$
 - iv) $\lambda \geq 0$, with $\lambda = 0$ if $g(x, y) < c$
or $\lambda > 0$ and $\lambda(g(x, y) - c) = 0 \Rightarrow$ complementary slackness condition.
 - v) $g(x, y) \leq c$

The points (x, y) , with associated λ , that solve ii), iii) and iv), are our solution candidates.

Ex: $\max x^2 + y^2 \quad \text{s.t. } (x-3)^2 + (y-2)^2 \leq 9$

i) $L = x^2 + y^2 - \lambda [(x-3)^2 + (y-2)^2 - 9]$

ii) $L'_1 = 2x - 2\lambda(x-3) = 0 \quad (1)$

$L'_2 = 2y - 2\lambda(y-2) = 0 \quad (2)$

iii) $\lambda \geq 0, \lambda[(x-3)^2 + (y-2)^2 - 9] = 0. \quad (3)$

iv) $(x-3)^2 + (y-2)^2 \leq 9 \quad (4)$.

~~start~~ start with (3).

case $\lambda = 0 \Rightarrow$ in (1) $2x = 0 \Rightarrow x = 0$

in (2) $y = 0$.

sub. $x=y=0$ into (4) $\Rightarrow 9+4 > 9 \Rightarrow$ not a solution.

case $\lambda > 0 \Rightarrow (x-3)^2 + (y-2)^2 = 9 \quad (5)$

$$\text{Now look at } ① \quad 2x = 2\lambda(x-3)$$

$$② \quad 2y = 2\lambda(y-2)$$

want to divide ① by ② to cancel λ . need $y \neq 0$, $y-2 \neq 0$.

check : if $y=0 \xrightarrow{②} 0 = -4\lambda \xrightarrow[\neq 0]{>0} \text{contradiction}$.

$\therefore \cancel{y-2} = 0 \Rightarrow \cancel{4} = 2\lambda \cdot 0 = 0 \Rightarrow \text{contradiction.}$

$$\text{Divide ① by ② : } \frac{x}{y} = \frac{x-3}{y-2}$$

$$\Rightarrow x(y-2) = (x-3)y.$$

$$\Rightarrow xy - 2x = xy - 3y$$

$$\Rightarrow 3y = 2x \Rightarrow y = \frac{2}{3}x \dots ⑥$$

$$\text{sub. ⑥ into ⑤ : } (x-3)^2 - \left(\frac{2}{3}x - 2\right)^2 = 9.$$

Sufficient conditions (for the Kuhn-Tucker)

suppose you have a constrained optimization problem with inequality constraints,

maximization

Then suppose (x_0, y_0) is the solution candidate given by the Kuhn-Tucker method.

~~write~~ with the Lagrangian:

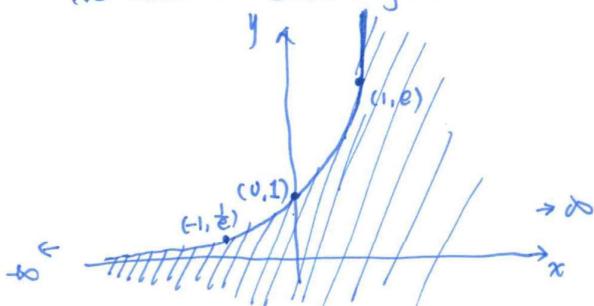
$$L(x, y) = f(x, y) - \lambda g(x, y) - c$$

If the Lagrangian is concave, then (x_0, y_0) is the max.

Ex: $\max 1-x^2$ s.t. $y-e^x \leq 0$

(a) sketch the domain.

We want to sketch $y \leq e^x \Rightarrow$ sketch $y=e^x$



(b) write down the K-T conditions.

i) $L(x, y) = 1-x^2 - \lambda(y-e^x)$

ii) $\begin{cases} L'_x = -2x + \lambda e^x = 0 \\ L'_y = -\lambda = 0 \end{cases}$

iii) $\lambda \geq 0, \lambda(y-e^x) = 0$

iv) $y \leq e^x$

} K-T conditions.

(c) find the points that satisfy K-T.

standard: ~~Discuss~~ $\lambda > 0$
 $\lambda = 0$

This is not necessary here
since we have $\lambda = 0$ from ii)
which give us $x=0, y \leq e^x$.

or Discuss $y \leq e^x$:

$$y < e^x$$

$$y = e^x$$

From ii) : $\lambda = 0 \Rightarrow x = 0 \Rightarrow y \leq e^0 = 1$.

Then (0, t) are solution candidates with $\lambda = 0, t \leq 1$

(d). Find the solution if it exists.

Method 1: evaluating the objective function at all the candidates, then compare them. But you need to prove that max exists.

Try extreme value theorem: our domain is not bounded, which means that the extreme value theorem does not guarantee a max.
⇒ can not use this method here.

Method 2:

The sufficient conditions.

$$L = 1-x^2 - \lambda(y-e^x)$$

Plug in $\lambda=0$ ⇒ $L = 1-x^2$ which is concave in (x,y) .

so our solution candidates solve the problem.

$$\begin{aligned} L_{xx} &= -2 < 0 \\ L_{yy} &= 0 \leq 0 \end{aligned}$$



Multiple Inequality Constraints

several variables/ constraints.

- One multiplier for each constraint.
- Complementary slackness for each multiplier / constraint.

$$\max f(x_1, x_2, \dots, x_n) \text{ s.t. } \begin{cases} g_1(x_1, \dots, x_n) \leq c_1 \\ \vdots \\ g_m(x_1, \dots, x_n) \leq c_m. \end{cases}$$

(i) ~~L~~ $L = f(x_1, \dots, x_n) - \sum_{j=1}^m \lambda_j (g_j - c_j)$

(ii) $L'_x = 0 \quad \text{for } i = 1, \dots, n$

(iii) $\lambda_j \geq 0$, with $\lambda_j = 0$ if $g_j(\vec{x}) < c_j$ for all j
or $\lambda_j (g_j(\vec{x}) - c_j) = 0$

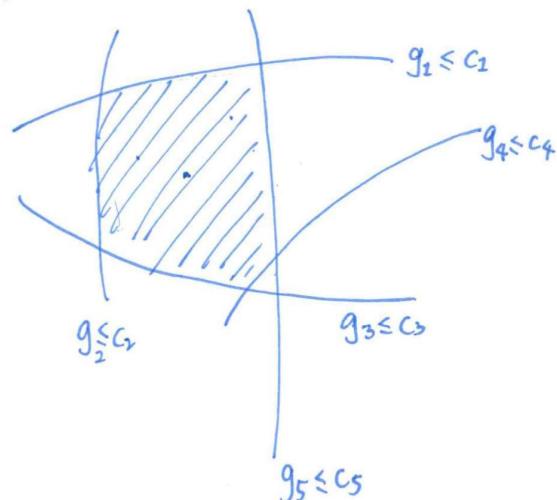
(iv) $g_j(\vec{x}) \leq c_j$ for all j .

Sufficient conditions: L concave after plugging in all the λ_j .

Note: If I want to make a Lagrange problem with 2 constraints, I would need at least 3 variables.

But for k-T problem, I could have any amount of constraints in two variable.

Multi-constraints sketch



The possible points of solution, are:

- Interior point, \Rightarrow no constraints bind
 - on one of the five curve segments.
 \Rightarrow one constraint binds, 4 not bind.
 - on one of the five intersection points between two of the five curves.
 \Rightarrow two constraints bind, 3 not bind.
- \Rightarrow only need to discuss 11 cases, \Rightarrow better than 32 cases

Terminology: "active" / "binding" constraint: one that holds with " $=$ "

often a good idea to discuss λ :

$$\lambda > 0 \quad \text{or} \quad \lambda = 0 \quad \text{for each } \lambda.$$

\downarrow binding constraint. \downarrow possibly binding

or we discuss the case where the constraint is

"binding" or "not binding"

$$\cancel{g(x) \leq c} \quad g(x) < c$$

Looking at the sketch: we have five constraints \Rightarrow 5 complementary slackness

For each constraint, we have 2 cases.

Then for 5 constraints $\Rightarrow 2^5 = 32$ cases. \Rightarrow too many.

For multiple constraints, it's often easier to look at the graph.

$$\text{Ex: } \max \frac{1}{2}(x^2 + y^2) \quad \text{s.t. } y \leq 1 - \alpha(x-1)$$

$$x \geq 0$$

$$y \geq 0$$

With $\alpha > 0$.

Q: Find all points that satisfy K-T.

$$(1) L = \frac{1}{2}(x^2 + y^2) - \lambda_1[y + \alpha(x-1) - 1] - \lambda_2(-x) - \lambda_3(-y)$$

$$(1) L_x = x - \alpha\lambda_1 + \lambda_2 = 0 \quad \dots \quad (1)$$

$$L_y = y - \lambda_1 + \lambda_3 = 0 \quad \dots \quad (2)$$

$$(ii) \lambda_1 \geq 0, \lambda_1(y + a(x-1) - 1) = 0 \dots (3)$$

$$\lambda_2 \geq 0, \lambda_2(-x) = 0 \dots (4)$$

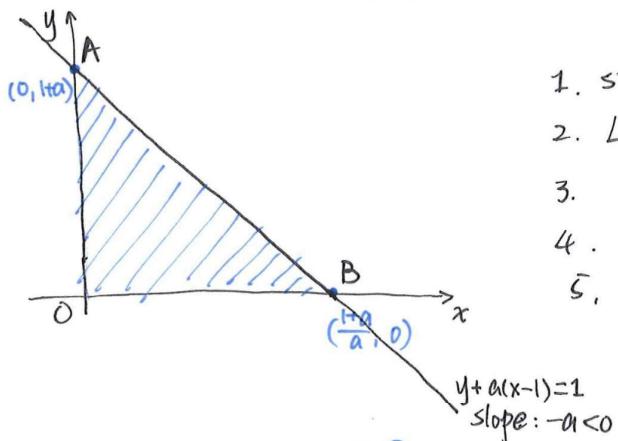
$$\lambda_3 \geq 0, \lambda_3(-y) = 0 \dots (5)$$

$$(iv) y + a(x-1) \leq 1 \dots (6)$$

$$-x \leq 0 \dots (7)$$

$$-y \leq 0 \dots (8)$$

Easier to look at the graph first.



Possible cases that satisfy $\lambda_i \geq 0$

1. stationary point ~~not~~ within the area AOB .
2. Line segment OB , not including point O, B
3. $\sim OA$, $\sim OB, A$
4. $\sim AB$, $\sim A, B$
5. The corner A
6. $\sim B$
7. $\sim O$

case 1, 7 $\lambda_1 = \lambda_2 = \lambda_3 = 0 \Rightarrow (x, y) = (0, 0)$

case 2, 6 Line OB , excl. O

$$\begin{aligned} y=0, x>0 &\xrightarrow{(4)} \lambda_2=0 \\ \xrightarrow{(2)} \lambda_1=\lambda_3 &\text{ either } \lambda_1=\lambda_3=0 \Rightarrow (x, y)=(0, 0) \\ \text{or } \lambda_1=\lambda_3>0 & \end{aligned}$$

$$\xrightarrow{(3)} y=1-a(x-1) \xrightarrow{y=0} x=\frac{1+a}{a} \Rightarrow \left(\frac{1+a}{a}, 0\right)$$

It's ok to get $(0, 0)$ here even though we excluded "point"

case 2, 6 Line OB , excl. O

$$\begin{aligned} y=0, x>0 &\xrightarrow{(4)} \lambda_2=0 \xrightarrow{(1)} x=a\lambda_1>0 \Rightarrow \lambda_1>0 \\ \xrightarrow{(2)} \lambda_1=\lambda_3 &\xrightarrow{\lambda_1=\lambda_3>0} \xrightarrow{(3)} y=1-a(x-1) \xrightarrow{y=0} x=\frac{1+a}{a} \Rightarrow \left(\frac{1+a}{a}, 0\right) \end{aligned}$$

case 3, 5 Line OA , excl. O

$$x=0, y>0 \xrightarrow{(5)} \lambda_3=0 \xrightarrow{(2)} y=\lambda_1>0$$

$$\xrightarrow{(1)} a\lambda_1=\lambda_2 \xrightarrow{a\lambda_1=\lambda_2>0} \xrightarrow{(3)} y+ a(x-1)=1 \xrightarrow{x=0} y=1+a \Rightarrow (0, 1+a)$$

case 4. Line AB, excl. A.B

$$x>0, y>0 \xrightarrow{④⑤} \lambda_2 = \lambda_3 = 0$$

$$\begin{aligned} \text{From } ① \quad &x = a\lambda_1 \\ ② \quad &y = \lambda_1 \end{aligned} \quad \left. \begin{aligned} x = ay \\ x = a\lambda_1 \end{aligned} \right\}$$

$$\begin{aligned} \text{We are on line AB} \Rightarrow y + a(x-1) - 1 = 0 &\xrightarrow{y=\frac{x}{a}} \frac{x}{a} + a(x-1) - 1 = 0 \\ &\Rightarrow x = \frac{a+a^2}{1+a^2} \Rightarrow y = \frac{1+a}{1+a^2} \\ \Rightarrow (x, y) = \left(\frac{a+a^2}{1+a^2}, \frac{1+a}{1+a^2} \right) \end{aligned}$$

Connection between λ and binding constraint.

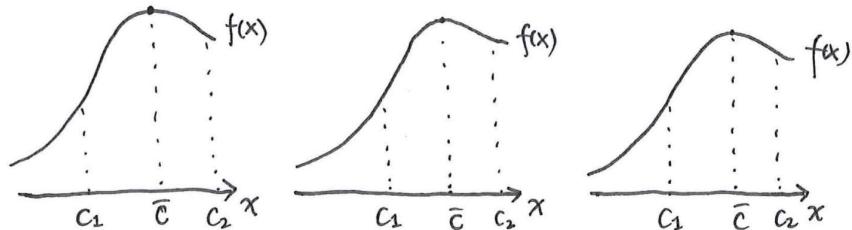
When we assume $\lambda=0$, we are testing the case where the corresponding constraint is " $g \leq c$ "

... assume $\lambda > 0$, " $g = c$ "

► In other words. $\lambda > 0 \Rightarrow g = c$

$\cancel{\lambda=0} \Rightarrow g=c \text{ or } g < c$

why?



$\max f(x)$. s.t. $x \leq c$

$$c = c_1$$

$$x^* = c_1$$

$$f(x^*) = f^*(c_1)$$

$$\lambda > 0$$

$$\lambda > 0 \Rightarrow g < c$$

$$c = c_2$$

$$x^* = \bar{x}$$

$$\lambda = 0$$

$$g < c$$

$$\lambda > 0$$

$$g = c$$

$$c = \bar{x}$$

$$x^* = \bar{x}$$

$$\lambda = 0$$

$$g = c$$

$$\lambda > 0 \text{ could imply } g < c, \text{ or } g = c$$

Envelope theorem

variable
 \uparrow parameter
 $\max_x f(x, \vec{r})$ for different r , we get different x^*

Let x^* be the solution, easy to see that $x^* = x^*(r)$

Then we have the value function:

$$f^*(r) = f(x^*(r), r)$$

$$\frac{df^*(r)}{dr} = \underbrace{f'_1(\cancel{x^*(r)}, r)}_{=0} \frac{dx^*(r)}{dr} + f'_2(x^*(r), r)$$

because x^* max ~~f(x, r)~~ $\Rightarrow f'_1(x^*, r) = 0$.

$$\Rightarrow \frac{df^*(r)}{dr} = f'_2(x^*(r), r)$$

- It only works on the value function / optimized objective function

Ex: $\max_x \pi(x, r) = rx - x^2$

FOC: $r - 2x = 0 \Rightarrow x = \frac{r}{2}$

~~2nd~~-derivative: $-2 < 0 \Rightarrow$ ~~strict~~ π is strictly concave $\Rightarrow x^* = \frac{r}{2}$ is global max

Then $\pi(x^*(r), r) = r \cdot \frac{r}{2} - \frac{r^2}{4} = \frac{1}{4}r^2 = \pi^*(r)$

$$\frac{d\pi^*(r)}{dr} = \frac{r}{2}$$

Envelope theorem: $\pi(x^*(r), r) = rx^* - (x^*)^2 = \pi^*(r)$

$$\frac{d\pi(r)}{dr} = \cancel{\pi'_1(x^*(r), r)} = x^*.$$

Multivariable-Envelope theorem

Let $\vec{x} = (x_1, x_2, \dots, x_n)$ n variables

$\vec{r} = (r_1, r_2, \dots, r_m)$ m parameters.

~~f~~ want to $\max_{\vec{x}} f(\vec{x}, \vec{r})$

Let $\vec{x}^*(\vec{r})$ be the value of \vec{x} that maximizes $f(\vec{x}, \vec{r})$

easy to see that $\vec{x}^* = \vec{x}^*(\vec{r})$, $f(\vec{x}^*(\vec{r}), \vec{r}) = f^*(\vec{r})$

Then $\frac{\partial f^*(\vec{r})}{\partial r_j} = \frac{\partial f(\vec{x}^*(\vec{r}), \vec{r})}{\partial r_j}$

provided that the partial derivatives exist.

constrained - envelope.

$$\max(\min) f(x, y) \text{ s.t. } g(x, y) = c$$

Let x^*, y^* be the solution candidates with corresponding $\lambda(c)$

$$f^*(c) = f(x^*(c), y^*(c))$$

$$\frac{df^*(c)}{dc} = \lambda(c)$$

$$\text{Proof}^1: \frac{df^*(c)}{dc} = \frac{\partial f(x^*, y^*)}{\partial x^*} \frac{\partial x^*(c)}{\partial c} + \frac{\partial f(x^*, y^*)}{\partial y^*} \frac{\partial y^*(c)}{\partial c}$$

recall that we get x^*, y^* by solving the Lagrange FOCs.

$$\text{s.t.: } \frac{\partial f(x^*, y^*)}{\partial x^*} - \lambda \frac{\partial g(x^*, y^*)}{\partial x^*} = 0$$

$$\frac{\partial f(x^*, y^*)}{\partial y^*} - \lambda \frac{\partial g(x^*, y^*)}{\partial y^*} = 0.$$

$$\hookrightarrow \frac{df^*(c)}{dc} = \lambda [g_1'(x^*, y^*) \frac{\partial x^*(c)}{\partial c} + g_2'(x^*, y^*) \frac{\partial y^*(c)}{\partial c}]$$

$$\text{since } g(x^*, y^*) = c \quad \begin{matrix} \text{Differentiating both sides wrt } c \\ \Rightarrow g_1'(x^*, y^*) \frac{\partial x^*(c)}{\partial c} + g_2'(x^*, y^*) \frac{\partial y^*(c)}{\partial c} = 1. \end{matrix}$$

$$\hookrightarrow \frac{df^*(c)}{dc} = \lambda$$

$$\text{Proof}^2: L(x, y, \lambda) = f(x, y) - \lambda(g(x, y) - c)$$

$$\left\{ \begin{array}{l} \cancel{\frac{\partial L}{\partial x}} = f'_1 - \lambda g'_1 = 0 \\ \cancel{\frac{\partial L}{\partial y}} = f'_2 - \lambda g'_2 = 0 \Rightarrow x^*, y^*, \lambda^*. \\ \cancel{\frac{\partial L}{\partial \lambda}} = g(x, y) - c = 0 \qquad \qquad \qquad \downarrow \\ \end{array} \right. \qquad \qquad \qquad \begin{matrix} x^*(c), y^*(c), \lambda^*(c) \end{matrix}$$

$$f^*(c) = f(x^*, y^*) = f(x^*, y^*) - \lambda^* \underbrace{(g(x^*, y^*) - c)}_{=0} = L(x^*, y^*, \lambda^*) = L^*(c)$$

$$\frac{df^*(c)}{dc} = \frac{dL^*(c)}{dc} = \cancel{\frac{\partial L(x^*, y^*, \lambda^*)}{\partial c}} = \lambda^*.$$

General case for Lagrange multiplier

Let $\vec{x} = (x_1, x_2, \dots, x_n)$, $\vec{c} = (c_1, c_2, \dots, c_m)$
 $\max(\min) f(\vec{x})$ s.t. $g_j(\vec{x}) = c_j$, $j = 1, 2, \dots, m$.

Let $\vec{x}^* = (x_1^*, x_2^*, \dots, x_n^*)$ satisfy the necessary conditions.

Assume each $x_i^*(\vec{c})$ is differentiable.

Then we have $f^*(\vec{c}) = f(\vec{x}^*(\vec{c}))$

$$\frac{\partial f^*(\vec{c})}{\partial c_j} = \lambda_j(\vec{c})$$

$$\begin{aligned} \text{sketch proof: } f^*(\vec{c}) &= L(\vec{x}^*, \vec{\lambda}^*) = L^*(\vec{c}) \\ &= f^*(\vec{x}^*) - \lambda_1^*(g_1(\vec{x}^*) - c_1) - \lambda_2^*(g_2(\vec{x}^*) - c_2) - \dots \\ &\dots - \lambda_j^*(g_j(\vec{x}^*) - c_j) - \dots - \lambda_m^*(g_m(\vec{x}^*) - c_m) \\ \frac{\partial f^*(\vec{c})}{\partial c_j} &= \frac{\partial L^*(\vec{c})}{\partial c_j} = \frac{\partial L(\vec{x}^*, \vec{\lambda}^*)}{\partial c_j} = \lambda_j^*(\vec{c}) \end{aligned}$$

Note: Without the Envelope theorem, you will have to differentiate ~~all the~~ $f(\vec{x}^*)$ wrt all the x^* 's, and all the $g_j(\vec{x}^*)$ wrt all the x^* 's, and all the $\lambda^*(\vec{c})$ wrt c_j, \dots to find $\frac{\partial f^*(\vec{c})}{\partial c_j}$. But with the envelope theorem, it's only one step.

The (General) Envelope theorem

$$\max(\min)_{\vec{x}} f(\vec{x}, \vec{r}) \text{ s.t. } g_j(\vec{x}, \vec{r}) = 0, \text{ for } j = 1, 2, \dots, m$$

$$L(\vec{x}, \vec{r}) = f(\vec{x}, \vec{r}) - \sum_{j=1}^m \lambda_j g_j(\vec{x}, \vec{r})$$

Let \vec{x}^* be the solution(candidates).

$$f^*(\vec{r}) = f(\vec{x}^*(\vec{r}), \vec{r})$$

If $f^*(\vec{r})$ and $\vec{x}^*(\vec{r})$ are differentiable.

$$\frac{\partial f^*(\vec{r})}{\partial r_h} = \frac{\partial L(\vec{x}^*(\vec{r}), \vec{r})}{\partial r_h}$$

for each $h = 1, 2, \dots, k$.

Ex: 2007 Autumn #4.

$$\max_{(x,y)} 4e^x + \frac{1}{2} Ax^2y^2 + e^{3y} \quad \text{s.t.} \quad \begin{cases} x^2 + By^2 \leq c \\ x \geq 0 \\ y \geq 0. \end{cases}$$

A, B, C are strictly positive constraints.

(a). State the k-T.

$$L = 4e^x + \frac{1}{2} Ax^2y^2 + e^{3y} - \lambda_1(x^2 + By^2 - c) - \lambda_2(-x) - \lambda_3(-y)$$

$$L'_x = 4e^x + Ax^2y^2 - 2\lambda_1x + \lambda_2 = 0 \quad \dots \quad (1)$$

$$L'_y = Ax^2y + 3e^{3y} - 2B\lambda_1y + \lambda_3 = 0 \quad \dots \quad (2)$$

$$\lambda_1 \geq 0, \quad \lambda_1(x^2 + By^2 - c) = 0 \quad \dots \quad (3)$$

$$\lambda_2 \geq 0, \quad \lambda_2(-x) = 0 \quad \dots \quad (4)$$

$$\lambda_3 \geq 0, \quad \lambda_3(-y) = 0 \quad \dots \quad (5)$$

conditions (1)-(5) are our k-T.

(b) Show that the k-T imply $x^2 + By^2 = c$ and $xy \neq 0$.

Note: Do not try to solve the problem.

$$\text{Let's assume } x^2 + By^2 < c \xrightarrow{(3)} \lambda_1 = 0 \xrightarrow{(1)} 4e^x + Ax^2y^2 + \underbrace{\lambda_2}_{>0} = 0 \quad \text{contradiction}$$

$$\text{Let's assume } x=0 \xrightarrow{(1)} 4 + \lambda_2 = 0 \Rightarrow \lambda_2 = -4 \xrightarrow{\text{contradiction}} x^2 + By^2 = c$$

$$\text{Let's assume } y=0 \xrightarrow{(2)} 3 + \lambda_3 = 0 \Rightarrow \lambda_3 = -3 \xrightarrow{\text{contradiction}} \begin{cases} x \neq 0, y \neq 0 \\ xy \neq 0 \end{cases}$$

Sth more on Envelope theorem

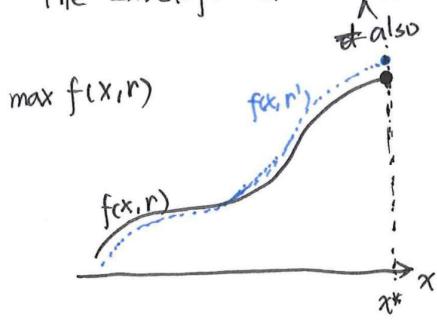
For details, see notes from before.

Now look at the sketch proof of Envelope.

$$\frac{df^*(r)}{dr} = \underbrace{\frac{\partial f(x^*(r), r)}{\partial x}}_{=0 \text{ at } x=x^*} \frac{\partial x^*(r)}{\partial r} + \frac{\partial f(x^*(r), r)}{\partial r}$$

works for all stationary points (max, min, saddle points)

The Envelope theorem works if x^* is an endpoint. (at the boundaries).



when r changes to r' . if the change is not too large, then the shape of the function curve would not change too much, and we achieve max at the same endpoint.

$$\frac{df^*(r)}{dr} = \underbrace{\frac{\partial f(x^*, r)}{\partial x}}_{>0 \text{ from the left}} \frac{\partial x^*(r)}{\partial r} + \frac{\partial f(x^*, r)}{\partial r} = 0 \text{ at the endpoint.}$$

~~Bottom line:~~ When you want to use the Envelope theorem, you don't need to check ~~the~~ whether the optimal points are interior or endpoints.

Envelope theorem holds for :

- max or min, whether interior stationary or endpoints.
- saddle points.

May fail if optimum is not unique.

Envelope in k-T

$$\max f(x, y) \quad \text{s.t. } g(x, y) \leq c$$

$$L = f(x, y) - \lambda(g(x, y) - c)$$

$$\Rightarrow (x^*, y^*) = (x^*(c), y^*(c))$$

$$\Rightarrow f^*(c) = f(x^*(c), y^*(c))$$

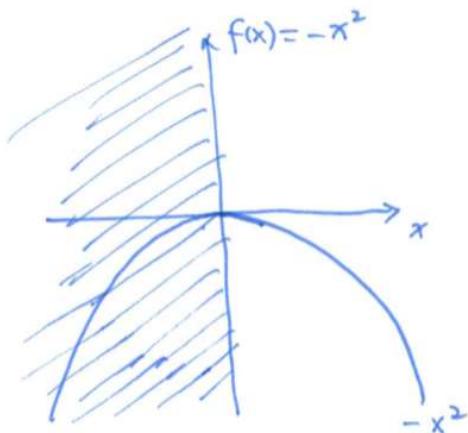
$$\frac{df^*(c)}{dc} = \frac{\partial L(x^*(c), y^*(c), \lambda^*(c))}{\partial c} = \lambda^*(c)$$

Why?

we either have $g(x^*, y^*) = c$, same as in the Lagrange problem.
or have $g(x^*, y^*) < c$, • in this case when c increases, nothing happens to x^*, y^* , and also $f(x^*, y^*)$.
 $\Rightarrow \frac{df^*(c)}{dc} = 0$.
• $\lambda = 0$ by complementary slackness.

It is possible to have both $\lambda = 0$ and $g = c$ if we let $g = c$ passes through a local maximum.

Ex: $\max (-x^2)$ s.t. $x \leq 0$.



$$\begin{aligned}f &= -x^2 \neq \lambda x \\L'_x &= -2x - \lambda = 0 \quad \dots (1) \\x &\geq 0, \lambda x = 0 \quad \dots (2)\end{aligned}$$

From (1) $\Rightarrow \lambda = -2x \xrightarrow{(2)} \cancel{\lambda = 0} \quad (-2x)x = 0$
 $\Rightarrow -2x^2 = 0 \Rightarrow x^* = 0.$
 $\lambda^* = -2x^* = 0.$

Note: Consider $\max f(x,y)$ s.t. $g(x,y) \leq c$.

for example,
if $f(x,y)$ have stationary point(s), (x_0, y_0) .

such that (x_0, y_0) lies within the set $g(x,y) \leq c$, or
(is interior)

mathematically, $g(x_0, y_0) < c$.

Then (x_0, y_0) together with $\lambda_0 = 0$ will surely satisfy the k-T.