

2 Production

N goods

1 output, $y \in \mathbb{R}_+$

$N-1$ inputs, $x \in \mathbb{R}_+^{N-1}$

$f(x)$ production function

$$f: \underbrace{\mathbb{R}_+^{N-1}}_{\text{inputs}} \rightarrow \underbrace{\mathbb{R}_+}_{\text{outputs}}$$

$$y = f(x)$$

notation in
Appendix B

What assumptions should we make about f ?

* Shutdown: $f(0) = 0$.

eg: f is the VHS production function

* Free disposal (monotonicity):

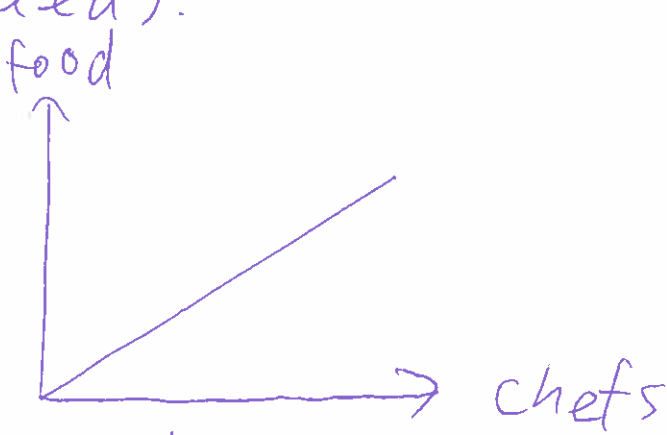
If $x \geq x'$ (i.e. $x_n \geq x'_n$ for all goods n) then $f(x) \geq f(x')$.

* Smoothness: f is twice continuously differentiable. Each partial derivative $\frac{\partial}{\partial x_i} f(x)$ is called the marginal productivity of x_i .

What assumption(s) would lead to ^(weakly) increase marginal cost?

* Decreasing marginal productivity

We say that a production function f has weakly decreasing marginal productivity in good 1 if $\frac{\partial f}{\partial x_1}(x)$ is weakly decreasing as x_1 increases (keeping x_2, \dots, x_{N-1} fixed).



* Weakly decreasing returns to scale:

For all $x \in \mathbb{R}_+^{N-1}$ and all $t > 1$, $f(tx) \leq t f(x)$. ↑ cheating!

1 big firm t small firms

* constant returns to scale:

For all $x \in \mathbb{R}_+^{N-1}$ and all $t > 0$, $f(tx) = t f(x)$.

^{weakly} * increasing returns to scale

For all $x \in \mathbb{R}_+^n$ and all $t > 1$,
 $f(tx) \geq t f(x)$.

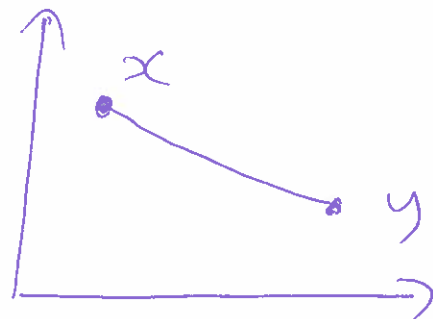
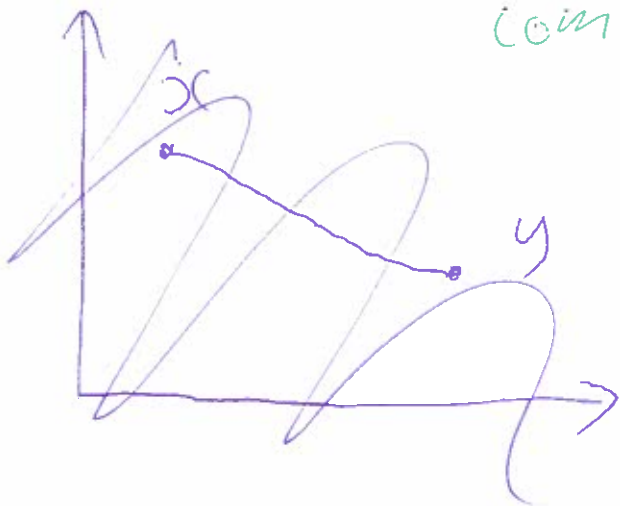
D Convex Geometry

Def A closed interval between two points $x, y \in \mathbb{R}^n$ is defined as

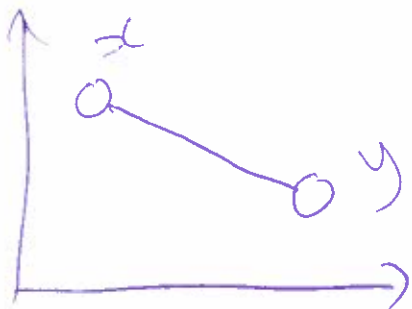
$$[x, y] = \{ \underbrace{ax + (1-a)y}_{\text{convex combination}} : \underbrace{a \in [0, 1]}_{\text{all numbers between 0 and 1 inclusive}} \}$$

convex
combination

all numbers
between 0 and
1 inclusive.



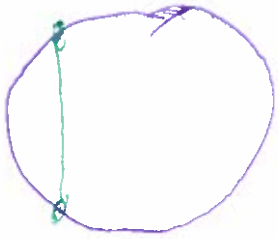
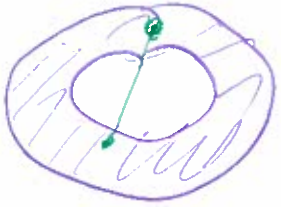
Open interval: $(x, y) = \{ ax + (1-a)y : a \in (0, 1) \}$
excludes the endpoints



$[x, y)$ and $(y, x]$ are similar.

Def ~~Let~~ Let $X \subseteq \mathbb{R}^n$. We say X is a convex set if for all $x, y \in X$, then $[x, y] \subseteq X$.

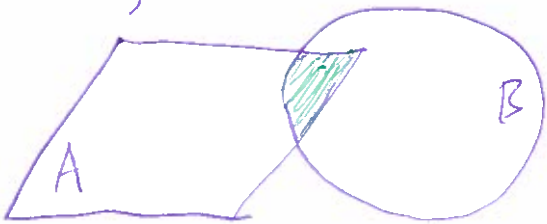
e.g. NOT convex:



e.g. are convex:



Theorem If A and B are convex sets, then $A \cap B$ is a convex set.

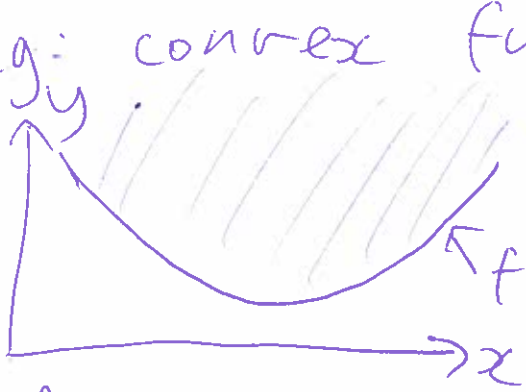


Proof: Pick any $x, y \in A \cap B$. Notice that $x, y \in A$. Since A is a convex set, $[x, y] \subseteq A$. Similarly $[x, y] \subseteq B$. Combining, we deduce that $[x, y] \subseteq A \cap B$. So $A \cap B$ is a convex set. \square

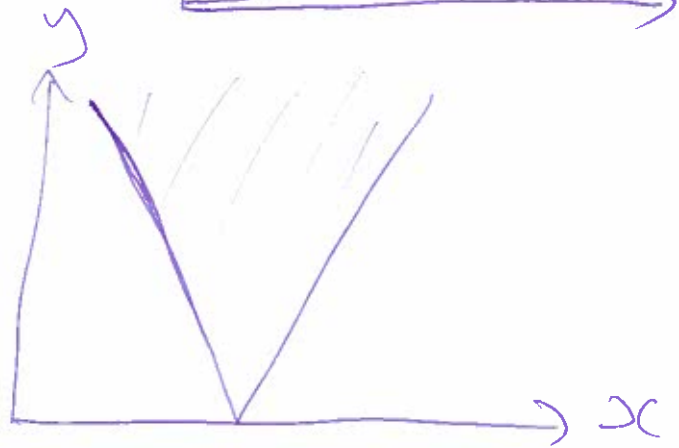
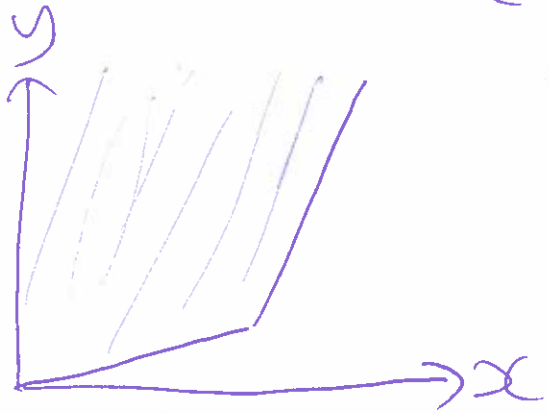
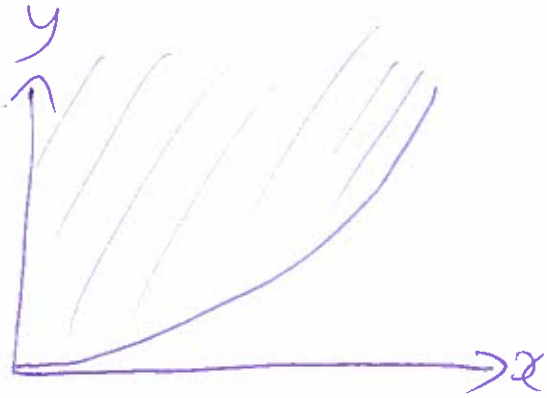
Def $f: X \rightarrow \mathbb{R}$ is a convex function if its hypergraph

$\{(x, y) : x \in X, y \geq f(x)\} = \text{hyper}(f)$
 is a convex set.

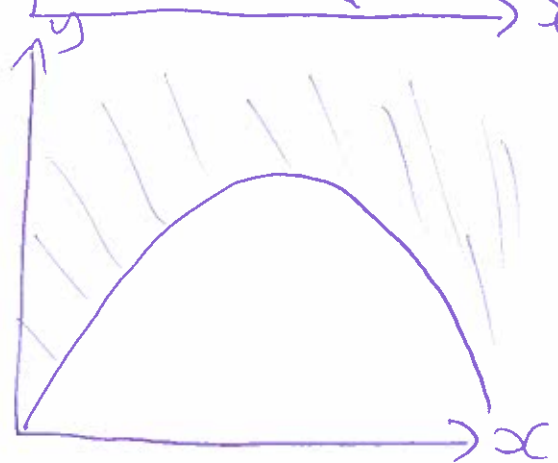
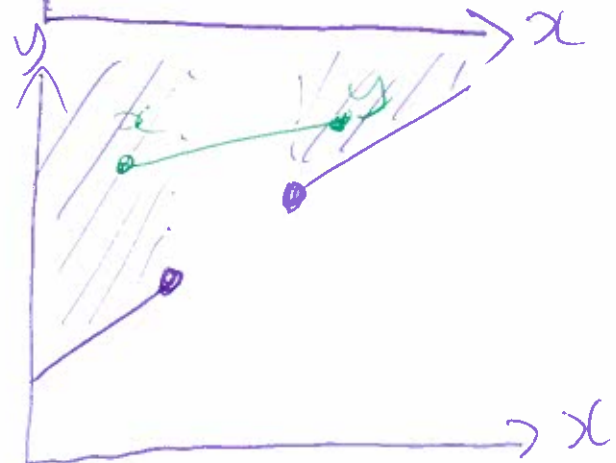
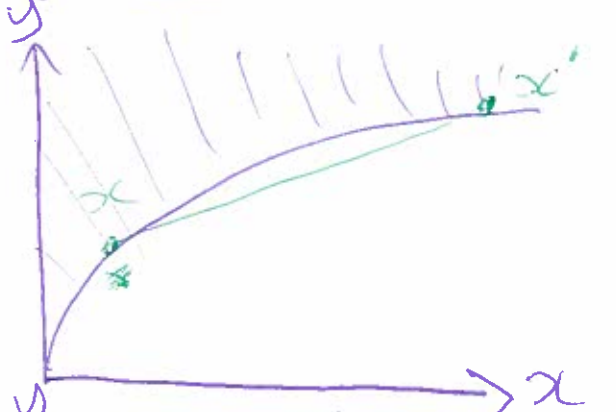
e.g. convex functions:



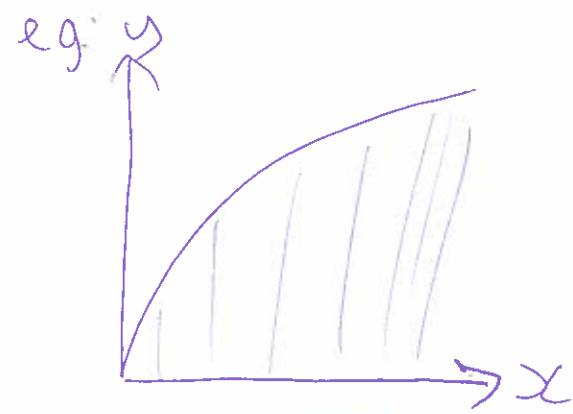
$\square \text{hyper}(f)$



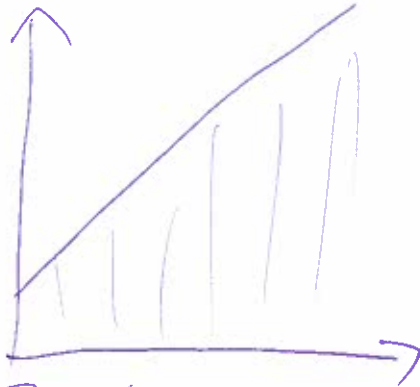
e.g. NOT convex functions:



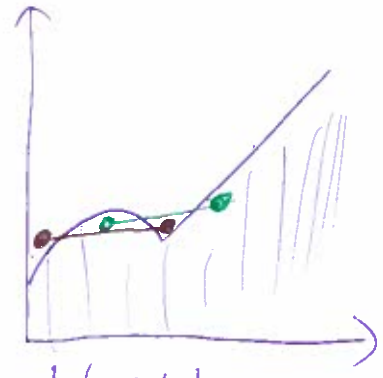
Def $f: X \rightarrow \mathbb{R}$ is a concave function if its hypograph
 $\text{hypo}(f) = \{(x, y) : x \in X, y \leq f(x)\}$
 is a convex set.



is ~~convex~~
 concave



Both concave
 & convex



Neither
 concave
 nor convex.

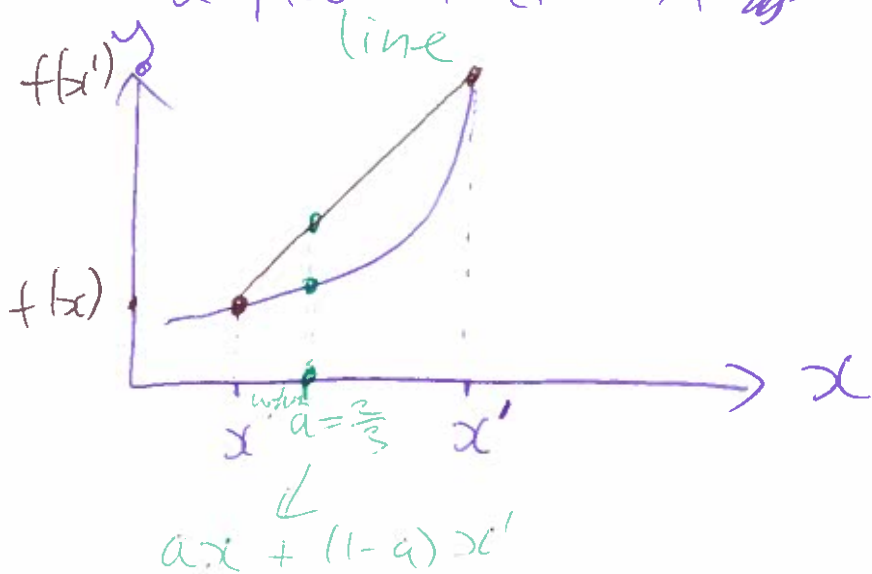
WARNING: There is no such thing
 as a concave set.

Theorem If $f: X \rightarrow \mathbb{R}$ is a convex
 function and X is open set then
 f is continuous.

Theorem Suppose $f: \mathbb{R} \rightarrow \mathbb{R}$ is
 differentiable. Then f is a ~~convex~~ convex
 function if and only if its derivative
 f' is weakly increasing.

Theorem Suppose $f: \mathbb{R} \rightarrow \mathbb{R}$ is twice differentiable. Then f is a convex function if and only if $f''(x) \geq 0$ for all x .

Theorem $f: X \rightarrow \mathbb{R}$ is a ^{concave} convex function if and only if for all $x, x' \in X$ and all $a \in (0, 1)$,
 $a f(x) + (1-a) f(x') \geq f(ax + (1-a)x')$.



"line is above curve"

Back to production functions:

Assume:

* f is a concave function.

\Rightarrow weakly decreasing marginal productivity
 and \Rightarrow weakly decreasing or constant returns to scale.

Claim Suppose $f: \mathbb{R}_+^{N-1} \rightarrow \mathbb{R}_+$ is concave and $f(0) = 0$. Then f has weakly decreasing returns to scale.

Proof Specifically, we want to prove that $f(tx) \leq tf(x)$ for all $t > 1$ and all $x \in \mathbb{R}_+^{N-1}$.

Let $s = \frac{1}{t}$, which means $s \in (0, 1)$.

By the theorem,

~~$$sf(tx) \leq sf(tx)$$~~

$$sf(tx) + (1-s)f(0) \leq f(stx + (1-s)0)$$

chose $a = s$ and $x = x$ and $x' = 0$

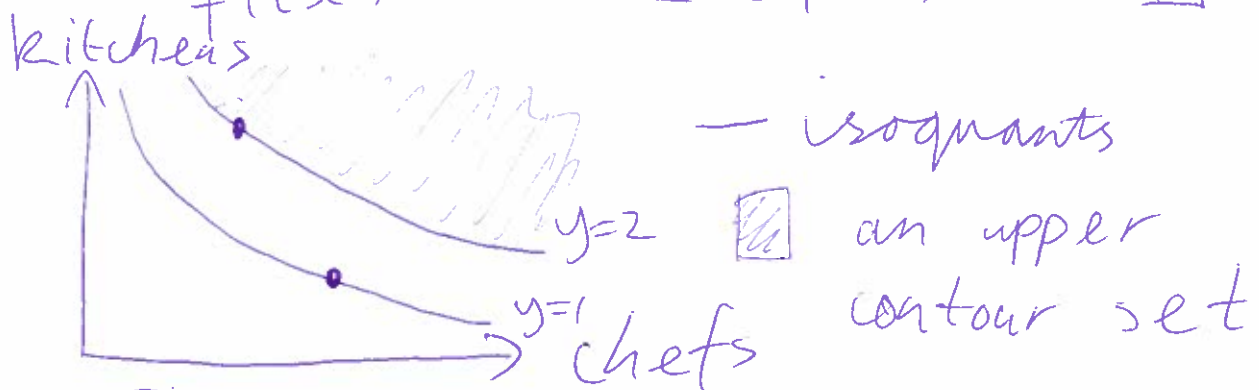
Simplifying,

$$sf(tx) + 0 \leq f(stx + 0)$$

$$\frac{1}{t} f(tx) \leq f\left(\frac{1}{t} tx\right)$$

$$\frac{1}{t} f(tx) \leq f(x)$$

$$f(tx) \leq tf(x). \quad \square$$



Def The upper contour set for output level y is

$$V(y) = \{x \in \mathbb{R}_+^{N-1} : f(x) \geq y\} = f^{-1}([y, \infty)).$$

(lower) \leq $(-\infty, y]$

Important: upper contour sets are NOT hypergraphs.

Back to Appendix D.

Def $f: X \rightarrow \mathbb{R}$ is a quasi-convex function if all its lower contour sets are ~~quasi~~ convex sets. Similarly, f is quasi-concave if all its upper contour sets are convex sets.

Theorem $f: X \rightarrow \mathbb{R}$ is quasi-convex if and only if

1. X is a convex set, and
2. for all ~~x, x'~~ $x, x' \in X$ and all $a \in (0, 1)$,
 $f(ax + (1-a)x') \leq \max \{f(x), f(x')\}$.

Hypergraphs vs upper contour sets



— f

 ~~hyper~~ $\text{hyper}(f)$

— the upper contour set for ~~prec~~ target \bar{y} $v(\bar{y})$.

Theorem If f is a convex function, then f is a quasi-convex function.

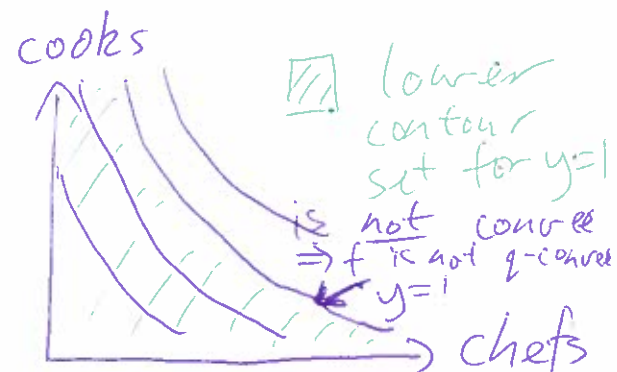
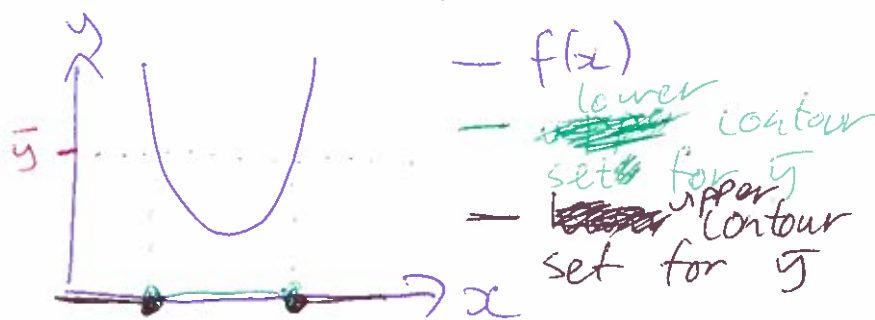
Back to production functions

could assume:

* f is a quasi-concave production function, i.e. each upper contour set $V(y)$ is convex.

Q: Are quasi-concave functions also quasi-convex?

A: Normally, no.



f is quasi-concave, but not quasi-convex.

2.2 Profit maximisation

$p \in \mathbb{R}_+$ ~~output~~ output price

$w \in \mathbb{R}_+^{N-1}$ input prices

Firm's profit function is:

$$\sum_{n=1}^{N-1} w_n x_n$$

//

$$\pi(p; w) = \max_{x \in \mathbb{R}_+^{N-1}} \underbrace{p f(x)}_{\text{revenue}} - \underbrace{w \cdot x}_{\text{expenditure}}$$

$$= p f(x(p; w)) - w \cdot x(p; w)$$

the factor demand function

⊛ Aside: If f is strictly concave, then there is only one optimal choice per $(p; w)$.

First-order condition w.r.t. x_i :

$$p \frac{\partial f(x)}{\partial x_i} = w_i$$

$$\frac{\text{FOC } x_i}{\text{FOC } x_j}$$

$$\frac{\frac{\partial f(x)}{\partial x_i}}{\frac{\partial f(x)}{\partial x_j}} = \frac{w_i}{w_j}$$

slope of isoquant

slope of "prices"

2.3 Upper Envelopes and Value Functions

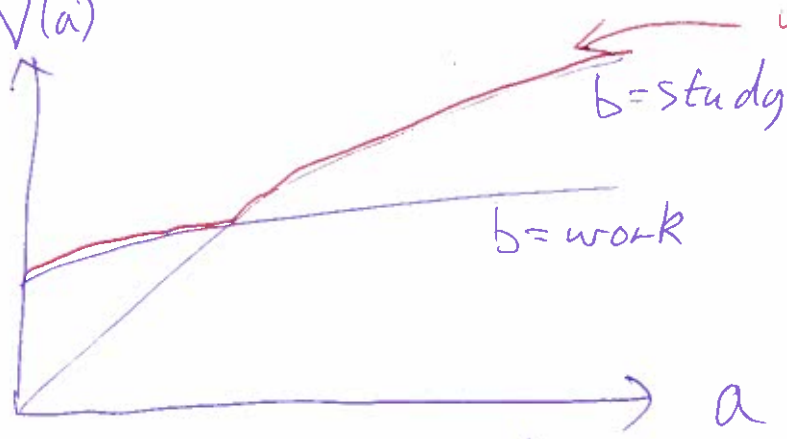
Problem: $\frac{\partial \pi(p, w)}{\partial p}$?

How do we differentiate a \max ^{policy function}?

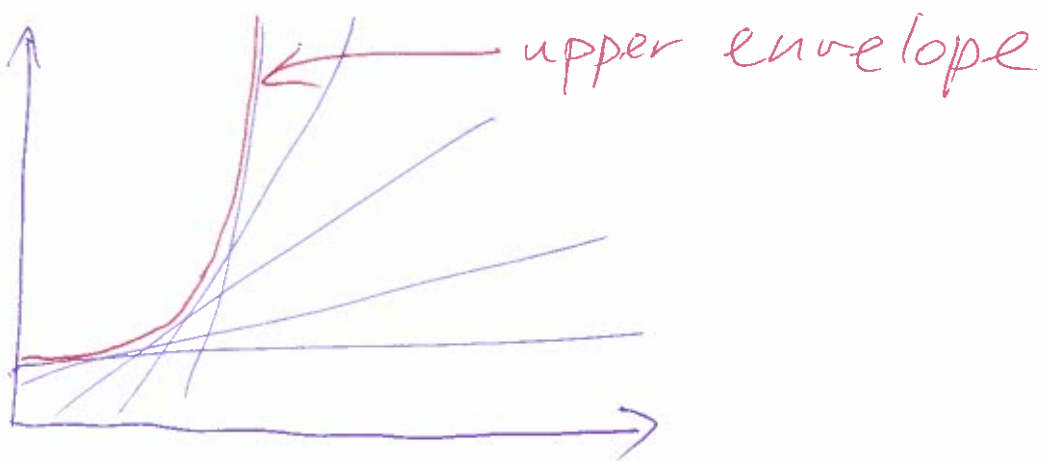
$$V(a) = \max_b v(a, b) = v(a, b(a))$$

$V(a)$ state variable
 a choice variable
 $v(a, b)$ objective function
 $b(a)$ policy function
 value function

Eg if $b \in \{\text{study, work}\}$, a assets.
 $V(a)$ upper envelope



If $b \in \mathbb{R}$, can look more complicated



Envelope Theorem Let

$v: \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$ be a differentiable function, and let $V(a) = \max_b v(a, b)$ be its value function (upper envelope), and $b(a)$ be its policy function.

If V is differentiable, then

$$V'(a) = \frac{\partial v(a, b)}{\partial a} \Big|_{b=b(a)}$$

or alternative notation,

$$V'(a) = v_a(a, b(a)).$$