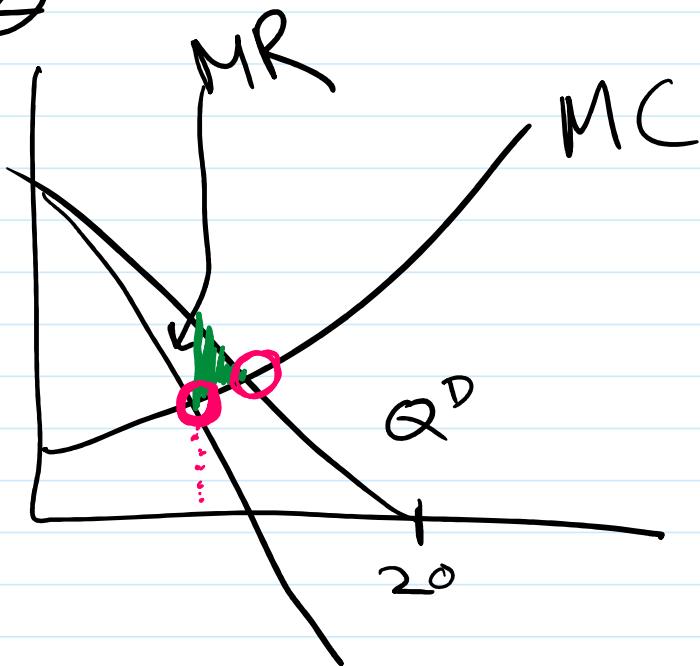


## Day 5 Notes

Friday, August 13, 2021

9:05 AM

(2)



Marg Rev:

$$\text{Revenue} = P \cdot Q$$

$$Q = 20 - 6P$$

inverse demand :

$$\frac{Q - 20}{-6} = P$$

$$P(Q) = \frac{20}{6} - \frac{Q}{6}$$

$$\text{Rev: } Q \cdot \left( \frac{20}{6} - \frac{Q}{6} \right)$$

Marg. Rev:  $\frac{d}{dQ} (\text{Rev})$

$$= \frac{20}{6} - \frac{2Q}{6}$$

$$MC = \frac{d}{dQ} TC = \frac{3Q^2}{3} = Q^2$$

Lower endpoint:

$$MR = MC$$

$$\frac{20}{6} - \frac{2Q}{6} = Q^2$$

$$Q^2 + \frac{Q}{3} - \frac{20}{6} = 0$$

Roots:

$$Q = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$= \frac{-\frac{1}{3} \pm \sqrt{\left(\frac{1}{3}\right)^2 - 4 \cdot 1 \cdot \left(-\frac{20}{6}\right)}}{2}$$

$$= \frac{-\frac{1}{3} \pm \sqrt{\frac{1}{9} + \frac{80}{6}}}{2}$$

$$= \frac{-\frac{1}{3} \pm \sqrt{13.4}}{2}$$

$$= \frac{-\frac{1}{3} \pm 3.66}{2}$$

$$Q = \frac{-\frac{1}{3} + 3.66}{2}$$

$$\approx 1.7 = Q^{\text{monop}}$$

Also solve  $MC = \text{Inverse demand}$

to get  $Q^{\text{comp}}$

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Next: integrate.

$$\int_{Q^{\text{monop}}}^{Q^{\text{comp}}} \left[ \left( \frac{20}{6} - \frac{Q}{6} \right) - Q^2 \right] dQ$$

$$= \left[ \frac{20}{6}Q - \frac{Q^2}{12} - \frac{Q^3}{3} \right]_{Q^{\text{monop}}}^{Q^{\text{comp}}}$$


---

## Euclidean space

A point in  $n$ -space is a vector.

$$(1, 2, 3, 4, 5)$$

$$\begin{bmatrix} f(x) \\ g(x) \\ h(x) \end{bmatrix} \quad [f \ g \ h]$$

In single variable calculus,  
 $f(x), x \in \mathbb{R}$ .

Now:  $f(x), x \in \mathbb{R}^N$ .

$x$  is a vector.

$\vec{x}$  vector

## Dot product

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \cdot \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = x_1 y_1 + x_2 y_2 + x_3 y_3$$

$$= X^T Y$$

Matrix mult:

$$AB = \boxed{(\text{row}_i \text{ of } A) \cdot (\text{col}_j \text{ of } B)}$$

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$U: \mathbb{R}^{k \times n} \rightarrow \underline{\mathbb{R}^m}$$

$$\begin{bmatrix} U_1(x') \\ U_2(x') \\ \vdots \\ U_m(x') \end{bmatrix} \quad (x' \in \mathbb{R}^k)$$

$U_m(x)$

$$f(x_1, x_2) = x_1^2 + 3x_1 \underline{x_2} - x_2^2$$

$$\frac{\partial f(x_1, x_2)}{\partial x_1} = \underline{2x_1 + 3x_2}$$

$$\frac{\partial f}{\partial x_2} = \underline{-2x_2 + 3x_1}$$

$$y = f(x)$$

$dy \equiv f'(x)dx$   $dx$  is a free variable

Now

$$z = f(\underbrace{x_1, x_2, \dots, x_n}_X)$$

$$dz \equiv f_1(x)dx_1 + f_2(x)dx_2 + \dots + f_n(x)dx_n$$

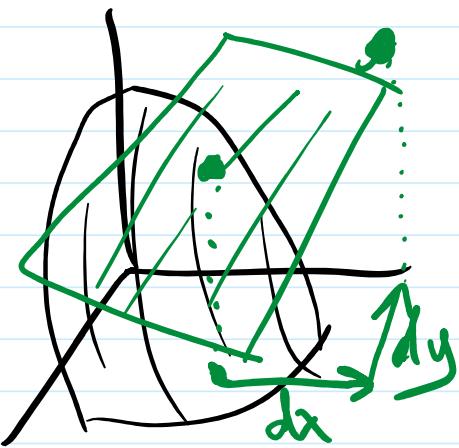


$dZ$  is a linear approx.

$$ax + by = c \quad \text{line}$$

$$ax + by + cz = d \quad \text{plane}$$

$dZ$  gives the tangent plane



$dZ$  gives  
the formula  
and when  
you choose  
 $dx, dy$ .

This is a linear approx.  
of the 3D fn.

$N > 3$ : hyperplane

## Jacobian

single-valued fn: row vector.  
Multi-valued fn: matrix

Let  $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$

$$J = Df = \begin{bmatrix} f'_1 & f'_2 & \cdots & f'_n \\ \vdots & \ddots & & \vdots \\ f'^m_1 & f'^m_2 & \cdots & f'^m_n \end{bmatrix}$$

$$f = (f^1, f^2, f^3, \dots, f^m)$$

$f^3_2$  is the partial derivative of  $f^3$  w.r.t.  $X_2$

If  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  then

$$J = Df = [f_1 \ f_2 \ \cdots \ f_n]$$

---

$$Ex 1 \text{ let } f(x, y) = (x^2 + y, y^3)$$

Ex] Let  $f(x, y) = (x^2+y, y^3)$

$$J = \begin{bmatrix} \frac{\partial f^1}{\partial x} & \frac{\partial f^1}{\partial y} \\ \frac{\partial f^2}{\partial x} & \frac{\partial f^2}{\partial y} \end{bmatrix}$$

$\uparrow$   $\uparrow$   
 $f^1$   $f^2$   
2 values

$$= \begin{bmatrix} 2x & 1 \\ 0 & 3y^2 \end{bmatrix}$$

### Gradient Vector

- 1) Only defined for single-value functions
- 2) It is the transpose of the Jacobian. So it a column vector.

$$\nabla f$$

Let  $z = f(x)$ . Then  $dz = \nabla f \cdot dx$

which means:  $dz = f_1 dx_1 + \dots + f_n dx_n$

Ex)  $f(x, y) = x^2 + y$

$$\nabla f = \begin{bmatrix} 2x \\ 1 \end{bmatrix}$$

---

### Total derivative

$f(u, v, w)$  but  $u(t)$

$v(t)$

$w(t)$

the  $\frac{df}{dt}$  is the total derivative  
w.r.t.

$$\frac{df}{dt} = \frac{\partial f}{\partial u} \cdot \frac{du}{dt} + \frac{\partial f}{\partial v} \cdot \frac{dv}{dt} + \frac{\partial f}{\partial w} \cdot \frac{dw}{dt}$$

### Multivariate Chain Rule

Ex]  $w = x^3yz + xy + z + 3$

Total differential:

$$dW = (3x^2yz + y)dx + (x^3z + x)dy + (x^3y + 1)dz$$

$$\text{Let } x = 2t + 1$$

$$y = 4t^2$$

$$z = \ln t$$

$$\frac{dW}{dt} = (3x^2yz + y) \cdot 2 + (x^3z + x) \cdot 8t$$

$$+ (x^3y + 1) \frac{1}{t}$$

$\rightarrow$  plug in  $x(t), y(t), z(t)$

$d$  or  $\partial$ ?

$\downarrow$   
total deriv.

$$f(x, y, t) \quad x(t), y(t)$$

$$\text{Then } \frac{df}{dt} = \frac{\partial f}{\partial x} \frac{dx}{dt} + \frac{\partial f}{\partial y} \frac{dy}{dt}$$

$$\frac{dt}{dt} = \frac{\partial x}{\partial t} dt + \underbrace{\frac{\partial y}{\partial t} dt}_{+ \frac{\partial f}{\partial t}} \neq \frac{df}{dt}$$

## Higher order derivatives

$$f: \mathbb{R}^{10} \rightarrow \mathbb{R}$$

$$\frac{\partial f}{\partial x_1} = f_1$$

[ ] [ ]

$$\frac{\partial}{\partial x_6} \left( \frac{\partial f}{\partial x_1} \right) = \underbrace{\frac{\partial^2 f}{\partial x_6 \partial x_1}}_{= f_{16}}$$

In economics :

$$\frac{\partial}{\partial x_6} \left( \frac{\partial f}{\partial x_1} \right) = \frac{\partial^2 f}{\partial x_1 \partial x_6}$$

$$\frac{\partial}{\partial x_3} \left( \frac{\partial}{\partial x_6} \left( \frac{\partial f}{\partial x_1} \right) \right) = \frac{\partial^3 f}{\partial x_1 \partial x_6 \partial x_3}$$

$f_{16}$

$f_{163}$

Young's Theorem:

In most cases:

$$\frac{\partial^2 f}{\partial x_1 \partial x_2} = \frac{\partial^2 f}{\partial x_2 \partial x_1}$$

ie.  $f_{12} = f_{21}$

---

Hessian

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

Then  $D^2 f = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \cdots & f_{nn} \end{bmatrix}$

Row index: first deriv.

Col index: 2nd deriv.

Hessian  $\mathbf{B}$ :

1) only defined for single-valued fns

2) square

3) symmetric

$$\text{so } [D^2 f]_{ij} = [D^2 f]_{ji}$$

because of Young's Theorem.

---

$$\boxed{\text{Ex}} \quad y = e^{x_1} + 2x_2 + 4x_1 x_2^2$$

Find Hessian:

$$H = D^2 y \underset{\text{2x2}}{\approx}$$

bec. there are 2 indep. variables.

$$y_1 = e^{x_1} + 4x_2^2$$

$$y_2 = 2 + 8x_1 x_2$$

$$y_{11} = e^{x_1} \quad y_{12} = 8x_2$$

$$y_{21} = 8x_2 \quad y_{22} = 8x_1$$

So  $D^2 y = \begin{bmatrix} e^{x_1} & 8x_2 \\ 8x_2 & 8x_1 \end{bmatrix}$

Symmetric

---

Young's Theorem does  
not require  $f_{12}$  and  $f_{21}$   
to be continuous on  $\mathbb{R}^n$ .

They need to be continuous  
in a neighborhood of  $x$ ,  
i.e., an open ball of any  
positive radius.

$$H = \begin{bmatrix} 2e^{-y} & -2xe^{-y} \\ -2xe^{-y} & e^{-y}(2 - 4y + x^2 + y^2) \end{bmatrix}$$


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Implicit function theorem

## Implicit function theorem

$G(x,y) = 0$  defines  $y$   
as a function of  $x$   
implicitly.

$$\frac{x^y}{\ln y^2} \cdot \arctan x = 0$$

We can't find  $y = f(x)$   
but we can find  $\frac{dy}{dx}$ .

$$\frac{dy}{dx} = -\frac{\frac{\partial G}{\partial x}}{\frac{\partial G}{\partial y}} \quad \text{where } G_y \neq 0$$

## Differential

$$dG = G_x dx + G_y dy$$

$$\frac{dG}{dx} = G_x + G_y \frac{dy}{dx}$$

[  $G(x,y)=0$  ] so  $dG=0$

$$\text{so } 0 = G_x + G_y \frac{dy}{dx}$$

$$-G_y \frac{dy}{dx} = G_x$$

[  $\frac{dy}{dx} = -\frac{G_x}{G_y}$  ]

Addendum: This is actually a precise derivation because  
 If  $y=f(x)$  then  $dy=f'(x)dx$  by definition and  
 Thus  $dy/dx=f'(x)dx/dx = f'(x)$

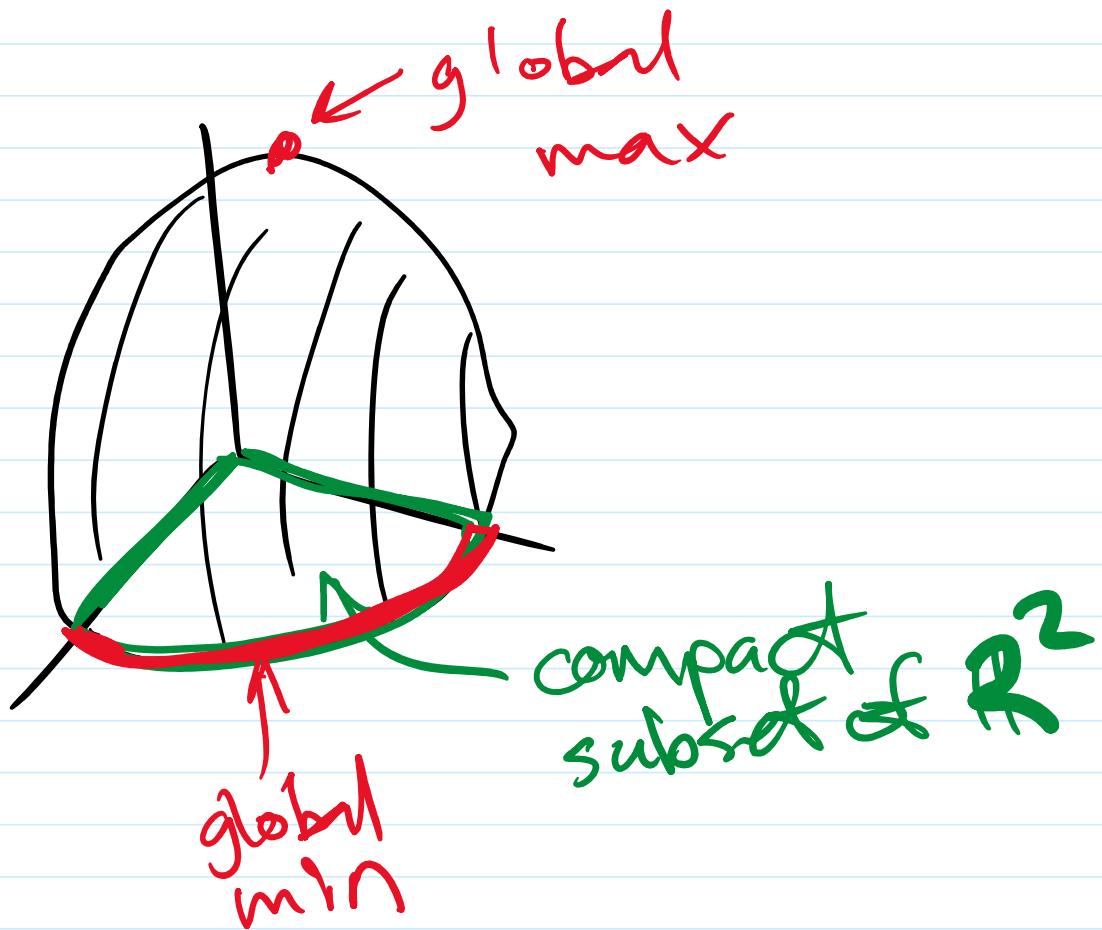
$\Delta G$  from  $X$

$= -\Delta G$  from  $Y$

# Weierstrauss

- 1) continuous
- 2) compact domain

→ closed and bounded



# Fixed Point Theorems

A fixed point of

A fixed point  $\alpha^*$   
the function  $f: X \rightarrow X$   
 $\beta$  an element  $x^* \in X$   
such that  $f(x^*) = x^*$ .

$$f(x) = x^2$$

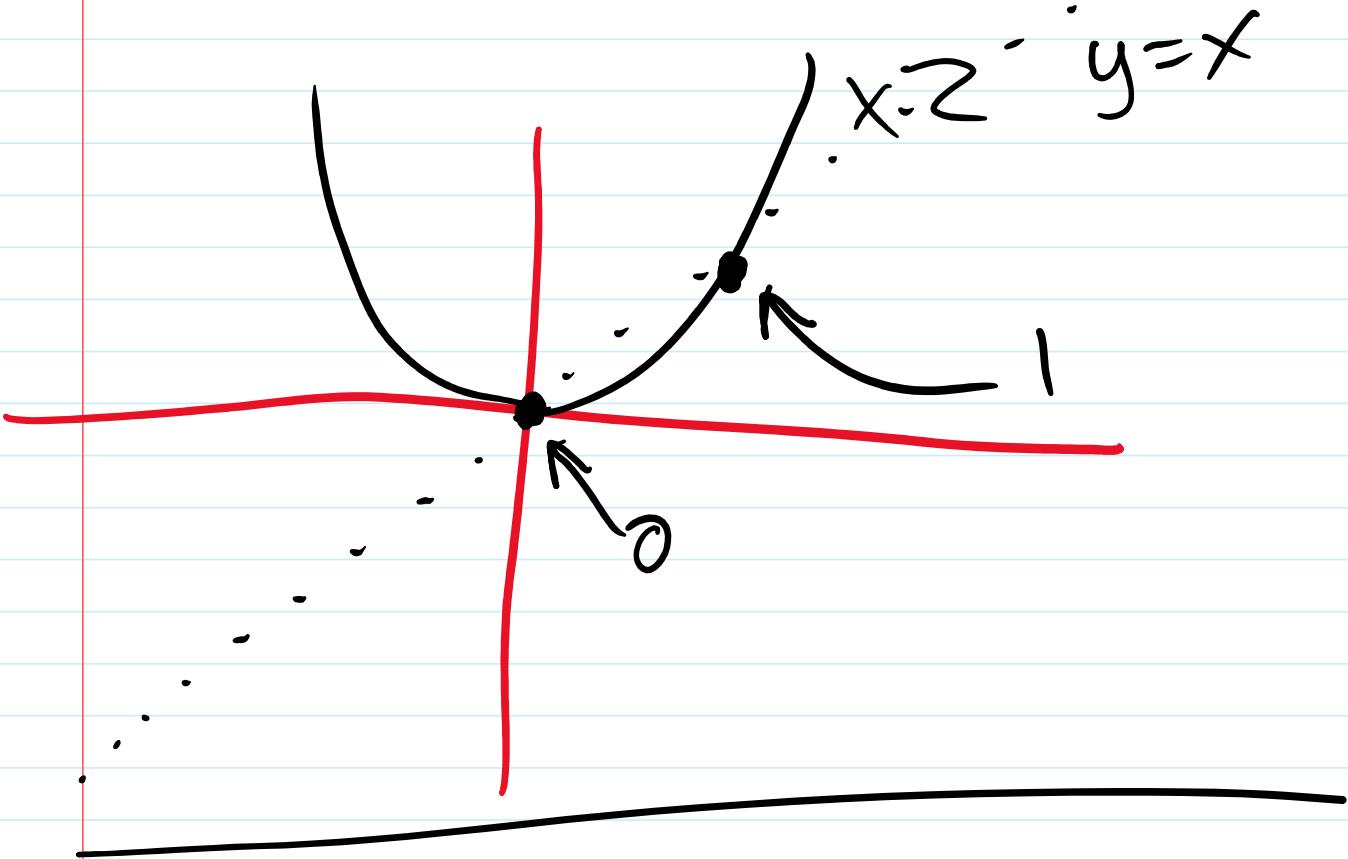
$$f(0) = 0 \quad \text{so } 0 \text{ is a fixed point}$$

$$f(1) = 1 \quad \text{so } 1 \text{ is another fixed point}$$

$$f(2) = 4 \quad \text{so } 2 \text{ is not a F.P.}$$

$$f(-1) = 1 \quad \text{so } -1 \in B$$

not



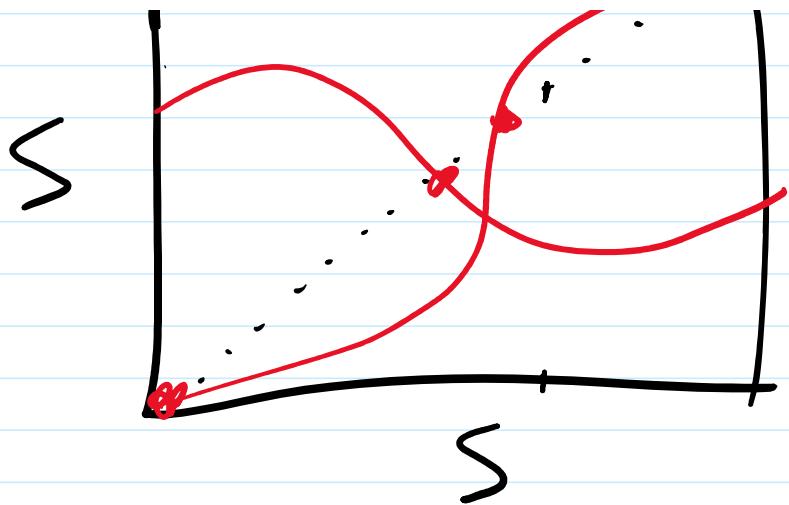
Brouwer's FPT:

If  $f: S \rightarrow S$  is continuous  
on  $S$ , it has a fixed point.

$S \subseteq \mathbb{R}^n$  such that  $S$  is compact.



Addendum:  $S$  should be both compact  
AND convex



Addendum:  $S$  should be both compact  
AND convex



## Convexity of fns in $\mathbb{R}^n$

A fn  $f$  is convex if

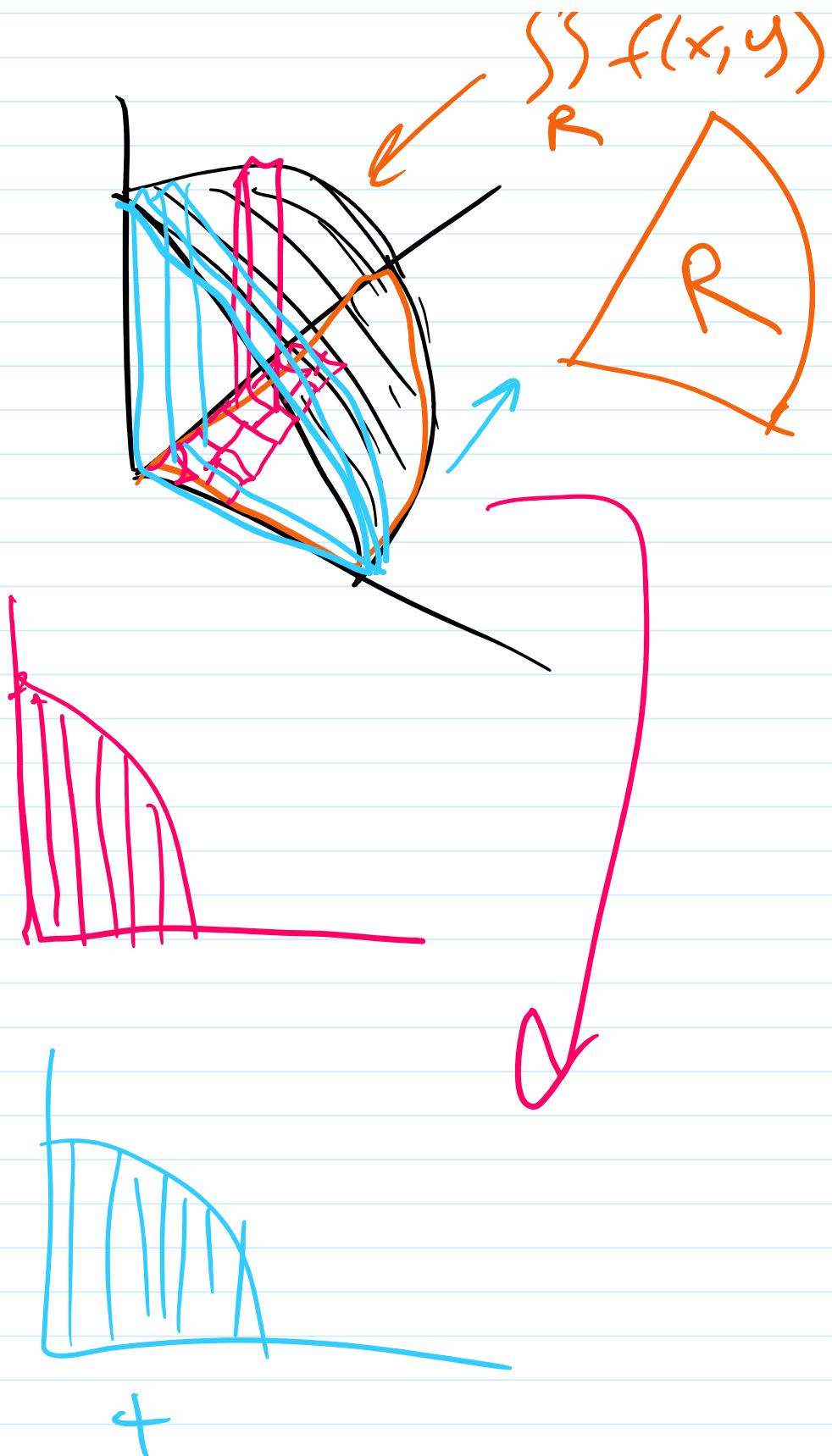
$$\begin{aligned} \forall x_1, x_2 \quad f(tx_1 + (1-t)x_2) \\ \leq t f(x_1) + (1-t)f(x_2) \end{aligned}$$

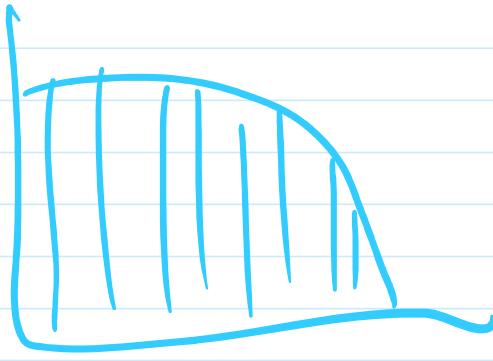
Same as before, but now  
 $x_1, x_2$  are vectors.

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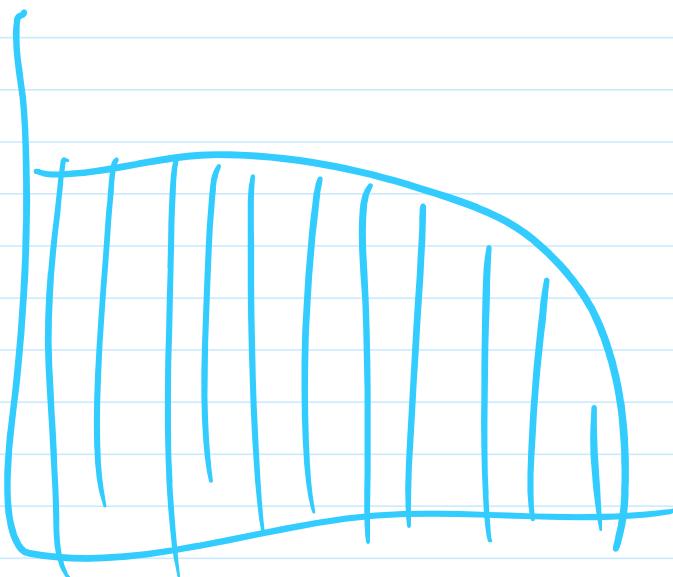
## Iterated Integrals

$$, \iint f(x,y)$$





+



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## Fubini's Theorem

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If  $f$  is continuous  
on  $R$  which is a  
rectangle:

$$R = \{(x, y) : a \leq x \leq b, c \leq y \leq d\}$$

then

$$\iint_R f(x, y) = \int_a^b \left\{ \int_c^d f(x, y) dy \right\} dx$$
$$= \int_a^b \left[ \int_c^d f(x, y) dy \right] dx$$

iterated integral.

Common in probability  
and stats.

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