

Lecture 13

- Taylor's series
- Rolle's theorem
 - Mean value theorem
 - Taylor's theorem or Taylor's series

- Roots problem
- Error in fixed point iteration method
 - Error in Newton-Raphson method

- Vectors and matrix
- Errors in $Ax = b$ problem
 - Condition number of matrix A
 - Norm of vector and matrix

Rolle's theorem

If a continuous & differentiable function

$f: [a, b] \rightarrow \mathbb{R}$ is such that

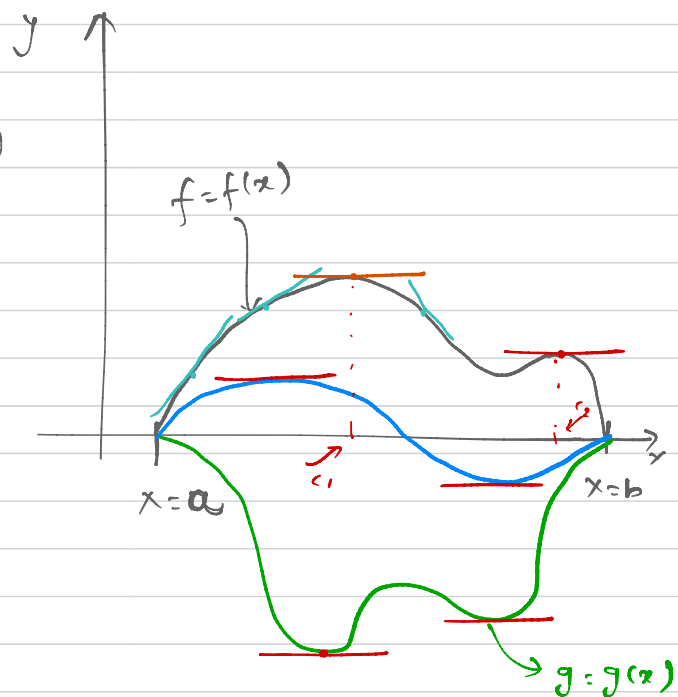
$$f(a) = 0, \quad f(b) = 0.$$

Then, there exist at least one

point c such that $a < c < b$

and

$$\frac{df}{dx}(c) = 0.$$



- [f needs to be continuous at all points $x \in [a, b]$
- [f needs to be differentiable at all points $x \in (a, b)$]

• Mean value theorem

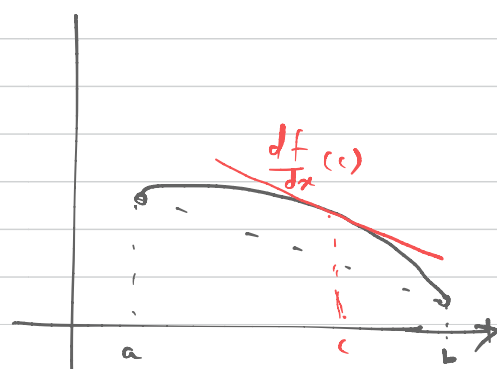
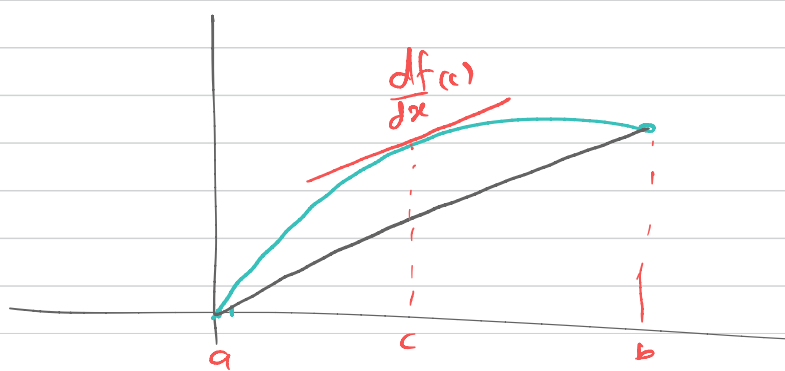
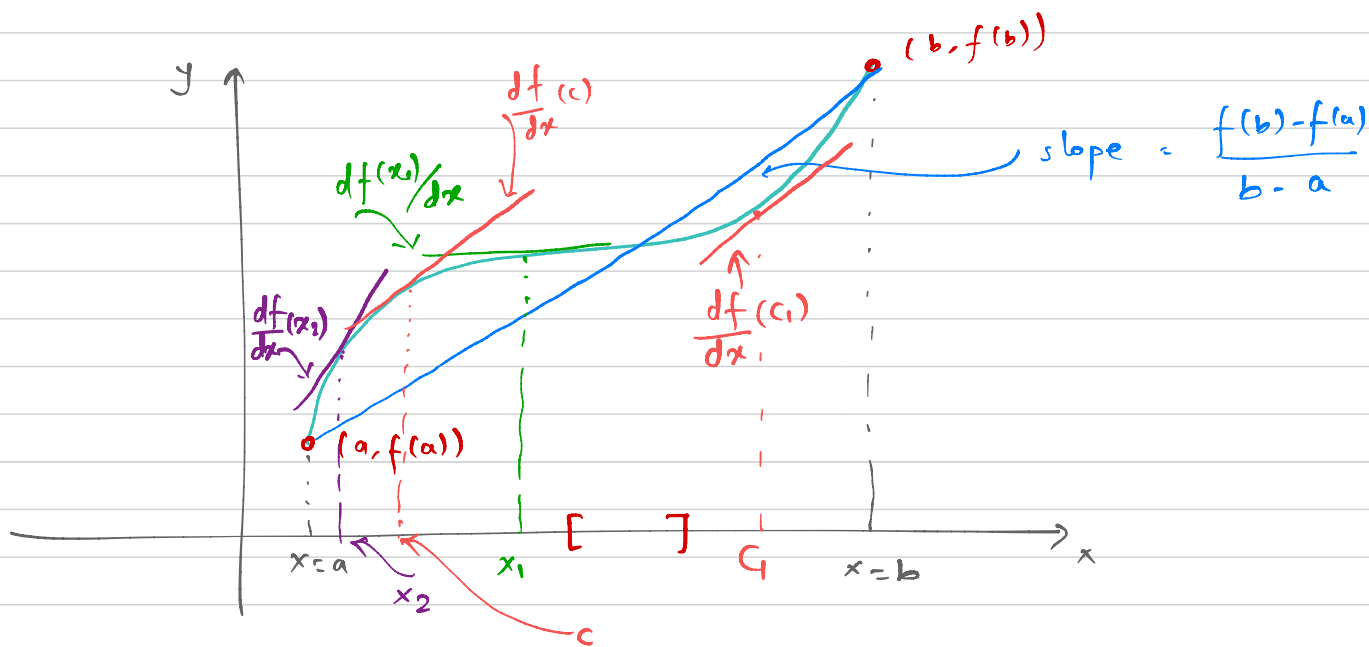
, $a < b$,

If function $f: [a, b] \rightarrow \mathbb{R}$ is continuous and differentiable at all points in interval $[a, b]$. Then there exist at least one point $c \in (a, b)$ ($a < c < b$) such that

$$\frac{df}{dx}(c) = \frac{f(b) - f(a)}{b - a}$$

consider a straight line in (x, y) plane that connects $(a, f(a))$ and $(b, f(b))$ then

$$\text{slope of that line} = \frac{f(b) - f(a)}{b - a}$$

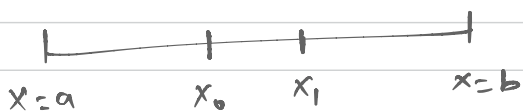


From mean value theorem

$$f(b) = f(a) + \frac{df}{dx}(c) (b-a)$$

there is one such $c \in (a,b)$

c depends on f, a, b .



Instead of applying mean value theorem in interval $[a,b]$, I will

$$f(x_1) = f(x_0) + f'(d) (x_1 - x_0)$$

$d \in (x_0, x_1)$

← apply in interval $[x_0, x_1]$

$f: [a,b] \rightarrow \mathbb{R}$, continuous & differentiable

MVT $\rightarrow f'(c) = \frac{f(b) - f(a)}{b - a} \quad f' = \frac{df}{dx}$

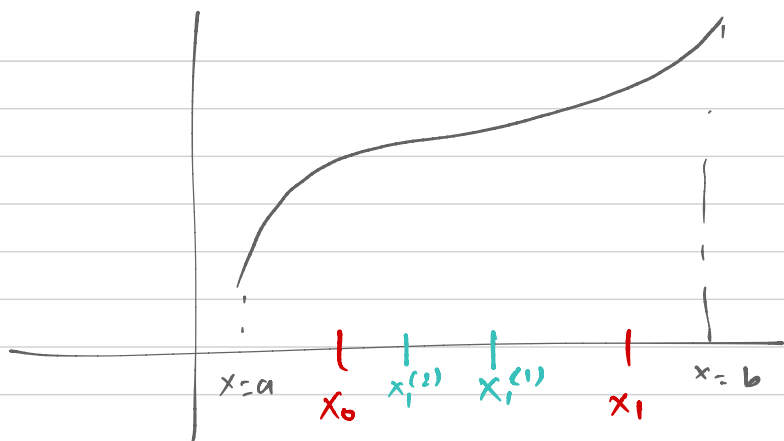
I can pick two points x_0, x_1 s.t. $a \leq x_0 < x_1 \leq b$
then MVT is still applicable to interval $[x_0, x_1]$

$$f'(d) = \frac{f(x_1) - f(x_0)}{x_1 - x_0}$$

if $|x_0 - x_1|$ is very small and since d is such that $x_0 < d < x_1$

we can approximately write

$$f(x_1) = f(x_0) + f'(d) (x_1 - x_0) \approx f(x_0) + f'(x_0) (x_1 - x_0)$$



Taylor's Theorem / Taylor's series

$f: [a, b] \rightarrow \mathbb{R}$ is continuous at all $x \in [a, b]$
 and derivatives upto n^{th} order of function f exist
 at all points $x \in (a, b)$,

$\frac{df}{dx}$, $\frac{d^2f}{dx^2}$, ..., $\frac{d^n f}{dx^n}$ exist for all $x \in (a, b)$.

Then there is some $c \in (a, b)$ such that

$$f(b) = f(a) + \frac{df}{dx}(a)(b-a) + \frac{1}{2!} \frac{d^2f}{dx^2}(a)(b-a)^2$$

$$+ \dots + \frac{1}{(n-1)!} \frac{d^{(n-1)}f}{dx^{(n-1)}}(a)(b-a)^{n-1}$$

$$+ \frac{1}{n!} \frac{d^n f}{dx^n}(c)(b-a)^n$$

c exist and depends on f , $\frac{df}{dx}$, $\frac{d^2f}{dx^2}$, ..., $\frac{d^n f}{dx^n}$

a, b

Observations

(\cdot) put $n=1 \rightarrow$ you get MVT

(.) Suppose upto N^{th} derivative exist

for any $1 \leq n \leq N$, Taylor's theorem holds

$$f(b) = \sum_{k=0}^{n-1} \frac{1}{k!} \frac{d^k f(a)}{dx^k} (b-a)^k + \frac{1}{n!} \frac{d^n f(c)}{dx^n} (b-a)^n$$

point c exist but
you don't know

where at $k=0$ (i) $\frac{d^0 f}{dx^0} = f$

(ii) $0! = 1$

$$f(b) = \sum_{k=0}^{n-1} \frac{1}{k!} \frac{d^k f(a)}{dx^k} (b-a)^k + \underbrace{\frac{1}{n!} \frac{d^n f(c)}{dx^n} (b-a)^n}_{\text{Remainder}}$$

Remainder

$R_n(a, b)$

$$f(b) = \sum_{k=0}^{n-1} \frac{1}{k!} \frac{d^k f(a)}{dx^k} (b-a)^k + R_n(a, b) (b-a)^n$$

if b and a are such that $|b-a|$ is small

then $(b-a)^n$ is smaller and

smaller with

higher n

$$f(b) \approx \sum_{k=0}^{n-1} \frac{1}{k!} \frac{d^k f(a)}{dx^k} (b-a)^k$$

Sketch of Taylor's theorem proof:

Consider a function $F: (a, b) \rightarrow \mathbb{R}$ s.t.

- $\frac{dF}{dx}, \dots, \frac{d^n F}{dx^n}$ exist

- $F(a) = 0, F(b) = 0$

- $\frac{dF}{dx}(a) = \frac{d^2 F}{dx^2}(a) = \dots = \frac{d^{n-1} F}{dx^{n-1}}(a) = 0$

Then there is $c \in (a, b)$ s.t.

$$\frac{d^n F}{dx^n}(c) = 0.$$

Proof: We have $F(a) = 0, F(b) = 0$

then from Rolle's theorem there is point $c_1 \in (a, b)$ s.t.

$$\frac{dF}{dx}(c_1) = 0$$

Take a new function $g = \frac{dF}{dx}$

Note that

$$g(a) = 0, g(c_1) = 0$$

So $g: [a, c_1] \rightarrow \mathbb{R}$ s.t. $g(a) = 0, g(c_1) = 0$

there is $c_2 \in (a, c_1)$ s.t.

$$\frac{dg}{dx}(c_2) = 0 \Rightarrow \frac{d^2 F}{dx^2}(c_2) = 0$$

⋮

You show by repeating above procedure, following

- $g = \frac{d^{n-2} F}{dx^{n-2}}$

(s.t. "such that")

• $g(a) = 0$

• $g(c_{n-2}) = 0$

& there is $c_{n-1} \in (a, c_{n-2})$ s.t.

$$\frac{dg}{dx}(c_{n-1}) = 0 \Rightarrow \frac{d^{n-1}F}{dx^{n-1}}(c_{n-1}) = 0$$

$h = \frac{d^{n-1}F}{dx^{n-1}}$

• $h(a) = 0$

• $h(c_{n-1}) = 0$

) further application of Rolle's theorem ensures there is a point $c_n \in (a, c_{n-1})$ s.t.

$$\frac{dh}{dx}(c_n) = 0$$

\Rightarrow $\frac{d^n F}{dx^n}(c_n) = 0$

proves our original theorem that there is a point $c \in (a, b)$ s.t. $\frac{d^n F}{dx^n}(c) = 0$

Now using above result for function F , we prove Taylor's theorem: In Taylor's theorem we have function f

- f is continuous at all $x \in [a, b]$
- f is differentiable at all $x \in (a, b)$

First look at polynomial as follows

$$P(x) = \sum_{k=0}^n \alpha_k (x-a)^k$$

$$(\cdot) \quad P(a) = \alpha_0, \quad (\cdot) \quad \frac{dP}{dx}(a) = \dots = \frac{d^{n-1}P}{dx^{n-1}}(a) = 0$$

Define $F(x) = f(x) - P(x)$

$$\alpha_k = \frac{1}{k!} \frac{d^k f}{dx^k}(a) \quad k=0, 1, 2, \dots, n-1$$

$$\boxed{\begin{array}{l} \frac{d^0 f}{dx^0} = f \\ 0! = 1 \end{array}}$$

$$\begin{array}{l} \cdot F(a) = 0, F(b) = 0 \\ \cdot \frac{dF}{dx}(a) = 0 \\ \cdot \frac{d^2 F}{dx^2}(a) = 0 \\ \cdot \vdots \\ \cdot \frac{d^{n-1} F}{dx^{n-1}}(a) = 0 \end{array}$$

$$\alpha_n = \frac{1}{(b-a)^n} \left(f(b) - \sum_{k=0}^{n-1} \alpha_k (b-a)^k \right)$$

Since F satisfies all the conditions, from previous theorem there is some $c \in (a, b)$ s.t.

$$\frac{d^n F}{dx^n}(c) = 0$$

$$\Rightarrow \frac{d^n f}{dx^n}(c) - \frac{d^n P}{dx^n}(c) = 0$$

$$\Rightarrow \frac{d^n f}{dx^n}(c) = \frac{d^n P}{dx^n}(c)$$

$$\Rightarrow \frac{d^n f}{dx^n}(c) = \frac{n!}{(b-a)^n} \left(f(b) - \sum_{k=0}^{n-1} \alpha_k (b-a)^k \right)$$

$$\Rightarrow \frac{1}{n!} \frac{d^n f}{dx^n}(c) (b-a)^n = f(b) - \sum_{k=0}^{n-1} \alpha_k (b-a)^k$$

$$\Rightarrow f(b) = \sum_{k=0}^{n-1} \alpha_k (b-a)^k + \frac{1}{n!} \frac{d^n f}{dx^n}(c) (b-a)^n$$

using the fact that $\alpha_k = \frac{1}{k!} \frac{d^k f}{dx^k}(a)$

Taylor's theorem is proved.

Roots problem

Error in fixed point iteration method

find x such that $x = g(x)$, g is some function
 $g: [a, b] \rightarrow \mathbb{R}$

$\hookrightarrow x_0, x_1 = g(x_0), x_2 = g(x_1), \dots, x_i = g(x_{i-1}), \dots$

Error at i^{th} iteration = $x_i - x_{i-1} = E_i$

$$E_i = x_i - x_{i-1} = g(x_{i-1}) - x_{i-1} = g(x_{i-1}) - g(x_{i-2})$$

from MVT: there is $\xi \in (a, b)$

$$g(x_{i-1}) = g(x_{i-2}) + \underbrace{g'(\xi)}_{E_{i-1}} (x_{i-1} - x_{i-2})$$

$$E_i = g'(\xi) E_{i-1}$$

$$e_i = |E_i| \Rightarrow \left[e_i \leq |g'(\xi)| e_{i-1} \leq \left\{ \max_{x \in (a,b)} |g'(x)| \right\} e_{i-1} \right]$$

$$\downarrow$$
$$e_i \leq \left\{ \max_{x \in (a,b)} |g'(x)| \right\} e_{i-1}$$

if $\max_{x \in (a,b)} |g'(x)| < 1$

then $e_i \rightarrow 0$

• Error in Newton-Raphson method

find x s.t. $f(x) = 0$

$f: [a, b] \rightarrow \mathbb{R}$

$$x_0 \longrightarrow x_1 = x_0 - \frac{f(x_0)}{f'(x_0)}$$

↓

$$x_2 = x_1 - \frac{f(x_1)}{f'(x_1)}$$

↓

⋮

$$x_i = x_{i-1} - \frac{f(x_{i-1})}{f'(x_{i-1})}$$

Define "True error"

$$E_{t,i} = x_t - x_i$$

↓
exact solution
i.e. $f(x_t) = 0$

↘ is i th approximate solution

Considers

$$E_{t,i+1} = x_t - x_{i+1}$$

$$= x_t - \left(x_i - \frac{f(x_i)}{f'(x_i)} \right)$$

$$= \underbrace{x_t - x_i}_{E_{t,i}} + \frac{f(x_i)}{f'(x_i)}$$

$$\Rightarrow E_{t,i+1} = E_{t,i} + \frac{f(x_i)}{f'(x_i)}$$

because $E_{t,i} = x_t - x_i \Rightarrow x_i = x_t - E_{t,i}$

then

from Taylor's series

$$f(b) = f(a) + f'(a)(b-a) + \frac{1}{2}f''(a)(b-a)^2 + \mathcal{R}_1$$

$$f'(b) = f'(a) + f''(a)(b-a) + \mathcal{R}_2$$

Substitute $b = x_i$, $a = x_t$

$$f(x_i) = \cancel{f(x_t)} + f'(x_t)(-E_{t,i}) + \frac{1}{2}f''(x_t)(E_{t,i})^2 + \mathcal{R}_1$$

$$f'(x_i) = f'(x_t) + f''(x_t)(-E_{t,i}) + \mathcal{R}_2$$

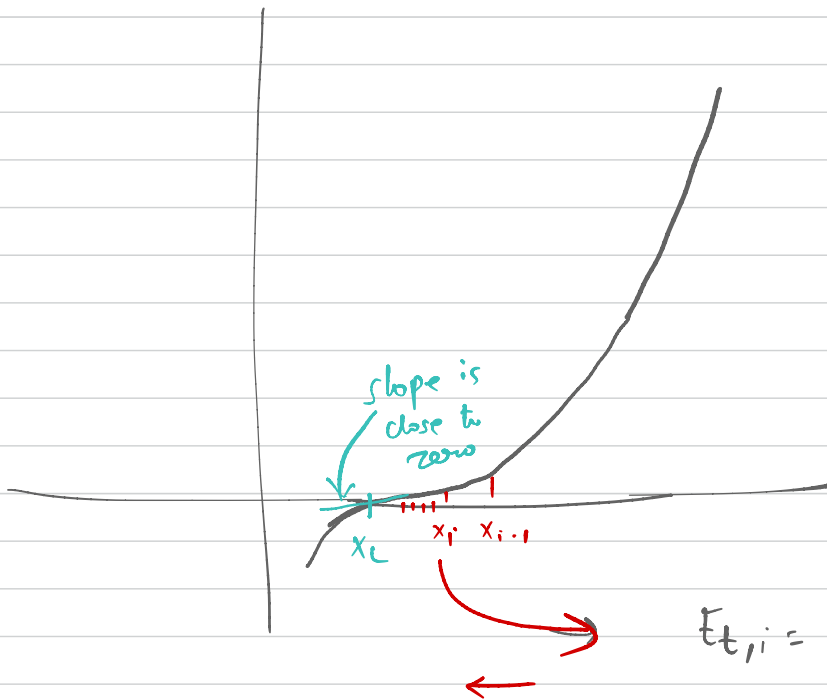
$$E_{t,i+1} = E_{t,i} + \frac{-f'(x_t)E_{t,i} + \frac{1}{2}f''(x_t)(E_{t,i})^2 + \mathcal{R}_1}{f'(x_t) - f''(x_t)E_{t,i} + \mathcal{R}_2}$$

$$= \frac{\cancel{E_{t,i}f'(x_t)} - f''(x_t)(E_{t,i})^2 + \mathcal{R}_2 E_{t,i} - \cancel{f'(x_t)E_{t,i}} + \frac{1}{2}f''(x_t)(E_{t,i})^2 + \mathcal{R}_1}{f'(x_t) - f''(x_t)E_{t,i} + \mathcal{R}_2}$$

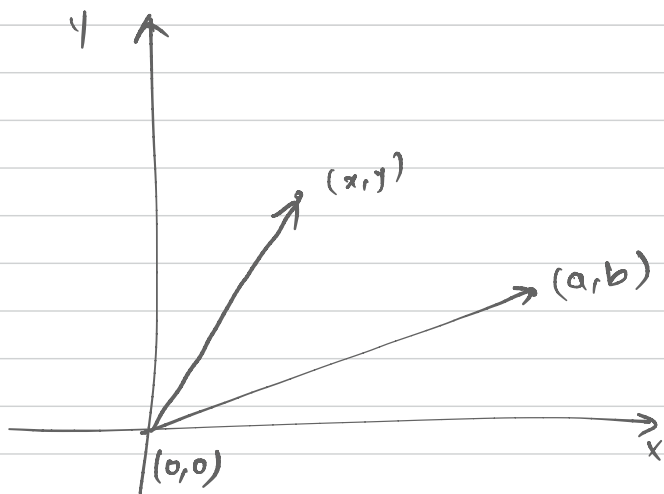
$$E_{t,i+1} = \frac{-\frac{1}{2} f''(x_t)}{f'(x_t) - f''(x_t) E_{t,i}} (E_{t,i})^2$$

$$\rightarrow E_{t,i+1} \approx \frac{-f''(x_t)}{2f'(x_t)} (E_{t,i})^2$$

Error reduces at quadratic speed.

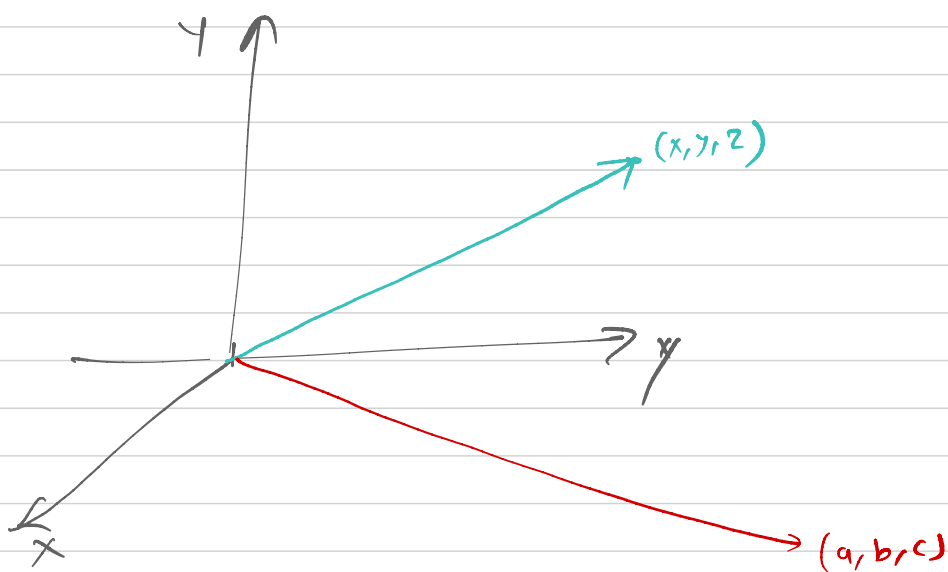


$$E_{t,i} = \frac{|f''(x_t)|}{2|f'(x_t)|} (E_{t,i-1})^2$$



(i) direction

(ii) length $l = \sqrt{x^2 + y^2}$



length = $\sqrt{x^2 + y^2 + z^2}$

length = $\sqrt{a^2 + b^2 + c^2}$

in n-dimension (meaning that vectors x has "n elements")

length = $\sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$

Norm: generalizes the notion of length/magnitude to vectors and matrices.

There are many ways to define a "norm" of a vector

(i) Euclidean norm of a vector

$$\|x\|_e = \|x\|_2 = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$$

↓
coincides with our notion of length of vectors.

(ii) $\|x\|_1 = \sum_{i=1}^n |x_i|$

(iii) $\|x\|_\infty = \max\{|x_1|, |x_2|, \dots, |x_n|\}$
 $= \max_{1 \leq i \leq n} \{|x_i|\}$

(iv) $\|x\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p}$ for any $p \in [1, \infty)$
↓
p-th norm of vector x

Norm of a matrix :

$$Ax = b$$

$$\|Ax\|_p \leq \|A\|_p \|x\|_p$$

→ $\|A\|_p := \max_{\substack{x \text{ vectors} \\ \|x\|_p \neq 0}} \frac{\|Ax\|_p}{\|x\|_p} = \max_{\|x\|_p = 1} \|Ax\|_p$

if $p=1$, $\|x\|_1$, $\|A\|_1$

$p=2$, $\|x\|_2$, $\|A\|_2$ ← Frobenius norm

$$p = \infty, \quad \|x\|_{\infty}, \quad \|A\|_{\infty}$$

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix}$$

$$\|A\|_p = \max_{\substack{\text{all } x \text{ vectors} \\ \|x\|_p = 1}} \|Ax\|_p$$

Representation of norm of A in terms of coefficients

$$(i) \quad p = 1, \quad \|A\|_1 = \max_{j=1,2,\dots,n} \left(\sum_{i=1}^n |a_{ij}| \right)$$

$$\begin{bmatrix} a_{11} & & & & a_{1n} \\ a_{21} & & & & a_{2n} \\ a_{i1} & a_{i2} & & & a_{in} \\ a_{n1} & & & & a_{nn} \end{bmatrix}$$

(A red oval highlights the j-th column elements $a_{1j}, a_{2j}, \dots, a_{nj}$. A blue oval highlights the i-th row elements $a_{i1}, a_{i2}, \dots, a_{in}$.)

$$(ii) \quad p = \infty, \quad \|A\|_{\infty} = \max_{i=1,2,\dots,n} \left(\sum_{j=1}^n |a_{ij}| \right)$$

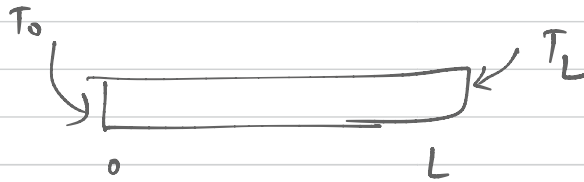
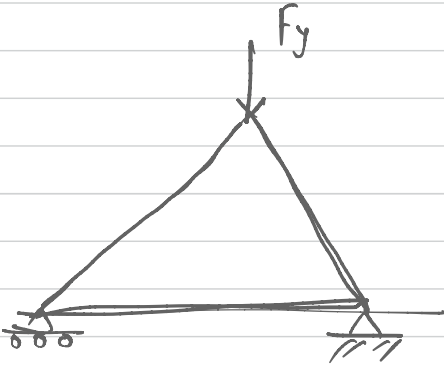
$$(iii) \quad p = 2, \quad \|A\|_2 = \sqrt{\sum_{i=1}^n \sum_{j=1}^n (a_{ij})^2}$$

• Error in $Ax = b$ problem

Original problem

$$Ax = b$$

x is a solution



$$Ax = b$$

$$x = \begin{bmatrix} T(x_1) \\ \vdots \\ T(x_{n-1}) \end{bmatrix}$$

new problem

$$Ax = \tilde{b}$$

\tilde{x} is a solution

Our goal is to relate error in data $\frac{\|b - \tilde{b}\|}{\|b\|}$

to error in solution $\frac{\|x - \tilde{x}\|}{\|x\|}$

propagation of errors

error in data



error in solution

b

$$Ax = b$$

$$A\tilde{x} = \tilde{b}$$

$$A(x - \tilde{x}) = b - \tilde{b}$$

$$\Rightarrow x = A^{-1}b$$

$$\tilde{x} = A^{-1}\tilde{b}$$

$$x - \tilde{x} = A^{-1}(b - \tilde{b})$$

$$\|x - \tilde{x}\|_p = \|A^{-1}(b - \tilde{b})\|_p \leq \|A^{-1}\|_p \|b - \tilde{b}\|_p$$

we also have

$$\|b\|_p = \|Ax\|_p \leq \|A\|_p \|x\|_p$$

$$\Rightarrow \frac{\|x - \tilde{x}\|_p}{\|x\|_p} \leq \frac{\|A^{-1}\|_p \|b - \tilde{b}\|_p}{\|x\|_p}$$

$$= \frac{1}{\|x\|_p} (\|A^{-1}\|_p \|b - \tilde{b}\|_p)$$

$$\leq \frac{\|A\|_p}{\|b\|_p} \|A^{-1}\|_p \|b - \tilde{b}\|_p$$

$$= \left[\|A\|_p \|A^{-1}\|_p \right] \left[\frac{\|b - \tilde{b}\|_p}{\|b\|_p} \right]$$

$$\|x\|_p \geq \frac{\|b\|_p}{\|A\|_p}$$
$$\Rightarrow \frac{\|A\|_p}{\|b\|_p} \geq \frac{1}{\|x\|_p}$$

$$\Rightarrow \frac{\|x - \tilde{x}\|_p}{\|x\|_p} \leq \left(\|A\|_p \|A^{-1}\|_p \right) \frac{\|b - \tilde{b}\|_p}{\|b\|_p}$$

depends only on A

condition number of matrix A

$$\text{cond}(A) = \|A\|_p \|A^{-1}\|_p$$

$$\frac{\|x - \tilde{x}\|_p}{\|x\|_p} \leq \text{Cond}(A) \frac{\|b - \tilde{b}\|_p}{\|b\|_p}$$

Roughly $\text{cond}(A) \propto \frac{1}{\det(A)}$

specially if A is singular i.e. A^{-1} does not exist

then $\text{cond}(A) = \infty$

$\text{cond}(A) \geq 1$

$$A = \begin{bmatrix} 1.01 & 0.99 \\ 0.99 & 1.01 \end{bmatrix}, \quad A^{-1} = \begin{bmatrix} 25.25 & -24.75 \\ -24.75 & 25.25 \end{bmatrix}$$

$$\text{cond}(A) = \|A\|_{\infty} \|A^{-1}\|_{\infty} = 100$$

$$2 = \max\{2, 2\}$$

$$\max\{50, 50\} = 50$$

$$\begin{aligned} &25.25 \\ &+ 24.75 \\ &= 50 \end{aligned}$$

$$\frac{\|x - \tilde{x}\|_{\infty}}{\|x\|_{\infty}} \leq 100 \frac{\|b - \tilde{b}\|_{\infty}}{\|b\|_{\infty}}$$

$$A = \begin{bmatrix} 1.001 & 0.999 \\ 0.999 & 1.001 \end{bmatrix} \rightarrow A^{-1}, \text{ cond}(A)$$