

Root Finding of Non-Linear Equations:

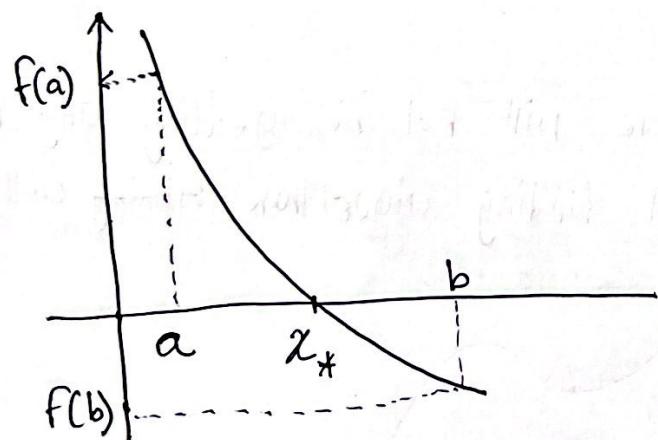
→ For powers of x which are low, we can easily find the root using approaches like:

$$\text{eg } f(x) = x^2 - 2x = 0 \\ \Rightarrow x(x-2) = 0 \\ x = 2, x = 0$$

→ But what if we are dealing with non-linear equations with high powers/ series/ polynomials/ rational functions? How can we find their root?

↳ We can apply some iterative algorithms to find the roots.

Bisection Root Finding Algorithm:

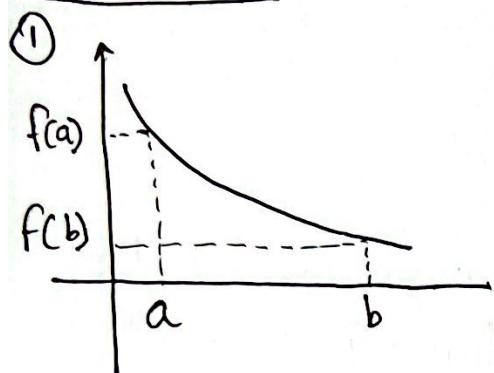


→ If root exists, the ~~value~~ value of the function changes sign.

here, $f(a) = +ve$ } Roots lies within $[a, b]$
 $f(b) = -ve$ } ~~changes~~ therefore it
 changes sign

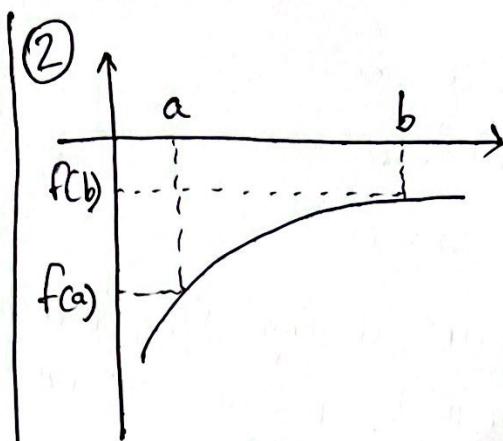
So, if $f(a) * f(b) < 0$ root exists between a and b .

Examples:



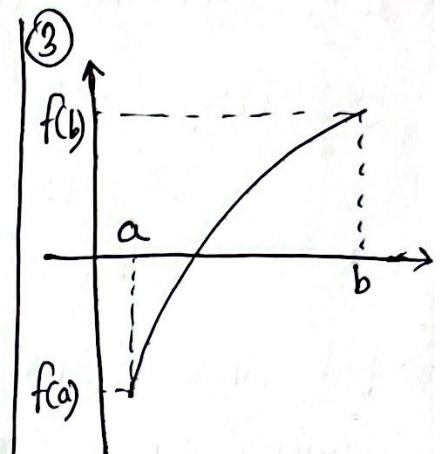
$$\begin{aligned}f(a) * f(b) \\= (+ve) * (+ve) \\= (+ve) \\> 0\end{aligned}$$

Root does not exist



$$\begin{aligned}f(a) * f(b) \\= (-ve) * (-ve) \\= (+ve) \\> 0\end{aligned}$$

Root does not exist

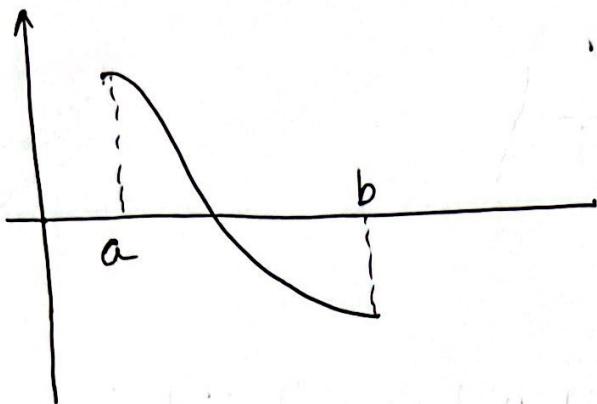


$$\begin{aligned}f(a) * f(b) \\= (-ve) * (+ve) \\= (-ve) \\< 0\end{aligned}$$

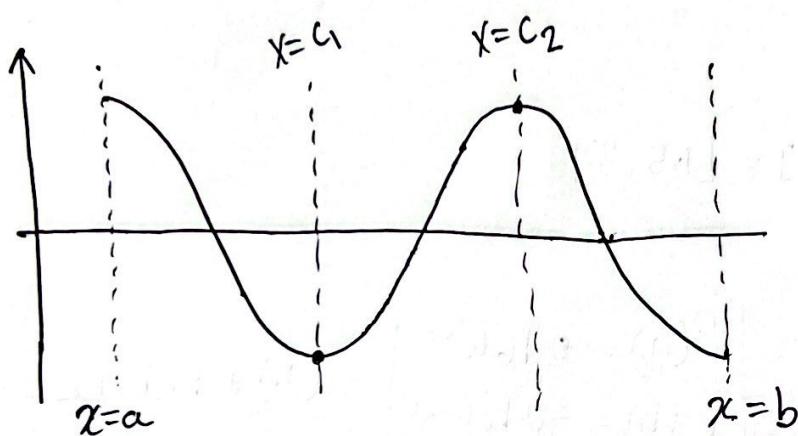
Root exists

For example ① and ②, we will not be getting any roots if we apply the any root finding algorithm within the interval $[a, b]$.

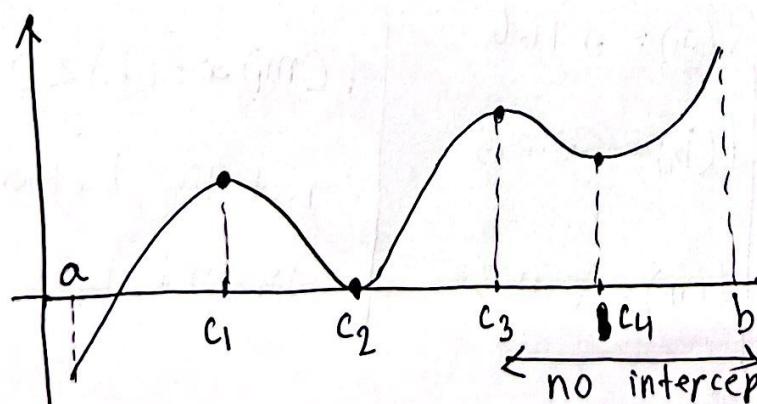
How to choose the right intervals :



$$[a, b] \rightarrow$$

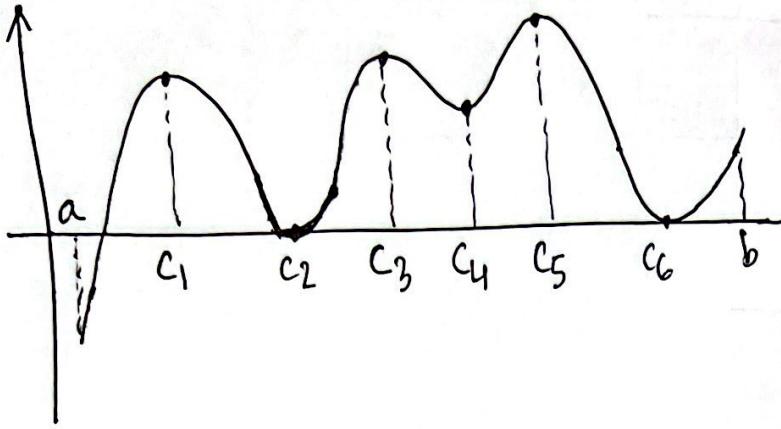


$$[a, b] = [a, c_1] \cup [c_1, c_2] \cup [c_2, b]$$



no intercept here, therefore can avoid.

$$[a, b] = [a, c_1] \cup [c_1, c_2] \cup [c_2, c_3]$$



$$[a, b] = [a, c_1] \cup [c_1, c_2] \cup [c_2, c_3] \cup [c_3, c_4] \cup [c_4, c_5] \cup [c_5, c_6] \cup [c_6, b]$$

Bisection Method:

$$f(x) = \frac{1}{x} - 0.5 \quad I = [1.5, 3]$$

$$a_0 = 1.5 \\ b_0 = 3$$

$$m_0 = \frac{a_0 + b_0}{2} = \frac{1.5 + 3}{2} = 2.25$$

$$\left| \begin{array}{l} f(a_0) = 0.166 > 0 \\ f(b_0) = -0.166 < 0 \\ f(m_0) = -0.055 < 0 \end{array} \right| \quad \begin{aligned} f(a_0) * f(m_0) &< 0 \\ \therefore \text{root lies between } a_0 \text{ and } m_0. \end{aligned}$$

$$a_1 = a_0 = 1.5$$

$$b_1 = m_0 = 2.25$$

$$m_1 = \frac{a_1 + b_1}{2} = \frac{1.5 + 2.25}{2} = 1.875$$

$$\left| \begin{array}{l} f(a_1) = 0.166 \\ f(b_1) = -0.055 \\ f(m_1) = 0.033 \end{array} \right|$$

$$f(m_1) * f(b_1) < 0$$

\therefore root lies between m_1 and b_1 .

Example

Use Bisection method to find solutions accurate within 10^{-3}
 for $f(x) = x^3 - 7x^2 + 14x - 6 = 0$ on interval $[1, 3.2]$

K	a_k	m_k	b_k	$f(a_k)$	$f(m_k)$	$f(b_k)$	$x_* \in [,]$
0	1	2.1	3.2	2	1.79	-0.11	$[2.1, 3.2]$
1	2.1	2.65	3.2	1.79	0.55	-0.11	$[2.65, 3.2]$
2	2.65	2.925	3.2	0.55	0.086	-0.11	$[2.925, 3.2]$
3	2.925	3.0625	3.2	0.86	-0.054	-0.11	$[2.925, 3.0625]$
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
9	2.998	3.000195	3.002	1.96×10^{-3}	-1.95×10^{-4}	-2.3×10^{-3}	$\boxed{< 10^{-3}}$

$$x_* = \underline{3.000}$$

Take upto 3 d.p. since error bound is 10^{-3} .

Finding number of iterations to find root:

Things that will be provided in the question:

① interval, eg: [1.5, 3]

② Machine epsilon / error / accuracy, eg: 1.1×10^{-16} bound

Formula:

$$n \geq \frac{\log(|b-a|) - \log(\epsilon)}{\log(2)} - 1$$

put -1 if question specifies Machine epsilon or error. If question specifies accuracy, then do not put -1.

Example

$$\text{interval} = [1.5, 3]$$

$$\epsilon_M = 1.1 \times 10^{-6}$$

Find minimum amount of iteration required to find the root with the error bound of the machine epsilon.

Solution

$$n \geq \frac{\log|3-1.5| - \log(1.1 \times 10^{-16})}{\log(2)} - 1$$

$$\geq 52.59$$

$$> 53$$

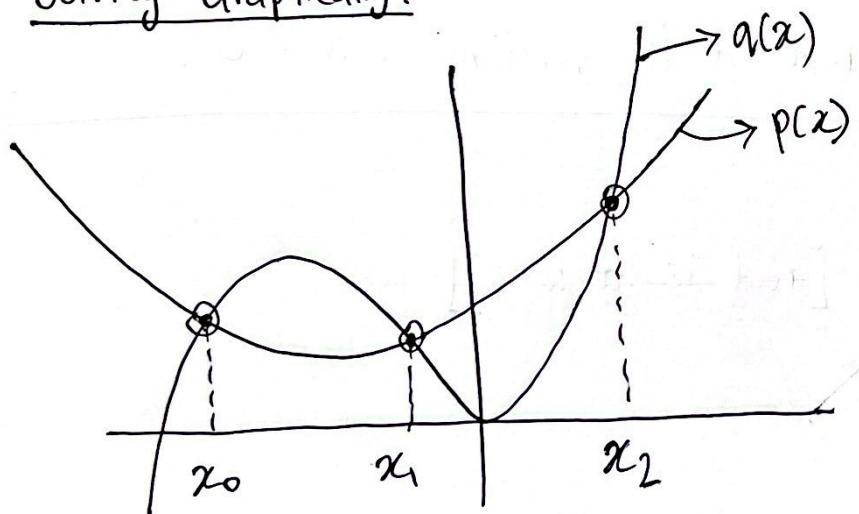
⊕ Fixed Point Iteration:

- We want to solve $f(x) = 0$
- Need to transform $f(x) = 0$ into a new form
- convert $f(x) = 0$ into $\boxed{g(x) = x}$

⊕ Algebra Recap:

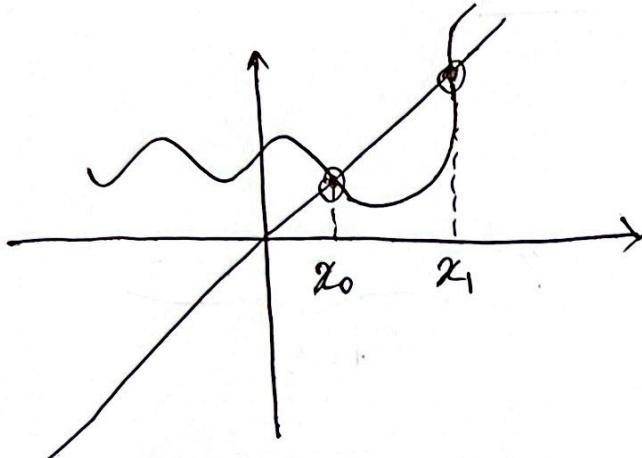
$$\underbrace{x^2 + 5x + 7}_{p(x)} = \underbrace{x^3 + 3x^2}_{q(x)} \rightarrow \underbrace{x^3 + 2x^2 - 5x - 7}_{f(x)}$$

Solving Graphically:



x_0, x_1, x_2 are the roots of the function $f(x)$

- Now imagine we have a function $f(x) = 0$
- Convert the function $f(x) = 0$ into $g(x) = x$
- The intersection of $g(x) = x$ should give the root of the function $f(x) = 0$.



x_0, x_1 should be the root of the function $f(x) = 0$.

Example:

$$f(x) = -\frac{1}{2}x + 1 = 0 \quad [\text{root is at } x=2]$$

$$\frac{x+2}{2} = x$$

\curvearrowleft \curvearrowright

$g(x)$ x

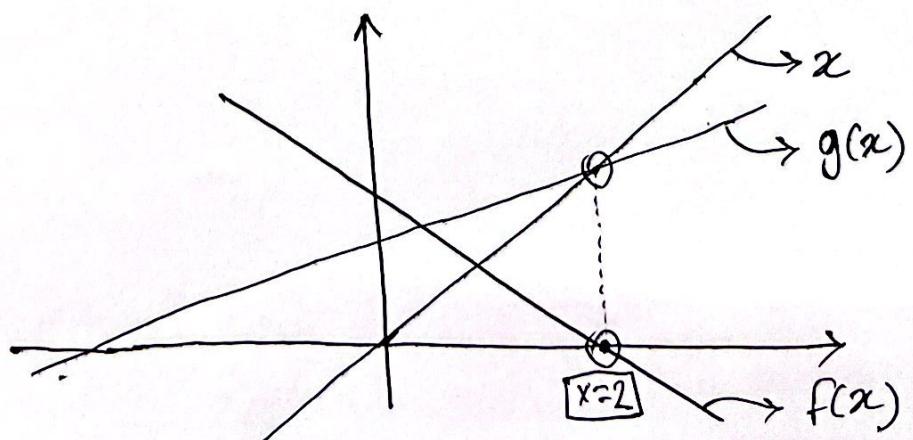
Solving numerically:

$$\frac{x+2}{2} = x$$

$$x+2 = 2x$$

$$\boxed{x=2}$$

Solving Graphically:



Converting $f(x) = 0$ into $g(x) = x$:

$$f(x) = x^2 - 2x - 3 = 0$$

[Roots are at $x = -1, 3$]

[Found using middle term, or quadratic root finding formula]

make x the subject

$$\textcircled{1} \quad x^2 - 2x - 3 = 0$$

$$x^2 = 2x + 3$$

$$x = \underbrace{\sqrt{2x+3}}_{\sim x} \quad g(x)$$

$$\textcircled{2} \quad x^2 - 2x - 3 = 0$$

$$\Rightarrow x(x-2) - 3 = 0$$

$$\Rightarrow x = \frac{3}{x-2} \quad \begin{matrix} \sim x \\ g(x) \end{matrix}$$

$$\textcircled{3} \quad x^2 - 2x - 3 = 0$$

$$\Rightarrow x^2 - x - x - 3 = 0$$

$$\Rightarrow x = \underbrace{x^2 - x - 3}_{\sim x} \quad g(x)$$

$$\textcircled{4} \quad x^2 - 2x - 3 = 0$$

$$\Rightarrow 2x^2 - 2x = x^2 + 3$$

$$\Rightarrow x(2x-2) = x^2 + 3$$

$$\Rightarrow x = \frac{x^2 + 3}{2x-2} \quad \begin{matrix} \sim x \\ g(x) \end{matrix}$$

Root Finding Formula:

$$g(x_k) = x_{k+1}$$

① $g(x) = \sqrt{2x+3}$, $x_0 = 0$

$$g(0) = 1.73$$

$$g(1.73) = 2.54$$

$$g(2.54) = 2.84$$

$$g(2.84) = 2.95$$

$$g(2.95) = 2.98$$

$$g(2.98) = 2.99$$

$$g(2.99) = 3$$

$g(3) = 3 \rightarrow$ Fixed point reached.

② $g(x) = x^2 - x - 3$, $x_0 = 0$

$$g(0) = -3$$

$$g(-3) = 9$$

$$g(9) = 69$$

} Diverges

③ $g(x) = \frac{x^2 + 3}{2x - 2}$, $x_0 = 0$

$$g(0) = -1.5$$

$$g(-1.5) = -1.05$$

$$g(-1.05) = -1$$

$g(-1) = -1 \rightarrow$ Fixed point reached.

2 Questions to answer:

① At which root will it converge to?

→ It will depend on the initial choice of x_0

→ It will also depend on the value of the converging rate, λ .

② Which form of $g(x)$ is convergent?

→ It will depend on the value of the converging rate, λ .

Elaborating the first Q/A:

$$① g(x) = \sqrt{2x+3}, x_0=0 \quad | \quad g(x) = \sqrt{2x+3}, x_0=42$$

$$g(0) = 1.73$$

$$g(42) = 9.33$$

$$g(1.73) = 2.54$$

$$g(9.33) = 4.65$$

$$g(2.54) = 2.84$$

$$g(4.65) = 3.51$$

$$g(2.84) = 2.95$$

$$g(3.51) = 3.17$$

$$g(2.95) = 2.98$$

$$g(3.17) = 3.06$$

$$g(2.98) = 2.99$$

$$g(3.06) = 3.02$$

$$g(2.99) = 3.00$$

$$g(3.02) = 3.01$$

$$g(3) = 3$$

$$g(3) = 3$$

→ Both $x_0=0$ & $x_0=42$ converges to the root, $x_* = 3$.

→ Even though $x_0=0$ is closer to $x_* = -1$, it converges to $x_* = 3$.

$$\textcircled{2} \quad g(x) = x^2 - x - 3, \quad x_0 = 0 \quad \left| \begin{array}{l} g(0) = -3 \\ g(-3) = 9 \\ g(9) = 69 \\ g(69) = 4.69 \times 10^3 \\ \vdots \\ \} \text{diverges} \end{array} \right. \quad \left| \begin{array}{l} g(x) = x^2 - x - 3, \quad x_0 = 42 \\ g(42) = 1.72 \times 10^3 \\ g(1.72 \times 10^3) = 2.95 \times 10^6 \\ g(2.95 \times 10^6) = 8.72 \times 10^{12} \\ \vdots \\ \} \text{Diverges} \end{array} \right.$$

\rightarrow Both $x_0 = 0$ and $x_0 = 42$ diverges rapidly.

$$\textcircled{3} \quad g(x) = \frac{x^2 + 3}{2x - 2}, \quad x_0 = 0 \quad \left| \begin{array}{l} g(0) = -1.5 \\ g(-1.5) = -1.05 \\ g(-1.05) = -1 \\ g(-1) = -1 \end{array} \right. \quad \left| \begin{array}{l} g(x) = \frac{x^2 + 3}{2x - 2}, \quad x_0 = 42 \\ g(42) = 21.6 \\ g(21.6) = 11.4 \\ g(11.4) = 6.39 \\ g(6.39) = 4.07 \\ g(4.07) = 3.19 \\ g(3.19) = 3.01 \\ g(3.01) = 3 \\ g(3) = 3 \end{array} \right.$$

$\rightarrow x_0 = 0$ and $x_0 = 42$ converges to 2 different roots.

$\rightarrow x_0 = 0$ converges to the nearest root, which is -1 , and $x_0 = 42$ converges to the nearest root, which is 3 . (42 is closer to 3 than -1).

Contraction Mapping Theory:

Find $g'(x)$

Find $g'(\text{root-1})$

Find $g'(\text{root-2})$

if $|g'(\text{root})| < 1$, $g(x)$ will be convergent.

$$\lambda = |g'(\text{root})|$$

↑
converging rate

$$① g(x) = \sqrt{2x+3} = (2x+3)^{\frac{1}{2}}$$

$$g'(x) = \frac{1}{2}(2x+3)^{-\frac{1}{2}}(2)$$

$$= (2x+3)^{-\frac{1}{2}}$$

$$= \frac{1}{\sqrt{2x+3}}$$

$$\lambda = |g'(-1)| = 1 \quad (\text{not } < 1)$$

$$\lambda = |g'(3)| = \frac{1}{3} \quad (< 1)$$

\therefore both $x_0=0, x_0=42$ converges to the root $x_* = 3$.

$$\textcircled{2} \quad g(x) = x^2 - x - 3$$

$$g'(x) = 2x - 1$$

$$\lambda = |g'(-1)| = |-3| = 3 \quad (\text{not } < 1)$$

$$\lambda = |g'(3)| = 5 \quad (\text{not } < 1)$$

\therefore no choices of x_0 will converge to any root. It will all diverge.

$$\textcircled{3} \quad g(x) = \frac{x^2 + 3}{2x - 2}$$

$$\lambda = |g'(-1)| = 0 \quad (< 1)$$

$$\lambda = |g'(3)| = 0 \quad (< 1)$$

\therefore will converge to both $x_1 = -1$ & $x_2 = 3$.

Since $x_0 = 0$ is closer to -1 , it will converge to -1 .

$x_0 = 42$ is closer to 3 , it will converge to 3 .

Example:

$$f(x) = x^3 - 2x^2 - x + 2$$

- (a) State the roots of the function $f(x)$.
- (b) Construct 3 different fixed point function $g(x)$ such that $f(x) = 0$
- (c) Find the converging rate of $g(x)$ and which root it will converge to.

Solution:

$$(a) f(x) = x^3 - 2x^2 - x + 2 = 0$$

$$\Rightarrow x^2(x-2) - 1(x-2) = 0$$

$$\Rightarrow (x^2-1)(x-2) = 0$$

$$x_* = +1$$

$$-1$$

$$+2$$

$$(b) (i) x^3 - 2x^2 - x + 2 = 0$$

$$x = \underbrace{x^3 - 2x^2 + 2}_{g(x)}$$

$$(ii) x^3 - 2x^2 - x + 2 = 0$$

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

$$\Rightarrow x = \frac{-2}{x^2 - 2x - 1}$$

$$(iii) x^3 - 2x^2 - x + 2 = 0$$

$$\Rightarrow 2x^2 = x^3 - x + 2$$

$$\Rightarrow x^2 = \frac{1}{2}(x^3 - x + 2)$$

$$\Rightarrow x = \frac{1}{\sqrt{2}} \sqrt{x^3 - x + 2}$$

$$\underbrace{x}_{g(x)}$$

$$(C)(i) \quad g(x) = x^3 - 2x^2 + 2$$

$$g'(x) = 3x^2 - 4x$$

$$\lambda = |g'(x_*)| = \begin{cases} 7 & \text{at } x_* = -1 \\ 1 & \text{at } x_* = 1 \\ 4 & \text{at } x_* = 2 \end{cases}, \text{ Divergent}$$

$$(ii) \quad g(x) = \frac{-2}{x^2 - 2x - 1}$$

$$g'(x) = \frac{4(x-1)}{(x^2 - 2x - 1)^2}$$

$$\lambda = |g'(x_*)| = \begin{cases} 2 & \text{at } x_* = -1 \\ 0 & \text{at } x_* = 1 \\ 4 & \text{at } x_* = 2 \end{cases}$$

$\therefore g(x)$ will converge to $x_* = 1$

$$(iii) \quad g(x) = \frac{1}{\sqrt{2}} (x^3 - x + 2)^{\frac{1}{2}}$$

$$g'(x) = \frac{3x^2 - 1}{2\sqrt{2} (x^3 - x + 2)^{1/2}}$$

$$\lambda = |g'(x_*)| = \begin{cases} 0.5 & \text{when } x_* = -1 \\ 0.5 & \text{when } x_* = 1 \\ 1.375 & \text{when } x_* = 2 \end{cases}$$

$\therefore g(x)$ will converge to $x_* = -1$ & 1 .

Order of Convergence:

- ① $\lambda = 0 \rightarrow$ Super linear convergence \rightarrow fastest convergence
 \rightarrow less iterations required to converge.
- ② $0 < \lambda < 1 \rightarrow$ linear convergence \rightarrow will converge
 \rightarrow But not as fast as $\lambda = 0$.
- ③ $\lambda = 1 \rightarrow$ ignore
- ④ $\lambda > 1 \rightarrow$ Diverge.

Newton's Method:



Slope of the tangent line:

$$\text{Slope} = \frac{f(x_{k+1}) - f(x_k)}{x_{k+1} - x_k} = \frac{-f(x_k)}{x_{k+1} - x_k} \quad \text{--- } \textcircled{1}$$

$$\text{Slope} = f'(x_k) \quad \text{--- } \textcircled{II}$$

Equating the two equations

$$f'(x) = \frac{-f(x_k)}{x_{k+1} - x_k}$$

$$x_{k+1} = x_k - \underbrace{\frac{f(x_k)}{f'(x_k)}}_{g(x)}$$

Example:

$$f(x) = \frac{1}{x} - 0.5 \quad [x_* \text{ is at } 2], \text{ assume } x_0 = 1.$$

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

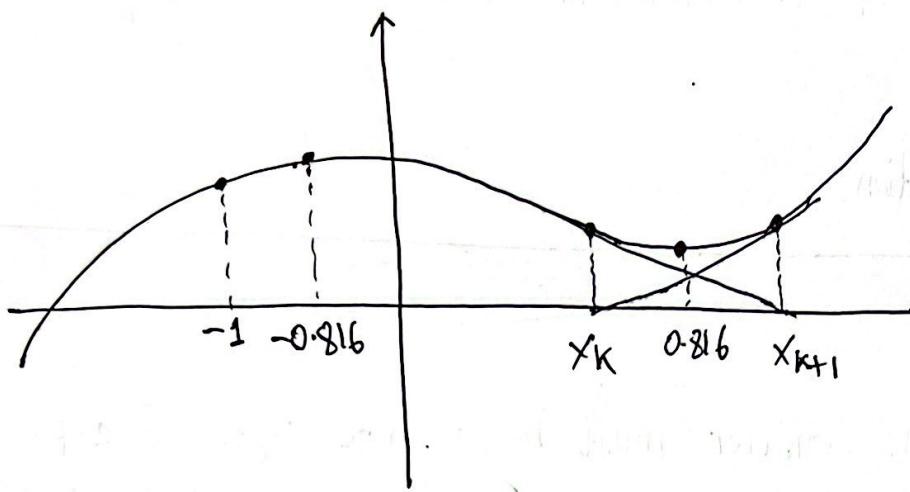
$$= x_k - \frac{\left(\frac{1}{x_k} - 0.5 \right)}{\frac{d}{dx} \left(\frac{1}{x_k} - 0.5 \right)}$$

$$x_{k+1} = 2x_k - 0.5x_k^2$$

<u>k</u>	<u>x_k</u>
0	1
1	1.5
2	1.875
3	1.9921875
4	1.999969482
5	2
6	2

Newton's Method will not work if there is a turning point between x_k and x_{k+1} .

Example:



Let's say the above function is $f(x) = x^3 - 2x + 2$

Finding the turning points:

$$f'(x) = 3x^2 - 2 = 0$$

$$\Rightarrow x = \pm \sqrt{\frac{2}{3}}$$

$$\therefore x = \pm 0.816$$

Make sure $x_0 < -0.816$

Example, $x_0 = -1$.

Example :

$$f(x) = x^2 - 2xe^{-x} + e^{-2x}, \quad x_0 = 1$$

Find the solution of this function within 10^{-5} using

- Newton's Method
- Aitken Acceleration.

Note:

0.00001

↗

- Within 10^{-5} means answer must be accurate upto 5 d.p.
[calculate answers upto 6 dp, then round upto 5 dp at the last]
- In the above question, what should we compare our answers to?
Should we compare our answers to $f(x)=0$ or compare our answer to the actual root, x_* ?
- If we compare to $f(x)=0$, we will reach our answer when $|f(x_k)| < 0.00001$, where k is the iteration number.
- If we compare to the actual root, x_* , we will reach our answer when $|x_* - x_k| < 0.00001$.
- This means that we compare to $f(x)=0$ when x_* is not given, or x_* cannot be found numerically.

Solution:

$$f(x) = x^2 - 2xe^{-x} + e^{-2x}$$

$$f'(x) = 2x - 2e^{-x} - 2x(-e^{-x}) - 2e^{-2x}$$

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

$$= x_k - \frac{x_k^2 - 2x_k e^{-x_k} + e^{-2x_k}}{2x_k - 2e^{-x_k} + 2x_k e^{-x_k} - 2e^{-2x_k}}$$

K	x_k	$f(x_k)$	if $ f(x_k) < 0.00001$?
0	1 <small>put $f(1)$</small> <small>↓ put (1) in iteration formula</small>	0.399576	NO
1	0.768941	0.093292	NO
2	0.664590	0.022532	NO
3	0.615033	0.005537	NO
4	0.590884	0.00137	NO
5	0.578963	0.000342	NO
6	0.573041	0.000085	NO
7	0.570089	2×10^{-5}	NO
8	0.568615	0.5×10^{-5}	Yes

Answer: $x_8 = 0.56862$ (upto 5 d.p)

Aitken Acceleration:

→ Used to accelerate convergence

Formula:

$$\hat{x}_{k+2} = x_k - \frac{(x_{k+1} - x_k)^2}{x_{k+2} - 2x_{k+1} + x_k}$$

→ starting from x_0 , every 2 iteration acceleration occurs.

e.g.: x_2, x_4, x_6, \dots .

$x_0 \rightarrow x_1 \rightarrow x_2 \rightarrow \hat{x}_2 \rightarrow x_3 \rightarrow x_4 \rightarrow \hat{x}_4 \rightarrow x_5 \rightarrow x_6$

\downarrow
 \hat{x}_6

Example:

$$f(x) = \frac{1}{x} - 0.5 \quad [x_* \text{ is at } 2]$$

→ construct a $g(x)$ so that $x=2$ is a fixed point of $g(x)$.

$$g(x) = x + \frac{1}{16} \left(\frac{1}{x} - 0.5 \right)$$

$$g(2) = 2$$

$$g'(x) = 1 + \frac{1}{16} \left(-\frac{1}{x^2} \right)$$

$$\lambda = |g'(2)| = 1 + \frac{1}{16} \left(-\frac{1}{2^2} \right) = 0.984375 \quad (< 1)$$

$\rightarrow \lambda$ is close to 1. It will converge, but it will be very slow.

\rightarrow lets start using $x_0 = 1.5$, keeping the calculations upto 7 s.f.

$$g(x) = x + \frac{1}{16} \left(\frac{1}{x} - 0.5 \right), x_0 = 1.5$$

~~0.6250000000000000~~

~~0.6250000000000000~~

$$x_0 = 1.5$$

$$x_1 = g(x_0) = 1.510417$$

$$x_2 = g(x_1) = 1.520546$$

$$x_3 = g(x_2) = 1.530400$$

$$x_4 = g(x_3) =$$

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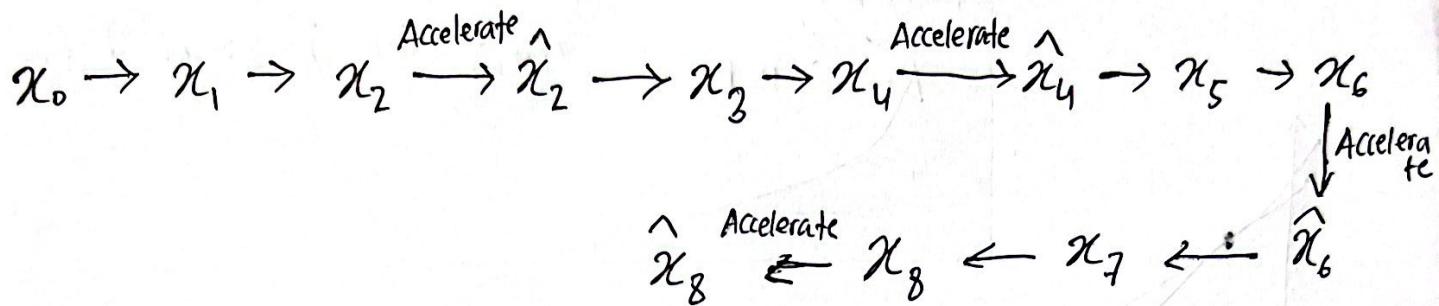
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$$x_{818} = g(x_{817}) = 1.999999$$

Now, Applying Aitken Acceleration:

$$\hat{x}_{k+2} = x_k - \frac{(x_{k+1} - x_k)^2}{x_{k+2} - 2x_{k+1} + x_k}$$



$$x_0 = 1.5$$

$$x_1 = g(x_0) = 1.510417$$

$$x_2 = g(x_1) = 1.520546$$

$$\hat{x}_2 = x_0 - \frac{(x_1 - x_0)^2}{x_2 - 2x_1 + x_0} = 1.877604$$

$$x_3 = g(\hat{x}_2) = 1.879641$$

$$x_4 = g(x_3) = 1.881642$$

$$\hat{x}_4 = \hat{x}_2 - \frac{(x_3 - \hat{x}_2)^2}{x_4 - 2x_3 + \hat{x}_2} = 1.992634$$

⋮

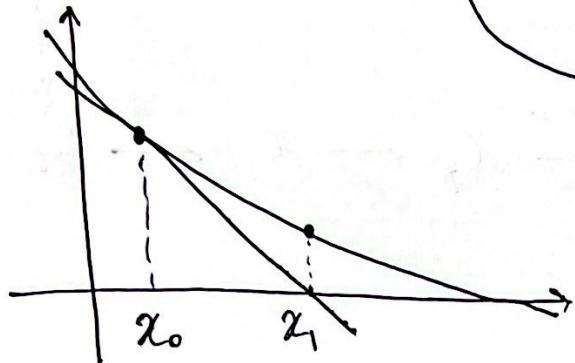
$$\hat{x}_8 = 2.000000$$

Secant Method / Quasi-Newton Method:

Newton's Method Recap:

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

→ replace $f'(x_k)$ with backward diff.



$$\text{backward differentiation} = \frac{f(x) - f(x-h)}{h}$$

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

$$= \frac{f(x_k) - f(x_{k-1})}{x_k - x_{k-1}}$$

} put this part instead of $f'(x_k)$

∴ Iteration formula for Secant Method:

$$x_{k+1} = x_k - \frac{f(x_k)(x_k - x_{k-1})}{f(x_k) - f(x_{k-1})}$$

Note: We need 2 starting points for Secant Method (x_0 and x_1).

Example

$$f(x) = \frac{1}{x} - 0.5 \quad x_0 = 0.25, x_1 = 0.5$$

$$x_{k+1} = x_k - \frac{f(x_k)(x_k - x_{k-1})}{f(x_k) - f(x_{k-1})}$$

$$= x_k - \frac{\left(\frac{1}{x_k} - 0.5\right)(x_k - x_{k-1})}{\left(\frac{1}{x_k} - 0.5\right) - \left(\frac{1}{x_{k-1}} - 0.5\right)}$$

k	x_k
0	0.25
1	0.5
2	0.6875
3	1.01562
4	1.3540
5	1.68205
6	1.8973
7	1.98367
8	1.99916
⋮	⋮
12	2.00000

Example:

$$f(x) = x_k^2 - 2x_k e^{-x_k} + e^{-2x_k} \quad \text{--- } ①$$

Newtons Method Iteration Formula :

$$x_{k+1} = x_k - \frac{x_k^2 - 2x_k e^{-x_k} + e^{-2x_k}}{2x_k - 2e^{-x_k} + 2x_k e^{-x_k} - 2e^{-2x_k}} \quad \text{--- } ②$$

Aitken Acceleration:

$$\hat{x}_{k+2} = x_k - \frac{(x_{k+1} - x_k)^2}{x_{k+2} - 2x_{k+1} + x_k} \quad \text{--- } ③$$

Flow:

check if within error bound, if not, go next

$$x_0 \xrightarrow{\text{eq.1}} f(x_0) \xrightarrow{\text{eq.2}} x_1 \xrightarrow{\text{eq.1}} f(x_1) \xrightarrow{\text{eq.2}} x_2 \xrightarrow{\text{eq.1}} f(x_2) \xrightarrow{\text{eq.3}}$$

$$\begin{array}{ccccccc} x_4 & \xleftarrow{\text{eq.2}} & f(x_3) & \xleftarrow{\text{eq.1}} & x_3 & \xleftarrow{\text{eq.2}} & f(\hat{x}_2) \xleftarrow{\text{eq.1}} \hat{x}_2 \\ \text{eq.1} \downarrow & & & & & & \leftarrow \\ & & f(x_4) & \xrightarrow{\text{eq.3}} & \hat{x}_4 & \xrightarrow{\text{eq.1}} & f(\hat{x}_4) \xrightarrow{\text{eq.2}} x_5 \end{array}$$

k	x_k	$f(x_k)$	if $ f(x_k) < 10^{-5}$?
0	1	$\xrightarrow{\text{eq.1}} 0.399576$	No
1	0.768941	$\xrightarrow{\text{eq.1}} 0.093292$	No
2	0.664590	$\xrightarrow{\text{eq.1}} 0.022532$	No
3	0.578651	$\xrightarrow{\text{eq.1}} 3.2 \times 10^{-4}$	No
4	0.572885	$\xrightarrow{\text{eq.1}} 8 \times 10^{-5}$	No
5	0.570011	$\xrightarrow{\text{eq.1}} 2 \times 10^{-5}$	No
6	0.567154	$\xrightarrow{\text{eq.1}} 2.8 \times 10^{-10}$	Yes

Answer: $x_6 = 0.56715$ (upto 5 d.p).

Linear Equations:

→ System of linear equations (exponent of all variables must be 1)

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2$$

⋮

$$a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n = b_n$$

→ Can be represented in a matrix form:

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$

$\underbrace{\quad\quad\quad}_{(n \times n) \text{ matrix, } A}$

$\underbrace{\quad\quad\quad}_{(n \times 1) \text{ matrix, } x}$

$\underbrace{\quad\quad\quad}_{(n \times 1) \text{ matrix, } b}$

$$A \cdot x = b$$

Solution:

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

Basic properties of A:

→ A should be a square matrix of shape $(n \times n)$

→ A must be non-singular [meaning $\det(A) \neq 0$]

Gaussian Elimination Method:

- A technique which transforms matrix A into triangular form (upper or lower)
- Solves $Ax = b$ without finding the inverse.
- Lower triangular matrix (L), and upper triangular matrix (U) are defined as follows:

$$L = \begin{bmatrix} l_{11} & 0 & \cdots & 0 \\ l_{21} & l_{22} & \cdots & 0 \\ \vdots & & & \\ l_{n1} & l_{n2} & \cdots & l_{nn} \end{bmatrix} \quad U = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ 0 & u_{22} & \cdots & u_{2n} \\ \vdots & & & \\ 0 & 0 & \cdots & u_{nn} \end{bmatrix}$$

Using a (4×4) Lower triangular matrix:

$$\begin{bmatrix} l_{11} & 0 & 0 & 0 \\ l_{21} & l_{22} & 0 & 0 \\ l_{31} & l_{32} & l_{33} & 0 \\ l_{41} & l_{42} & l_{43} & l_{44} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}$$

$$l_{11} x_1 + 0 \cdot x_2 + 0 \cdot x_3 + 0 \cdot x_4 = b_1$$

$$\Rightarrow x_1 = \frac{b_1}{l_{11}}$$

$$l_{21} x_1 + l_{22} x_2 = b_2$$

$$x_2 = \frac{b_2 - l_{21} x_1}{l_{22}}$$

number of operations:

1 div

1 div, 1 mult, 1 sub

number of operations:

$$l_{31}x_1 + l_{32}x_2 + l_{33}x_3 = b_3$$

$$x_3 = \frac{b_3 - l_{31}x_1 - l_{32}x_2}{l_{33}}$$

→ 1 div, 2 mult, 2 sub

$$l_{41}x_1 + l_{42}x_2 + l_{43}x_3 + l_{44}x_4 = b_4$$

$$x_4 = \frac{b_4 - l_{41}x_1 - l_{42}x_2 - l_{43}x_3}{l_{44}}$$

→ 1 div, 3 mult, 3 sub

This is a "TOP DOWN" approach because we found x_1 first, then x_2, x_3, x_4 .

Total number of operations:

For finding x_n , we need 1 div, $(n-1)$ mult, $(n-1)$ sub.

$$\textcircled{a} \quad 1 + (n-1) + (n-1) = 1 + 2(n-1)$$

$$\therefore \text{total num of operations} = \sum_{j=1}^n [1 + 2(j-1)]$$

$$= \sum_{j=1}^n (2j - 1)$$

$$= 2 \sum_{j=1}^n j - \sum_{j=1}^n 1$$

$$= n^2 + n - n$$

$$= n^2$$

Gaussian Elimination Method:

- To make a matrix into a triangular form, we apply Gaussian Elimination.
- Need to apply row operations.
- 1st row operation will make all elements below a_{11} into 0.

Example:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

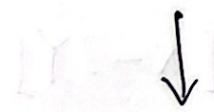
$$= \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ 0 & a_{22}' & a_{23}' \\ 0 & a_{32}' & a_{33}' \end{bmatrix} \quad r_2' = r_2 - \boxed{\frac{a_{21}}{a_{11}}} r_1 \quad m_{21}$$

$$r_3' = r_3 - \boxed{\frac{a_{31}}{a_{11}}} r_1 \quad m_{31}$$

$$\begin{bmatrix} x & x & x & x \\ x & x & x & x \\ x & x & x & x \\ x & x & x & x \end{bmatrix}$$



$$\begin{bmatrix} x & x & x & x \\ 0 & x & x & x \\ 0 & x & x & x \\ 0 & x & x & x \end{bmatrix}$$



$$\begin{bmatrix} x & x & x & x \\ 0 & x & x & x \\ 0 & 0 & x & x \\ 0 & 0 & x & x \end{bmatrix}$$



$$\begin{bmatrix} x & x & x & x \\ 0 & x & x & x \\ 0 & 0 & x & x \\ 0 & 0 & 0 & x \end{bmatrix}$$

Example:

$$x_1 + 2x_2 + x_3 = 0$$

$$x_1 - 2x_2 + 2x_3 = 4$$

$$2x_1 + 12x_2 - 2x_3 = 4$$

$$A = \begin{bmatrix} 1 & 2 & 1 \\ 1 & -2 & 2 \\ 2 & 12 & -2 \end{bmatrix} \quad b = \begin{bmatrix} 0 \\ 4 \\ 4 \end{bmatrix}$$

Augmented Matrix:

$$\left[\begin{array}{ccc|c} 1 & 2 & 1 & 0 \\ 1 & -2 & 2 & 4 \\ 2 & 12 & -2 & 4 \end{array} \right] \rightarrow r_2' = r_2 - \frac{1}{1} r_1 \quad [x - Y]$$

$$\rightarrow r_3' = r_3 - \frac{2}{1} r_1 \quad [x - 2Y]$$

$$\left[\begin{array}{ccc|c} 1 & 2 & 1 & 0 \\ 0 & -4 & 1 & 4 \\ 0 & 8 & -4 & 4 \end{array} \right] \rightarrow r_3' = r_3 - \frac{8}{4} r_2 \quad [x + 2Y]$$

$$\left[\begin{array}{ccc|c} 1 & 2 & 1 & 0 \\ 0 & -4 & 1 & 4 \\ 0 & 0 & -2 & 12 \end{array} \right]$$

$$\begin{array}{l|l|l} -2x_3 = 12 & -4x_2 + x_3 = 4 & x_1 + 2x_2 + x_3 = 0 \\ x_3 = -6 & -4x_2 - 6 = 4 & x_1 + 2(-2.5) + (-6) = 0 \\ & x_2 = -2.5 & x_1 = 11 \end{array}$$

LU Decomposition:

→ Need to decompose matrix A into LU

$$A = \left[\begin{array}{cccc} 2 & 4 & 3 & 5 \\ -4 & -7 & -5 & -8 \\ 6 & 8 & 2 & 9 \\ 4 & 9 & -2 & 14 \end{array} \right] \rightarrow R_2' = R_2 - (-\frac{4}{2})R_1$$

$$\rightarrow R_3' = R_3 - (\frac{6}{2})R_1$$

$$\rightarrow R_4' = R_4 - (\frac{4}{2})R_1$$

$$= \left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ -2 & 1 & 0 & 0 \\ 3 & 1 & 0 & 0 \\ 2 & 1 & 1 & 0 \end{array} \right] \left[\begin{array}{cccc} 2 & 4 & 3 & 5 \\ 0 & 1 & 1 & 2 \\ 0 & -4 & -7 & -6 \\ 0 & 1 & -8 & 4 \end{array} \right] \rightarrow R_3' = R_3 - (-\frac{4}{1})R_2$$

$$\rightarrow R_4' = R_4 - (\frac{1}{1})R_2$$

$$= \left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ -2 & 1 & 0 & 0 \\ 3 & -4 & 1 & 0 \\ 2 & 1 & 1 & 0 \end{array} \right] \left[\begin{array}{cccc} 2 & 4 & 3 & 5 \\ 0 & 1 & 1 & 2 \\ 0 & 0 & -3 & 2 \\ 0 & 0 & -9 & 2 \end{array} \right] \rightarrow R_4' = R_4 - (\frac{-9}{-3})R_3$$

$$= \left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ -2 & 1 & 0 & 0 \\ 3 & -4 & 1 & 0 \\ 2 & 1 & 3 & 1 \end{array} \right] \left[\begin{array}{cccc} 2 & 4 & 3 & 5 \\ 0 & 1 & 1 & 2 \\ 0 & 0 & -3 & 2 \\ 0 & 0 & 0 & -4 \end{array} \right]$$

Steps:

$$\boxed{A} \cdot x = b$$

↓
decompose
LU

$$L \boxed{U x} = b$$

↓
y

$$L y = b \longrightarrow \begin{bmatrix} 1 & 0 & 0 \\ l_{21} & 1 & 0 \\ l_{31} & l_{32} & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

Solve for y [find y_1, y_2, y_3]

$$\boxed{U x = y}$$

$$\begin{bmatrix} u_{11} & u_{12} & u_{13} \\ 0 & u_{22} & u_{23} \\ 0 & 0 & u_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

Solve for x [find x_1, x_2, x_3]

Example:

$$\begin{bmatrix} 1 & 2 & 1 \\ 1 & -2 & 2 \\ 2 & 12 & -2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 4 \\ 4 \end{bmatrix}$$

$$A \cdot x = b$$

↓

LU

$$A = \begin{bmatrix} 1 & 2 & 1 \\ 1 & -2 & 2 \\ 2 & 12 & -2 \end{bmatrix} \rightarrow R_2' = R_2 - \left(\frac{1}{1}\right) R_1$$
$$\rightarrow R_3' = R_3 - \left(\frac{2}{1}\right) R_1$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 2 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 1 \\ 0 & -4 & 1 \\ 0 & 8 & -4 \end{bmatrix} \rightarrow R_3' = R_3 - \left(\frac{8}{-4}\right) R_2$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 2 & -2 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 1 \\ 0 & -4 & 1 \\ 0 & 0 & -2 \end{bmatrix}$$

L

U

$$A \cdot x = b$$

↓ decompose

LU

$$\begin{array}{l} L \\ \boxed{U \cdot x = b} \\ \downarrow \\ y \end{array}$$

$$L \cdot y = b$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 2 & -2 & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 4 \\ 4 \end{bmatrix}$$

$$\boxed{y_1 = 0}$$

$$y_1 + y_2 = 4, \quad \boxed{y_2 = 4}$$

$$2y_1 + (-2y_2) + y_3 = 4$$

$$(2 \times 0) + (-2 \times 4) + y_3 = 4$$

$$\boxed{y_3 = 12}$$

$$\rightarrow U \cdot x = y$$

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & -4 & 1 \\ 0 & 0 & -2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 4 \\ 12 \end{bmatrix}$$

$$-2x_3 = 12$$

$$\boxed{x_3 = -6}$$

$$-4x_2 + x_3 = 4$$

$$-4x_2 - 6 = 4$$

$$\boxed{x_2 = -2.5}$$

$$x_1 + 2x_2 + x_3 = 0$$

$$x_1 + 2(-2.5) + (-6) = 0$$

$$\boxed{x_1 = 11}$$

Advantage:

- This method can be used to solve linear system that differ by the values of 'b' only. We need to compute L and U only once.
- But in Gaussian Elimination Method, if 'b' changes, we need to restart row operations from the very beginning.

Frobenius Matrix:

$$F^{(1)} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -m_{21} & 1 & 0 & 0 \\ -m_{31} & 0 & 1 & 0 \\ -m_{41} & 0 & 0 & 1 \end{bmatrix} \quad F^{(2)} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 \\ 0 & -m_{42} & 0 & 1 \end{bmatrix} \quad F^{(3)} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & -m_{43} & 1 \end{bmatrix}$$

$$L = (F^{(1)})^{-1} (F^{(2)})^{-1} (F^{(3)})^{-1}$$

$$A = \begin{bmatrix} 1 & 2 & 1 \\ 1 & -2 & 2 \\ 2 & 12 & -2 \end{bmatrix} \rightarrow R_2' = R_2 - \left(\frac{1}{1}\right) R_1$$

$$\rightarrow R_3' = R_3 - \left(\frac{2}{1}\right) R_1$$

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & -4 & 1 \\ 0 & 8 & -4 \end{bmatrix} \rightarrow R_3' = R_3 - \left(\frac{8}{-4}\right) R_2$$

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & -4 & 1 \\ 0 & 0 & -2 \end{bmatrix}$$

$$F^{(1)} = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ -2 & 0 & 1 \end{bmatrix} \quad F^{(2)} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 2 & 1 \end{bmatrix}$$

$$L = \left(F^{(1)}\right)^{-1} \left(F^{(2)}\right)^{-1}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ -2 & 0 & 1 \end{bmatrix}^{-1} \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 2 & 1 \end{bmatrix}^{-1}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 2 & -2 & 1 \end{bmatrix}$$

Least Square Approximation:

→ Well defined linear system has equal number of variables & equations.

Example:

$$\begin{aligned}x_1 + 2x_2 + x_3 &= 0 \\x_1 - 9x_2 + 7x_3 &= 2 \\2x_1 + 3x_2 + 5x_3 &= 5\end{aligned}$$

$$A \cdot x = b$$

$$\rightarrow \begin{bmatrix} 1 & 2 & 3 \\ 1 & -9 & 7 \\ 2 & 3 & 5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \\ 5 \end{bmatrix}$$

square matrix
of $\boxed{n} \times n$; ; ;
 $n \times \boxed{1} \rightarrow n \times 1$

→ If we have a system where number of equations > number of variables, it is called an over-determined system.

How do we solve over-determined system?

Example:

$$\begin{aligned}x_1 + 2x_2 + x_3 &= 0 \\x_1 - 9x_2 + 7x_3 &= 2 \\x_1 + 3x_2 + 5x_3 &= 4 \rightarrow \\2x_1 + 11x_2 - 9x_3 &= 5 \\9x_1 + x_2 - x_3 &= 7\end{aligned}$$

$$\begin{bmatrix} 1 & 2 & 1 \\ 1 & -9 & 7 \\ 1 & 3 & 5 \\ 2 & 11 & -9 \\ 9 & 1 & -1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \\ 4 \\ 5 \\ 7 \end{bmatrix}$$

$\boxed{m} \times n ; ; ; n \times \boxed{1} ; m \times 1$

$$A \cdot x = b$$

→ Least square approximation method is a way to find an approximate solution of an over-determined system.

over-determined

$$\begin{matrix} \downarrow \\ A \cdot x = b \end{matrix}$$
$$\begin{matrix} \downarrow \\ (m \times n) \quad (n \times 1) \quad (m \times 1) \end{matrix}$$

How to solve such problems?

→ multiply A^T on both hand sides.

$$\begin{matrix} A^T \quad A \quad | \quad x \\ \downarrow \quad \downarrow \quad \downarrow \\ (n \times m) \quad (m \times n) \quad (n \times 1) \end{matrix} = \begin{matrix} A^T \cdot b \\ \downarrow \\ (n \times m) \quad (m \times 1) \end{matrix}$$
$$\begin{matrix} \downarrow \\ (n \times n) \quad (n \times 1) \end{matrix} \quad \downarrow \quad (n \times 1)$$

Example

From polynomial chapter:

If we had $\underbrace{(n+1)}$ nodes, we calculated the values of $\underbrace{(n+1)}$ coefficients
 x_0, x_1, \dots, x_n a_0, a_1, \dots, a_n

using vandermonde matrix.

Well-defined system

$$\rightarrow \begin{bmatrix} 1 & x_0^1 & x_0^2 & \dots & x_0^n \\ 1 & x_1^1 & x_1^2 & \dots & x_1^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n^1 & x_n^2 & \dots & x_n^n \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} f(x_0) \\ f(x_1) \\ \vdots \\ f(x_n) \end{bmatrix}$$

But now, let's say

we have $\underbrace{(m+1)}$ nodes, but we need to calculate $\underbrace{(n+1)}$ coefficients
 x_0, x_1, \dots, x_m a_0, a_1, \dots, a_n

[Remember $m > n$]

Over-determined system

$$\rightarrow \begin{bmatrix} 1 & x_0^1 & x_0^2 & \dots & x_0^n \\ 1 & x_1^1 & x_1^2 & \dots & x_1^n \\ 1 & x_2^1 & x_2^2 & \dots & x_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_m^1 & x_m^2 & \dots & x_m^n \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} f(x_0) \\ f(x_1) \\ f(x_2) \\ \vdots \\ f(x_m) \end{bmatrix}$$

Example:

$$a_0 + a_1 x$$

number of coefficients = 2

We want to fit a straight line through the following nodes

$$\begin{array}{lll} x_0 = -3 & x_1 = 0 & x_2 = 6 \\ f(x_0) = 0 & f(x_1) = 0 & f(x_2) = 2 \end{array}$$

number of nodes = 3

$$P_1(x_0) = a_0 + a_1(x_0) = f(x_0) \rightarrow a_0 + a_1(-3) = 0$$

$$P_1(x_1) = a_0 + a_1(x_1) = f(x_1) \rightarrow a_0 + a_1(0) = 0$$

$$P_1(x_2) = a_0 + a_1(x_2) = f(x_2) \rightarrow a_0 + a_1(6) = 2$$

$$\begin{bmatrix} 1 & -3 \\ 1 & 0 \\ 1 & 6 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

$$A \cdot x = b$$

Multiplying A^T on both sides.

$$\left[\begin{array}{ccc} 1 & 1 & 1 \\ -3 & 0 & 6 \end{array} \right] \left[\begin{array}{cc} 1 & -3 \\ 1 & 0 \\ 1 & 6 \end{array} \right] \left[\begin{array}{c} a_0 \\ a_1 \end{array} \right] = \left[\begin{array}{ccc} 1 & 1 & 1 \\ -3 & 0 & 6 \end{array} \right] \left[\begin{array}{c} 0 \\ 0 \\ 2 \end{array} \right]$$
$$\left\{ \begin{array}{c} \\ \end{array} \right. \quad \left\{ \begin{array}{c} \\ \end{array} \right.$$
$$\left[\begin{array}{cc} 3 & 3 \\ 3 & 45 \end{array} \right] \left[\begin{array}{c} a_0 \\ a_1 \end{array} \right] = \left[\begin{array}{c} 2 \\ 12 \end{array} \right]$$

Now apply Gaussian elimination/LU/inverse method to find the values of a_0 and a_1 .

Applying inverse method:

$$\left[\begin{array}{c} a_0 \\ a_1 \end{array} \right] = \left[\begin{array}{cc} 3 & 3 \\ 3 & 45 \end{array} \right]^{-1} \left[\begin{array}{c} 2 \\ 12 \end{array} \right]$$

$$= \left[\begin{array}{c} 3/7 \\ 5/21 \end{array} \right]$$

$$\therefore a_0 = 3/7, \quad a_1 = 5/21$$

$$\therefore P_1(x) = \frac{3}{7} + \frac{5}{21}x$$

Orthogonality:

→ To understand orthogonality, we need to understand vector dot product / inner product first.

→ Vector dot product returns a scalar value (a number)

2 types of notations → matrix notation $\rightarrow \mathbf{x}^T \cdot \mathbf{y}$
 vector notation $\rightarrow \vec{\mathbf{x}} \cdot \vec{\mathbf{y}}$

$$\mathbf{x} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix}$$

① Matrix Notation = $\mathbf{x}^T \cdot \mathbf{y}$

$$= [1 \quad 2 \quad 3] \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix}$$

shape \rightarrow (1 × 3) ; (3 × 1)

= ↴ returns a scalar / number

② Vector Notation = $\vec{\mathbf{x}} \cdot \vec{\mathbf{y}}$

$$= (1 \times 4) + (2 \times 5) + (3 \times 6)$$

↳ returns a scalar / number

Inner product with itself = ℓ_2 -norm

$$\text{eg. } \vec{\mathbf{x}} \cdot \vec{\mathbf{x}} \text{ or } \mathbf{x}^T \mathbf{x}$$

Dot product:

$$a = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

$$a \cdot b = a_1 b_1 + a_2 b_2 + a_3 b_3$$

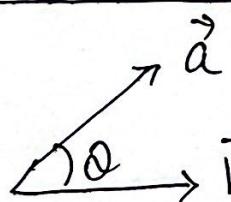
↳ returns a scalar/number.

Length / magnitude of a vector:

$$a = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$$

$$|a| = \sqrt{(a_1)^2 + (a_2)^2 + (a_3)^2}$$

Dot product (Second approach):



$$a \cdot b = |a| |b| \cos \theta$$

$$\cos \theta = \frac{a \cdot b}{|a| |b|}$$

Orthogonal Vectors:

If \angle between 2 vectors = 90° or $\frac{\pi}{2}$

In other words, if 2 vectors are perpendicular to each other,
the vectors are orthogonal.

For orthogonal vectors, their dot product is 0. Because:

$$\vec{a} \cdot \vec{b} = |\vec{a}| |\vec{b}| \cos\left(\frac{\pi}{2}\right) \rightarrow 0$$

$$\therefore \vec{a} \cdot \vec{b} = 0$$

$$\text{or } \vec{a}^T \vec{b} = 0$$

Let's consider a set of vector S.

$$S = \{ \vec{a}, \vec{b}, \vec{c} \}$$

Set S is an orthogonal set if

$$\vec{a} \cdot \vec{b} = 0$$

$$\vec{b} \cdot \vec{c} = 0$$

$$\vec{c} \cdot \vec{a} = 0$$

i.e. each vector is perpendicular to each other.

Orthonormality:

- If ① the vectors are orthogonal (dot product=0)
 ② the length of the vectors = 1 (unit vectors)

Then the vectors are orthonormal.

$$\vec{a} = \begin{bmatrix} 4 \\ 2 \\ 1 \end{bmatrix} \quad b = \begin{bmatrix} 1 \\ -3 \\ 2 \end{bmatrix}$$

Checking if orthogonal:

$$\vec{a} \cdot \vec{b} = (4 \times 1) + (2 \times -3) + (1 \times 2) = 0 \quad [\because \text{orthogonal}]$$

Converting into orthonormal (by making length = 1):

$$\hat{a} = \frac{\vec{a}}{|\vec{a}|} = \frac{1}{\sqrt{21}} \begin{bmatrix} 4 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 4/\sqrt{21} \\ 2/\sqrt{21} \\ 1/\sqrt{21} \end{bmatrix} \rightarrow |\hat{a}| = \sqrt{\left(\frac{4}{\sqrt{21}}\right)^2 + \left(\frac{2}{\sqrt{21}}\right)^2 + \left(\frac{1}{\sqrt{21}}\right)^2} = 1$$

$$\hat{b} = \frac{\vec{b}}{|\vec{b}|} = \frac{1}{\sqrt{14}} \begin{bmatrix} 1 \\ -3 \\ 2 \end{bmatrix} = \begin{bmatrix} 1/\sqrt{14} \\ -3/\sqrt{14} \\ 2/\sqrt{14} \end{bmatrix} \rightarrow |\hat{b}| = \sqrt{\left(\frac{1}{\sqrt{14}}\right)^2 + \left(\frac{-3}{\sqrt{14}}\right)^2 + \left(\frac{2}{\sqrt{14}}\right)^2} = 1$$

→ Process of making vectors into unit vectors (length=1) is called normalization

→ By doing so, we only change the magnitude, not the direction.

→ Hence, they are still orthogonal

→ Since they are orthogonal and has length=1 (unit vectors), the vectors are orthonormal.

Example:

Consider the set of vectors, S :

$$S = \left\{ \frac{1}{\sqrt{5}} (2, 1)^T, \frac{1}{\sqrt{5}} (1, -2)^T \right\}$$

Show if the set S is orthonormal or not.

Solution:

$$\begin{aligned} S &= \left\{ \frac{1}{\sqrt{5}} \begin{bmatrix} 2 \\ 1 \end{bmatrix}, \frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ -2 \end{bmatrix} \right\} \\ &= \left\{ \begin{bmatrix} \frac{2}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} \end{bmatrix}, \begin{bmatrix} \frac{1}{\sqrt{5}} \\ -\frac{2}{\sqrt{5}} \end{bmatrix} \right\} \\ &\quad \downarrow \qquad \downarrow \\ &\quad \vec{u}_1 \qquad \vec{u}_2 \end{aligned}$$

$$\vec{u}_1 \cdot \vec{u}_2 = \left(\frac{2}{\sqrt{5}} \times \frac{1}{\sqrt{5}} \right) + \left(\frac{1}{\sqrt{5}} \times -\frac{2}{\sqrt{5}} \right) = 0 \quad [\because \text{orthogonal}]$$

$$|\vec{u}_1| = \sqrt{\left(\frac{2}{\sqrt{5}}\right)^2 + \left(\frac{1}{\sqrt{5}}\right)^2} = 1 \quad [\because \text{orthonormal}]$$

$$|\vec{u}_2| = \sqrt{\left(\frac{1}{\sqrt{5}}\right)^2 + \left(-\frac{2}{\sqrt{5}}\right)^2} = 1$$

\therefore Yes, the set of vectors are orthonormal.

Theorem:

Orthogonal / orthonormal matrices are matrices in which the column vectors form an ~~orthogonal~~ ^[Orthonormal] set (each column vector has length one, and is orthogonal to all other column vectors).

For square orthonormal matrices, the inverse is simply the transpose.

Properties: $Q^{-1} = Q^T$

$$Q Q^T = I$$

$$Q^T Q = I$$

Example:

$$Q = \begin{bmatrix} \vec{a} \\ \vec{b} \end{bmatrix}$$

$$\vec{a} = \begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix} \quad \vec{b} = \begin{bmatrix} 1/\sqrt{2} \\ -1/\sqrt{2} \end{bmatrix}$$

$$\vec{a} \cdot \vec{b} = (1/\sqrt{2} \times 1/\sqrt{2}) + (1/\sqrt{2} \times -1/\sqrt{2}) = 0 \quad [\because \text{orthogonal}]$$

$$|\vec{a}| = \sqrt{\left(\frac{1}{\sqrt{2}}\right)^2 + \left(\frac{1}{\sqrt{2}}\right)^2} = 1 \quad [\because \text{orthonormal}]$$

$$|\vec{b}| = \sqrt{\left(\frac{1}{\sqrt{2}}\right)^2 + \left(-\frac{1}{\sqrt{2}}\right)^2} = 1$$

→ This makes the columns of the matrix orthonormal to each other.

- ∴ The matrix Q will have the properties :
 - ① $Q^{-1} = Q^T$
 - ② $Q Q^T = I$
 - ③ $Q^T Q = I$

Gram - Schmidt Process:

Lets have a basis (u_1, u_2, \dots, u_n) from a vector space. Gram - Schmidt process takes the basis (u_1, u_2, \dots, u_n) and forms a new orthogonal basis (p_1, p_2, \dots, p_n) . We can later transform these orthogonal basis into orthonormal basis (q_1, q_2, \dots, q_n) .

Original basis : u_1, u_2, u_3

↓
Gram Schmidt Process

Orthogonal basis : p_1, p_2, p_3

↓ normalization

Orthonormal basis : q_1, q_2, q_3

$$1) p_1 = u_1$$

$$2) p_2 = u_2 - \frac{u_2 \cdot p_1}{p_1 \cdot p_1} p_1$$

$$3) p_3 = u_3 - \frac{u_3 \cdot p_1}{p_1 \cdot p_1} p_1 - \frac{u_3 \cdot p_2}{p_2 \cdot p_2} p_2$$

Example:

$$u_1 = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} \quad u_2 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \quad u_3 = \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix}$$

1) ~~approx~~ $p_1 = u_1 = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$

2) $p_2 = u_2 - \frac{u_2 \cdot p_1}{p_1 \cdot p_1} p_1$

$$= \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} - \frac{(1 \times 1) + (0 \times -1) + (1 \times 1)}{(1 \times 1) + (-1 \times -1) + (1 \times 1)} \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} - \frac{2}{3} \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} - \begin{bmatrix} 2/3 \\ -2/3 \\ 2/3 \end{bmatrix}$$

$$\begin{array}{r} F = 2/3 \\ F = 0 \\ F = - \end{array}$$

$$= \begin{bmatrix} 1/3 \\ 2/3 \\ 1/3 \end{bmatrix}$$

$$③ P_3 = U_3 - \frac{U_3 \cdot P_1}{P_1 \cdot P_1} P_1 - \frac{U_3 \cdot P_2}{P_2 \cdot P_2} P_2$$

$$= \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix} - \frac{(1 \times 1) + (1 \times -1) + (2 \times 1)}{(1 \times 1) + (-1 \times -1) + (1 \times 1)} \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} - \frac{\left(1 \times \frac{1}{3}\right) + \left(1 \times \frac{2}{3}\right) + \left(2 \times \frac{1}{3}\right)}{\left(\frac{1}{3} \times \frac{1}{3}\right) + \left(\frac{2}{3} \times \frac{2}{3}\right) + \left(\frac{1}{3} \times \frac{1}{3}\right)} \begin{bmatrix} 1/3 \\ 2/3 \\ 1/3 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix} - \frac{2}{3} \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} - \frac{5}{2} \begin{bmatrix} 1/3 \\ 2/3 \\ 1/3 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 2/3 \\ -2/3 \\ 2/3 \end{bmatrix} - \begin{bmatrix} 5/6 \\ 5/3 \\ 5/6 \end{bmatrix}$$

$$= \begin{bmatrix} -1/2 \\ 0 \\ 1/2 \end{bmatrix}$$

P_1, P_2, P_3 form an orthogonal basis

If we want orthonormal basis, we can divide each vectors by its length.
(normalization).

$$\textcircled{1} \quad q_1 = \frac{P_1}{|P_1|} = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1/\sqrt{3} \\ -1/\sqrt{3} \\ 1/\sqrt{3} \end{bmatrix}$$

$$\textcircled{2} \quad q_2 = \frac{P_2}{|P_2|} = \frac{1}{\sqrt{6}/3} \begin{bmatrix} 1/3 \\ 2/3 \\ 1/3 \end{bmatrix} = \begin{bmatrix} \sqrt{6}/6 \\ \sqrt{6}/3 \\ \sqrt{6}/6 \end{bmatrix}$$

$$\textcircled{3} \quad q_3 = \frac{P_3}{|P_3|} = \frac{1}{\sqrt{2}/2} \begin{bmatrix} -1/2 \\ 0 \\ 1/2 \end{bmatrix} = \begin{bmatrix} -\sqrt{2}/2 \\ 0 \\ \sqrt{2}/2 \end{bmatrix}$$

QR Decomposition:

Any real $(m \times n)$ matrix "A" with $m > n$ can be written in the form :

$$A = QR$$

Where Q is a $(m \times n)$ matrix with orthonormal columns

R is an upper triangular matrix of shape $(n \times n)$

Orthonormal matrix. Therefore has the properties:

$$\begin{matrix} A &= & Q & R \\ && \downarrow & \\ && Q & \\ && \downarrow & \\ m \times n & & m \times n & n \times n \end{matrix}$$

$$Q Q^T = I_{nn}$$

$$Q^T Q = I_{nn}$$

→ Multiplying Q^T on both sides.

$$Q^T A = \boxed{Q^T Q} R$$

$$Q^T A = \boxed{I} R$$

$$Q^T A = R$$

$$\boxed{R = Q^T A}$$

Example of QR Decomposition:

$$A = QR$$

Starting with A

$$A = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \vdots & \vdots & & \vdots \\ u_{m1} & u_{m2} & \dots & u_{mn} \end{bmatrix}$$

$u_1 \quad u_2 \quad \dots \quad u_n$

convert u into orthogonal vectors p (Gram-Smidt process)

convert p into orthonormal vectors q (normalization)

$$A = \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}$$

$u_1 \quad u_2$

$$p_1 = u_1 = \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}$$

$$P_2 = U_2 - \frac{U_2 \cdot P_1}{P_1 \cdot P_1} P_1$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \frac{\begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \cdot \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}}{\begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix} \cdot \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}} \cdot \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \frac{(1 \times 3) + (2 \times 6) + (2 \times 0)}{(3 \times 3) + (6 \times 6) + (0 \times 0)} \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \frac{1}{3} \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

$$\therefore P_1 = \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix} \quad P_2 = \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

P_1 and P_2 are orthogonal.

→ Now convert P_1 and P_2 into unit vectors. We will call the unit vectors q_1 and q_2 .

$$q_1 = \frac{P_1}{|P_1|} = \frac{1}{3\sqrt{5}} \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix} = \begin{bmatrix} \sqrt{5}/5 \\ 2\sqrt{5}/5 \\ 0 \end{bmatrix}$$

$$q_2 = \frac{P_2}{|P_2|} = \frac{1}{2} \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\therefore q_1 = \begin{bmatrix} \sqrt{5}/5 \\ 2\sqrt{5}/5 \\ 0 \end{bmatrix} \quad q_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

q_1 and q_2 are orthonormal

$$\therefore Q = \begin{bmatrix} \sqrt{5}/5 & 0 \\ 2\sqrt{5}/5 & 0 \\ 0 & 1 \end{bmatrix} \quad A = \begin{bmatrix} 3 & 1 \\ 6 & 2 \\ 0 & 2 \end{bmatrix}$$

$$R = Q^T A$$

$$= \begin{bmatrix} \sqrt{5}/5 & 2\sqrt{5}/5 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 3 & 1 \\ 6 & 2 \\ 0 & 2 \end{bmatrix}$$

$$= \begin{bmatrix} 3\sqrt{5} & \sqrt{5} \\ 0 & 2 \end{bmatrix}$$

$$A = Q R$$

$$\begin{bmatrix} 3 & 1 \\ 6 & 2 \\ 0 & 2 \end{bmatrix} = \begin{bmatrix} \sqrt{5}/5 & 0 \\ 2\sqrt{5}/5 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 3\sqrt{5} & \sqrt{5} \\ 0 & 2 \end{bmatrix}$$

Check if $Q \cdot R = A$ in your calculator.

Example 2

$$\begin{array}{lll} x_0 = -3 & x_1 = 0 & x_2 = 6 \\ f(x_0) = 0 & f(x_1) = 0 & f(x_2) = 2 \end{array}$$

$$A \cdot x = b$$
$$\left[\begin{array}{c|c} 1 & -3 \\ 1 & 0 \\ 1 & 6 \end{array} \right] \quad \left[\begin{array}{c} a_0 \\ a_1 \end{array} \right] = \left[\begin{array}{c} 0 \\ 0 \\ 2 \end{array} \right]$$

$\downarrow \quad \downarrow$

$$u_1 \quad u_2$$

$$p_1 = u_1 = \left[\begin{array}{c} 1 \\ 1 \\ 1 \end{array} \right]$$

$$p_2 = u_2 - \frac{u_2 \cdot p_1}{p_1 \cdot p_1} p_1$$

$$= \left[\begin{array}{c} -3 \\ 0 \\ 6 \end{array} \right] - \frac{(-3 \times 1) + (0 \times 1) + (6 \times 1)}{(1 \times 1) + (1 \times 1) + (1 \times 1)} \left[\begin{array}{c} 1 \\ 1 \\ 1 \end{array} \right]$$

$$= \left[\begin{array}{c} -3 \\ 0 \\ 6 \end{array} \right] - 1 \left[\begin{array}{c} 1 \\ 1 \\ 1 \end{array} \right]$$

$$= \left[\begin{array}{c} -4 \\ -1 \\ 5 \end{array} \right]$$

$$P_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$P_2 = \begin{bmatrix} -4 \\ -1 \\ 5 \end{bmatrix}$$

P_1 and P_2 are orthogonal vectors.

$$q_1 = \frac{P_1}{\|P_1\|} = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ 1/\sqrt{3} \end{bmatrix}$$

$$q_2 = \frac{P_2}{\|P_2\|} = \frac{1}{\sqrt{42}} \begin{bmatrix} -4 \\ -1 \\ 5 \end{bmatrix} = \begin{bmatrix} -4/\sqrt{42} \\ -1/\sqrt{42} \\ 5/\sqrt{42} \end{bmatrix}$$

$$\therefore Q = \begin{bmatrix} 1/\sqrt{3} & -4/\sqrt{42} \\ 1/\sqrt{3} & -1/\sqrt{42} \\ 1/\sqrt{3} & 5/\sqrt{42} \end{bmatrix}$$

→ matrix Q has orthonormal columns.

$$R = Q^T A$$

$$= \begin{bmatrix} 1/\sqrt{3} & 1/\sqrt{3} & 1/\sqrt{3} \\ -4/\sqrt{42} & -1/\sqrt{42} & 5/\sqrt{42} \end{bmatrix} \begin{bmatrix} 1 & -3 \\ 1 & 0 \\ 1 & 6 \end{bmatrix}$$

$$R = \begin{bmatrix} \sqrt{3} & \sqrt{3} \\ 0 & \sqrt{42} \end{bmatrix}$$

$$A x = b$$

Applying Least square approximation method by applying A^T on both sides.

$$\begin{matrix} A^T & A & x & = & A^T b \\ \downarrow & \downarrow & \downarrow & & \downarrow \\ (QR)^T & (QR) & x & = & (QR)^T b \end{matrix}$$

$$R^T \boxed{Q^T Q} R x = R^T Q^T b$$

$$\downarrow I_{nn} \quad [\text{because } Q = \text{orthonormal matrix}]$$

$$\cancel{R^T} R x = \cancel{R^T} Q^T b$$

$$\boxed{\cancel{R^T} R x = Q^T b}$$

$$R_2 = Q^T b$$

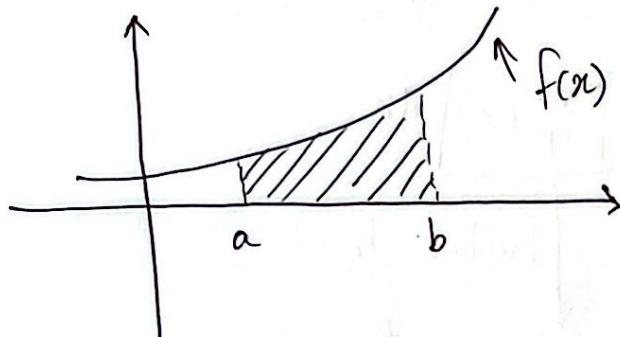
$$\begin{bmatrix} \sqrt{3} & \sqrt{3} \\ 0 & \sqrt{42} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 1/\sqrt{3} & 1/\sqrt{3} & 1/\sqrt{3} \\ -4/\sqrt{42} & -1/\sqrt{42} & 5/\sqrt{42} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

$$\begin{bmatrix} \sqrt{3} & \sqrt{3} \\ 0 & \sqrt{42} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 2/\sqrt{3} \\ 5\sqrt{2}/\sqrt{21} \end{bmatrix}$$

$$\begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 3/7 \\ 5/21 \end{bmatrix}$$

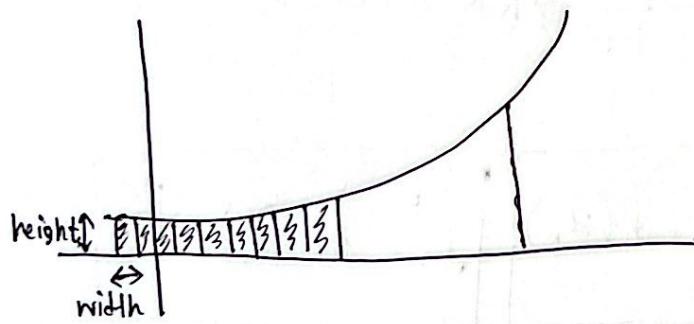
Integration:

$$I(f) = \int_a^b f(x) dx$$



→ Integration gives the area under $f(x)$ within the bound $a \& b$.

→ By definition, integration is an infinite sum.



$$\int_a^b f(x) dx = \lim_{n \rightarrow \infty} \sum_{i=1}^n \underbrace{f_i(\tilde{x}_i)}_{\text{height}} \underbrace{\Delta x}_{\text{width}}$$

→ Numerical integration replace function $f(x)$ with interpolating polynomial of degree n that passes through $(n+1)$ nodes

$$\text{Actual Integration} = I(f) = \int_a^b f(x) dx$$

$$\text{Numerical Integration} = I_n(f) = \int_a^b [P_n(x)] dx$$

↓
writing $P_n(x)$ using lagrange basis

This polynomial $P_n(x)$ must be interpolated with equidistant nodes x_0, x_1, \dots, x_n ←
equally spaced.

$$\therefore I_n(f) = \int_a^b \sum_{i=0}^n l_k(x) \cdot f(x_k) dx$$

$$= \boxed{\sum_{K=0}^n f(x_k)} \quad \boxed{\int_a^b l_k(x) dx}$$

↓
 σ_k (~~weight function~~
(weighted factors))

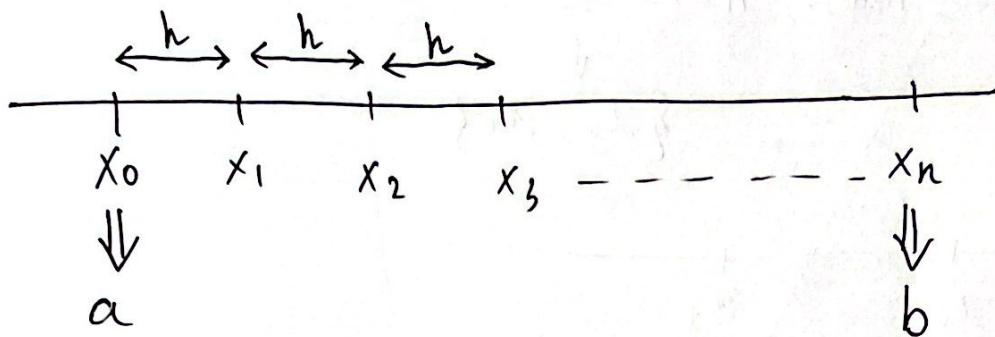
$$\therefore \boxed{I_n(f) = \sum_{K=0}^n \sigma_k \cdot f(x_k)}$$

↑
Newton cotes' Formula .

Newton Cote's Formula

Closed
open

Finding $x_0, x_1 \dots x_n$ Using closed Newton cote's Formula:



→ 'a' and 'b' are integration intervals.

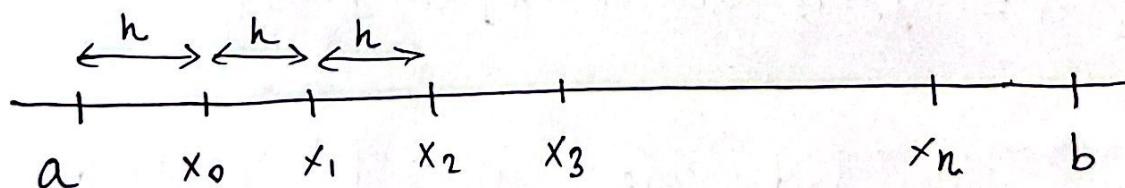
$$\rightarrow h = \frac{b-a}{n}$$

$$x_0 = a$$

$$x_1 = x_0 + h$$

$$x_2 = x_1 + h = x_0 + 2h$$

Finding $x_0, x_1 \dots x_n$ using open Newton cote's Formula :



$$\boxed{h = \frac{b-a}{n+2}}$$

$$x_0 = a + h$$

$$x_1 = a + 2h$$

$$x_2 = a + 3h$$

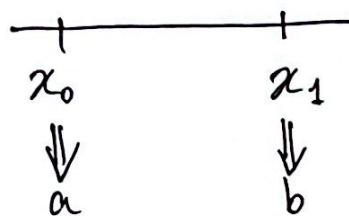
Trapezium / Trapezoidal Rule:

→ Closed Newton Cotes formula with $n=1$

$$n = \text{degree of polynomial} = 1$$

$$\therefore \text{number of nodes} = n+1 = 2$$

$$\{x_0, x_1\}$$



[because closed Newton Cotes]

$$I_n(f) = \int_a^b p_n(x) dx$$

$$I_1(f) = \int_a^b p_1(x) dx$$

$$p_1(x) = l_0(x) f(x_0) + l_1(x) f(x_1)$$

$$I_1(f) = \int_a^b [l_0(x) f(x_0) + l_1(x) f(x_1)] dx$$

$$= \underbrace{\int_a^b l_0(x) dx}_{\sigma_0} \cdot f(x_0) + \underbrace{\int_a^b l_1(x) dx}_{\sigma_1} \cdot f(x_1)$$

$$\therefore I_1(f) = \sigma_0 f(x_0) + \sigma_1 f(x_1)$$

$$J_0 = \int_a^b l_0(x) dx$$

$$= \int_a^b \frac{x - x_1}{x_0 - x_1} dx$$

$$= \int_a^b \frac{x - b}{a - b} dx$$

$$= \frac{1}{a-b} \int_a^b (x-b) dx$$

$$= \frac{1}{a-b} \left[\frac{x^2}{2} - bx \right]_a^b$$

$$= \frac{1}{a-b} \left(\frac{b^2}{2} - b^2 - \frac{a^2}{2} + ab \right)$$

$$= \frac{b-a}{2}$$

$$J_1 = \int_a^b l_1(x) dx$$

$$= \frac{1}{b-a} \int_a^b (x-a) dx$$

⋮

$$= \frac{b-a}{2}$$

$$\begin{aligned}
 \therefore I_1(f) &= \int_a^b P_1(x) dx \\
 &= \sigma_0 f(x_0) + \sigma_1 f(x_1) \\
 &= \sigma_0 f(a) + \sigma_1 f(b) \\
 &= \frac{b-a}{2} f(a) + \frac{b-a}{2} f(b) \\
 &= \frac{b-a}{2} (f(a) + f(b))
 \end{aligned}$$

$$\therefore I_1(f) = \frac{b-a}{2} [f(a) + f(b)]$$

Example:

Find $\underbrace{I(f)}_{\text{Actual}}$ and $\underbrace{I_1(f)}_{\text{Numerical}}$ of the function e^x on interval $[0, 2]$.

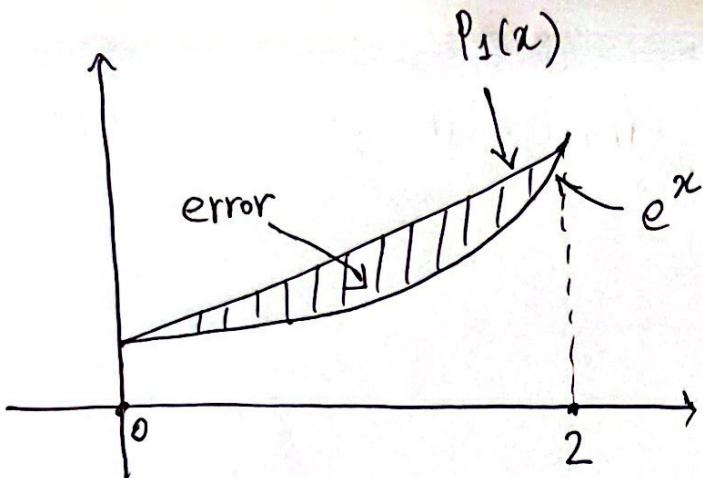
Solution:

$$I(f) = \int_0^2 e^x dx = [e^x]_0^2 = e^2 - e^0 = 6.389 \quad [\text{Actual}]$$

$$I_1(f) = \frac{b-a}{2} [f(a) + f(b)]$$

$$= \frac{2-0}{2} [e^0 + e^2] = 8.389 \quad [\text{numerical approx}]$$

$$\% \text{ error} = \frac{I - I_1}{I} \times 100 = 31.3 \% \quad [\text{error is large bcz degree 1 polynomial is used}]$$



- We can find the upper bound of the error.
- If a function $f(x)$ is interpolated by a degree n polynomial, error can be found using Cauchy's Theorem.

$$\text{Upper bound error } |f(x) - P_n(x)| \leq \left| \frac{f^{(n+1)}(\xi)}{(n+1)!} (x-x_0)(x-x_1)\dots(x-x_n) \right|$$

For integration, upper bound error =

$$|I - I_n| \leq \left| \frac{f^{(n+1)}(\xi)}{(n+1)!} \right| \int_a^b |(x-x_0)(x-x_1)\dots(x-x_n)| dx$$

Need to find max
value within $[a; b]$

Example:

Computing the upper bound of error for the previous example.

$$\rightarrow n = 1$$

$$f(x) = e^x$$

$$a = 0$$

$$b = 2$$

Solution:

$$\begin{aligned}
 & \text{Finding the max of } \left| \frac{f^{(n+1)}(\xi)}{(n+1)!} \right| \text{ within } [0, 2] \\
 &= \left| \frac{f^{(2)}(\xi)}{2!} \right| \\
 &= \left| \frac{e^\xi}{2!} \right|
 \end{aligned}$$

$f(x) = e^x$
 $f^{(1)}(x) = e^x$
 $f^{(2)}(x) = e^x$
 $\therefore f^{(2)}(\xi) = e^\xi$

$$\text{Max of } \frac{e^\xi}{2!} \text{ within } [0, 2] = \frac{e^2}{2!}$$

$$\begin{aligned}
 & \rightarrow \int_a^b |(x-x_0)(x-x_1)| dx \\
 &= \int_a^b |(x-a)(x-b)| dx = \int_0^2 |(x^2 - 2x)| dx \\
 &= \left| \left[\frac{x^3}{3} - \frac{2x^2}{2} \right]_0^2 \right| = \frac{4}{3}
 \end{aligned}$$

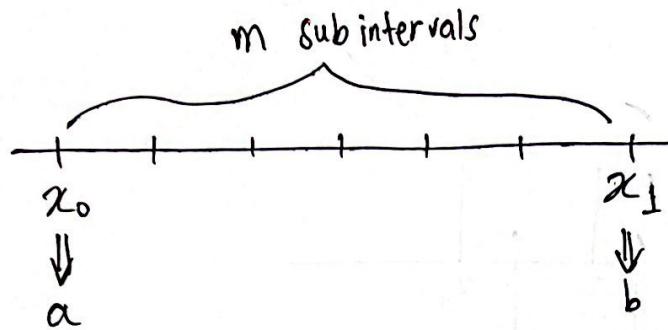
$$\therefore \text{upper bound of error} \leq \frac{e^2}{2!} \times \frac{4}{3} \approx 4.926.$$

Composite Newton - Cotes Formula:

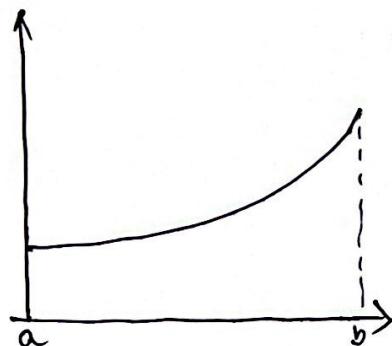
→ This method improves result without increasing num. of nodes.

→ Basic idea is to divide the interval $[a, b]$ into m sub intervals.

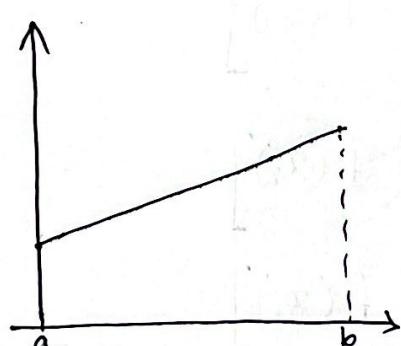
When $n=1$:



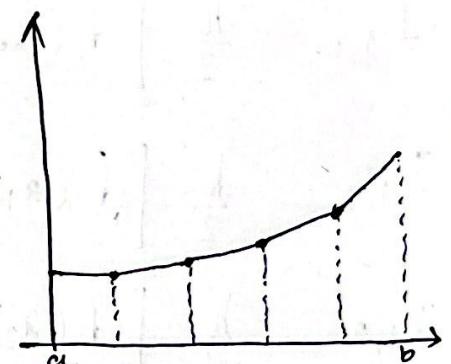
→ For each subinterval, we apply trapezium rule, then add them up.



Actual integration
 $I(f)$



Newton-Cotes with $n=1$
 $I_1(f)$



Composite Newton Cotes
with $n=1$
 $C_{1,m}(f)$

→ Total sum is denoted by $C_{1,m}(f)$ and called composite Newton's Cote's

for degree 1

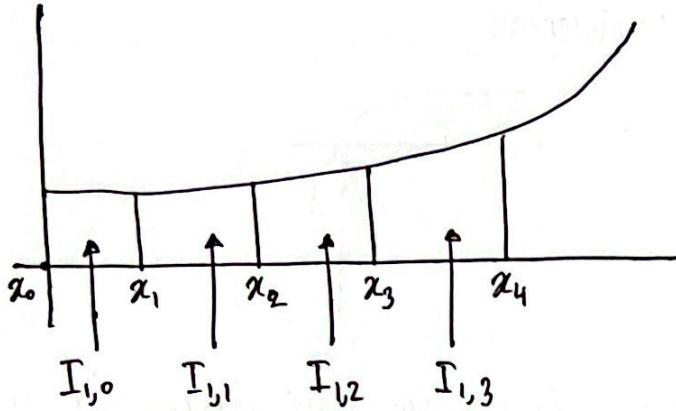
for m sub interval

→ For m sub intervals, we define

$$h = \frac{b-a}{m}$$

Apply Trapezium Rule for each sub interval

$$I_1(f) = \text{Trapezium Rule} = \frac{b-a}{2} [f(a) + f(b)] \\ = \frac{h}{2} [f(a) + f(b)]$$



$$I_{1,0} = \frac{h}{2} [f(x_0) + f(x_1)]$$

$$I_{1,1} = \frac{h}{2} [f(x_1) + f(x_2)]$$

$$I_{1,2} = \frac{h}{2} [f(x_2) + f(x_3)]$$

⋮

$$I_{1,m-1} = \frac{h}{2} [f(x_{m-2}) + f(x_{m-1})]$$

$$I_{1,m} = \frac{h}{2} [f(x_{m-1}) + f(x_m)]$$

$$C_{1,m}(f) = \frac{h}{2} [f(x_0) + 2f(x_1) + 2f(x_2) + 2f(x_3) + \dots + 2f(x_{m-1}) + f(x_m)]$$

Example:

$$f(x) = e^x$$

$$a=0$$

$$b=2$$

$$\rightarrow \text{Exact result} = I(f) = \int_0^2 e^x dx = 6.389056$$

\rightarrow Composite Newton Cotes with num of subintervals = 2 ($m=2$):

Step 1: Find h

$$h = \frac{b-a}{m} = \frac{2-0}{2} = 1$$

Step 2: Find $x_0, x_1, x_2, \dots, x_m$

- \rightarrow Remember: If $m=2$, find x_0 to x_2
- If $m=3$, find x_0 to x_3
- If $m=4$, find x_0 to x_4 .

$$x_0 = a = 0 \quad [\text{since trapezium rule follows closed Newton Cotes}]$$

$$x_1 = x_0 + h = 0 + 1 = 1$$

$$x_2 = x_1 + h = 1 + 1 = 2$$

Step 3: Find $C_{1,m}(f)$

$$\begin{aligned} C_{1,2}(f) &= \frac{h}{2} [f(x_0) + 2f(x_1) + f(x_2)] \\ &= \frac{1}{2} [e^0 + 2e^1 + e^2] \\ &= 6.91281 \end{aligned}$$

\rightarrow Composite Newton Cotes with num of sub intervals = 3 ($m=3$):

$$h = \frac{b-a}{m} = \frac{2-0}{3} = \frac{2}{3}$$

Find x_0 to x_3 :

$$x_0 = a = 0$$

$$x_1 = x_0 + h = 0 + \frac{2}{3} = \frac{2}{3}$$

$$x_2 = x_1 + h = \frac{2}{3} + \frac{2}{3} = \frac{4}{3}$$

$$x_3 = x_2 + h = \frac{4}{3} + \frac{2}{3} = 2$$

$$C_{1,3}(f) = \frac{h}{2} \left[f(x_0) + 2f(x_1) + 2f(x_2) + f(x_3) \right]$$

$$= \frac{2/3}{2} \left[e^0 + 2e^{2/3} + 2e^{4/3} + e^2 \right]$$

$$= 6.62395$$

\rightarrow Composite Newton Cotes with $m=4$:

$$C_{1,4} = \frac{0.5}{2} \left[e^0 + 2e^{0.5} + 2e^1 + 2e^{1.5} + e^2 \right] = 6.52161$$

Error decreases as m increases

Simpson's Rule:

$$\text{Trapezium Rule} = \int_a^b P_1(x) dx$$

$$\text{Simpson's Rule} = \int_a^b P_2(x) dx$$

$$I_2(f) = \int_a^b P_2(x) dx$$

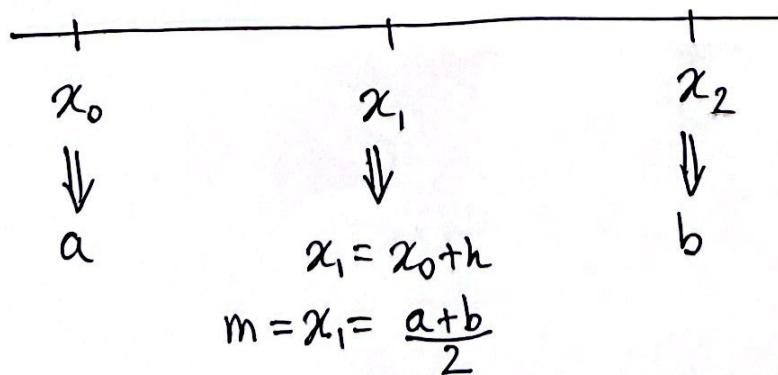
$$P_2(x) = l_0(x) f(x_0) + l_1(x) f(x_1) + l_2(x) f(x_2)$$

$$I_2(f) = \int_a^b [l_0(x) f(x_0) + l_1(x) f(x_1) + l_2(x) f(x_2)] dx$$

$$= \underbrace{\int_a^b l_0(x) dx}_{\sigma_0} \cdot f(x_0) + \underbrace{\int_a^b l_1(x) dx}_{\sigma_1} \cdot f(x_1) + \underbrace{\int_a^b l_2(x) dx}_{\sigma_2} \cdot f(x_2)$$

$$\therefore I_2(f) = \sigma_0 f(x_0) + \sigma_1 f(x_1) + \sigma_2 f(x_2)$$

Here, since $n=2$, number of nodes $= n+1 = 3 \rightarrow \{x_0, x_1, x_2\}$



$$\begin{aligned}
 J_0 &= \int_a^b l_0(x) dx \\
 &= \int_a^b \frac{(x-x_1)(x-x_2)}{(x_0-x_1)(x_0-x_2)} dx \\
 &= \int_a^b \frac{(x-m)(x-b)}{(a-m)(a-b)} dx \\
 &= \frac{1}{(a-m)(a-b)} \int_a^b (x-m)(x-b) dx \\
 &= \frac{1}{6} (b-a)
 \end{aligned}$$

$$\begin{aligned}
 J_1 &= \int_a^b l_1(x) dx \\
 &= \vdots \\
 &= \frac{2}{3} (b-a)
 \end{aligned}$$

$$\begin{aligned}
 J_2 &= \int_a^b l_2(x) dx \\
 &= \vdots \\
 &= \frac{1}{6} (b-a)
 \end{aligned}$$

$$\begin{aligned}
 I_2(f) &= \sigma_0 f(x_0) + \sigma_1 f(x_1) + \sigma_2 f(x_2) \\
 &= \sigma_0 f(a) + \sigma_1 f(m) + \sigma_2 f(b) \\
 &= \frac{1}{6} (b-a) f(a) + \frac{2}{3} (b-a) f(m) + \frac{1}{6} (b-a) f(b) \\
 &= \frac{b-a}{6} \left[f(a) + 4f(m) + f(b) \right] \\
 &= \frac{b-a}{6} \left[f(a) + 4f\left(\frac{a+b}{2}\right) + f(b) \right]
 \end{aligned}$$

Exactness:

For numerical integration, upper bound of error =

$$|I - I_n| = \left| \frac{1}{(n+1)!} f^{(n+1)}(\xi) \int_a^b (x-x_0)(x-x_1)\dots(x-x_n) dx \right|$$

→ If $f^{(n+1)}(\xi) = 0$, error = 0

→ In that case, Newton Cotes will give exact answers

→ The above formula was derived using Cauchy's Theorem.

Cauchy's Theorem:

$$|f(x) - P_n(x)| = \underbrace{\left| \frac{1}{(n+1)!} f^{(n+1)}(\xi) (x-x_0)(x-x_1)\dots(x-x_n) \right|}_{\text{error}}$$

$$f(x) - P_n(x) = \text{error}$$

$$f(x) = P_n(x) + \text{error}$$

→ If error = 0,

$$\boxed{f(x) = P_n(x)}$$

→ $f(x)$ is a n -degree polynomial

→ $f(x)$ is a polynomial itself.

→ If $f(x)$ itself is a polynomial, $I_n(f)$ will give exact result since
error = 0.

→ This implies that trapezium rule $I_1(f)$ is exact for all functions $f(x) = P_1(x)$

→ In other words, if we have a degree 1 polynomial, $P_1(x)$ and we apply both the actual integration, $I(f)$, and numerical integration, $I_1(f)$, we will get the exact result.

Definition:

The degree of exactness is the largest integer, n , for which the formula is exact for all polynomials, $P_n(x)$.

Example:

Find (a) Actual integration, $I(f)$

(b) Newton Cote's integral using $n=2$, $I_2(f)$

for the following functions:

$$\textcircled{1} \quad f(x) = 1$$

$$\textcircled{2} \quad f(x) = x$$

$$\textcircled{3} \quad f(x) = x^2$$

$$\textcircled{4} \quad f(x) = x^3$$

$$\textcircled{5} \quad f(x) = x^4$$

$$\textcircled{1} \quad f(x) = 1$$

$$(a) \text{Exact} = I(f) = \int_a^b 1 \, dx = b-a \quad \boxed{\text{match / zero error}}$$

$$(b) \text{Newton Cotes} = I_2(f) = \frac{b-a}{6} [1+4+1] = b-a \quad \boxed{\text{match / zero error}}$$

$$\textcircled{2} \quad f(x) = x$$

$$(a) \text{Exact} = I(f) = \int_a^b x \, dx = \frac{1}{2} (b^2 - a^2) \quad \boxed{\text{match / zero error}}$$

$$(b) \text{Newton Cotes} = I_2(f) = \frac{b-a}{6} \left[a + 4 \left(\frac{a+b}{2} \right) + b \right] = \frac{1}{2} (b^2 - a^2) \quad \boxed{\text{match / zero error}}$$

$$\textcircled{3} \quad f(x) = x^2$$

$$(a) \text{Exact} = I(f) = \int_a^b x^2 \, dx = \frac{1}{3} (b^3 - a^3) \quad \boxed{\text{match}}$$

$$(b) \text{Newton Cotes} = I_2(f) = \frac{b-a}{2} \left[a^2 + 4 \left(\frac{a+b}{2} \right)^2 + b^2 \right] = \frac{1}{3} (b^3 - a^3) \quad \boxed{\text{match}}$$

$$\textcircled{4} \quad f(x) = x^3$$

$$(a) \text{Exact} = I(f) = \int_a^b x^3 \, dx = \frac{1}{4} (b^4 - a^4) \quad \boxed{\text{Match}}$$

$$(b) \text{Newton Cotes} = I_2(f) = \frac{b-a}{6} \left[a^3 + 4 \left(\frac{a+b}{2} \right)^3 + b^3 \right] = \frac{1}{4} (b^4 - a^4) \quad \boxed{\text{Match}}$$

$$⑤ f(x) = x^4$$

$$(a) \text{Exact} = I(f) = \int_a^b x^4 dx = \frac{1}{5} (b^5 - a^5)$$

$$(b) \text{Newton Cotes} = I_2(f) = \frac{b-a}{6} \left[a^4 + 4\left(\frac{a+b}{2}\right)^4 + b^4 \right] \neq \frac{1}{5} (b^5 - a^5)$$

∴ Above result shows that Simpson's formula, $I_2(f)$, gives exact result upto degree 3 polynomial, and error becomes non-zero from degree 4 polynomial and higher.

→ Degree of exactness is exactly 3 for Simpson's Rule, $I_2(f)$.