

* Day-12 *

7th May, 2021

* Calculus *

- 1) Functions, Scalar Derivative, Definition, Intuition, Common Rules of Differentiation, chain Rule
- 2) Partial Derivatives, Gradient, Concept, Intuition, Properties, Directional Derivative.
- 3) Gradient of Vector Valued functions, Gradient of Matrices.
- 4) Linearization and Multivariate Taylor Series
- 5) Optimization Using Gradient Descent, Constrained optimization and Lagrange multipliers.
- 6) Vector and Matrix Calculus, Jacobian.
- 7) Gradient Algorithm, Local/Global maxima & minima, Saddle Point, Convex functions.

* Funⁿ :- If it is generally return as $f(x)$.

It means there is some mathematical formulation by which you are connecting two variables.
generally, $y = f(x)$

fun^n can be any form. such linear or non-linear.

Ex. eq. $y = 2x + 3$

y is in form of function $(2x+3)$, which is linear function.

* Constant function :-

If $f(x) = k$, where k is constant is said to be constant funⁿ.

* Power function :-

If $f(x) = x^n$ is said to be power funⁿ.

* Trigonometric function :-

If $f(x) = \sin x, \cos x, \tan x, \cot x, \operatorname{cosec} x, \sec x$ are said to be Trigonometric function.

* Exponential funⁿ

If $f(x) = e^x$ or $f(x) = a^x$ are said to be exponential function.

* Logarithmic function :-

If $f(x) = \log x$ is said to be logarithmic funⁿ.

* Derivatives :-

If $y = f(x)$ is 1st derivative can be given as

$$y' = f'(x) \text{ or } \frac{dy}{dx} = \frac{df(x)}{dx}$$

* Derivative means Rate of change of Variable *

Ex.

$$y = 2x + 3$$

$$\frac{dy}{dx} = \underline{\underline{2}}$$

Some Standard functions :-

A) Constant funⁿ :-

IF $f(x) = K$ then $f'(x) = 0$.

B) Power funⁿ :-

1) If $f(x) = x^n$ then $f'(x) = nx^{n-1}$

2) If $f(x) = \sqrt{x}$ then $f'(x) = \frac{1}{2\sqrt{x}}$

3) If $f(x) = \frac{1}{x}$ then $f'(x) = -\frac{1}{x^2}$

4) If $f(x) = x$ then $f'(x) = 1$.

C) Trigonometric funⁿ :-

1) $\frac{d}{dx} \sin x = \cos x$

2) $\frac{d}{dx} \cos x = -\sin x$

$$3) \frac{d}{dx} \tan x = \sec^2 x$$

$$4) \frac{d}{dx} \cot x = -\operatorname{cosec}^2 x$$

$$5) \frac{d}{dx} \sec x = \sec x \cdot \tan x. \quad 6) \frac{d}{dx} \operatorname{cosec} x = -\operatorname{cosec} x \cdot \cot x.$$

7) Exponential fun :-

$$7) \frac{d}{dx} e^x = e^x \quad \Rightarrow \frac{d}{dx} a^x = a^x \log a$$

8) Logarithmic fun :-

$$8) \frac{d}{dx} \log x = \frac{1}{x} \quad \Rightarrow \frac{d}{dx} \log_a x = \frac{1}{x} \log_e a$$

9) Derivatives of Inverse Trigonometric fun :-

$$9) \frac{d}{dx} \sin^{-1} x = \frac{1}{\sqrt{1-x^2}} \quad 2) \frac{d}{dx} \cos^{-1} x = \frac{-1}{\sqrt{1-x^2}}$$

$$3) \frac{d}{dx} \tan^{-1} x = \frac{1}{1+x^2} \quad 4) \frac{d}{dx} \cot^{-1} x = \frac{-1}{1+x^2}$$

$$5) \frac{d}{dx} \sec^{-1} x = \frac{1}{x \sqrt{x^2-1}} \quad 6) \frac{d}{dx} \operatorname{cosec}^{-1} x = \frac{-1}{x \sqrt{x^2-1}}$$

$$\underline{1.} \quad y = 2x+3$$

If $x_1=1$ then $y_1=5$

change x by small amount dx .

$$\therefore x_2 = x + dx = 1 + 0.1 = 1.1$$

$$\text{then } y_2 = 2(1.1) + 3 = 5.2$$

$$\Delta y = y_2 - y_1 = 5.2 - 5 = 0.2$$

limiting case Δy can be written as \underline{dy}

dy - giving us the change in y , not rate.

To find rate of change $\frac{dy}{dx}$, we have to take derivative with respect to some variable. e.g. x .

$$\begin{aligned}\frac{dy}{dx} &= \frac{d}{dx}(2x+3) \\ &= \underline{\underline{2}}\end{aligned}$$

Note :-

$$\frac{dy}{dx} = f'(x)$$

$$dy = f'(x)dx$$

2) $dy = ? \quad y = x^2 + 5$

$$\underline{\underline{dy = 2x dx}}$$

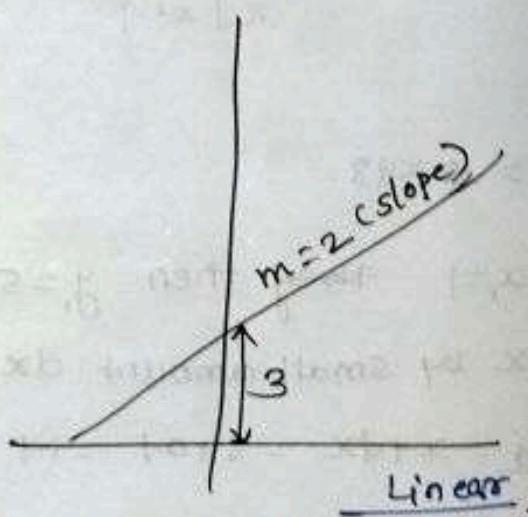
3) $y = \sin x + x^2$

$$= \cos x dx + 2x dx$$

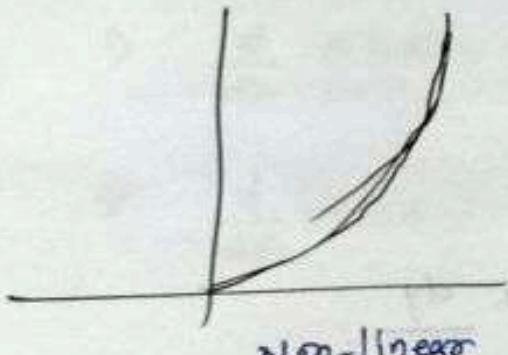
* Linear \Rightarrow Linear funⁿ:

can be given as $y = mx + c$.

for e.g. $y = 2x + 3$.



* Non-linear funⁿ.



e.g. $y = 2x^2 + 3$

$$y = 2x^2 + c$$

The change in dy is proportional to change in dx .
 i.e. $dy \propto dx$
 $\therefore dy = F'(x) dx$

where $F'(x) = \text{Differential}$, this gives idea how the value of y is changing with respect to x .

* If $z = f(x, y)$.

$$dz = \frac{\partial f}{\partial x} dx + \frac{\partial f}{\partial y} dy$$

e.g. $z = 3x^2 - y$

~~$dz =$~~

$$dz = 6xy dx + 3x^2 dy$$

$dz \rightarrow$ Total differential

$\left. \begin{array}{l} dz \\ \hline \partial z \\ \hline \partial x \\ \hline \end{array} \right\} \rightarrow$ Partial differential.

* Some Common Rules :-

$$\begin{aligned} d(u \cdot v) &= u \cdot dv + v \cdot du \\ &= u \cdot v' + v \cdot u' \end{aligned}$$

Q. ① $y = x^2 \sin x$.

$$dy = 2x \cdot \sin x + x^2 \cos x$$

$$\textcircled{2} \quad y = x^2 \sin x e^x$$

$$dy = 2x \sin x e^x + x^2 \cos x e^x + x^2 \sin x e^x$$

$$\textcircled{3} \quad d\left(\frac{u}{v}\right) = \frac{\cancel{u'v} - \cancel{vu'}}{v^2}$$

Ex ① $y = \frac{x^2}{\sin x} = \frac{\sin x \cdot 2x - x^2 \cos x}{\sin^2 x}$

$$= \frac{\sin x \cdot 2x}{\sin^2 x} - \frac{x^2 \cos x}{\sin^2 x}$$

$$\left(\frac{\cos}{\sin} = \cot \right) = \frac{2x}{\sin x} - \frac{x^2 \cot x}{\sin x}$$

$$\left(\frac{1}{\sin} = \cosec \right) = 2x \cosec x - x^2 \cdot \cot x \cdot \cosec x.$$

Fraction of function : / chain rule

(200000)

$$\frac{dy}{dx} = \frac{dy}{du} \times \frac{du}{dx} \times \frac{du}{dx} \quad \text{--- chain Rule.}$$

Ex 2 $y = \sin^2(3x+5)$.

$$\text{if } u = 3x+5$$

$$\therefore y = \sin^2 u$$

$$\text{if } v = \sin u$$

$$\therefore y = v^2$$

By chain rule

$$= \frac{dV}{dU} * \frac{dU}{dx} * \frac{dU}{dx}$$

$$= 2V \times \frac{d}{dU} (U) * \frac{d}{dU} (U) \times \frac{d}{dx} (U)$$

Put values of U, V & U

$$= \frac{d}{dU} (V^2) \times \frac{d}{dU} (\sin U) \times \frac{d}{dx} (3x+5)$$

$$= 2V \times \cos U \times 3$$

Put values of U, V

$$= 2 \sin U \times \cos (3x+5) \times 3$$

$$\boxed{dy = 6 \cdot \sin U \times \cos (3x+5)}$$

$$= 3 \cdot \underline{\sin (3x+5)} \cdot \cos (3x+5).$$

$$\boxed{\cancel{dy = 3 \sin (6x+10)}} - \cancel{3 \sin A \cos}$$

Explanation

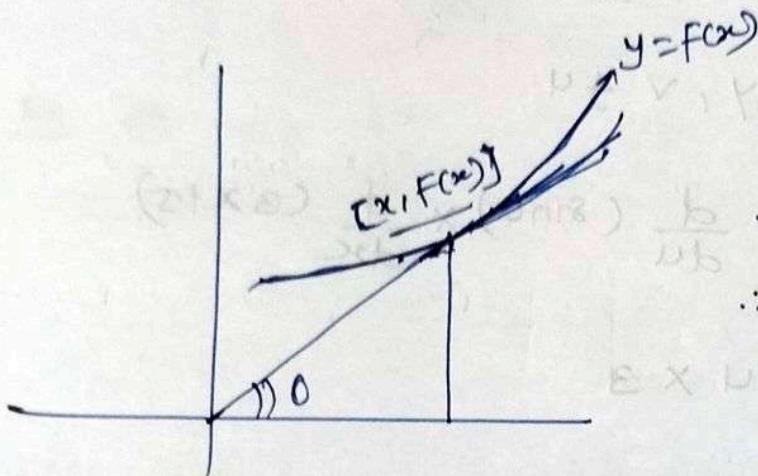
$$\underline{\cos(A+B) \cos(A+B)} = \underline{\sin(2A+2B)}$$

(*)

$$y = f(x) \rightarrow dy = \underbrace{(f'(x))dx}_{\text{Also referred as } \frac{dy}{dx}}$$

$$y' = \frac{df}{dx}$$

Also referred as $\frac{dy}{dx}$

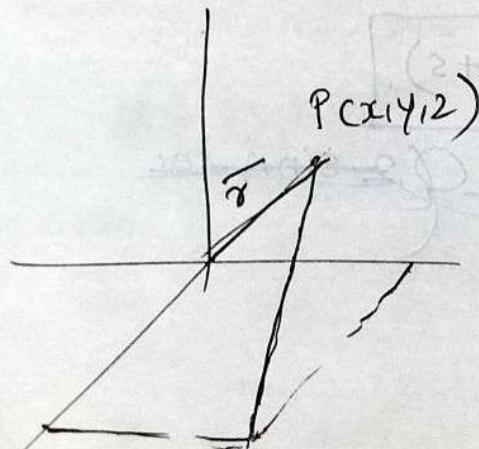


$$\text{if } y = 3x^2$$

find slope at $x=2$.

$$\therefore \frac{dy}{dx} \Big|_{x=2} = 6x = 12$$

* If there is object in space whose position is given as (x_1, y_1, z_1) . how vector can return as.



Vector \vec{r} can be given as

$$\vec{r} = x_1 i + y_1 j + z_1 k$$

$$d\vec{r} = dx_1 i + dy_1 j + dz_1 k \quad \text{---(1)}$$

$$\text{If } u = f(x_1, y_1, z_1)$$

$$du = ?$$

$$du = \frac{\partial F}{\partial x} dx + \frac{\partial F}{\partial y} dy + \frac{\partial F}{\partial z} dz$$

$$= \left[\left(\frac{\partial F}{\partial x} \right) i + \left(\frac{\partial F}{\partial y} \right) j + \left(\frac{\partial F}{\partial z} \right) k \right] \cdot [dx_1 i + dy_1 j + dz_1 k]$$

$$= \left[i \frac{\partial}{\partial x} + j \frac{\partial}{\partial y} + k \frac{\partial}{\partial z} \right] \cdot f \cdot d\vec{r} \quad (\vec{d}r = \text{from } \textcircled{1})$$

$$\boxed{du = \nabla f \cdot d\vec{r}}$$

$$\text{where } \nabla = \left[i \frac{\partial}{\partial x} + j \frac{\partial}{\partial y} + k \frac{\partial}{\partial z} \right]$$

It is called del operator.

- * If you want to find overall change of any function i.e. du → there is other way which is taking the Gradient of that fun' and then taking the inner product with the differential element or position vector i.e. $\frac{d\vec{r}}{s}$

$$\text{i.e. } \boxed{du = \nabla f \cdot d\vec{r}}$$

where du = Overall change in fun'

∇f = Gradient of function.

$d\vec{r}$ = position vector.

- * When you multiplied del operator with any scalar function, then it become Gradient of that scalar fun'.

i.e. ∇F . $\nabla \rightarrow$ Del operator.

$F \rightarrow$ scalar fun'. for e.g. $u = F(x, y, z)$

* Problem. $\mathbf{U} = 3x^2y + 3z^2$.

$$\nabla \mathbf{U} = \underbrace{(6xy)i + (3x^2)j + (6z)k}_{\sqrt{\frac{\partial U}{\partial x}} = \sqrt{3x^2 + y + z^2}}$$

Explanation

$$\begin{aligned}\nabla \mathbf{U} &= \left[\frac{\partial}{\partial x} [3x^2y + 3z^2] i \right] + \left[\frac{\partial}{\partial y} [3x^2y + 3z^2] j \right] \\ &\quad + \left[\frac{\partial}{\partial z} [3x^2y + 3z^2] k \right]\end{aligned}$$

* Gradient = $(\nabla \mathbf{U})$

- ⇒ Gradient tell that how the funⁿ is changing.
- ⇒ Gradient tell the direction in which the rate of change of scalar funⁿ is maximum.

Ex $\mathbf{U} = 3x^2y - 3z^2 + 5xyz$

find the gradient at $(1, 1, 1)$

$$\begin{aligned}\nabla \mathbf{U} &= [6xy - 6xz + 5yz] i + [3x^2 - 0 + 5xz] j \\ &\quad + [0 - 3x^2 + 5xy] k.\end{aligned}$$

= Put $x, y, z = 1$

$$[6 - 6 + 5] i + [3 - 0 + 5] j + [-3 + 5] k = \underline{5i + 8j + 2k}$$

$dU = \nabla U \cdot d\vec{r}$

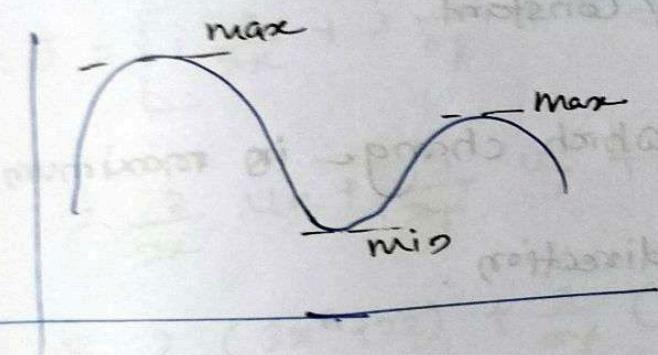
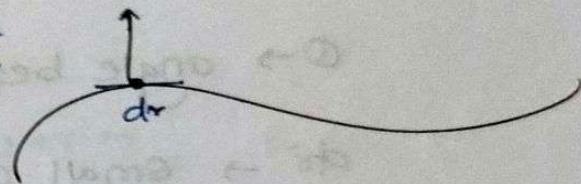
If we looking for the maximum rate of change $\|U\|$
then $\boxed{dU=0}$

If the function is maximum or minimum then its differential will be Zero
i.e. slope of funⁿ

i.e. $\nabla U \cdot d\vec{r} = 0$

which mean. $\nabla U = 0$ or $d\vec{r} = 0$ or $\theta = 90^\circ$

$d\vec{r}$ will be on the surface



At the maximum point slope will be zero.

i.e. $m = \frac{dy}{dx} = 0$.

If $y = 3x^2 - 2x + 5$

$$\frac{dy}{dx} = 6x - 2 = 0$$

$$\therefore x = 2/6 = 1/3$$

$$\boxed{x = 1/3}$$

$x = 1/3$ is the point at which funⁿ have maximum value
or minimum value

* Day - 13 *

9th May 2022

Recalling :-

$$d\mathbf{u} = \nabla u \cdot d\vec{s}$$

↳ scalar

$\nabla u \rightarrow$ have both direction and magnitude.

In vector form - $|\nabla u| |d\vec{s}| \cdot \cos \theta$

① \rightarrow angle between ∇u and $d\vec{s}$

$d\vec{s} \rightarrow$ small change

$|d\vec{s}| =$ fixed / constant.

Finding the direction in which change is maximum.

$\nabla u \rightarrow$ is in normal direction.

When the angle b/w ∇u and $d\vec{s}$ is 0

i.e. $\underline{\underline{\cos \theta = 1}}$

Then there change in unit is maximum.

If $\theta = 90^\circ \rightarrow$ change is zero.

If $\theta = 180^\circ \rightarrow$ the magnitude will be the same
but there is only change in sign.

Gradient of vector valued function :-

* It is generally called Divergence.

Divergence of any vector :-

$$\text{let } \vec{u} = (u_x)i + (u_y)j + (u_z)k$$

↳ vector function.

$$u_x = 3x^2 + 2z$$

$$u_y = -3z^3y$$

$$u_z = 4xyz$$

When we take derivative diversion.

$$\nabla \cdot \vec{u} = \left[i \frac{\partial}{\partial x} + j \frac{\partial}{\partial y} + k \frac{\partial}{\partial z} \right] \cdot [u_x i + u_y j + u_z k]$$

$$= \frac{\partial}{\partial x} u_x + \frac{\partial}{\partial y} u_y + \frac{\partial}{\partial z} u_z$$

$$= \frac{\partial}{\partial x} (3x^2 + 2z) + \frac{\partial}{\partial y} (-3z^3y) + \frac{\partial}{\partial z} (4xyz)$$

$$= 6x + (-3z^3) + 4xy$$

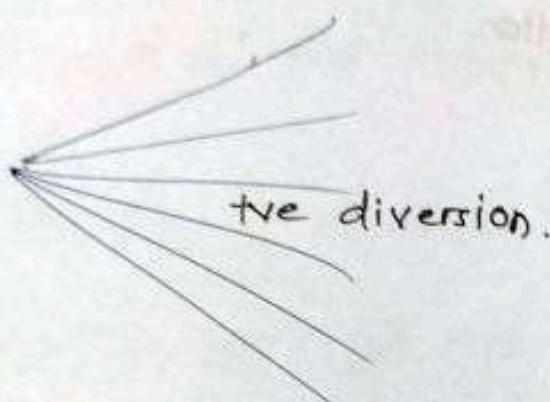
$$\boxed{\nabla \cdot \vec{u} = 6x - 3z^3 + 4xy} \quad \text{It is scalar function.}$$

When we take diversion of any vector function, we will get an scalar.

* Physical meaning of diversion :-

Literal meaning of diversion \rightarrow It is more like Spreading.

If it is moving away from Origin its called +ve Diversion.



Way by which something (for e.g. traffic) "Spreading out" is called Diversion

* Reverse diversion is called Conversion or -ve diversion.
means. "Spreading in"

∇U = When ∇ operator operate with scalar we get vector \Rightarrow which is called Gradient

$\nabla \overline{U}$ = When ∇ operator operate with vector we get scalar \Rightarrow This is called Diversion

$$Ex: r = \sqrt{x^2 + y^2 + z^2} \quad \nabla r = ?$$

$$\rightarrow r = (x^2 + y^2 + z^2)^{1/2}$$

$$\nabla r = \frac{1}{2} (x^2 + y^2 + z^2)^{-1/2} [2xi + 2yj + 2zk]$$

$$= (x^2 + y^2 + z^2)^{-1/2} [xi + yj + zk]$$

$$= \frac{[xi + yj + zk]}{\sqrt{x^2 + y^2 + z^2}} = \frac{\vec{r}}{|\vec{r}|} = \hat{r}$$

* If you take gradient of scalar function we will get unit vector.

$$Ex: f(x, y, z) = e^x \cdot \sin y \cdot \ln(z)$$

$$\nabla f = ? \quad \nabla(\nabla f) = ?$$

$$\nabla f = \left(i \frac{\partial}{\partial x} + j \frac{\partial}{\partial y} + k \frac{\partial}{\partial z} \right) \cdot e^x \cdot \sin y \cdot \ln(z)$$

$$= \frac{\partial}{\partial x} (e^x \cdot \sin y \cdot \ln(z)) i + \frac{\partial}{\partial y} (e^x \cdot \sin y \cdot \ln(z)) j \\ + \frac{\partial}{\partial z} (e^x \cdot \sin y \cdot \ln(z)) k$$

$$= e^x \cdot \sin y \cdot \ln(z) i + e^x \cos y \cdot \ln(z) j \\ + e^x \frac{\sin y}{z} k$$

$$= e^x \left[\sin y \ln(z) i + \cos y \ln(z) j + \frac{\sin y}{z} k \right]$$

$$\nabla \cdot (\nabla f) = \left(\frac{\partial}{\partial x} i + \frac{\partial}{\partial y} j + \frac{\partial}{\partial z} k \right) \left[e^x (\sin y \ln(z) i + \cos y \ln(z) j + \frac{\sin y}{z} k) \right]$$

$$= \frac{\partial}{\partial x} \left[e^x \sin y \ln(z) \right] i + \frac{\partial}{\partial y} \left[e^x \cos y \ln(z) \right] j + \frac{\partial}{\partial z} \left[e^x \frac{\sin y}{z} \right]$$

$$= e^x \cancel{\sin y \ln(z)} - e^x \cancel{\sin y \ln(z)} + e^x \sin y \left(\frac{-1}{z^2} \right)$$

$$\boxed{\nabla \cdot (\nabla f) = - \frac{e^x \sin y}{z^2}}$$

Answer is -ve which means the vector function is actually converging.

* Curl of Vector Function :-

$\nabla \cdot \vec{A} \rightarrow$ Divergence

$\nabla \times \vec{A} \rightarrow$ Curl

↓

It will give you the assurance how the vector "fun" is turning around any point.
i.e. there is change in direction.

Curl ie $\nabla \times \vec{A}$ - it will result in vector function

$$\nabla \cdot \vec{A} = \begin{vmatrix} i & j & k \\ \frac{\partial}{\partial x} & \frac{\partial}{\partial y} & \frac{\partial}{\partial z} \\ A_x & A_y & A_z \end{vmatrix}$$

$$= i \left[\frac{\partial}{\partial y} (A_z) - \frac{\partial}{\partial z} (A_y) \right] - j \left[\frac{\partial}{\partial x} (A_z) - \frac{\partial}{\partial z} (A_x) \right] + k \left[\frac{\partial}{\partial x} (A_y) - \frac{\partial}{\partial y} (A_x) \right]$$

If will give the rate at which the vector function is getting turned.

$$\vec{A} = 3x^2y \mathbf{i} + 2yz \mathbf{k}$$

$$\nabla \times \vec{A} = \begin{vmatrix} i & j & k \\ \frac{\partial}{\partial x} & \frac{\partial}{\partial y} & \frac{\partial}{\partial z} \\ 3x^2y & 0 & 2yz \end{vmatrix}$$

$$= i \left(\frac{\partial}{\partial y} (2yz) \right) - j \left(\frac{\partial}{\partial x} (2yz) - \frac{\partial}{\partial z} (3x^2y) \right) + k \left[0 - \frac{\partial}{\partial y} (3x^2y) \right]$$

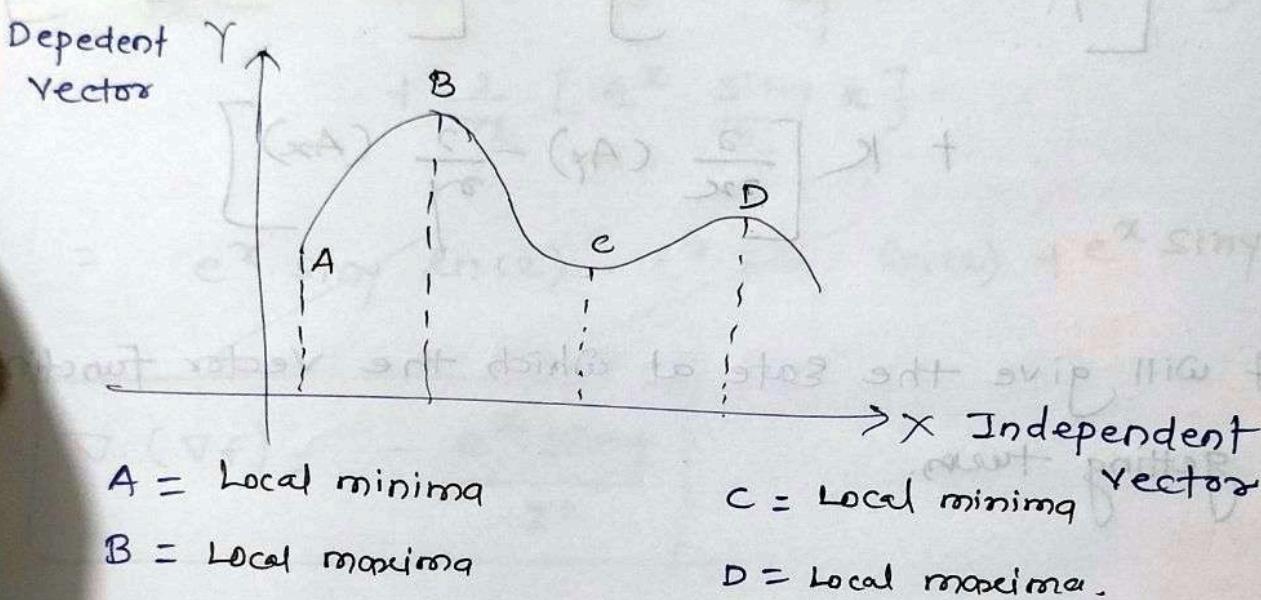
$$= 2z \mathbf{i} - 0 + (-3x^2) \mathbf{k}$$

$$= \underline{2z \mathbf{i} - 3x^2 \mathbf{k}}$$

$$|\vec{\nabla}| = \sqrt{2^2 + (-3)^2} = \sqrt{4+9} = \sqrt{13}$$

This will tell us how the vector is changing in particular direction.

* Increasing / Decreasing fun? :-



From point A to B function is increasing i.e. $\frac{dy}{dx} > 0$

If you increase x then function is increasing
 i.e. the slope is tve.

From point B to C function is decreasing i.e. $\frac{dy}{dx} < 0$.

If you increase x then function is decreasing
 i.e. the slope is -ve.

Points A, B, C, D = are called point of Extremum.

$$\text{i.e. } \frac{dy}{dx} = 0$$

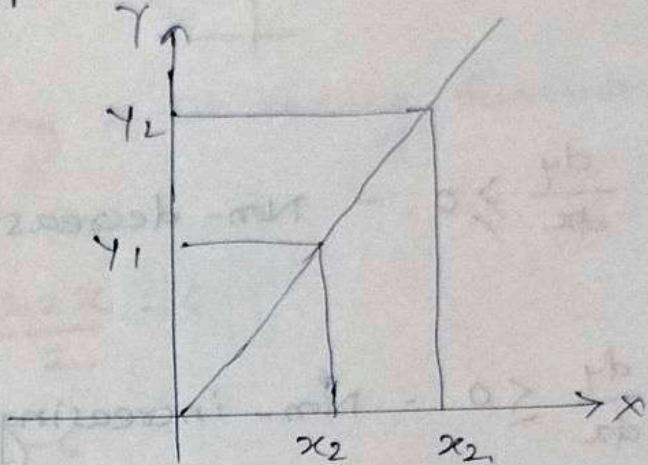
Because tangent at all these points is parallel
i.e. $\alpha = \theta$, the slope is zero

* Show function is increasing :-

$$y = f(x)$$

If $x_1 < x_2$ & $f(x_1) < f(x_2)$.

Then function is called
increasing funⁿ.



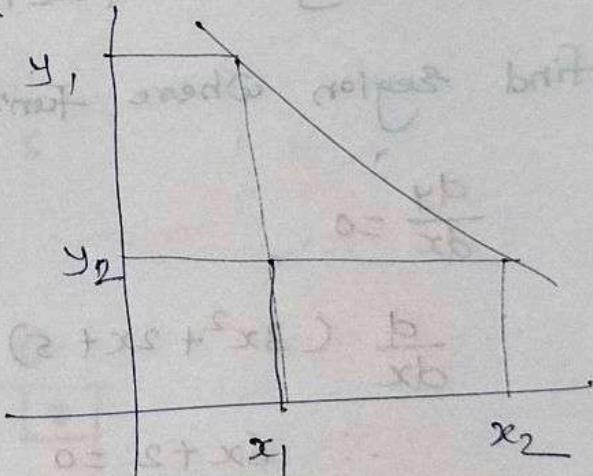
If $x_1 < x_2$ But $f(x_1) > f(x_2)$

Then function is called decreasing funⁿ

This is called Zero derivative test.

Where we find function

is increasing or decreasing
without finding derivative.

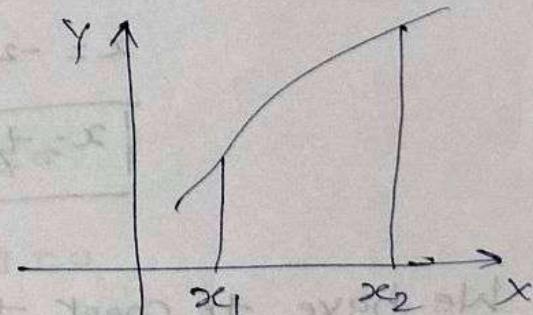


* First Derivative Test :-

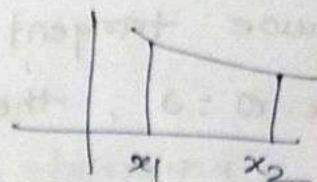
$$y = f(x)$$

If $\frac{dy}{dx} > 0$

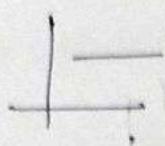
i.e. The function is strictly increasing.



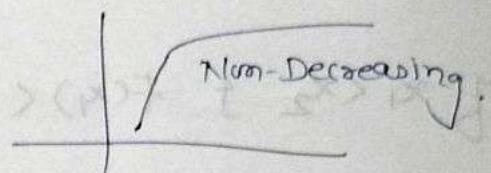
If $\frac{dy}{dx} < 0 \rightarrow$ function is strictly decreasing.



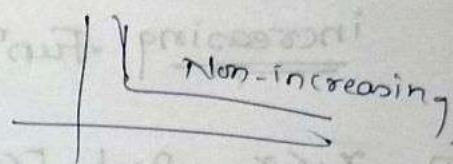
if $\frac{dy}{dx} = 0$



If $\frac{dy}{dx} \geq 0 \rightarrow$ Non-decreasing



if $\frac{dy}{dx} \leq 0 \rightarrow$ Non-increasing



Example :-

$$y = 3x^2 + 2x + 5$$

find region where fun' is increasing / Decreasing

→

$$\frac{dy}{dx} = 0$$

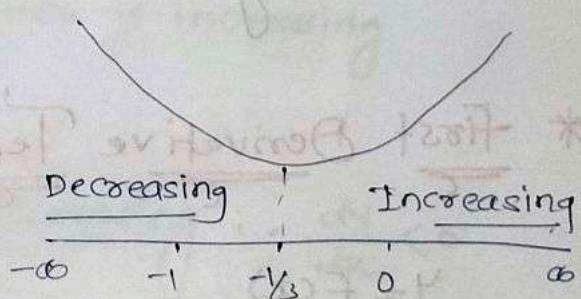
$$\therefore \frac{d}{dx}(3x^2 + 2x + 5) = 0$$

$$\therefore 6x + 2 = 0$$

$$\therefore 6x = -2$$

$$x = -\frac{1}{3}$$

$$\boxed{x = -\frac{1}{3}}$$



We have to check the point is maxima or minima.

$$\frac{dy}{dx} = 6x + 2$$

$$\text{if } x = 0 \quad \frac{dy}{dx} = 2 > 0$$

$$\text{at } x=1 \\ \frac{dy}{dx} = 6(-1) + 2 = -6 + 2 = \frac{-4 < 0}{\text{c}}$$

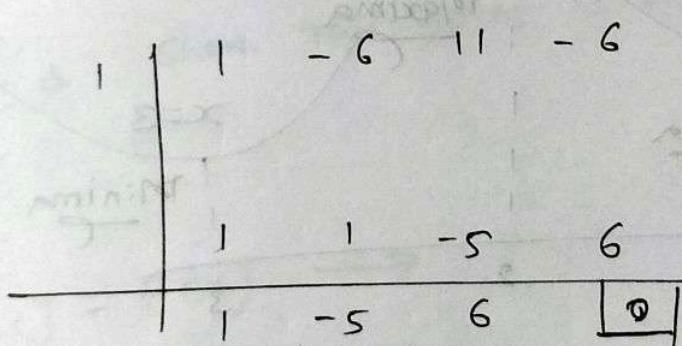
Example :- $y = \frac{x^4}{4} - 2x^3 + \frac{11x^2}{2} - 6x$

Find region for increasing & decreasing function.

$$\rightarrow \frac{dy}{dx} = \frac{4x^3}{4} - 6x^2 + \frac{22x}{2} - 6$$

$$\frac{dy}{dx} = x^3 - 6x^2 + 11x - 6$$

$$\text{for } x=1 \quad \frac{dy}{dx} = 0$$



$$\therefore x^2 - 5x + 6 = 0$$

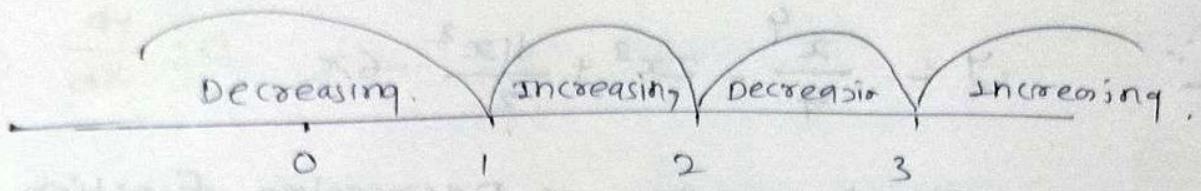
$$\therefore x^2 - 2x - 3x + 6 = 0$$

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

$$\therefore x-2 = 0 \text{ or } x-3 = 0$$

$$\boxed{x=2} \text{ or } \boxed{x=3}$$

$$\therefore \boxed{x=1, 2, 3}$$



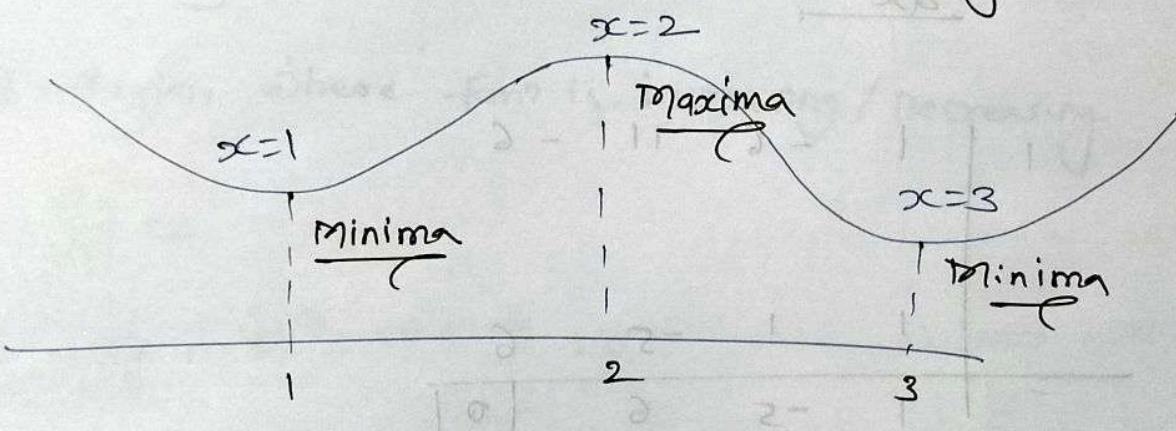
at $x=0$

$$\frac{dy}{dx} = x^3 - 6x^2 + 11x - 6 = 0 - 6 = \underline{\underline{-6}}$$

i.e funⁿ is decreasing.

at $\boxed{x=1.5}$ \rightarrow funⁿ is increasing.

$\boxed{x=2.0}$ \rightarrow funⁿ is decreasing.

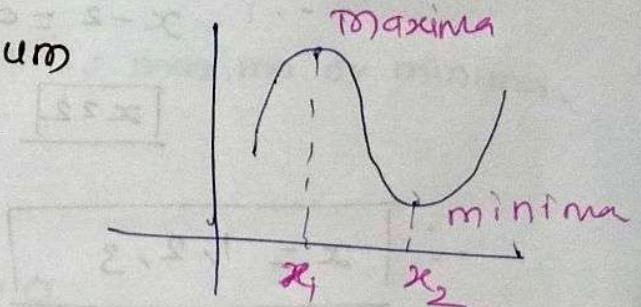


* Second Derivative Test:

$\frac{d^2y}{dx^2} = 0$ for Both maxima & minima

To find the point is maximum or minimum we go for the Second derivative test.

i.e,



$\frac{d^2y}{dx^2} > 0 \rightarrow$ minima

$\frac{d^2y}{dx^2} < 0 \rightarrow$ maxima

$\frac{d^2y}{dx^2} = 0 \rightarrow$ Point of Inflection. Inflation
i.e. Point where sign of slope changes

If the slope rate is +ve before inflation then
slope rate becomes -ve after inflation.

$$y = F(x)$$

$\frac{dy}{dx} \Rightarrow$ shows the points of Extremum.

$\frac{d^2y}{dx^2} \Rightarrow$ shows the point is maxima / minima.

Suppose-

$$y = F(x) \rightarrow 1^{\text{st}} \text{ Gen}$$

$$g = \frac{dy}{dx} \rightarrow 2^{\text{nd}} \text{ Gen} \quad (g \text{ is son of } y)$$

$$h = \frac{dg}{dx} = \frac{d^2y}{dx^2} \rightarrow 3^{\text{rd}} \text{ Gen} \quad (h \text{ is son of } g \text{ & Grandson of } y)$$

If $g=0 \Rightarrow$ we get Extremum of y .

If $h=0 \Rightarrow$ we get Extremum of g .
Also, get Inflation of y .

* Day-12 *

10th May, 2022

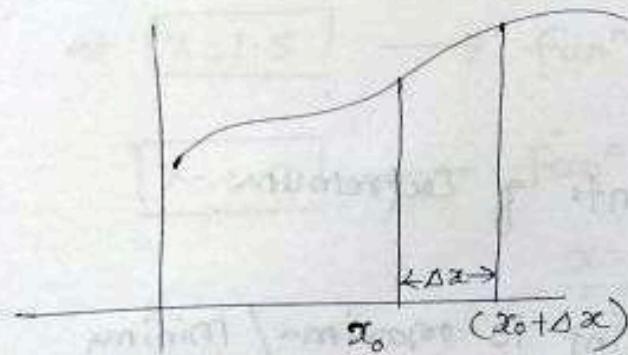
Tuesday

* Taylor Series ..

$$y = f(x)$$

$x = x_0 \rightarrow$ called initial value

$y = f(x_0) \rightarrow$ called initial function value



$$y = f(x)$$

Taylor Expansion :

$$y = f(x) \Big|_{x=x_0} + \frac{1}{1!} \frac{d}{dx} f(x) \Big|_{x=x_0} \frac{dx}{dx} + \frac{1}{2!} \frac{d^2}{dx^2} f(x) \Big|_{x=x_0} \frac{dx^2}{dx^2}$$

$$\therefore y = \sum_{i=0}^{\infty} \frac{1}{i!} f^{(i)}(x_0) (dx)^i$$

E - $y = 3x^2 + 2$. Expand the y about $x=2$.

$$y = f(x) \Big|_{x=2} + \frac{1}{1!} \frac{d}{dx} f(x) \Big|_{x=2} \Delta x + \frac{1}{2!} \frac{d^2}{dx^2} f(x) \Big|_{x=2} \Delta x^2$$

$$\therefore f(x)_{x=2} = (3x^2 + 2)_{x=2} = 3(2^2) + 2 = 14$$

$$\frac{1}{1!} \frac{d}{dx} (3x^2 + 2) \Delta x = \underline{6x} \text{ at } x=2 = \underline{\underline{12}} \Delta x$$

$$\frac{1}{2!} \frac{d^2}{dx^2} (3x^2 + 2) = \frac{1}{2} 6 = 3 \Delta x^2.$$

$$\therefore y = 14 + 12 \Delta x + 3 \Delta x^2$$

$$\therefore y = 3 \Delta x^2 + 12 \Delta x + 14$$

$$\Delta x = x - x_0$$

$$\text{at } \Delta x = x_0 = 2$$

$$\boxed{y = 14}$$

$$\therefore \Delta x = 0$$

$$\text{at } x_0 = 1$$

$$\therefore \Delta x = 1$$

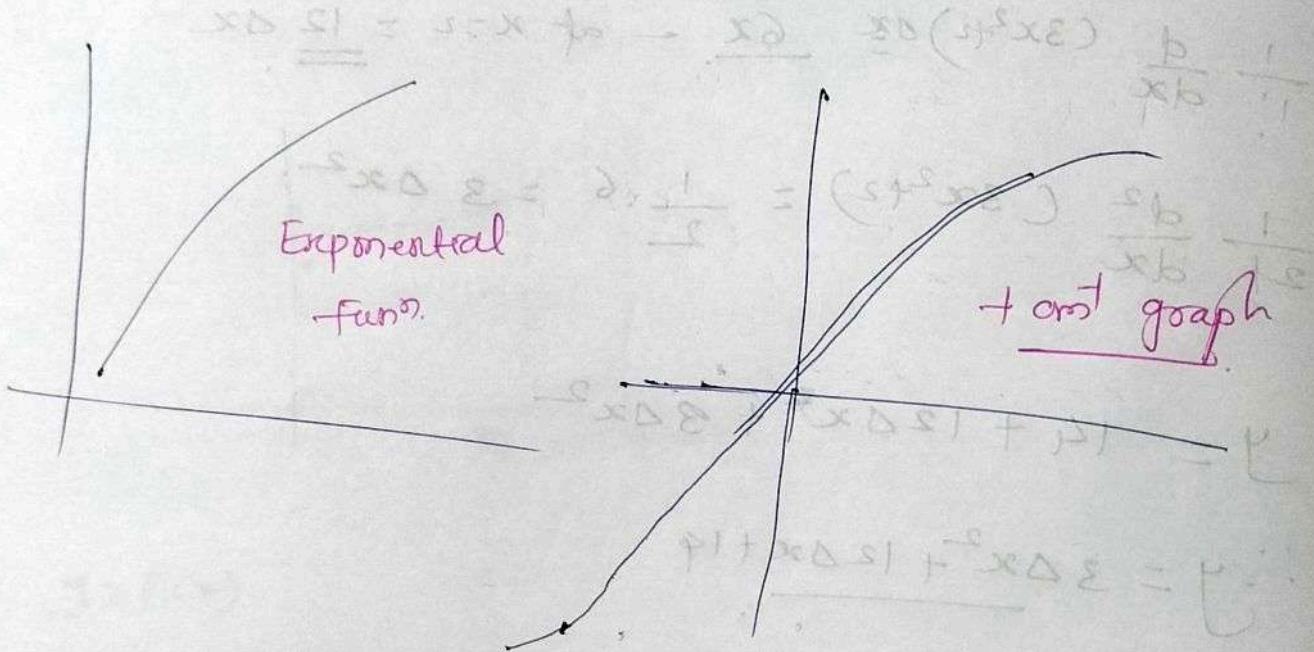
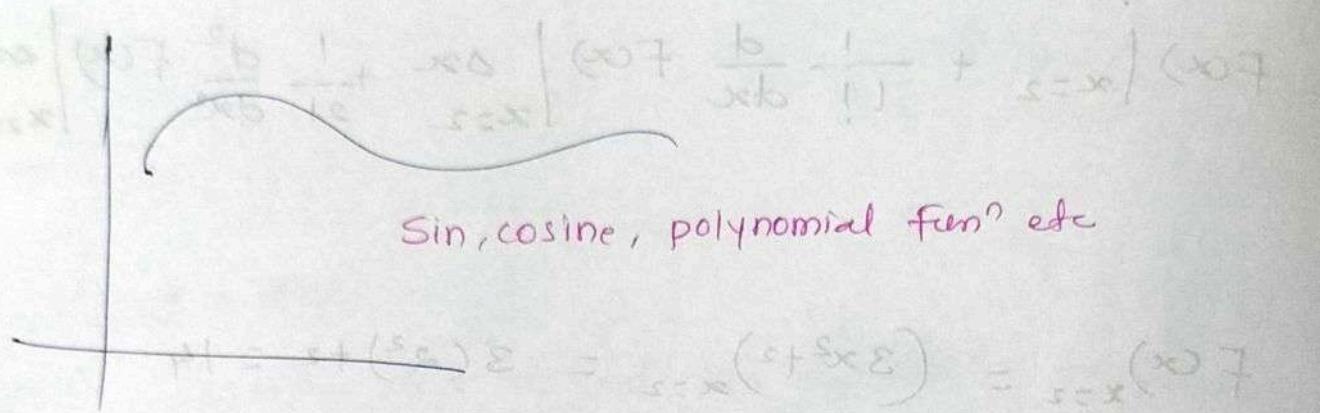
$$y = 3 + 12 + 14 = 29$$

$$\boxed{y = 29}$$

* We can fit multiple function on same data

* Taylor series is used to approximate the function.

* Graphs of some funⁿ



* Exponential series - by Taylor series method

1) Exponential

$$y = e^x \text{ at } x=0$$

$$= \frac{d}{dx} f(x) + \frac{1}{1!} \left. \frac{d}{dx} f(x) \right|_{x=0} \cdot 0x + \frac{1}{2!} \left. \frac{d^2}{dx^2} f(x) \right|_{x=0} \cdot 0x^2 + \dots$$

$$= e^x \Big|_{x=0} + 1 \cdot e^x \Big|_{x=0} \cdot 0x + \frac{1}{2} e^x \Big|_{x=0} \cdot 0x^2 + \dots$$

$$= 1 + 0x + \frac{0x^2}{2} + \dots$$

$$\boxed{\begin{aligned} \Delta x &= x \\ \therefore y &= 1 + x + \frac{x^2}{2} + \frac{x^3}{3} + \dots \end{aligned}}$$

2) Sin fun?

$y = \sin x$ at $x = 0$.

$$\begin{aligned} y &= F(x) \Big|_{x=0} + \frac{1}{1!} \frac{d}{dx} F(x) \Big|_{x=0} \Delta x + \frac{1}{2!} \frac{d^2}{dx^2} F(x) \Big|_{x=0} \Delta x^2 + \dots \\ &= \sin x \Big|_{x=0} + \frac{d}{dx} (\sin x) \Big|_{x=0} \Delta x + \frac{1}{2} \frac{d^2}{dx^2} (\sin x) \Big|_{x=0} \Delta x^2 + \dots \\ &= 0 + \cos x \Big|_{x=0} - \frac{1}{2} \sin x \Big|_{x=0} \Delta x^2 + \dots \\ &= 0 + \Delta x - \frac{1}{2!} \times 0 - \frac{1}{3!} \Delta x^3 + \dots \end{aligned}$$

$$\boxed{\begin{aligned} \Delta x &= x \\ \therefore y &= x - \frac{x^3}{3!} + \frac{x^5}{5!} - \frac{x^7}{7!} + \dots \end{aligned}}$$

* Taylor Series - For 2D

$$z = F(x, y) \quad \frac{1}{1!} \frac{\partial F}{\partial y} \Big|_{\substack{x=x_0 \\ y=y_0}} \Delta y$$

$$z = F(x, y) \Big|_{\substack{x=x_0 \\ y=y_0}} + \frac{1}{1!} \frac{\partial F}{\partial x} \Big|_{\substack{x=x_0 \\ y=y_0}} \Delta x + \frac{1}{2!} \frac{\partial^2 F}{\partial x^2} \Big|_{\substack{x=x_0 \\ y=y_0}} \Delta x^2$$

$$+ \frac{1}{2!} \frac{\partial^2 F}{\partial y^2} \Big|_{\substack{x=x_0 \\ y=y_0}} \Delta y^2 + \dots$$

$$\text{Ex} - z = 3x^2 + y^2$$

$$z = f(x) \left| \begin{array}{c} + \frac{1}{1!} \frac{\partial f}{\partial x} \\ x=0 \\ y=0 \end{array} \right| \left. \begin{array}{c} \Delta x \\ x=0 \\ y=0 \end{array} \right| + \frac{1}{1!} \frac{\partial f}{\partial y} \left| \begin{array}{c} \Delta y \\ x=0 \\ y=0 \end{array} \right|$$

$$+ \frac{1}{2!} \frac{\partial^2 f}{\partial x^2} \left| \begin{array}{c} \Delta x^2 \\ x=0 \\ y=0 \end{array} \right| + \frac{1}{2!} \frac{\partial^2 f}{\partial y^2} \left| \begin{array}{c} \Delta y^2 \\ x=0 \\ y=0 \end{array} \right| + \dots$$

$$z = (3x^2 + y^2) + \frac{1}{1!} (6x + y^2) \Delta x + \frac{1}{1!} (3x^2 + 2y) \Delta y$$

$$+ \frac{1}{2!} (6 + y^2) \Delta x^2 + \frac{1}{2!} (3x^2 + 2) \Delta y^2$$

at $x=0$ & $y=0$

$$z = 0 + 0 + 0 + \frac{1}{2} 6 \Delta x^2 + \frac{1}{2} 2 \Delta y^2$$

$$\therefore \boxed{z = 3 \Delta x^2 + \Delta y^2}$$

- * Fourier Series is used when func' is periodic in nature
- * Maclaurin Series is special case of Taylor Series where initial point is origin.
- * Linear function doesn't have 2nd derivative only have first derivative.
- * Non-linear function have more than 1 derivatives.

* Day - 13 * 24th May, 2022
 Tuesday

A Jacobian matrix :-

It is the extension of $\frac{\partial F}{\partial x}$.

If $F_1(x, y, z)$, $F_2(x, y, z)$, $F_3 \in \mathbb{R}^{x, y, z}$,

then Jacobian matrix can be given as.

$$J = \begin{bmatrix} \frac{\partial F_1}{\partial x} & \frac{\partial F_1}{\partial y} & \frac{\partial F_1}{\partial z} \\ \frac{\partial F_2}{\partial x} & \frac{\partial F_2}{\partial y} & \frac{\partial F_2}{\partial z} \\ \frac{\partial F_3}{\partial x} & \frac{\partial F_3}{\partial y} & \frac{\partial F_3}{\partial z} \end{bmatrix} \rightarrow \text{Jacobian matrix.}$$

$$\begin{bmatrix} F(x, y) \\ g(x, y) \end{bmatrix}$$

$\rightarrow x_0, y_0 \rightarrow$ Initial Point

By Taylor series.

$$f(x, y) \left|_{\begin{array}{c} x_0 \\ y_0 \end{array}} + \frac{1}{1!} \frac{\partial f(x, y)}{\partial x} \right|_{\begin{array}{c} x_0 \\ y_0 \end{array}} \left|_{\Delta x} + \frac{1}{1!} \frac{\partial f(x, y)}{\partial y} \right|_{\begin{array}{c} x_0 \\ y_0 \end{array}} \left|_{\Delta y} \right.$$

$$g(x, y) \left|_{\begin{array}{c} x_0 \\ y_0 \end{array}} + \frac{1}{1!} \frac{\partial g(x, y)}{\partial x} \right|_{\begin{array}{c} x_0 \\ y_0 \end{array}} \left|_{\Delta x} + \frac{1}{1!} \frac{\partial g(x, y)}{\partial y} \right|_{\begin{array}{c} x_0 \\ y_0 \end{array}} \left|_{\Delta y} \right.$$

If can be written as

$$\begin{bmatrix} f(x,y) \\ g(x,y) \end{bmatrix} + \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \\ \frac{\partial g}{\partial x} & \frac{\partial g}{\partial y} \end{bmatrix}_{x_0=0, y_0=0} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} + \dots$$

$\underbrace{\qquad\qquad\qquad}_{\downarrow}$

Jacobian Matrix

Ex.

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

$$g(x,y) = x + y - 2xy$$

Find Linear expansion / Linearic funⁿ. at (x_0, y_0) $(1, 1)$

→

$$\Delta x = 0.1$$

$$\Delta y = 0.2$$

$$\begin{aligned} f(x,y)_{1,1} &= x^2 + y^2 + 2xy \\ &= 1+1+2 = 4 \end{aligned}$$

$$\begin{aligned} g(x,y)_{1,1} &= x+y-2xy \\ &= 1+1-2 = 0 \end{aligned}$$

$$J = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \\ \frac{\partial g}{\partial x} & \frac{\partial g}{\partial y} \end{bmatrix} = \begin{bmatrix} 2x + 2y^2 + 2y & 0 + 2y + 2x \\ 1 + 0 - 2y & 0 + 1 - 2x \end{bmatrix}_{1,1}$$

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

$$= \begin{bmatrix} 4 \\ 0 \end{bmatrix} + \begin{bmatrix} 4 & 4 \\ -1 & -1 \end{bmatrix} \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}$$

$$= \begin{bmatrix} 4 \\ 0 \end{bmatrix} + \begin{bmatrix} 0.4 + 0.8 \\ -0.1 - 0.2 \end{bmatrix}$$

$$= \begin{bmatrix} 4 \\ 0 \end{bmatrix} + \begin{bmatrix} 1.2 \\ -0.3 \end{bmatrix} = \begin{bmatrix} 5.2 \\ -0.3 \end{bmatrix}$$

* Hessian Matrix :-

The Hessian matrix or Hessian is a square matrix of second-order partial derivatives of a scalar-valued function or scalar-field.

It describes the local curvature of a function of many variables.

Hessian matrix is a square matrix.

It is represented as

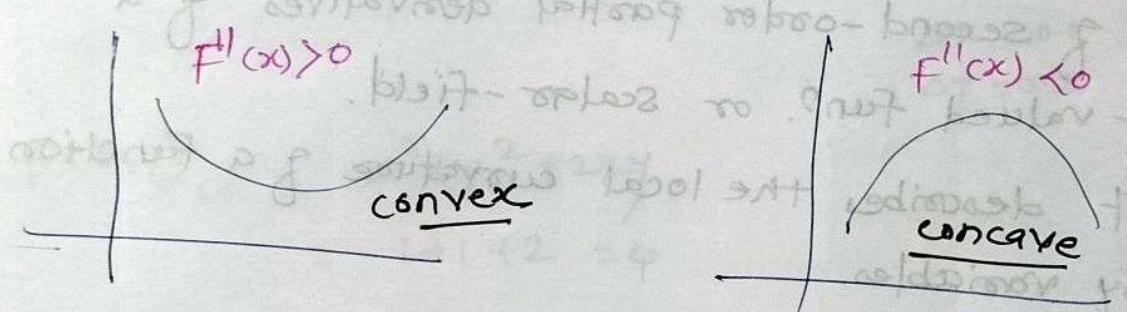
$$f(x,y)$$

$$H = \begin{bmatrix} \frac{\partial^2 F}{\partial x^2} & \frac{\partial^2 F}{\partial x \partial y} \\ \frac{\partial^2 F}{\partial y \partial x} & \frac{\partial^2 F}{\partial y^2} \end{bmatrix}$$

$$f(x,y,z)$$

$$H = \begin{bmatrix} \frac{\partial^2 F}{\partial x^2} & \frac{\partial^2 F}{\partial x \partial y} & \frac{\partial^2 F}{\partial x \partial z} \\ \frac{\partial^2 F}{\partial y \partial x} & \frac{\partial^2 F}{\partial y^2} & \frac{\partial^2 F}{\partial y \partial z} \\ \frac{\partial^2 F}{\partial z \partial x} & \frac{\partial^2 F}{\partial z \partial y} & \frac{\partial^2 F}{\partial z^2} \end{bmatrix}$$

- * Hessian matrix will give the curvature in multidimensional space.
- * Hessian matrix are often used in machine learning and data science algorithms for optimizing a function of interest.
- * In Convex optimization - Hessian matrix is positive, which is semi-definite matrix.
- * The hessian matrix of convex function is positive. which means it can be zero or positive But can't be less than zero.



- * If 2nd derivative of any function is +ve then it's a convex function.
- * If 2nd derivative of any function is -ve then it's a concave function.
- * Hessian matrix is ≥ 0 - for convex funⁿ.
- * Hessian matrix is ≤ 0 for concave funⁿ.
- * If $H \geq 0$ i.e. convex fun. will give local minima.

- * If $H < 0$ i.e. concave funⁿ. will give Local maxima.
- * Positive Definite matrix - will give Local minima
- * Semi-positive Definite matrix will give Local maxima, Local minima, & Saddle point.

* 25th May, 2022 *

Wednesday

- * Method for checking matrix positive definite or not.

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

if $a_{11} > 0$

$$\text{if } \det \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} > 0$$

if $\det(A) > 0$

then the ~~pos~~ matrix is positive Definite matrix

Ex. $A = \begin{bmatrix} 1 & -3 & 2 \\ 2 & 1 & 4 \\ 1 & 2 & 4 \end{bmatrix}$

$\rightarrow a_{11} = 1$

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} 1 & -3 \\ 2 & 1 \end{bmatrix} = 1 + 6 = 7$$

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} 1 & -3 & 2 \\ 2 & 1 & 4 \\ 1 & 2 & 4 \end{bmatrix} = 1(4-8) + 3(8-4) + 2(4-1) = -4 + 12 + 6 = \underline{\underline{14}}$$

Matrix A is positive definite matrix.

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

One of these values is less than zero.

then the given matrix is Semi-positive definite matrix.

* All the eigen values of positive Definite matrix are positive

But all positive eigen values doesn't necessary that matrix is positive Definite.

* If the matrix is positive definite then it will give local minima.

* cond³ for Negative definite matrix:

1) determinant of odd order submatrix is < 0

2) determinant of even order Submatrix is > 0

\Leftrightarrow

-ve	+ve	-ve	
a_{11}	a_{12}	a_{13}	a_{14}
a_{21}	a_{22}	a_{23}	a_{24}
a_{31}	a_{32}	a_{33}	a_{34}
a_{41}	a_{42}	a_{43}	a_{44}

* Eigen-values of Negative definite matrix are negative.

for Local maxima -

$F_{xx} < 0 \leftarrow 1^{\text{st}} \text{ order}$

$F_{xx} \cdot F_{yy} - F_{xy}^2 > 0$

If the matrix is -ve Definite then it will give local maxima.

* If $F_{xx} \cdot F_{yy} - F_{xy}^2 \leq 0$

Then this is the condⁿ for saddle point.

- * If all the eigen values are positive \rightarrow test gives Local minima.
- * If all the eigen values are negative \rightarrow test gives Local maxima.
- * If all the eigen values are mixed \rightarrow test gives saddle point.
- * If all the eigen values is zero \rightarrow then test is inconclusive.

What is Calculus?

$$\bar{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \quad \bar{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

X = set of variable. X is vector of variable

Y = set of function. Y is vector of function.

$$[Y = Y(x)] \rightarrow Y \text{ is a function of } X.$$

Y can be written as.

$$Y = \begin{bmatrix} y_1(x_1, x_2, \dots, x_n) \\ y_2(x_1, x_2, \dots, x_n) \\ \vdots \\ y_m(x_1, x_2, \dots, x_n) \end{bmatrix}$$

X and Y are vectors not scalars.

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} & \frac{\partial y_1}{\partial x_3} & \dots & \frac{\partial y_1}{\partial x_n} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} & \frac{\partial y_2}{\partial x_3} & \dots & \frac{\partial y_2}{\partial x_n} \\ \vdots & & & & \\ \frac{\partial y_n}{\partial x_1} & \dots & \frac{\partial y_n}{\partial x_2} & \frac{\partial y_n}{\partial x_3} & \dots & \frac{\partial y_n}{\partial x_n} \end{bmatrix}^T$$

If's a
Jacobian
Matrix.

If \mathbf{y} is scalar . $\mathbf{y} = [y]$

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \left[\frac{\partial y}{\partial x_1} \quad \frac{\partial y}{\partial x_2} \quad \dots \quad \frac{\partial y}{\partial x_n} \right]^T$$

If x is scalar .

$$\frac{\partial \mathbf{y}}{\partial x} = \left[\frac{\partial y_1}{\partial x} \quad \frac{\partial y_2}{\partial x} \quad \dots \quad \frac{\partial y_m}{\partial x} \right]^T$$

Ex.

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$y_1 = x_1^2 - x_2$$

$$y_2 = x_3^2 + 3x_2$$

$$\rightarrow \frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \mathbf{J}^T = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} & \frac{\partial y_1}{\partial x_3} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} & \frac{\partial y_2}{\partial x_3} \end{bmatrix}$$

$$= \begin{bmatrix} 2x_1 & -1 & 0 \\ 0 & 3 & 2x_3 \end{bmatrix}^T = \begin{bmatrix} 2x_1 & 0 \\ -1 & 3 \\ 0 & 2x_3 \end{bmatrix}$$

* Some Properties *

i) $\frac{\partial}{\partial x} [Cx] = C^T [Y] = Y$

where $C = \begin{bmatrix} C_{11} & C_{12} & \dots & C_{1n} \\ C_{21} & C_{22} & \dots & C_{2n} \\ \vdots & & & \\ C_{n1} & \dots & \dots & C_{nn} \end{bmatrix}$

\downarrow
It's matrix of constant.

i.e. coeff of variable.

Ex

$$\begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$x_1 + 3x_2$$

$$2x_1 + 4x_2$$

$$\frac{\partial y_1}{\partial x_1} = 1 \quad \frac{\partial y_2}{\partial x_1} = 2$$

$$\frac{\partial y_1}{\partial x_2} = 3 \quad \frac{\partial y_2}{\partial x_2} = 4$$

$$\Rightarrow \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$$

Hence proved

$$\Rightarrow \frac{\partial}{\partial x} [x^T c] = c$$

$$\Rightarrow \frac{\partial}{\partial x} [x^T x] = 2x$$

$$\rightarrow x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$x^T = [x_1 \ x_2]$$

$$x^T x = [x_1 \ x_2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \Rightarrow [x_1^2 + x_2^2]$$

$$\frac{\partial}{\partial x} [x^T x] = \frac{\partial}{\partial x} [x_1^2 + x_2^2]$$

$$= \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix} = 2 \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\boxed{\frac{\partial}{\partial x} [x^T x] = 2 \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}}$$

Hence Proved

$$4) \frac{\partial}{\partial x} [x^T c x] = 2cx$$

if c is Symmetric

$$\frac{\partial}{\partial x} [x^T c x] = cx + c^T x - \text{if } c \text{ isn't Symmetric}$$

Ex - $g(x) = 2x_1 + 5x_2 + 12x_3$, $c = [2, 5, 12]$
 $x = [x_1 \ x_2 \ x_3]$

$$g = \begin{bmatrix} 2 & 5 & 12 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad W = x^T$$

$$g = c \cdot w$$

$$\frac{\partial g}{\partial x} = \begin{bmatrix} \frac{\partial g}{\partial x_1} \\ \frac{\partial g}{\partial x_2} \\ \frac{\partial g}{\partial x_3} \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial x_1} (2x_1 + 5x_2 + 12x_3) \\ \frac{\partial}{\partial x_2} (2x_1 + 5x_2 + 12x_3) \\ \frac{\partial}{\partial x_3} (2x_1 + 5x_2 + 12x_3) \end{bmatrix} = \begin{bmatrix} 2 \\ 5 \\ 12 \end{bmatrix} = c^T$$

~~$[x_1 \ x_2]$ = $x^T x$~~

~~$[x_1 \ x_2 \ x_3] = x^T x$~~

Thursday

* Gradient Descent Optimization :-

$f(x)$ - is objective function.

There are two possibilities, either you try to minimise it or maximise it

min: $f(x)$ → Loss function
max: $f(x)$ → Gain function

We try to minimise the loss and maximise the gain

$y = mx + c$ → Eqⁿ of straight line

$y \Rightarrow$ Dependent Variable

$m \Rightarrow$ Slope

$x \Rightarrow$ Independent Variable

$c \Rightarrow$ Intercept.

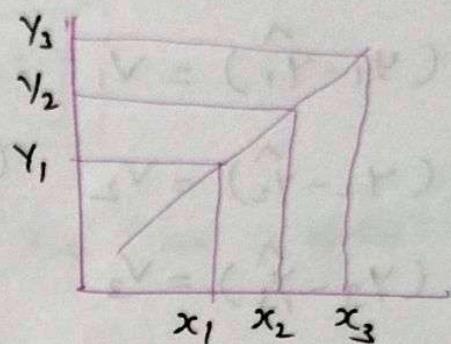
m & c are required for finding defining a model.

m & c are parameters.

values of x & y are changing but m & c are fixed for entire line.

Line is differentiated by

Parameter i.e., $\frac{m+c}{T}$.



* Methods to find parameter :-

* Least Squares : Regression (Linear)

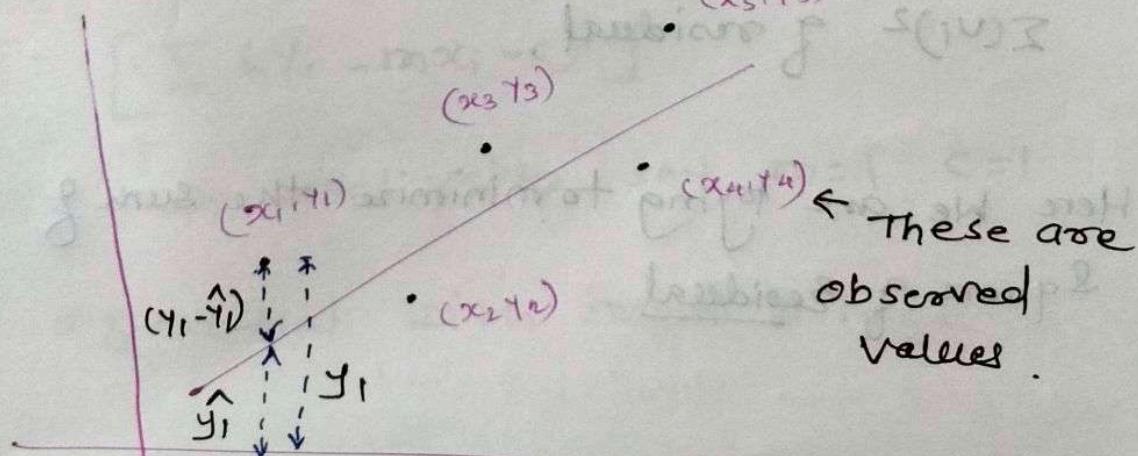
1) $y = mx + c$ - Linear model.

2) $y = ax_1 + bx_2 + c$ → Linear model

3) $y = ax_1^2 + bx_2^2 + cx_1x_2 + d$ → Linear model

4) $y = a^2x_1 + b^2x_2 + c^3x_3$ → Non-linear model

5) $y = e^{ax}$ → Non-linear model



These are
observed
values.

i. $y = mx + c$ — model.

$$\hat{y}_i = mx_i + c$$

$\hat{y} \rightarrow$ value of x_i through model at x_i

$$(y_i - \hat{y}_i) = v_i$$

$$(y_2 - \hat{y}_2) = v_2$$

$$(y_3 - \hat{y}_3) = v_3$$

$$(y_4 - \hat{y}_4) = v_4$$

} - called Residual

Residual value → It is the difference between observed value & estimated value

→

$$(\sum v_i)^2 \rightarrow \text{objective fun'}$$

↓
This should be minimum.

$$(\sum v_i)^2 = (v_1^2 + v_2^2 + v_3^2 + v_4^2 + v_5^2)$$

We need to minimize the value of objective fun'

$\sum (v_i)^2$ of residual.

Here we are trying to minimize the sum of square of residual.

* objective funⁿ $\rightarrow \min [\sum v_i^2]$

$$v_i = y_i - \hat{y}_i$$

$$v_i = y_i - (mx_i + c)$$

$$F = \min [\sum (y_i - mx_i - c)^2]$$

* If we are changing the line means
Changing in m & c.

We have to optimise (minimum) the objective
function by changing m & c.

We can take

$$\left. \begin{array}{l} \frac{\partial F}{\partial m} = 0 \\ \frac{\partial F}{\partial c} = 0 \end{array} \right\}$$

This approach is called
Linear Regression or Least
Square method.

* Gradient Descent method

$$F = [\sum (y_i - mx_i - c)^2]$$

Let their initial values, say $m=1$ $c=1$

find differential with respect to m & c

$$\frac{\partial F}{\partial m} \Big|_{\substack{m=1 \\ c=1}} = \quad \text{Here will gradient with respect to } m$$

$$\frac{\partial F}{\partial c} \Big|_{\substack{m=1 \\ c=1}} = \quad \text{Here will gradient with respect to } c.$$

Gradient is just like slope in $\frac{dy}{dx}$

We have to move in the direction where slope is minimise.

Ex - $y = mx + b$

Let start, $m=0.5$ - Initial value

When $m=0.5$ $\hat{y}_1 = ?$

$$\hat{y}_1 = 0.5x + 3$$

$$= 0.5(1) + 3 \quad \dots (x=1)$$

$$= 3.5$$

x	y
1	4.1
2	4.9
3	6.2

$$\hat{y}_2 = 0.5x + 3$$

$$= 0.5(2) + 3 \quad \dots (x=2)$$

$$= 4$$

$$\hat{y}_3 = 0.5x + 3$$

$$= 0.5(3) + 3 \quad \dots (x=3)$$

$$= 4.5$$

$\hat{y}_1, \hat{y}_2, \hat{y}_3 \rightarrow$ Predicted Value

$$\begin{aligned} v_1 &= y_1 - \hat{y}_1 = 4.1 - 3.5 = 0.6 \\ v_2 &= y_2 - \hat{y}_2 = 4.9 - 4 = 0.9 \\ v_3 &= y_3 - \hat{y}_3 = 6.2 - 4.5 = 1.7 \end{aligned} \quad \left. \begin{array}{l} \\ \\ \end{array} \right\} \text{Residual value}$$

$$F = \sum_{i=1}^3 v_i^2 = (0.6)^2 + (0.9)^2 + (1.7)^2 = 0.36 + 0.81 + 2.89 = 4.06$$

$F = \sum v_i^2$

$\frac{4.06}{3} = \underline{\underline{1.35}}$

$$* y = mx + 3$$

$$-\sum v_i^2 = \sum (y_i - mx_i - 3)^2$$

$$\begin{aligned} \frac{d}{dm} & (y_i - mx_i - 3)^2 \\ &= [2(y_i - mx_i - 3)(-x_i)] \end{aligned}$$

$$\text{Total sum} = [2(4.1 - m(1) - 3)(-1)]$$

$$+ [2[4.9 - m(2) - 3](-2)]$$

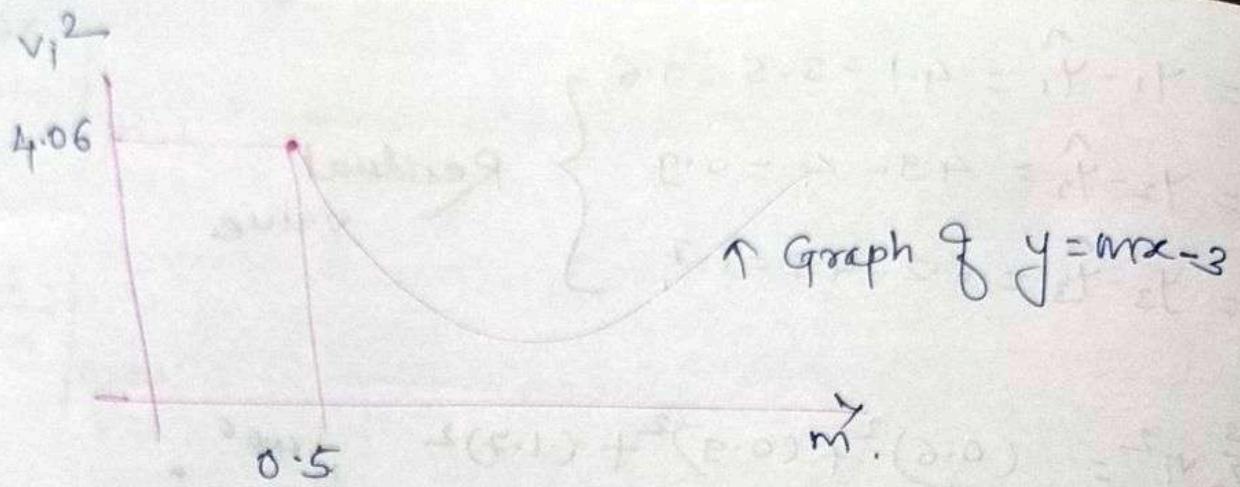
$$+ [2[6.2 - m(3) - 3](-3)]$$

$$\begin{aligned} &= 2(4.1 - m - 3)(-1) + 2(4.9 - 2m - 3)(-2) \\ &\quad + 2(6.2 - 3m - 3)(-3) \end{aligned}$$

$$= -2(1.1 - m) - 4(1.9 - 2m) - 6(3.2 - 3m)$$

$$= -2.2 + 2m - 7.6 + 8m - 19.2 + 18m$$

$$= -29 + 28m = -15 \quad (\text{slope } \frac{\partial S}{\partial m} \text{ for } m=0.5) \quad \text{Residual}$$



Aim is - we have to find the point at which V_i is minimum.

\downarrow
 V_i means - Residual.

* Slope, $m = \tan\theta$

* Learning Rate :-

α is chosen by trial of error

$$\alpha = \text{Step size} = 0.01 \quad (\text{Assumed}).$$

$$\Delta m = \alpha \left(\frac{\partial}{\partial x} \sum V_i^2 \right)$$

$$= 0.01 \times (-15) = -0.15$$

$$m_1 = m_0 - \Delta m = 0.5 - (-0.15)$$

$$= 0.65$$

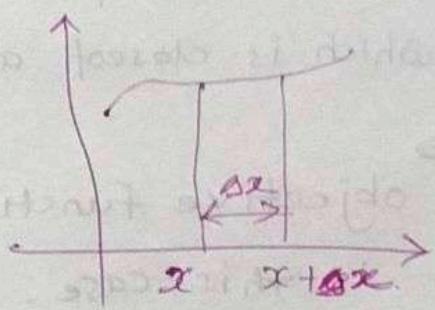
$$\text{If } \alpha = 0.005$$

$$m = m_0 - \alpha \nabla (V_i^2)$$

$$= 0.5 + 0.075 = 0.575$$

* Taylor Series:-

$$f(x) = f(x) \Big|_{x=x_0} + f'(x) \Big|_{x=x_0} \Delta x$$



$$f(x+\Delta x) = f(x) + f'(x) \Delta x$$

$$f(x+\Delta x) = f(x) + f'(x) \Delta x$$

$$\therefore f'(x) = \frac{f(x+\Delta x) - f(x)}{\Delta x}$$

* 27th May, 2022 *

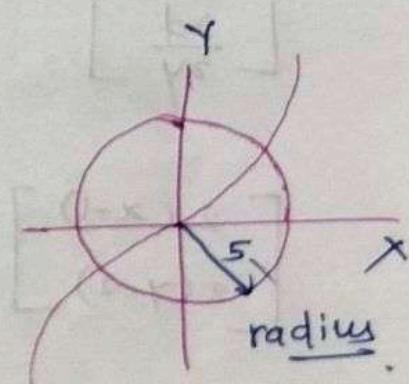
Friday

$$\text{If } f(x) = x$$

$$[0 \leq x \leq 10]$$

$$f(x)|_{\min} = 0$$

$$f(x)|_{\max} = 10$$



* Lagrange Multipliers:-

$$y = f(x) = x^2 \quad \text{--- It is a objective function.}$$

We want to maximize or minimize this function.

$$\text{constraint : } x^2 + y^2 = 25$$

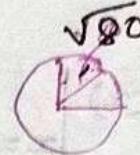
Ex - find the point on circle $x^2 + y^2 = 80$

which is closest and farther from $(1, 2)$.

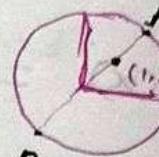


objective function is distance

In this case.



closest pt.



B farthest pt.

$$\text{Max or min } d = (x-1)^2 + (y-2)^2$$

constraint - Point lies on the circle.

$$x^2 + y^2 = 80$$

$$\nabla d = \lambda \nabla c$$

where

$\nabla d \rightarrow$ Gradient of objective function.

$\lambda \rightarrow$ constant i.e. Lagrange multiplier.

$\nabla c \rightarrow$ Gradient of constraint.

$$\therefore \begin{bmatrix} \frac{\partial d}{\partial x} \\ \frac{\partial d}{\partial y} \end{bmatrix} = \lambda \begin{bmatrix} \frac{\partial}{\partial x} & c \\ \frac{\partial}{\partial y} & c \end{bmatrix}$$

$$\begin{bmatrix} 2(x-1) \\ 2(y-2) \end{bmatrix} = \lambda \begin{bmatrix} 2x \\ 2y \end{bmatrix}$$

$$2(x-1) = 2\lambda x \quad \textcircled{1} \rightarrow x-1 = \lambda x \quad \textcircled{1}$$

$$2(y-2) = 2\lambda y \quad \textcircled{2} \rightarrow y-2 = \lambda y \quad \textcircled{2}$$

$$\text{from } \textcircled{1} \quad \lambda = \frac{x-1}{x}$$

$$\text{from } \textcircled{2} = \frac{y-2}{y} = \lambda$$

$$\therefore \frac{x-1}{x} = \frac{y-2}{4}$$

$$\therefore xy - y = xy - 2x$$

$$\therefore \boxed{y = 2x}$$

$$\therefore x^2 + y^2 = 80 \rightarrow x^2 + (2x)^2 = 80$$

$$x^2 + 4x^2 = 80$$

$$x^2 + 8x^2 + 4x^2 = 80$$

$$5x^2 + 8x^2 = 80$$

$$\therefore x^2 + (2x)^2 = 80$$

$$\therefore x^2 + 4x^2 = 80$$

$$\therefore 5x^2 = 80$$

$$x^2 = 80/5 = 16$$

$$\boxed{x = \pm 4}$$

$$\frac{80}{5} = 16$$

$$\boxed{\pm 4}$$

$$\rightarrow x-1 = kx$$

$$4-1 = k(4)$$

$$\boxed{k = \frac{3}{4}}$$

$$x-1 = kx$$

$$-4-1 = k(-4)$$

$$-5 = -4k$$

$$\boxed{k = \frac{5}{4}}$$

~~K = 5/4~~

$$\rightarrow y-2 = ky$$

$$y-2 = \frac{3}{4}y$$

$$4y-8 = 3y$$

$$\boxed{y=8}$$

$$\rightarrow y-2 = ky$$

$$y-2 = \frac{5}{4}y$$

$$4y-8 = 5y$$

$$\boxed{y=-8}$$

I - find the dimension of box with maximum vol.

If the total surface area is 64 unit.



condition - Total Surface area = 64

$$2(lb + bh + lh) = 64$$

$$lb + bh + lh = 32$$

$$\text{as } l = b = h$$

$$3l^2 = 32$$

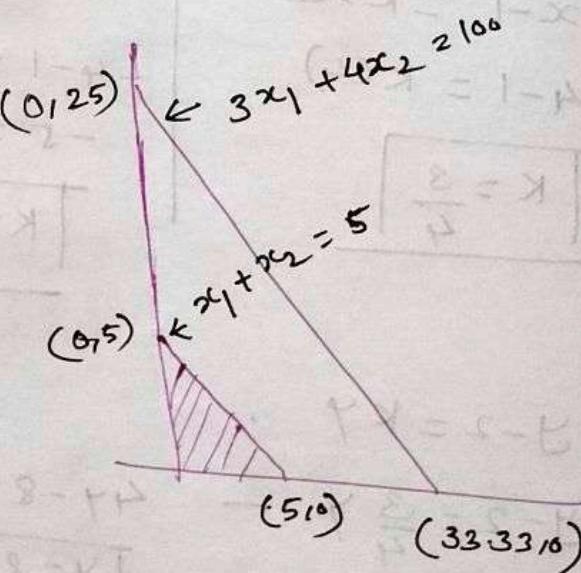
$$l^2 = \frac{32}{3}$$

$$l = \sqrt{\frac{32}{3}}$$

Ex

$$3x_1 + 4x_2 \leq 100$$

$$x_1 + x_2 \leq 5$$



* If objective funⁿ is non-linear.

- Use Lagrange's multipliers.

* If you have c₁ & c₂ selected → use PCA

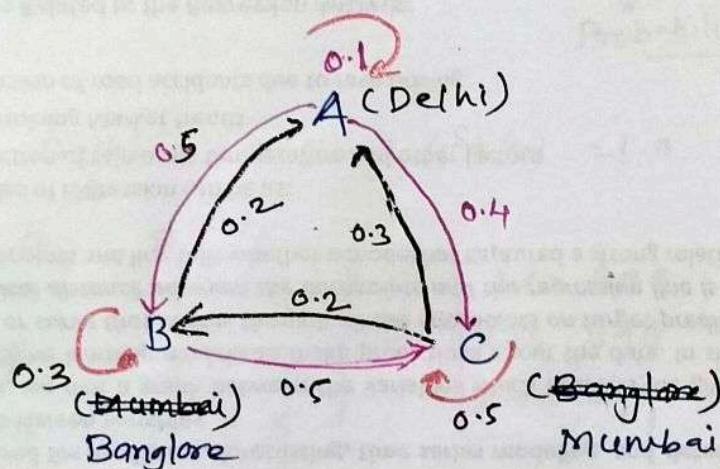
* 30th May, 2022 *

Tuesday

* Markov chain / Process :-

Markov chain is process or stochastic model in which there are sequence of events and each event depends on previous event

For ex. - Suppose there are 3 cities A, B & C



Some one in city A - there is possibility that he go to city A or city B.

Probability of person goes to Mumbai from Delhi is 0.5. and for Delhi-Mumbai is 0.4

and there is also one possibility that he/she remains in the same city, don't go to any other city
(Prob - 0.1)

1114, for Bangalore

- 1) Bangalore - Mumbai - 0.2
 - 2) Bangalore - Delhi - 0.5
 - 3) Remain in Bangalore - 0.3

1117, for Mumbai

- 1) Mumbai - Delhi - 0.3
 - 2) Mumbai - Bangalore - 0.2
 - 3) Remain in Mumbai - 0.5

This process are called as "Markov chain"

Inp - The sum of total outward arrow should be equal to 1
 \downarrow
Probability).

$$\text{i.e. At Delhi} \rightarrow 0.5 + 0.4 + 0.1 = 1.0$$

$$T = \begin{matrix} & \begin{matrix} A & B & C \end{matrix} \\ \begin{matrix} A \\ B \\ C \end{matrix} & \begin{bmatrix} 0.1 & 0.2 & 0.3 \\ 0.2 & 0.3 & 0.2 \\ 0.4 & 0.5 & 0.5 \end{bmatrix} \end{matrix} = \begin{bmatrix} AA & B \rightarrow A & C \rightarrow A \\ A \rightarrow B & B \rightarrow B & C \rightarrow B \\ A \rightarrow C & B \rightarrow C & C \rightarrow C \end{bmatrix}$$

$\nearrow A, B, C$ are states.

This matrix, T is also called as transition matrix.

and If take sum of each column, it is equal to 1.

1

$$T = A \begin{bmatrix} A & B \\ B & A \end{bmatrix} \quad \text{No. of states} = 2.$$

if state $[0.4 \ 0.6] \rightarrow$ from this we can say that there is probability that particle has 46% chance

that it is state A + 60% chance that particle is state B.

$$\Rightarrow \begin{bmatrix} A \\ 1,0 \end{bmatrix} \rightarrow \text{Particle is in state A}$$
$$\Rightarrow \begin{bmatrix} B \\ 0,1 \end{bmatrix} \rightarrow \text{Particle is in state B.}$$

Ex \Rightarrow Today's Date 30th May, 2022, Weather = Sunny.

Depending on the weather cond'n, we can what we expect the temp of tomorrow.

High probability is that tomorrow is sunny because today's weather is sunny.

$$T = \begin{array}{c|ccc} & S & C & R \\ \hline S & 0.5 & 0.4 & 0.1 \\ C & 0.3 & 0.3 & 0.5 \\ R & 0.2 & 0.3 & 0.2 \end{array}$$

$$\text{State vector for 1st June} = V = \begin{bmatrix} 0.25 \\ 0.25 \\ 0.50 \end{bmatrix}$$

What will be the weather cond'n on 2nd June is

$T \cdot V = \text{Transition matrix} \times \text{value error}$

$$= \begin{bmatrix} 0.5 & 0.4 & 0.1 \\ 0.3 & 0.3 & 0.5 \\ 0.2 & 0.3 & 0.2 \end{bmatrix} \begin{bmatrix} 0.25 \\ 0.25 \\ 0.50 \end{bmatrix}$$

$$= \begin{bmatrix} 0.375 \\ 0.400 \\ 0.225 \end{bmatrix}$$

Markov matrix - you will get 1 as one of the eigen values. It's a universal truth.

* Diagonalisation of Matrix :-

$$\rightarrow \boxed{A = P D P^{-1}}$$

Diagonalisation of matrix A.

P = Matrix of eigen vector of A.

D = Diagonal matrix of eigen values of A

$$\therefore \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} v_1 & v_2 \\ v_{11} & v_{21} \\ v_{12} & v_{22} \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} v_{11} & v_{21} \\ v_{12} & v_{22} \end{bmatrix}^{-1}$$

$v_1 = [v_{11} \ v_{12}] \rightarrow$ Eigen vector for eigen value λ_1 ,

$v_2 = [v_{21} \ v_{22}] \rightarrow$ Eigen vector for eigen value λ_2 .

* The

$$\therefore A^2 = [P D P^{-1}] [P D P^{-1}]$$

$$\boxed{A^2 = P D^2 P^{-1}}$$

* IF any matrix (Transition matrix) is multiplied by its eigen vector then it gives $\underline{\lambda} \underline{v}$.

$\therefore \overbrace{TV = \lambda V} \text{ is called Stationary state for } \lambda = 1$

$$\boxed{T \cdot TV = V}$$

| As $\lambda = 1$ For Stationary

$$\underline{\underline{\lambda = 1}}$$

$$\begin{bmatrix} 0.5 & 0.3 & 0.2 \\ 0.2 & 0.1 & 0.3 \\ 0.3 & 0.6 & 0.5 \end{bmatrix}$$

Eigen values for this matrix.

$$\lambda_1 = 1, \quad \lambda_2 = \frac{-1 + \sqrt{21}}{20}, \quad \lambda_3 = \frac{1 + \sqrt{21}}{20}$$

Eigen vector corresponding these eigen values.

$$v_1 = \begin{bmatrix} 9/13 \\ 19/39 \\ 1 \end{bmatrix} \quad v_2 = \begin{bmatrix} -3 + \sqrt{21}/6 \\ -3 + \sqrt{21}/6 \\ 1 \end{bmatrix}$$

$$Tv_1 = \lambda_1 v_1$$

$$\boxed{Tv_1 = v_1} \quad - \text{for } \lambda_1 = 1$$

v_1 is called stationary state \rightarrow sum of stationary vectors is $\frac{1}{T}$.

$$\begin{bmatrix} 0.5 & 0.3 & 0.2 \\ 0.2 & 0.1 & 0.3 \\ 0.3 & 0.6 & 0.5 \end{bmatrix} \begin{bmatrix} 9/13 \\ 19/39 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 0.5 \times \frac{9}{13} + 0.3 \times \frac{19}{39} + 0.2 \times 1 \\ 0.2 \times \frac{9}{13} + 0.1 \times \frac{19}{39} + 0.3 \times 1 \\ 0.3 \times \frac{9}{13} + 0.6 \times \frac{19}{39} + 0.5 \times 1 \end{bmatrix} = \begin{bmatrix} 9/13 \\ 19/39 \\ 1 \end{bmatrix}$$

Hence proved.

Markov chain is used to find

- 1) Stationary state
- 2) Last / final state

Ex.

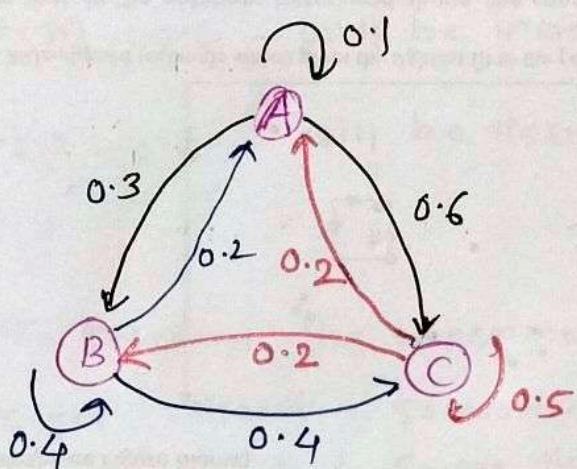
Transition matrix, T

$$T = \begin{bmatrix} A & B & C \\ A & 0.1 & 0.2 & 0.3 \\ B & 0.3 & 0.4 & 0.2 \\ C & 0.6 & 0.4 & 0.5 \end{bmatrix}$$

A = Delhi

B = Mumbai

C = Bangalore



Diagrammatical representation of Transition matrix

- If you are sure that person is in Delhi, then the state vector is $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$
- If you are sure that person is in Mumbai, then the state vector is $\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$
- If you are sure that person is in Bangalore, then the state vector is $\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$

If take coin and toss it 10 times.

Result	1	2	3	4	5	6	7	8	9	10
	T	H	H	T	T	H	T	H	T	T

$$\text{Probability of getting Head, } P(H) = \frac{4}{10} = 0.4$$

$$\text{Probability of getting Tail, } P(T) = \frac{6}{10} = 0.6$$

$$\therefore [0.4 \quad 0.6]$$

If we increase the number of experiments.

$P(H) = 0.4$ - will be increase and close to 0.5 }

if $P(T) = 0.6$ - will be decrease and close to 0.5. }
It is called limiting sense.

If we ~~take~~ perform the experiment 1,00,000 times
and we get Head - 50,000 times and
Tail - 50,000 times.

so the probability is $[1/2 \quad 1/2]$

We already know that the probability is $1/2$. So there
is no need to perform simulation.

- We can prove the same thing using Markov chain
or Markov process.

In the case of No. of experiment is 10.

Relative frequency given by, $RF = \frac{n}{N}$.

$n \rightarrow$ No. of outcomes

$N \rightarrow$ No. of experiments.

$$RF(H) = 4/10 = 0.4 \quad RF(T) = 6/10 = 0.6$$

When N becomes ∞ .

$\therefore R.F = \frac{n}{\infty} \Rightarrow$ Probability otherwise it's just relative frequency.

E. Transition matrix for coin problem

$$T = \begin{matrix} & H & T \\ H & 0.5 & 0.5 \\ T & 0.5 & 0.5 \end{matrix}$$

Eigenvalues are $\lambda_1 = 1 \quad \lambda_2 = 0$

Eigen vectors are $\begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \begin{bmatrix} -1 \\ 1 \end{bmatrix}$

\therefore If we consider $v_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ - But it's not stationary state

\therefore So, stationary state for coin problem, i.e. $\begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$

$$\boxed{\begin{bmatrix} -1 \\ 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}}$$

Explanation
How we get
stationary state

- To clear confusion regarding previous problem
for stationary stat.

Consider 3×3 Transition matrix and its eigenvector

$$v = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}$$

$$\rightarrow Tv = \lambda v$$

$$\left[\quad \right]_{3 \times 3} \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix} = 1 \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}$$

↓
For now it's not stationary state

If ~~not~~ we want to convert this to
stationary state.

$$\begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix} \rightarrow \text{Sum of column is } 4$$

then divide the vector by 4

$$\therefore \begin{bmatrix} 2/4 \\ 1/4 \\ 1/4 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.25 \\ 0.25 \end{bmatrix} \rightarrow \text{Now the sum is } 1$$

↓
Now, we call it as stationary state.