

- 1) data
- 2) EDA ↗ iPynB.
Null value
outlier
imbalanced
- 3) PreProcessing ↗
Scaling
- 4) model building. ↗
F.g.
Dim red.
- 5) evaluation. ↗

Lin reg
Log reg
Svm.

Pc A.

Data :- $(R \times C)$ \rightarrow Housing

$f_1 \ f_2 \ f_3 \dots f_{10} \rightarrow M_1 \rightarrow \text{Acc} \rightarrow 75\%$.

$f_1 \ f_2 \ f_3 \dots f_{20} \rightarrow M_2 \rightarrow \text{Acc} \rightarrow 80\%$.

$f_1 \ f_2 \ f_3 \dots f_{50} \rightarrow M_3 \rightarrow \text{Acc} \rightarrow 85\%$.

$f_1 \ f_2 \ f_3 \dots f_{100} \rightarrow M_4 \rightarrow \text{Acc} \rightarrow 70\%$.

Training accuracy will be high but test accuracy will be low due to over fitting accuracy decreases

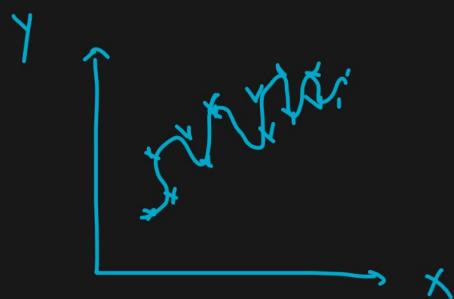
because we used features which are not really related to output

Curse of dimensionality. \rightarrow So many feature. \rightarrow 

 \rightarrow Linear reg \rightarrow



\rightarrow overfitting. \rightarrow



feature Selection. → Select subset of the feature.

Dim Red. → transform your data into low dim.

$$f_1 \ f_2 \ f_3 \ f_4 \ \dots \ f_{100}$$

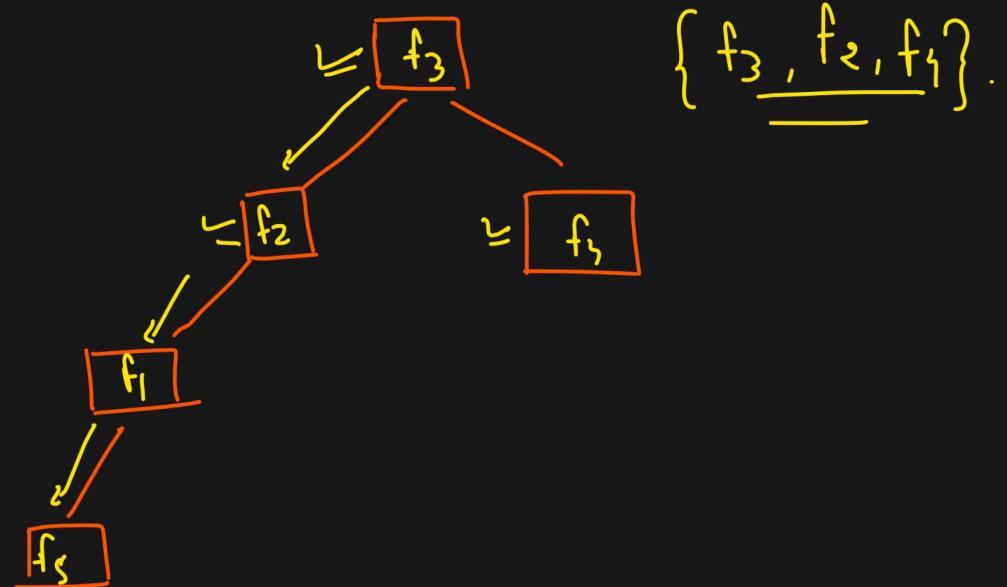


Linear reg. (any model)

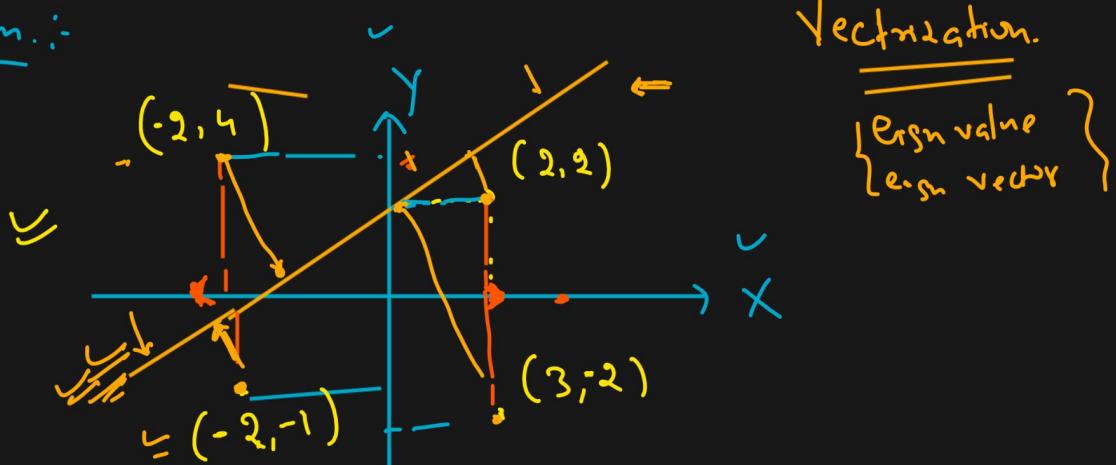
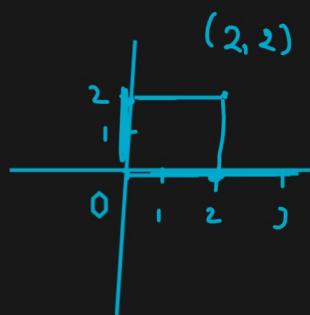
$$\left\{ \begin{array}{l} f_1 \rightarrow f_0 \\ f_1 \rightarrow f_{20} \\ f_1 \rightarrow f_{50} \end{array} \right\} \rightarrow g_0 \left\{ \begin{array}{l} \rightarrow g_0 \\ \rightarrow g_0 \\ \rightarrow g_0 \end{array} \right\} X$$

- 1) corr.
- 2) chisquare.
- 3) ANOVA
- 4) backward elimination.
- 5) feature importance

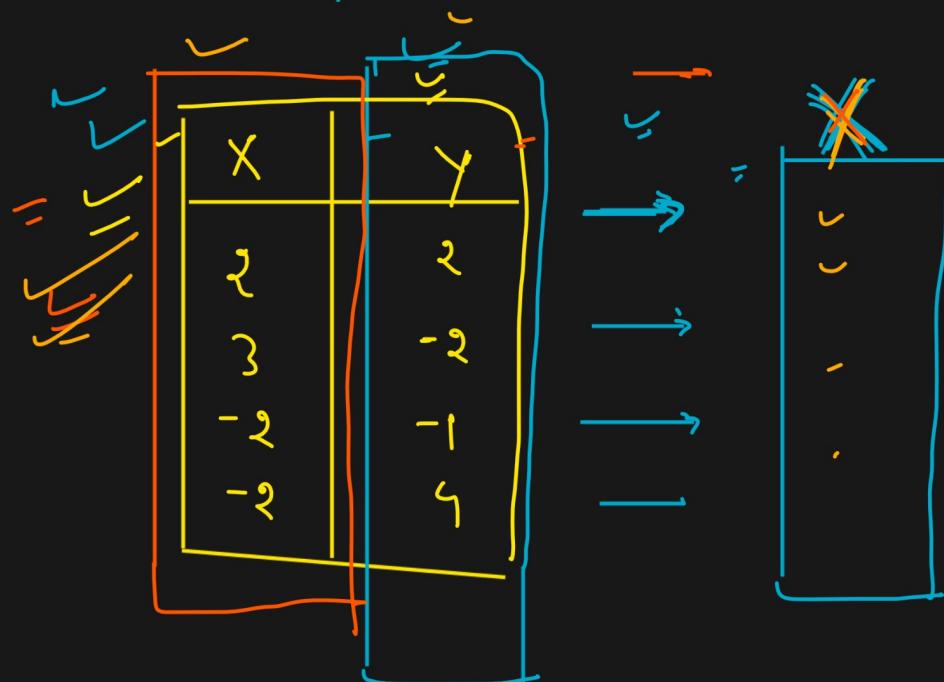
\Leftarrow Decision tree. $\boxed{f_1 \ f_2 \ f_3 \ f_4 \ f_5}$



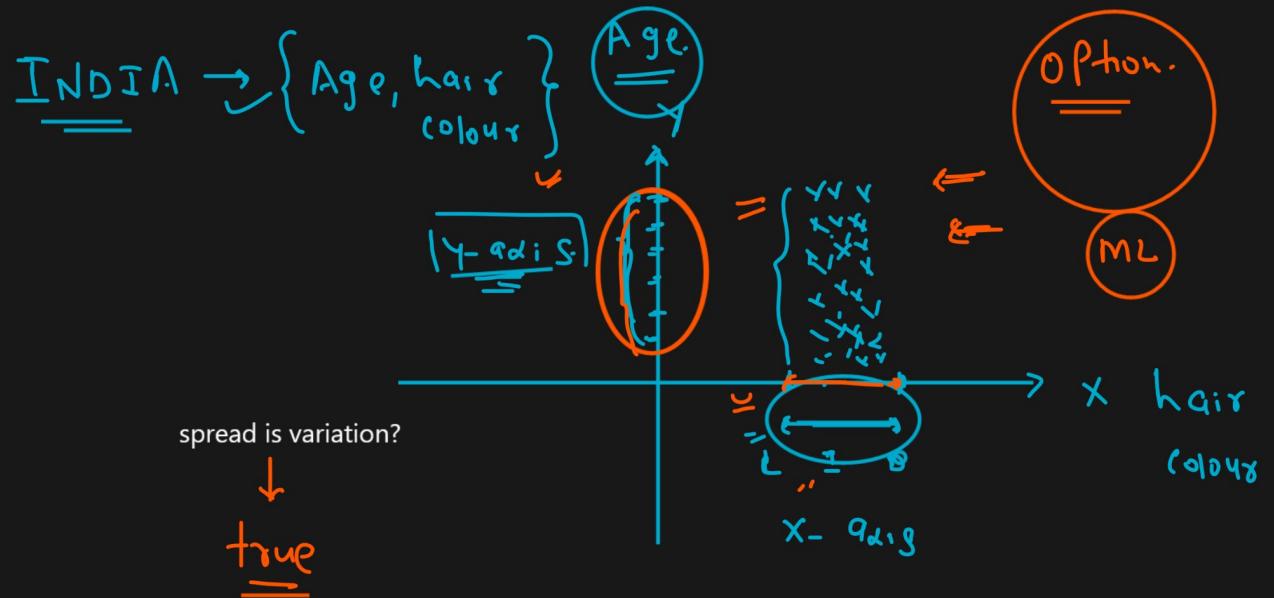
Dimension Reduction :-



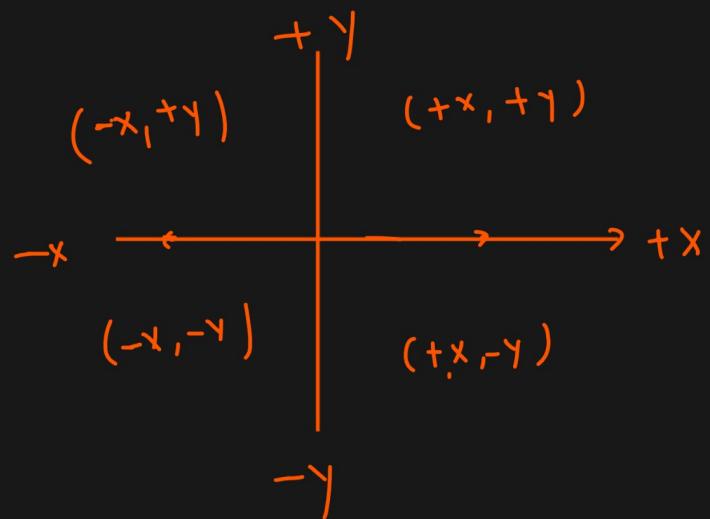
Vectornization.
Eigenvalue
Eigen vector



PCA - Basic.



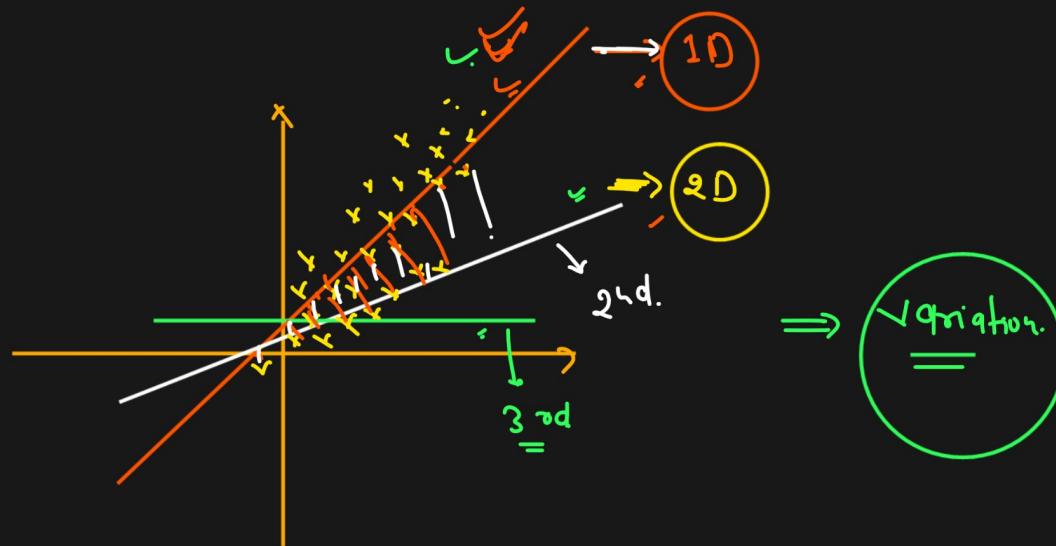
Spread of the data on y axis \Rightarrow too high.
 " " " " x axis \Rightarrow too low



reducing dimensionality of data by transforming data points on a plane

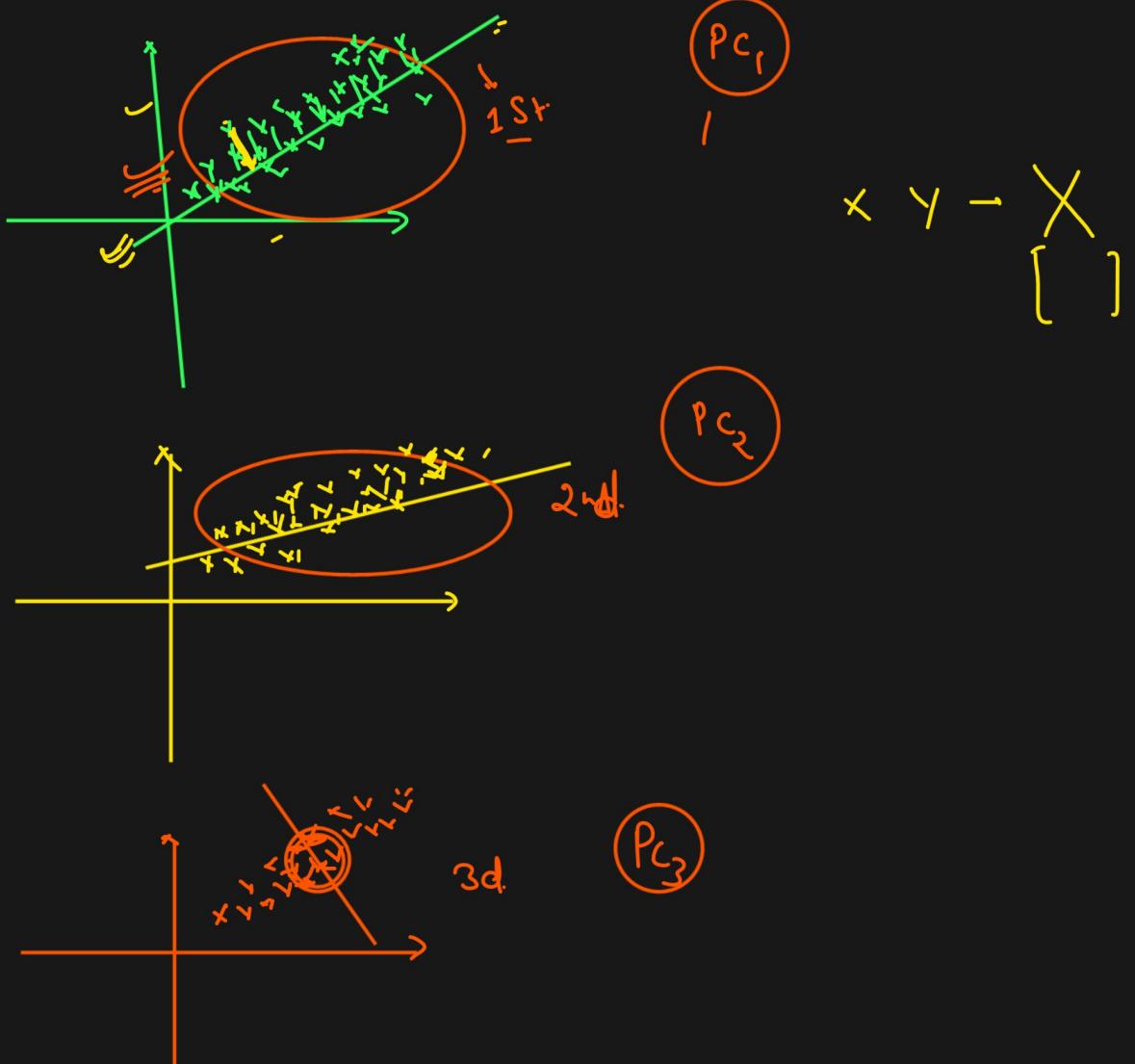
feature selection - Where we select subset of feature those are important .

in feature selection we eliminate features but in dimension reduction we project data in one dimension not eliminate



$\text{PCA} \Rightarrow \underline{\text{Dim red.}} \quad \underline{4 \text{ D.}} \rightarrow \underline{2 \text{ D.}}, \underline{1 \text{ D.}}, \underline{3 \text{ D.}}$

\uparrow
 $\underline{\text{Visulization.}}$

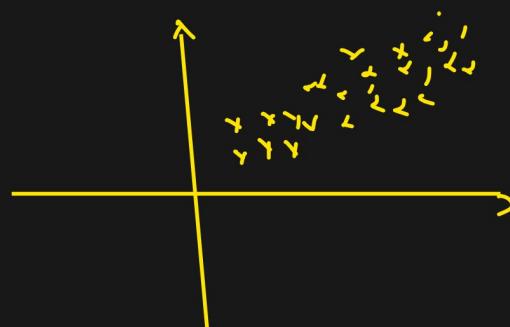
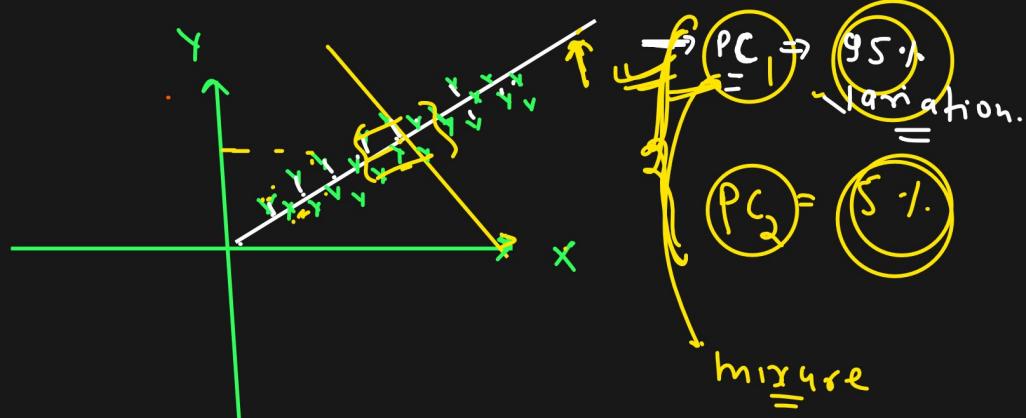


when pca is use and why?

when there is to much features

pca is used when our data is very large

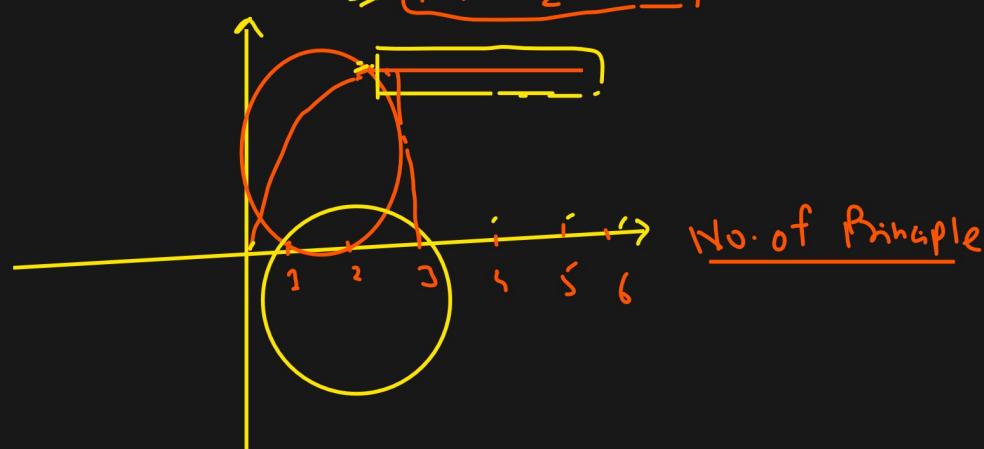
When we have more features in our dataset and which causes curse of dimensionality



We can have more than
one Principle Component

$$\Rightarrow \frac{\text{PC}_1}{\text{PC}_1 + \text{PC}_2} = \frac{95}{100} = 0.95$$

$$\text{Variation} = \frac{v}{(\text{PC}_1 + \text{PC}_2 + \text{PC}_3)} \quad N \rightarrow 100\% =$$



PCA

① Scaling or Std.
↓ ↓
Min-max Standard
= Scaling

- ② Covariance matrix
- ③ Eigen value and Eigen vector
- ④ Principle component

= (Scaling) :- Transforming a data within certain range.

$$\overbrace{[0, 1]}^{\text{Min - Max.}}$$

$$\begin{matrix} \text{min} \\ \uparrow \\ \text{max} \\ \uparrow \end{matrix}$$

$$\overbrace{\text{Data Points} : - (a_1, a_2, a_3, a_4, \dots, a_{100})}^{\downarrow}$$

$$\overbrace{[\text{min}, \text{max}]}^{\text{Scaling of the data.}}$$

$$\text{min}$$

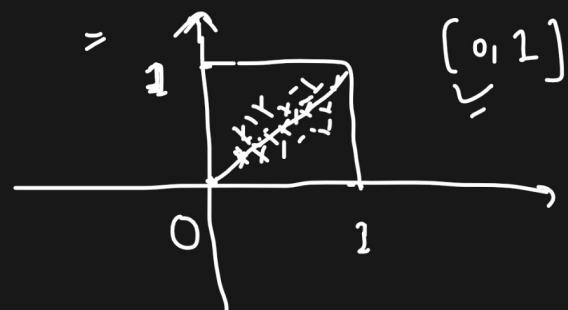
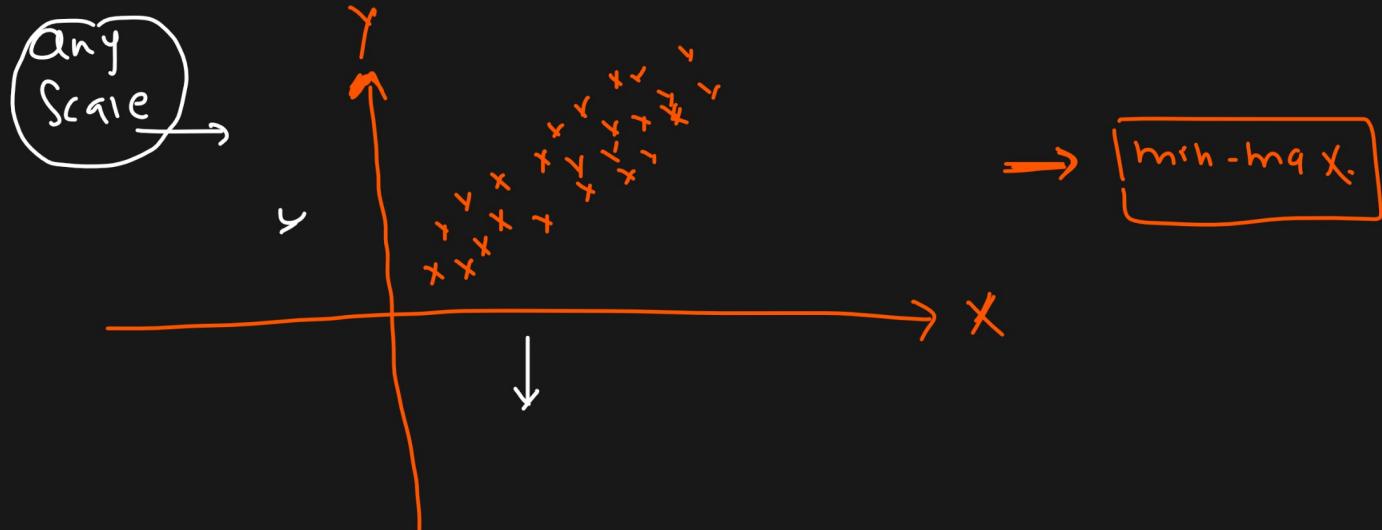
$$[0, 1]$$

$$\boxed{\frac{\text{Data Point} - \text{min.}}{\text{max} - \text{min.}}}$$

$$\Rightarrow \frac{\text{min} - \text{min.}}{\text{max} - \text{min.}} = 0 \quad \boxed{\frac{[\text{min}]}{[\text{max}]}} = 0$$

$$[a_1, -a_1, \dots] \Rightarrow$$

$$\frac{\max - \min}{\max - \min} = 1$$



Standard Scalg :- $\{a_1, \dots, a_{100}\}$



$$\text{S. S. formula} \Rightarrow \frac{\text{Data Point} - \mu}{\sigma} \Rightarrow$$

ζ_{SD}

$\left. \begin{array}{l} \text{mean} = 0 \\ \text{std deviation} = 1 \end{array} \right\}$

$$2, 5, 8, 9, 10 \Rightarrow \mu = \frac{34}{5} = 7$$

↓
 ζ_{SD}

$$\sigma \Rightarrow \zeta$$

$$\left[\frac{\text{D.P} - \mu}{\sigma} \right] \Rightarrow \left[\frac{2-\mu}{\sigma}, \frac{5-\mu}{\sigma}, \frac{8-\mu}{\sigma}, \frac{9-\mu}{\sigma} \right]$$

ζ_{SD}

$$- \frac{10-\mu}{\sigma}$$

$$\Rightarrow [\zeta, \zeta, \zeta, \zeta, \zeta] \xrightarrow{\text{mean} = 0} \Rightarrow \text{std} = 1$$



$$② \text{ Variance} \equiv$$

$$\equiv \frac{(x - \bar{x})^2}{n}$$

$x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14},$

\downarrow mean

deviation from mean:

$$\equiv \frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \dots + (x_n - \bar{x})^2}{n} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

$$x - \bar{x}$$

$$\rightarrow \text{Cov}(x, y) \Rightarrow \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

3 variable

3x3

PCA →

- 1 Sed
- 2 Cov.

Data Points \rightarrow SND

$$\begin{array}{c} \mu = 0 \\ \sigma = 1 \end{array} \quad \text{mean} = 0$$

$$\text{Cov}(x, y) \Rightarrow \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

$$\text{Variance} = \text{Cov}(x, x) \Rightarrow \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \Rightarrow \frac{1}{n} \sum_{i=1}^n (x_i)^2$$

$$= \Rightarrow \frac{1}{n} \sum_{i=1}^n (x_i - 0)(y_i - 0)$$

$$\cdot \Rightarrow \frac{1}{n} \sum_{i=1}^n (\underline{x_i})(\underline{y_i}) \leftarrow \text{Dot product}$$

x	y
0.5	0.8
1	2.5
1.0	2.0
2.0	4.0
2.5	5.0

$$\Rightarrow \square \text{ Cov}(x, y) = \text{Value } \circlearrowleft$$

$$\Rightarrow \textcircled{2} \quad \text{SND} \quad \text{Cov}(x, y) = \text{Value } \circlearrowleft$$

Dot Product :- multiplication of the data point followed by summision.

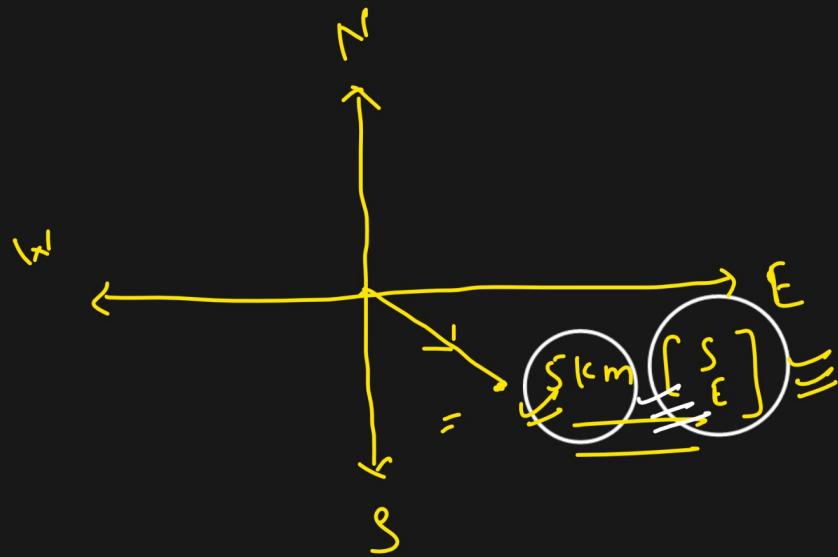
$$\sqrt{(x_1 y_1 + x_2 y_2 + x_3 y_3 + x_4 y_4 - \dots)} = \underline{\text{scalar value}}$$

③

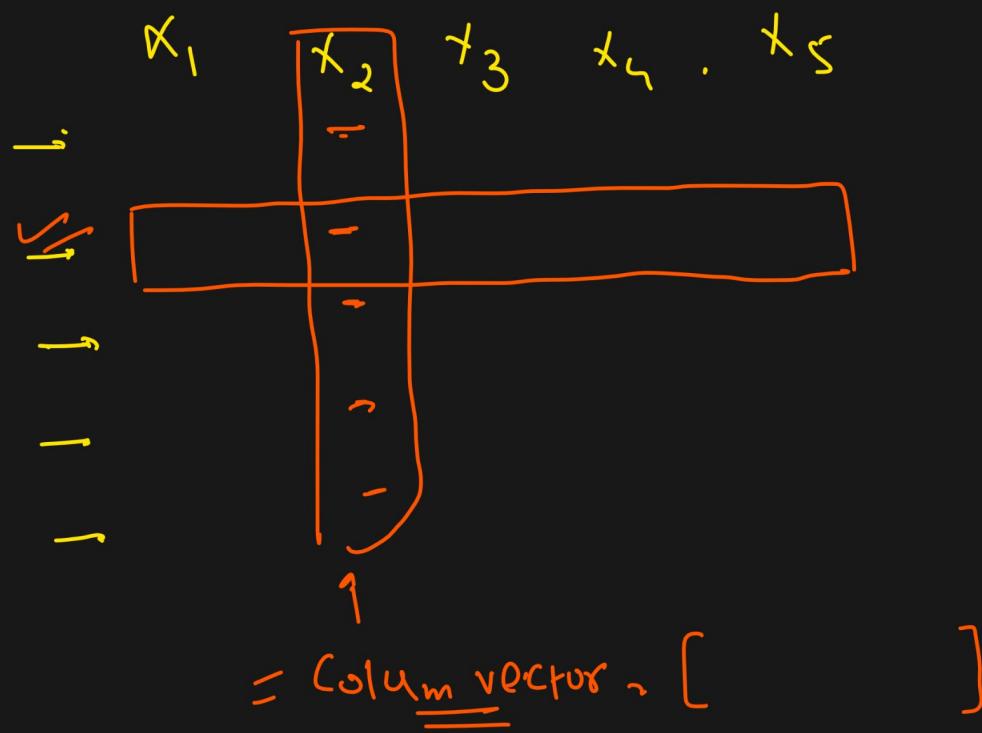
Eigen value & eigen vector

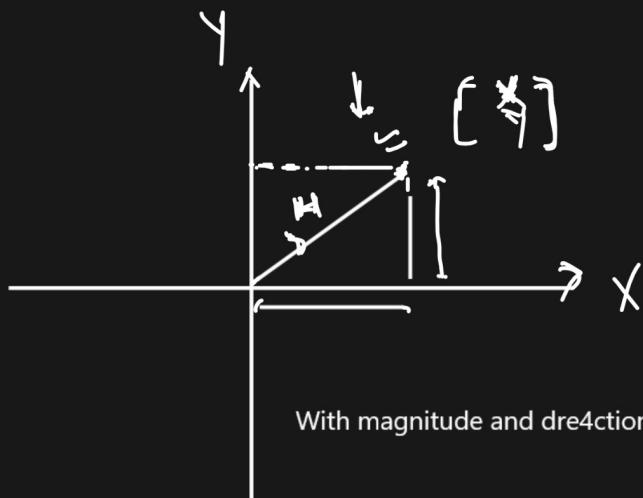
Scalar value :- Simple int value.

Vector :- Scalar value + Direction.

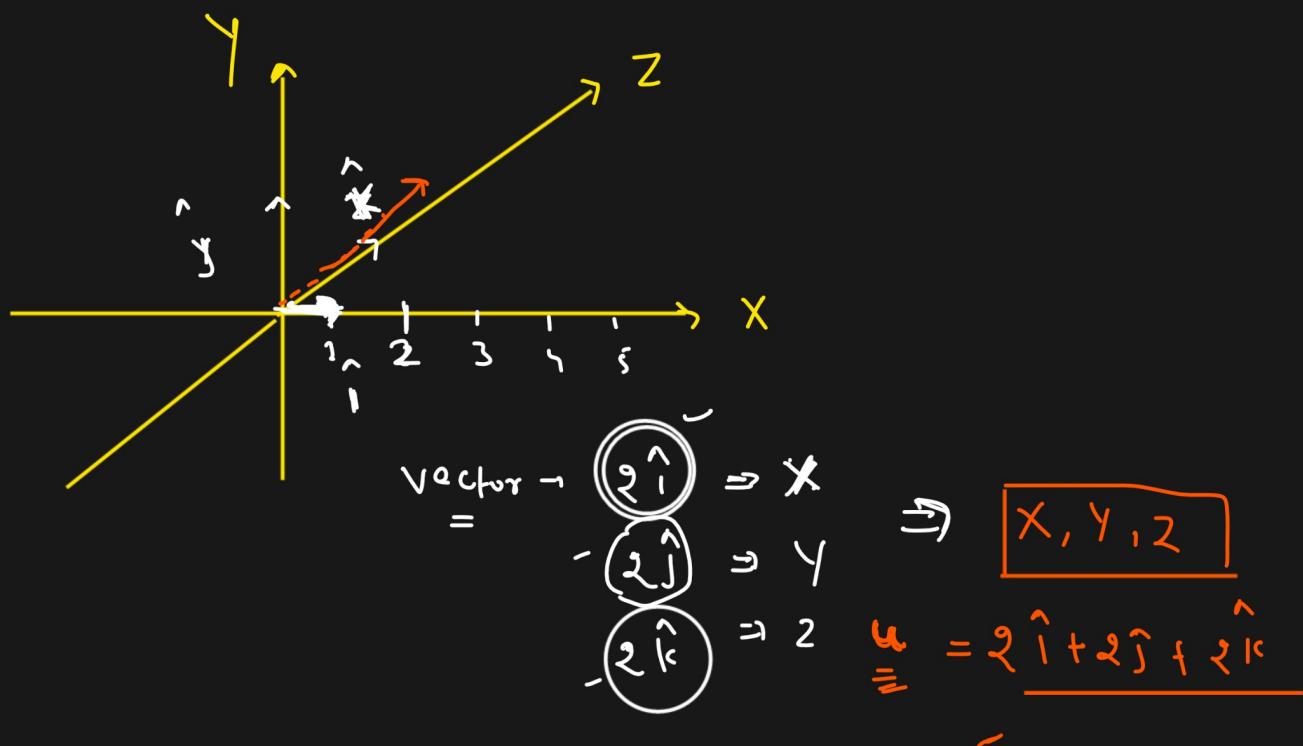


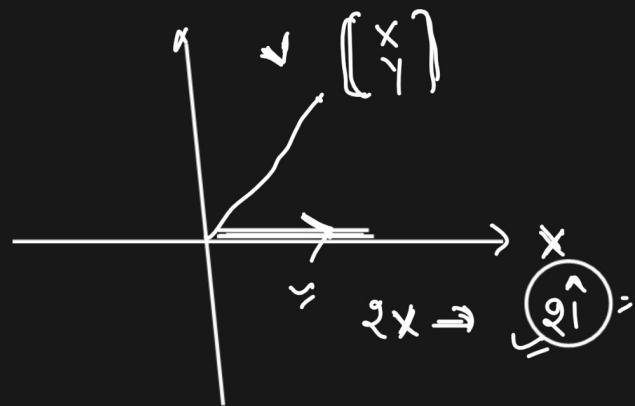
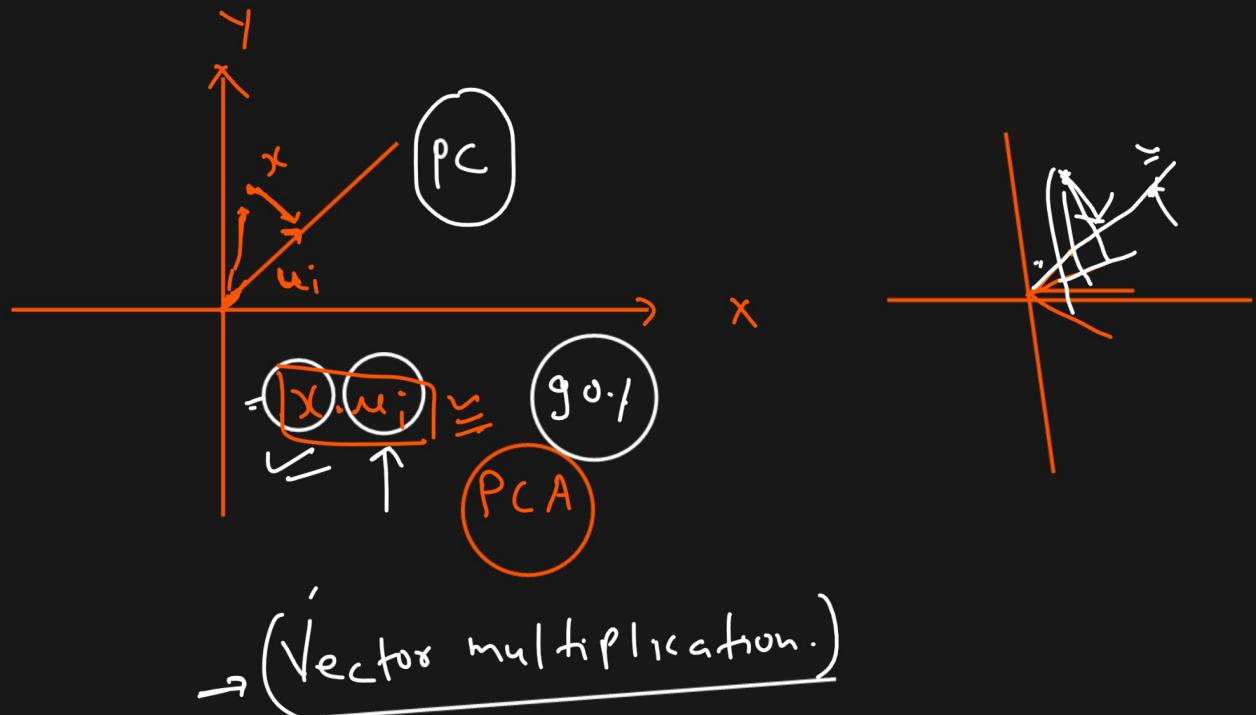
Machine learning :- $\overset{R \times C}{=}$





With magnitude and direction we can represent vector





2 is scalar and I, j, k is unit vector

Unit vector is nothing just its a magnitude with value 1 and its represents a specific direction

Eigen value and Eigen vector.

$$\text{Solve } |C - \lambda I| = 0$$

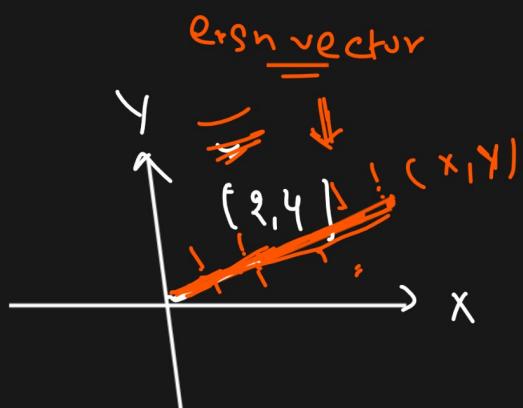
$$= C\vec{v} = \lambda\vec{v}$$



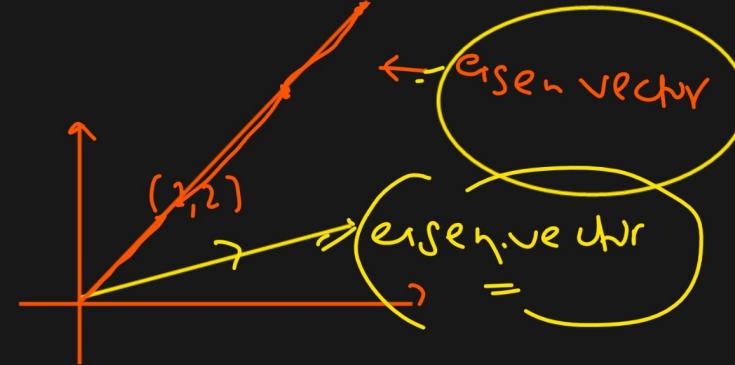
2, 4, 6, 8

$$\begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \times \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 3 \\ 3 \end{pmatrix}$$

Data :- $\begin{pmatrix} 3 \\ 3 \end{pmatrix} \Rightarrow$ Vector \rightarrow ρ_C



$$\begin{aligned} & \cdot \quad \begin{bmatrix} 1 \\ 2 \end{bmatrix} \\ = & \textcircled{2} \leftarrow \begin{bmatrix} 3 \\ 1 \end{bmatrix} \\ & \textcircled{4} \leftarrow \begin{bmatrix} 4 \\ 8 \end{bmatrix} \end{aligned}$$



$\boxed{\underline{A} \underline{V} = \lambda \underline{V}} \Rightarrow A V - \lambda V = 0$

~~$(A - \lambda I) V = 0$~~

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

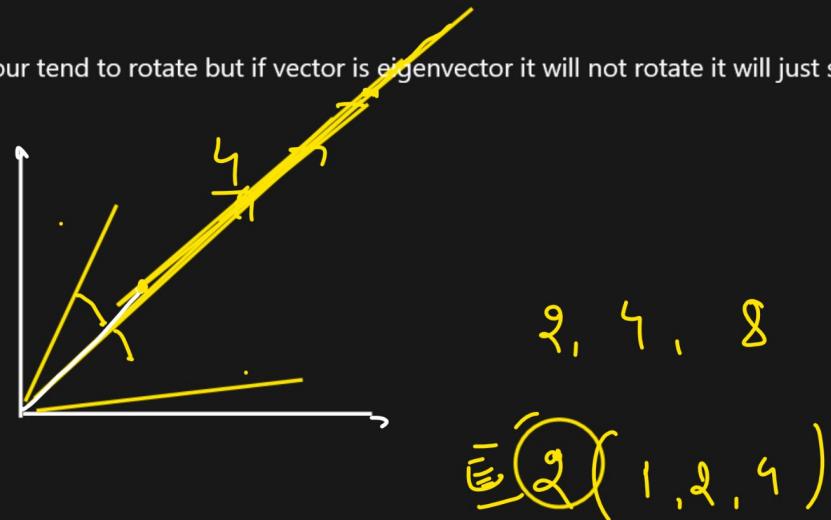
$\therefore \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \underline{2} \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \end{bmatrix} =$

$\Rightarrow \boxed{\begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \textcircled{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix}}$

Ex. \Rightarrow

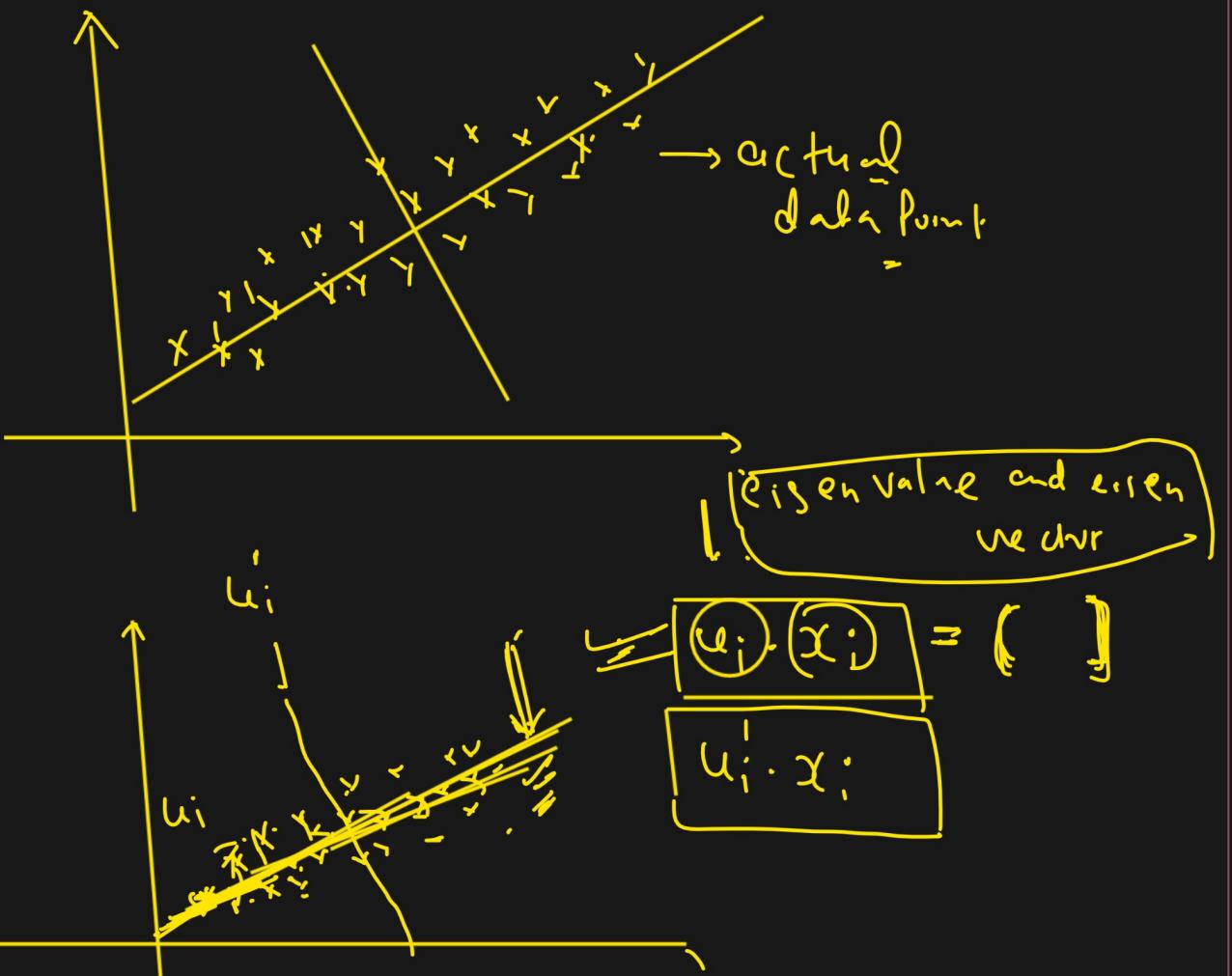
$$\begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 3 \\ 3 \end{bmatrix} = \begin{bmatrix} 9 \\ 3 \end{bmatrix}$$

when matrix * vector our tend to rotate but if vector is eigenvector it will not rotate it will just stretch the vector



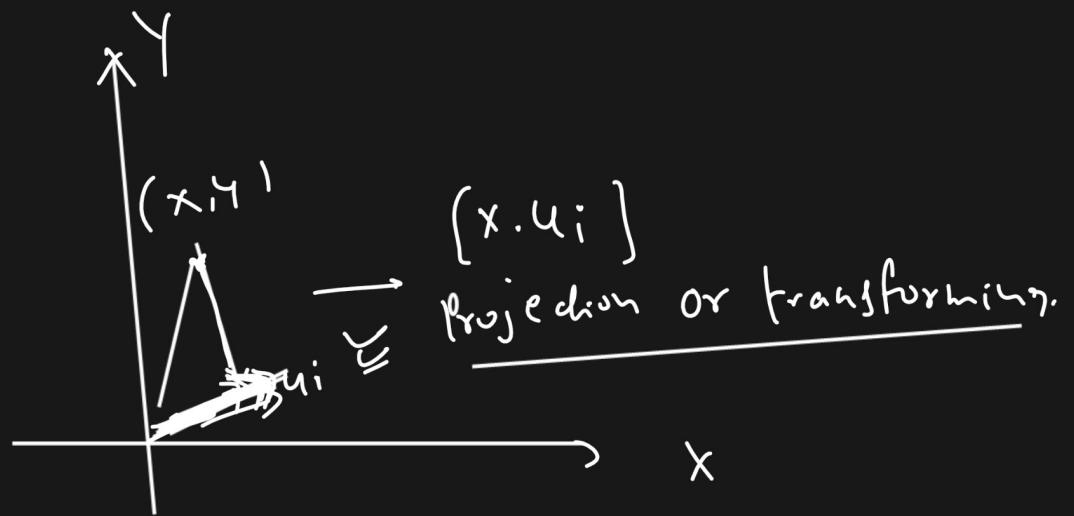
$9, 3, 8$

$E(9)(1, 2, 3)$



$$\begin{array}{c}
 - \begin{array}{|c c|} \hline & X & Y \\ \hline & & \\ \end{array} \\
 \begin{array}{cc} 2.5 & 2.4 \\ 0.5 & 0.7 \\ 2.2 & 2.9 \\ 1.9 & 2.2 \end{array} \\
 \leftarrow \begin{array}{cc} 3.1 & 3.0 \\ 2.3 & 2.7 \\ 2 & 1.6 \\ 1 & 1.1 \\ 1.5 & 1.6 \\ 1.1 & 0.9 \end{array} \\
 = \boxed{\begin{array}{l} \textcircled{1} \text{ Std.} \\ \textcircled{2} \text{ Cov.} \\ \textcircled{3} \text{ eigen value and} \\ \text{eigen vector} \\ \textcircled{4} \text{ Principle component} \end{array}}
 \end{array}$$

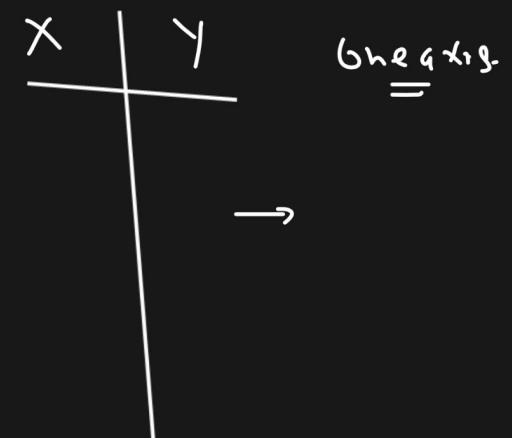
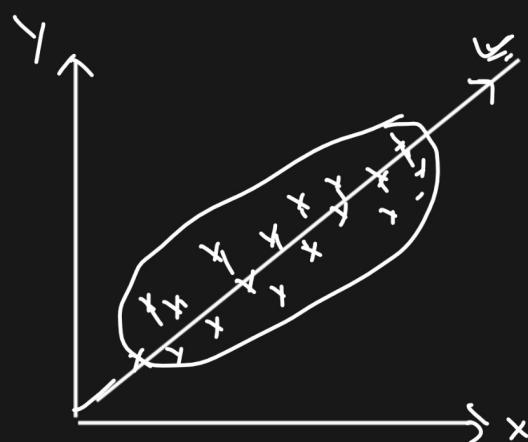
\Rightarrow single vector



$$\begin{pmatrix} x \\ y \end{pmatrix} \left(u_i \right) \Rightarrow$$

1.) F.S. (Subset)

2.) (DimRed.)



PCA
t-SNE

PCA → ① Standardization ✓

② Cov mat. =

2 feature
=

(2 × 2)

③ Eigen val and eig. vector

④ Principle component.

$$R \rightarrow \begin{bmatrix} & & C \\ & \downarrow & \\ \boxed{1 & 2} & \xrightarrow{T} & \begin{bmatrix} 1 \\ 2 \end{bmatrix} \end{bmatrix}$$

$$A = \begin{bmatrix} \overline{1} & \overline{3} \\ \overline{2} & \overline{4} \end{bmatrix} \quad B = \begin{bmatrix} \overline{3} \\ \overline{1} \end{bmatrix}$$

$\underbrace{(2 \times 2)}_{=}$ $\underbrace{(2 \times 1)}_{=}$

$$\begin{bmatrix} (1 \times 3) + (2 \times 4) \\ (2 \times 3) + (4 \times 4) \end{bmatrix}$$

$$= \begin{bmatrix} 15 \\ 22 \end{bmatrix}_{(2 \times 1)}$$

$\Leftrightarrow \boxed{A \times v = \lambda \times v}$

↑ ↑ ↓ Vector
 matrix vector scalar value

$$\Leftrightarrow \boxed{A v - \lambda v = 0}$$

↓ ↓ ↓
 | $v (A - \lambda I) = 0$ } → eigenvalue.

$$\Leftrightarrow |\Lambda - \lambda I| = 0$$

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

$$\begin{bmatrix} 3 & 6 \\ 5 & 4 \end{bmatrix} - \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} = 0$$

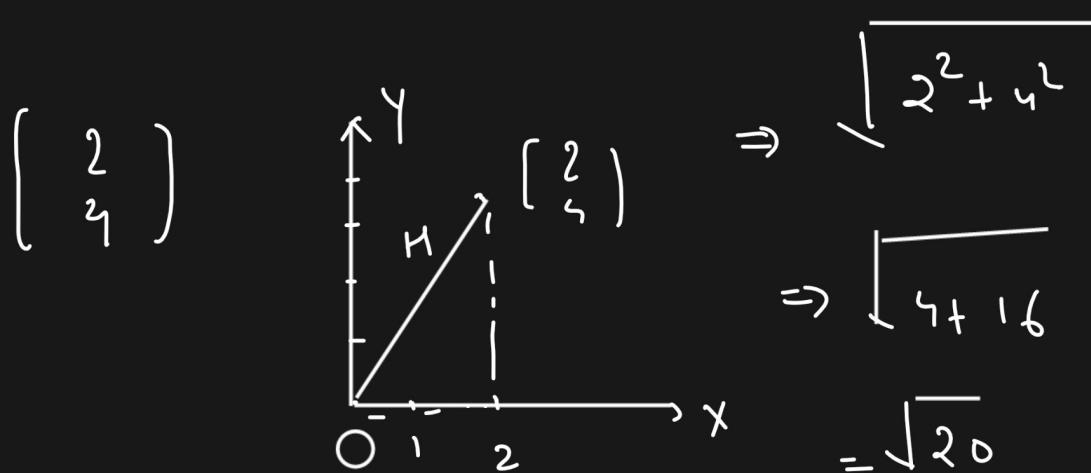
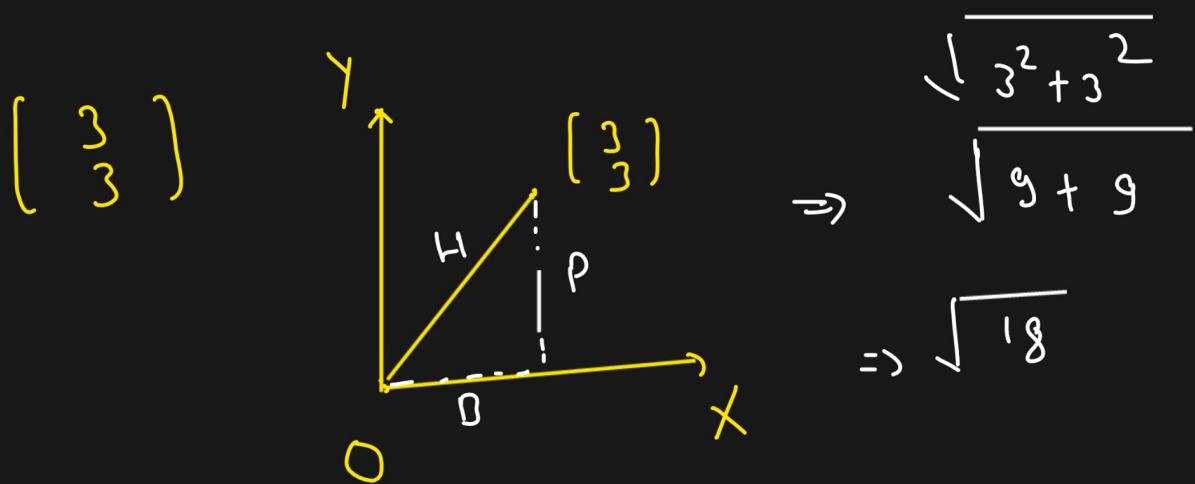
$$\begin{bmatrix} 3-\lambda & 6-0 \\ 5-0 & 4-\lambda \end{bmatrix} = 0$$

$$\boxed{\begin{bmatrix} 3-\cancel{\lambda} & \cancel{6} \\ \cancel{5} & 4-\lambda \end{bmatrix} = 0}$$

$$(3-\lambda)(4-\lambda) - 30 = 0$$

$$12 - 3\lambda - 4\lambda + \lambda^2 - 30 = 0$$

$$\begin{aligned} & \left\{ \lambda^2 - 7\lambda - 18 = 0 \right. \\ & \left. \Rightarrow \begin{cases} \lambda_1 = 9 \\ \lambda_2 = 2 \end{cases} \right\} \end{aligned}$$



Square mat \times v = $\lambda \times v$

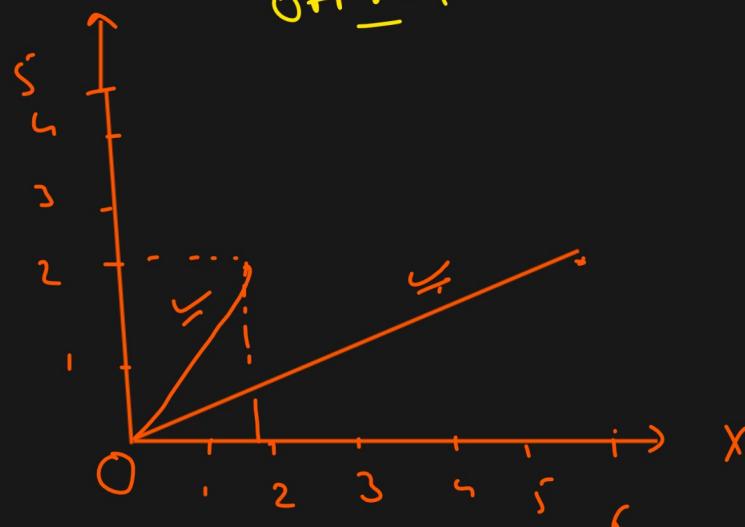
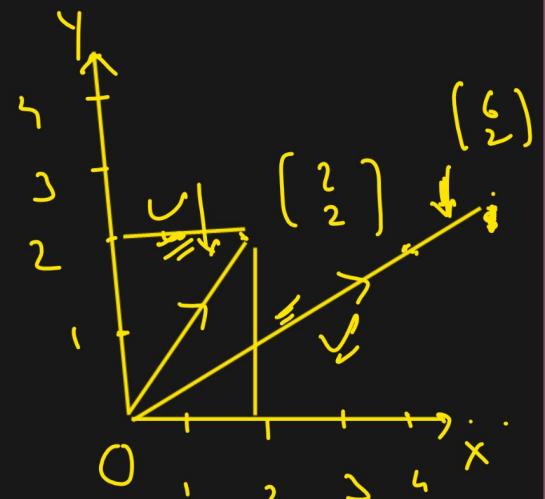
$$\begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \end{bmatrix} = \begin{bmatrix} 6 \\ 2 \end{bmatrix}$$

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

mat \times $\begin{bmatrix} 2 \\ 2 \end{bmatrix}$ = $\begin{bmatrix} 6 \\ 2 \end{bmatrix}$

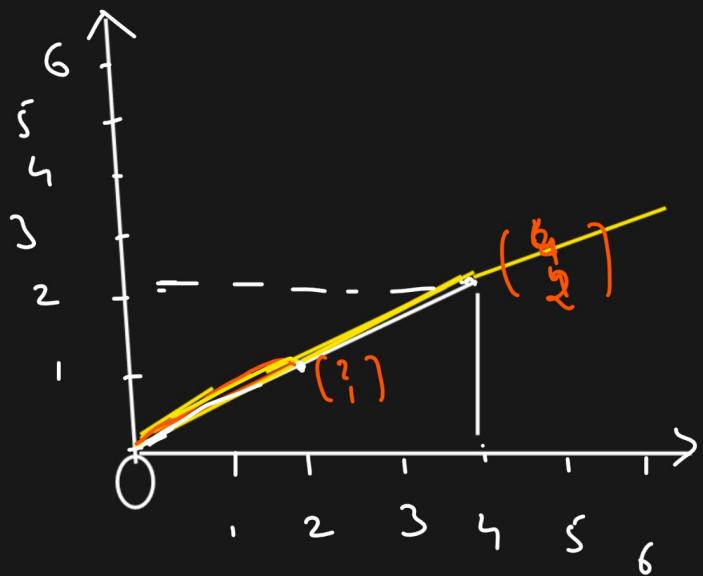
off result

- 1) s+d
- 2) cov mat



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

mat \equiv vec ?



$$\checkmark \quad \text{mat} \times \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \end{bmatrix}$$

$$\Rightarrow \text{mat} \times \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$\text{mat} \times \begin{pmatrix} 3 \\ 1 \end{pmatrix} = \begin{pmatrix} 4 \\ 2 \end{pmatrix} \Rightarrow \begin{pmatrix} 2 \\ 3 \end{pmatrix} = \begin{pmatrix} 4 \\ 2 \end{pmatrix} - \begin{pmatrix} 3 \\ 2 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

erstes

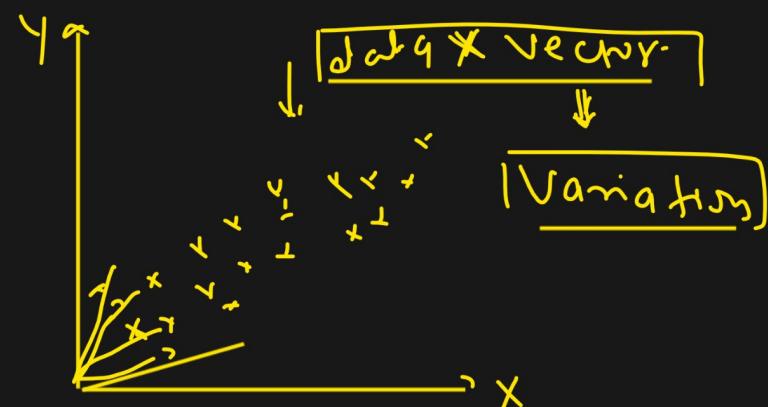
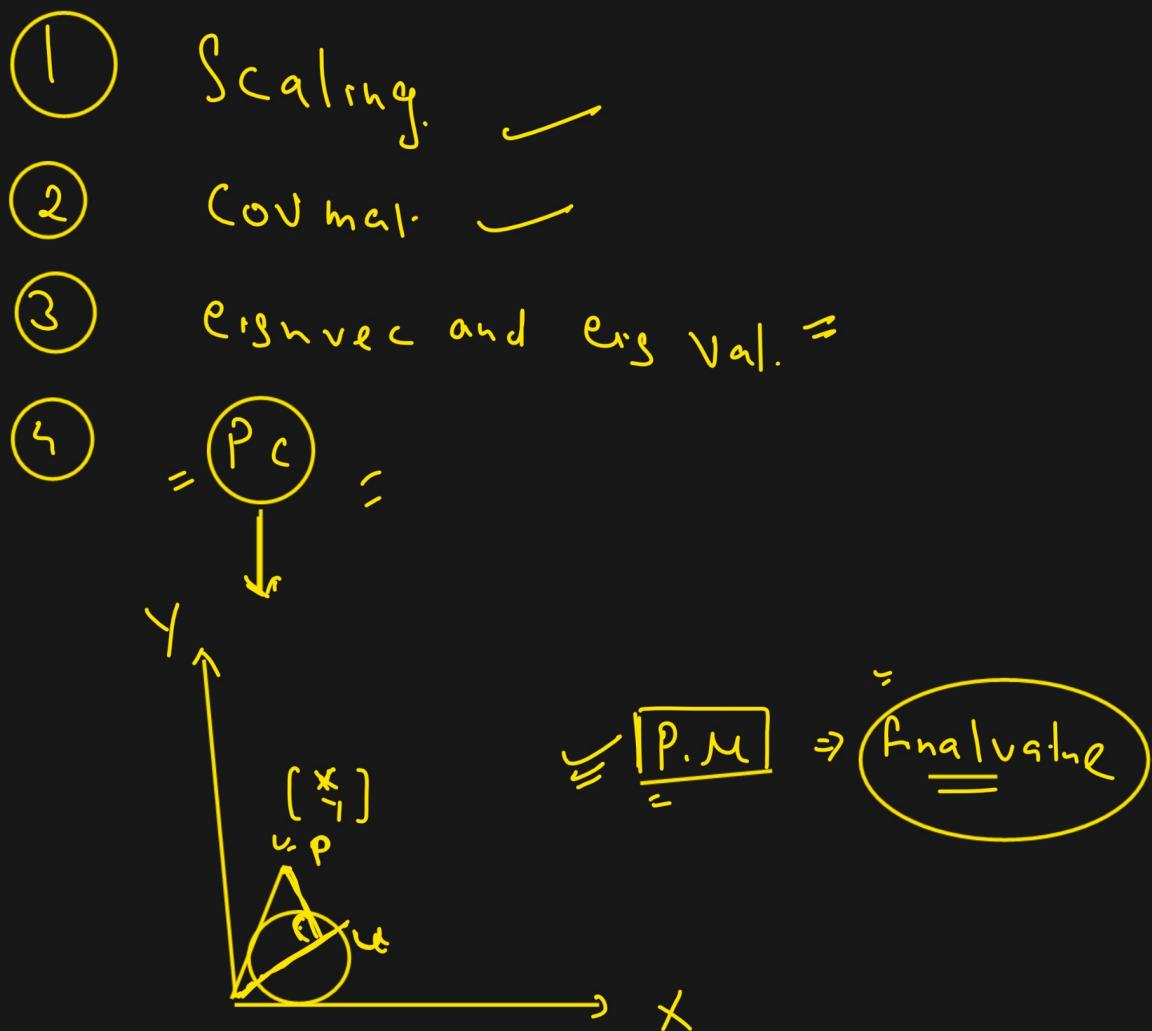
Frage:

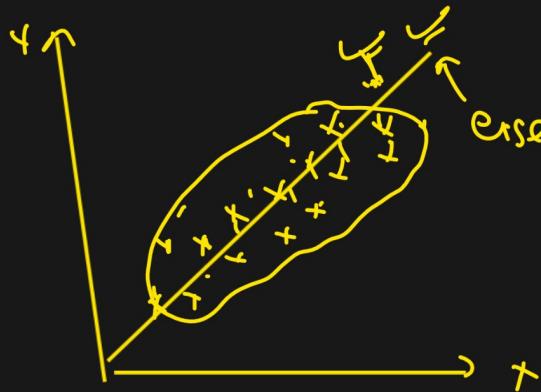
$$\begin{pmatrix} 1 & 2 \\ 1 & 0 \end{pmatrix} \Rightarrow \left. \begin{array}{l} \lambda_1 = ? -1 \\ \lambda_2 = ? \quad 2 \end{array} \right\} =$$

$$\boxed{(A - \lambda I) = 0}$$

$$v_1 =$$

$$v_2 =$$





Q. this is 3×3 mat you have to find out eigen vector and eigen value of this mat.

$$\boxed{mat \times v = \lambda \times v}$$

$$m \times v = \lambda \times v \Rightarrow m v - \lambda v = 0$$

$$\underbrace{\lambda(m - \lambda I)}_0 = 0$$

