



SNS COLLEGE OF TECHNOLOGY

Coimbatore-35
An Autonomous Institution

Accredited by NBA – AICTE and Accredited by NAAC – UGC with 'A++' Grade
Approved by AICTE, New Delhi & Affiliated to Anna University, Chennai

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

23AMB201 - MACHINE LEARNING

II YEAR IV SEM

UNIT IV – UNSUPERVISED LEARNING ALGORITHM

TOPIC 8 – Principal Component Analysis

Redesigning Common Mind & Business Towards Excellence



Build an Entrepreneurial Mindset Through Our Design Thinking Framework



Principal Components Analysis



1. PCA comes under the Unsupervised Machine Learning category
2. The main goal of PCA is to **reduce the number of variables in a data collection while retaining as much information as feasible**. Principal component analysis in machine learning can be mainly used for Dimensionality Reduction and important feature selection.
3. Correlated features to Independent features

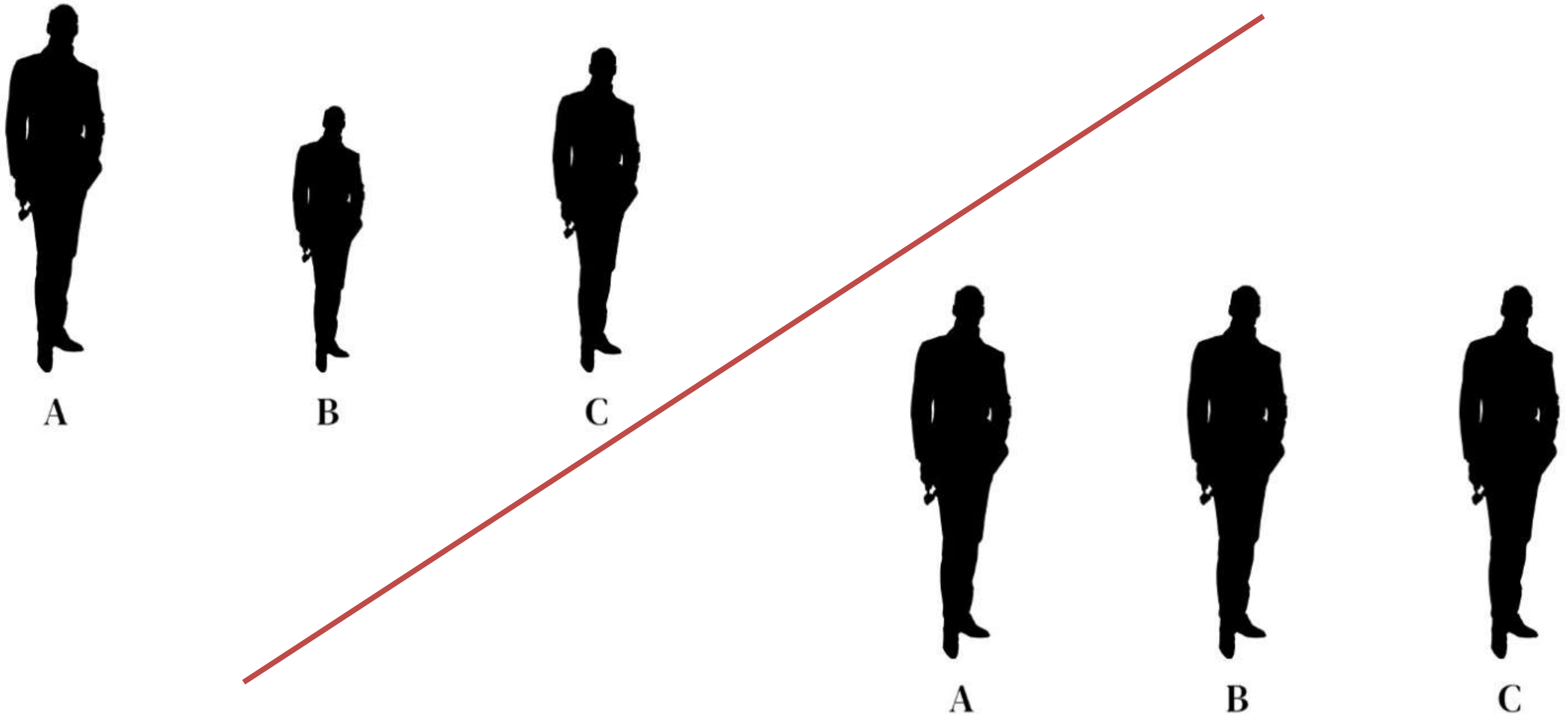
When should Principal Component Analysis be used in ML?

1. Whenever we need to know our features are independent of each other
2. Whenever we need fewer features from higher features





Intuition behind PCA: we need to find the tallest person





Basic Terminologies of PCA

1. **Variance:** For calculating the variation of data distributed across the dimensionality of the graph
2. **Covariance:** Calculating dependencies and relationship between features
3. **Standardizing data:** Scaling our dataset within a specific range for unbiased output
4. **Covariance matrix:** Used for calculating interdependencies between the features or variables and also helps in reducing it to improve the performance
5. **EigenVectors:** The eigenvectors aim to find the largest dataset variance to calculate the Principal Component.
6. **Eigenvalue:** The eigenvalue indicates variance in a particular direction

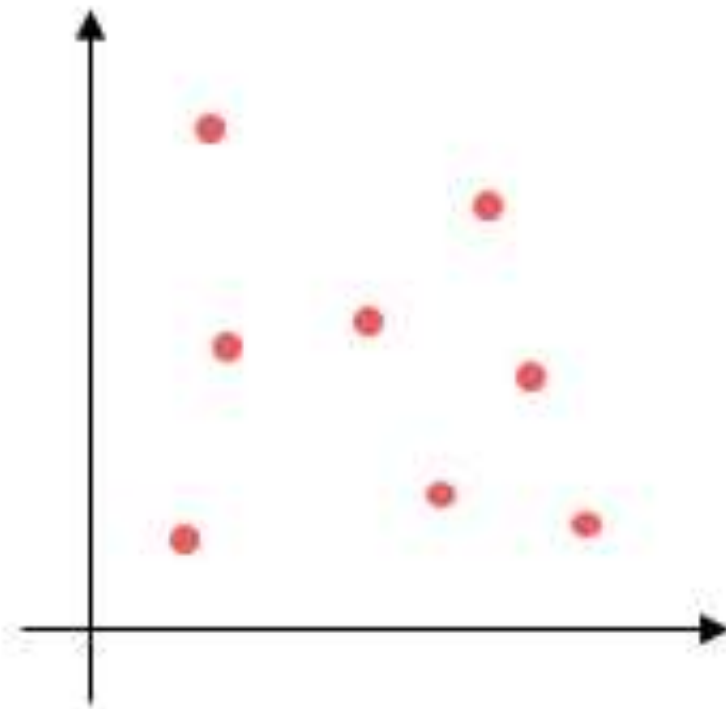
$$Cov(x, y) = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{n}$$

Diagram illustrating the formula for Covariance:

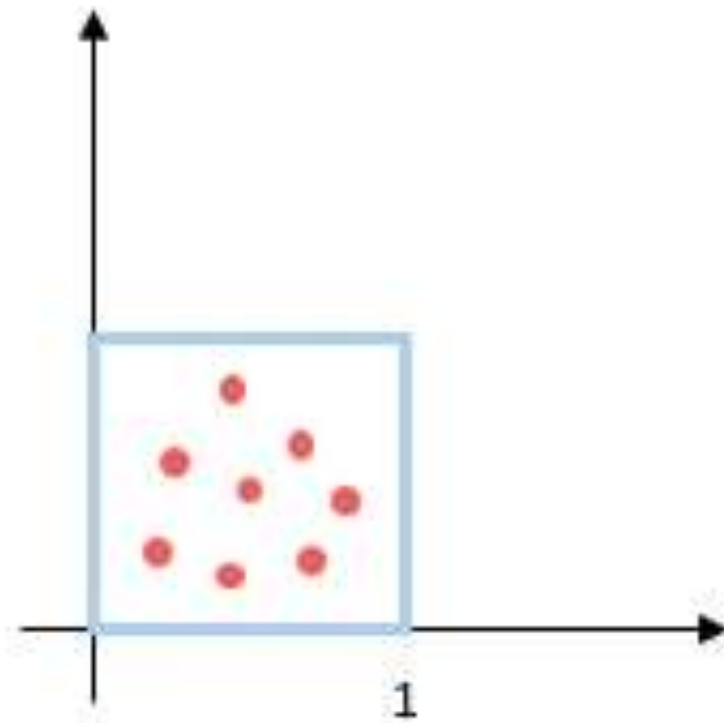
- x_i : data value of X
- $\bar{x}$: mean value of X
- y_i : data value of Y
- $\bar{y}$: mean value of Y
- n : Number of data values



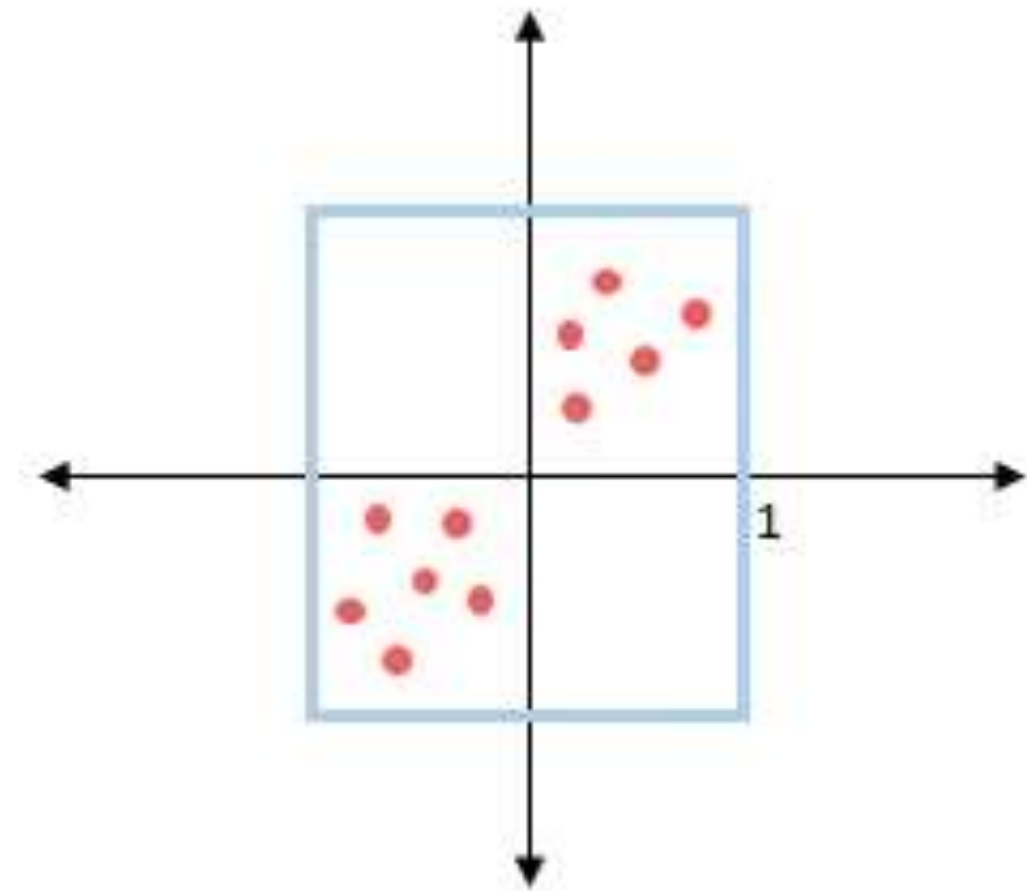
PCM



Actual Data



After normalizing



After standardization



How Does PCA Work?



1. Original Data
2. Normalize the original data (mean =0, variance =1)
3. Calculating covariance matrix
4. Calculating Eigen values, Eigen vectors, and normalized Eigenvectors
5. The eigenvectors represent the principal components, while the eigenvalues indicate the importance of each principal component.
6. Calculating Principal Component (PC)
7. Plot the graph for orthogonality between PCs





How Does PCA Work?

Consider dataset,

Feature	sample 1	sample 2	sample 3	sample 4
a	4	8	13	7
b	11	4	5	14

Step 1:

No. of features, $D = 2$ (a, b)

No. of samples, $N = 4$ (sample 1, sample 2, sample 3, sample 4)

Step 2:

calculating mean,

$$\bar{a} = \frac{4 + 8 + 13 + 7}{4} = 8$$

$$\bar{b} = \frac{11 + 4 + 5 + 14}{4} = 8.5$$



How Does PCA Work?

Step 3:

calculating covariance matrix, between features,
In the given dataset, ordered features are as,

$(a, a), (a, b), (b, a), (b, b)$

$$\text{Cov}(a, a) = \frac{1}{N-1} \sum_{i=1}^N (a_i - \bar{a})(a_i - \bar{a})$$

$$= \frac{1}{N-1} \sum_{k=1}^N (a_i - \bar{a})^2 \rightarrow \text{for same feature}$$

$$= \frac{1}{4-1} [(4-8)^2 + (8-8)^2 + (13-8)^2 + (7-8)^2]$$

$$= \frac{4^2 + 0 + 5^2 + 1^2}{3} = \frac{16 + 0 + 25 + 1}{3}$$

$$= \frac{42}{3} = \underline{\underline{14}}$$



How Does PCA Work?

$$\begin{aligned}\text{cov}(a,b) &= \frac{1}{N-1} \sum_{k=1}^N (a_i - \bar{a})(b_i - \bar{b}) \\ &= \frac{1}{4-1} [(4-8)(11-8.5) + (8-8)(4-8.5) + \\ &\quad (13-8)(5-8.5) + (7-8)(14-8.5)] \\ &= \frac{1}{3} [(-4)(2.5) + (0) + (5)(-3.5) + (-1)(5.5)] \\ &= \frac{1}{3} [-10 - 17.5 - 5.5] = \frac{-33}{3} = \underline{\underline{-11}}\end{aligned}$$

$$\begin{aligned}\text{cov}(b,a) &= \frac{1}{N-1} \sum_{k=1}^N (b_i - \bar{b})(a_i - \bar{a}) \\ &= \text{cov}(a,b) \\ &= -11\end{aligned}$$



How Does PCA Work?

$$\begin{aligned}\text{cov}(b, b) &= \frac{1}{N-1} \sum_{i=1}^N (b_i - \bar{b})(b_i - \bar{b}) \\&= \frac{1}{N-1} \sum_{i=1}^N (b_i - \bar{b})^2 \\&= \frac{1}{4-1} [(11-8.5)^2 + (4-8.5)^2 + (5-8.5)^2 + (14-8.5)^2] \\&= \frac{1}{3} [(2.5)^2 + (-4.5)^2 + (-3.5)^2 + (5.5)^2] \\&= \frac{1}{3} [6.25 + 20.25 + 12.25 + 30.25] \\&= \frac{69}{3} = \underline{\underline{23}}\end{aligned}$$

Hence covariance matrix can be

$$S = \begin{bmatrix} \text{cov}(a, a) & \text{cov}(a, b) \\ \text{cov}(b, a) & \text{cov}(b, b) \end{bmatrix} = \begin{bmatrix} 14 & -11 \\ -11 & 23 \end{bmatrix}$$



How Does PCA Work?

Step 4:-

calculate Eigen value, Eigen vectors, Normalized Eigen vectors.

In order calculate Eigen value,

$$\det(S - \lambda I) = 0$$

$$I(\text{Identity matrix}) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\lambda I = \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix}$$

$$\det \left(\begin{bmatrix} 14 & -11 \\ -11 & 23 \end{bmatrix} - \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} \right) = 0$$

$$\det \begin{pmatrix} 14 - \lambda & -11 \\ -11 & 23 - \lambda \end{pmatrix} = 0.$$

$$(14 - \lambda)(23 - \lambda) - (-11 \times -11) = 0$$

$$322 - 14\lambda - 23\lambda + \lambda^2 - 121 = 0$$



How Does PCA Work?

$$201 - 37\lambda + \lambda^2 = 0.$$

After rearranging,

$$\lambda^2 - 37\lambda + 201 = 0.$$

' λ ' can be calculated by quadratic eqn,

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

$$a = 1$$

$$b = -37$$

$$c = 201$$

$$= \frac{-(-37) \pm \sqrt{(-37)^2 - 4(1)(201)}}{2(1)}$$

$$= \frac{37 \pm \sqrt{1369 - 804}}{2} = \frac{37 \pm \sqrt{565}}{2}$$

$$= \frac{37 \pm 23.76}{2} \Rightarrow \frac{37 + 23.76}{2}, \frac{37 - 23.76}{2}$$

$$= \frac{60.76}{2}, \frac{13.24}{2}$$

Eigen
values.

$$\boxed{\lambda_1 = 30.38, \lambda_2 = 6.62}$$



How Does PCA Work?

So, while arranging in descending order,

$$\lambda_1 > \lambda_2 > \dots$$

Hence, $\lambda_1 = 30.38$

$$\lambda_2 = 6.62$$

We are going to find out Eigenvectors for Eigen value, $\lambda = 30.38$.

$$(S - \lambda_1 I) U_1 = 0$$

Labels:
 - S : Covariance matrix
 - λ_1 : 30.38
 - I : Identity matrix
 - U_1 : Eigenvectors of λ_1

$$\left(\begin{pmatrix} 14 & -11 \\ -11 & 23 \end{pmatrix} - 30.38 \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right) U_1 = 0$$

Assume $U_1 = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$

Hence,

$$\begin{pmatrix} 14 & -11 \\ -11 & 23 \end{pmatrix} - \begin{pmatrix} 30.38 & 0 \\ 0 & 30.38 \end{pmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$



How Does PCA Work?

$$\begin{pmatrix} 14 - 30.38 & -11 \\ -11 & 23 - 30.38 \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{pmatrix} -16.38 & -11 \\ -11 & -7.38 \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$-16.38 u_1 - 11 u_2 = 0 \rightarrow \textcircled{1}$$

$$-11 u_1 - 7.38 u_2 = 0 \rightarrow \textcircled{2}$$

So, from this if we need to calculate u_1, u_2

$$\textcircled{1} \times 7.38 \Rightarrow 120.88 u_1 - 81.18 u_2 = 0$$

$$\textcircled{2} \times -11 \Rightarrow +121 u_1 + 81.18 u_2 = 0$$

$$0.12 u_1 = 0$$

$$\boxed{u_1 = 0}$$

then, apply u_1 in $\textcircled{1}$, then

$$-16.38 \times 0 - 11 u_2 = 0$$

$$\boxed{u_2 = 0}$$



How Does PCA Work?

this can't be possible, hence

$$\begin{bmatrix} (14-\lambda_1) & (-11) \\ (-11) & (28-\lambda_1) \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$(14-\lambda_1)u_1 - 11u_2 = 0 \rightarrow (a)$$

$$-11u_1 + (28-\lambda_1)u_2 = 0 \rightarrow (b)$$

from (a),

$$(14-\lambda_1)u_1 - 11u_2 = 0$$

$$(14-\lambda_1)u_1 = 11u_2$$

$$\frac{u_1}{11} = \frac{u_2}{14-\lambda_1} = A \text{ (Assigning)}$$

Assume A=1,

$$\frac{u_1}{11} = \frac{u_2}{14-\lambda_1} = A = 1$$

$$\text{Hence, } \frac{u_1}{11} = 1 \Rightarrow u_1 = 11$$

$$\begin{aligned} \frac{u_2}{14-\lambda_1} &= 1 \Rightarrow u_2 = 14-\lambda_1 \\ &= 14-30.38 \\ &= -16.38 \end{aligned}$$

$$\text{Hence Eigenvector for } \lambda_1 \Rightarrow \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} 11 \\ -16.38 \end{bmatrix}$$



Calculating PC

Then if we want to normalize the eigen vectors,

$$n_1 = \begin{bmatrix} 11 / \sqrt{11^2 + 16.38^2} \\ -16.38 / \sqrt{11^2 + 16.38^2} \end{bmatrix} \quad / \text{dividing by} \\ \text{the length.}$$

$$= \begin{bmatrix} \frac{11}{19.73} \\ -16.38/19.73 \end{bmatrix} = \begin{bmatrix} 0.5575 \\ -0.8302 \end{bmatrix}$$

Now, calculate eigen vectors for $\lambda_2 = 6.62$

$$(S - \lambda_2 I) v_2 = 0$$

$$\begin{bmatrix} (14 - \lambda_2) & -11 \\ -11 & (23 - \lambda_2) \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$(14 - \lambda_2) v_1 - 11 v_2 = 0 \rightarrow (c)$$

$$-11 v_1 - (23 - \lambda_2) v_2 = 0 \rightarrow (d)$$

from (c),

$$(14 - \lambda_2) v_1 - 11 v_2 = 0$$

$$(14 - \lambda_2) v_1 = 11 v_2$$

$$\therefore \frac{v_1}{11} = \frac{v_2}{14 - \lambda_2} = B \text{ (Assume)}$$



Calculating PC

Assume $B = 1$,

$$\frac{u_1}{11} = \frac{u_2}{14 - \lambda_2} = B = 1$$

$$\text{Hence, } \frac{u_1}{11} = 1 \Rightarrow u_1 = 11$$

$$\begin{aligned} \frac{u_2}{14 - \lambda_2} &= 1 \Rightarrow u_2 = 14 - \lambda_2 \\ &= 14 - 6.62 \\ &= 7.38 \end{aligned}$$

$$\text{Hence, Eigen Vector for } \lambda_2 = \begin{bmatrix} 11 \\ 7.38 \end{bmatrix}$$

If we want to normalize eigen vector,

$$\begin{aligned} n_2 &= \begin{bmatrix} 11 / \sqrt{11^2 + 7.38^2} \\ 7.38 / \sqrt{11^2 + 7.38^2} \end{bmatrix} = \begin{bmatrix} 11 / 13.24 \\ 7.38 / 13.24 \end{bmatrix} \\ &= \begin{bmatrix} 0.8308 \\ 0.5574 \end{bmatrix} \end{aligned}$$



Normalized Eigen vector

Step 5: New dataset,

Feature	sample1	sample2	sample3	sample4
a	4	8	13	7
b	11	4	5	14

1st PC	P_{11}	P_{12}	P_{13}	P_{14}
	sample1	sample2	sample3	sample4

$$\begin{aligned}P_{11} &= \eta_1^T \begin{bmatrix} 4-8 \\ 11-8.5 \end{bmatrix} \\&= \begin{bmatrix} 0.5575 & -0.8302 \end{bmatrix} \begin{bmatrix} -4 \\ 2.5 \end{bmatrix} \\&= (-2.23 - 2.0755) \\&= -4.305\end{aligned}$$

$$\begin{aligned}P_{12} &= \eta_1^T \begin{bmatrix} 8-8 \\ 4-8.5 \end{bmatrix} \Rightarrow (0.5575 - 0.8302) \begin{pmatrix} 0 \\ -4.5 \end{pmatrix} \\&= 0 + 3.7359 = 3.7359\end{aligned}$$

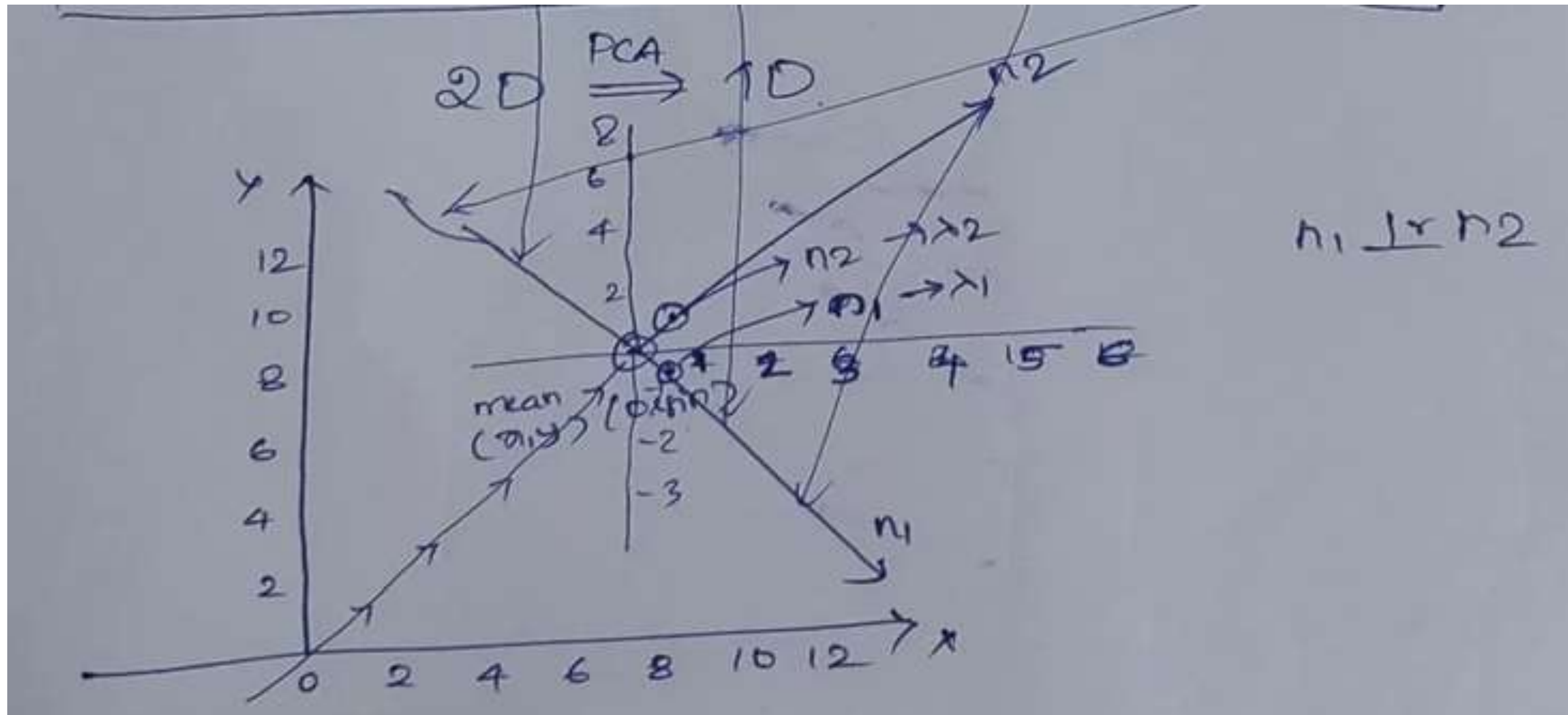
$$\begin{aligned}P_{13} &= \eta_1^T \begin{bmatrix} 13-8 \\ 5-8.5 \end{bmatrix} \Rightarrow (0.5575 - 0.8302) \begin{pmatrix} 5 \\ -3.5 \end{pmatrix} \\&= 2.7875 + 2.90575 = 5.692\end{aligned}$$

$$\begin{aligned}P_{14} &= \eta_1^T \begin{bmatrix} 7-8 \\ 14-8.5 \end{bmatrix} = (0.5575 - 0.8302) \begin{pmatrix} -1 \\ 5.5 \end{pmatrix} \\&= -0.5575 - 4.5661 \\&= -5.123\end{aligned}$$

$$PC1 = \begin{bmatrix} -4.305 & 3.7359 & 5.692 & -5.123 \end{bmatrix}$$

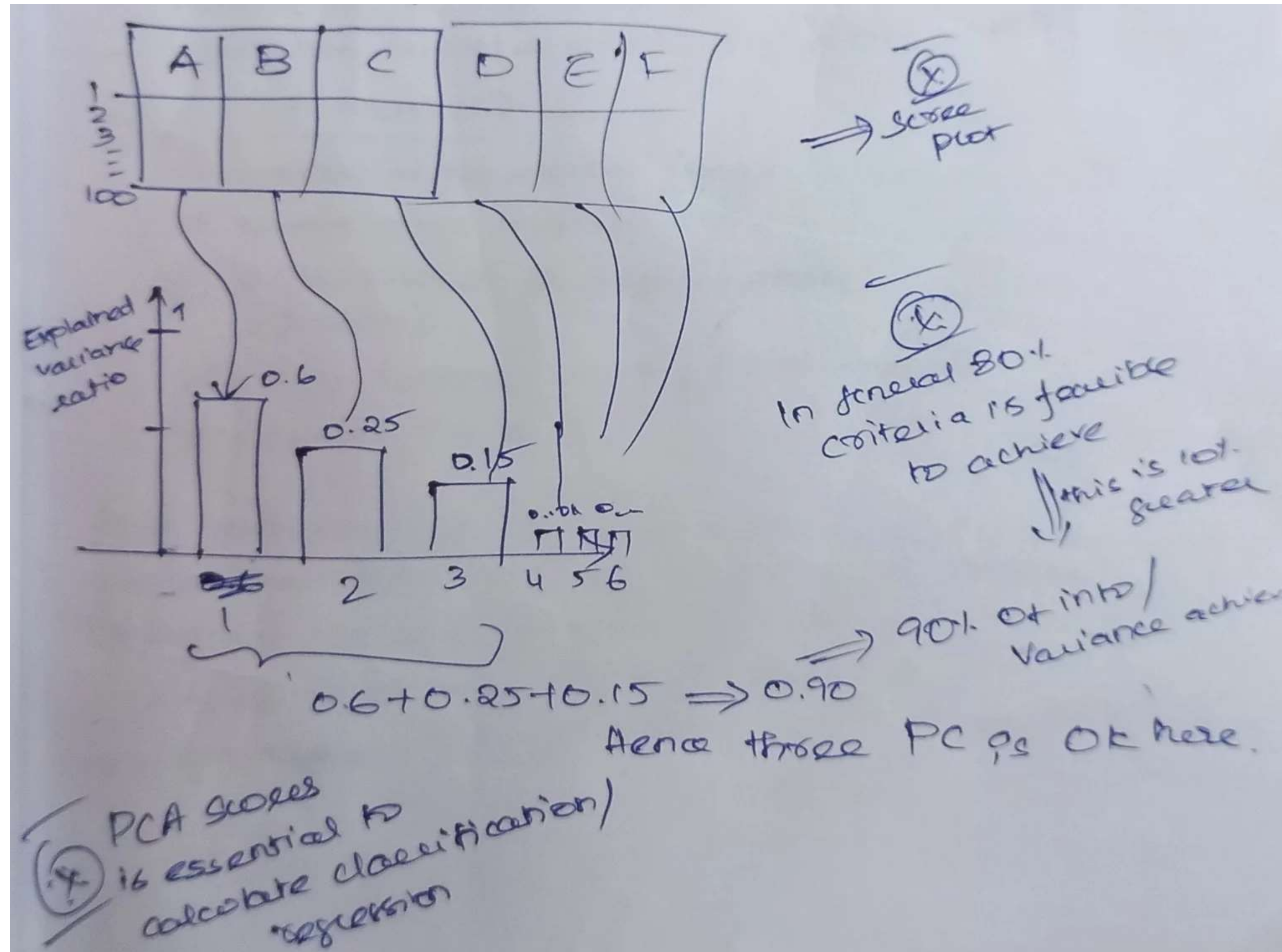


Normalized Eigen vector





How Many PCAs are Needed for Any Data?





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