

PCA explained step by step

- ① what & why
- ② Some mathematics refresh
- ③ EigenValue & EigenVector
- ④ Steps to Calculate PCA manually
- ⑤ Compare results with sklearn
- ⑥ Summary

feature reduction tech

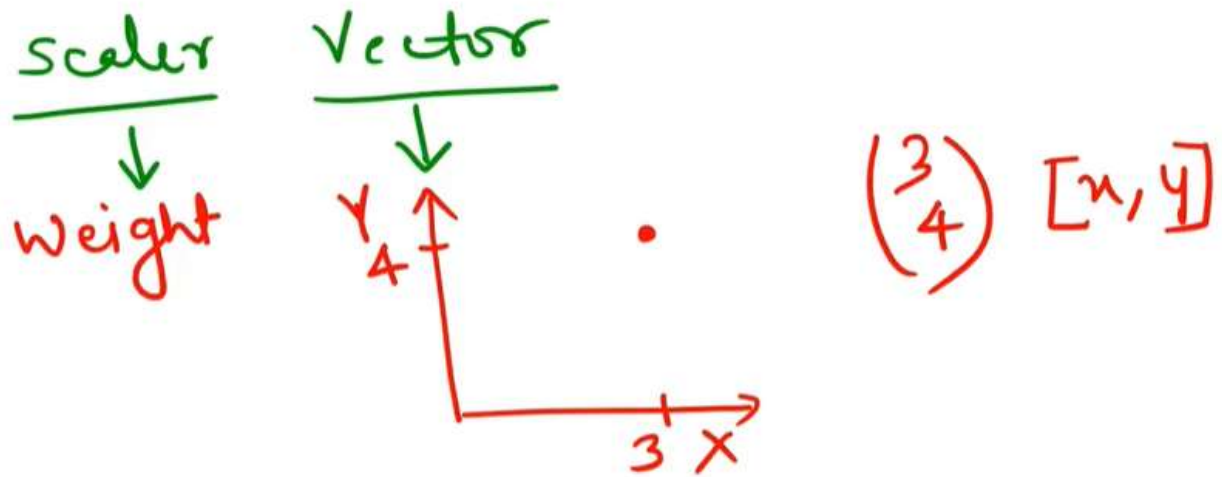
$x_1, x_2, \dots, x_{15}, \dots, x_{100}$

PCA

\checkmark \checkmark \checkmark \downarrow
 $PC1, PC2, PC3, \dots, P_{100}$

\downarrow N
 $80\% + 15 + 3 \mid \dots$

▼ What is Scaler & Vector



Matrix Transpose & Multiplication

$$A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \xrightarrow{T} \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix}$$

2×2

$$B = \begin{bmatrix} 1 \\ 3 \\ 4 \end{bmatrix} \quad 2 \times 2$$

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

Eigen Value & Eigen Vector

$$\underline{A} \underline{V} = \underline{\lambda} \underline{V}$$

\downarrow \downarrow
Value vector

$$\begin{bmatrix} 3 & 6 \\ 5 & 4 \end{bmatrix} \times V = \lambda \times V$$

$$\underline{V} \left(\underline{M} - \underline{\lambda I} \right) = 0 \quad \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

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

$$\underline{V} \left(\underline{M} - \underline{\lambda I} \right) = 0 \quad \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

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

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

$$(3-1)(4-1) - 30 = 0 \quad \lambda = 9, \lambda = -2$$

▼ Steps for Developing PCA

→ Physics Maths
 s1 a b
 s2 c d

Step1 → Define Data

Step2 → Make Data mean

Double-click (or enter) to edit

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```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from numpy.linalg import eig
```

```
Marks = np.array([[3,4],[2,8],[6,9]])
print(Marks)
```

```
[[3 4]
 [2 8]
 [6 9]]
```

```
Marks_df= pd.DataFrame(Marks,columns=["Physics","Maths"])
Marks_df
```

	Physics	Maths
0	3	4
1	2	8
2	6	9

```
plt.scatter(Marks_df["Physics"],Marks_df["Maths"])
```

<matplotlib.collections.PathCollection at 0x7f6ba68dc950>



```
#making data mean Centric
Meanbycolumn=np.mean(Marks.T,axis=1)
print(Meanbycolumn)
```

```
[3.66666667 7.          ]
```

```
Scaled_Data = Marks- Meanbycolumn
Scaled_Data
```

```
array([[ -0.66666667, -3.          ],
       [-1.66666667,  1.          ],
       [ 2.33333333,  2.          ]])
```

```
Marks
```

```
array([[3, 4],
       [2, 8],
       [6, 9]])
```

```
print(Marks_df["Physics"].mean())
print(Marks_df["Maths"].mean())
```

```
3.6666666666666665
7.0
```

step 3 → Covariance matrix a.b

```
#Find Covariance matrix of above scaled data
Cov_mat= np.cov(Scaled_Data.T)
Cov_mat
```

```
array([[4.33333333, 2.5      ],
       [2.5      , 7.      ]])
```

find the Eigen Value and Eigen Vector of the above Covariance matrix

step 4 → find λ_1, λ_2
 $\underline{V_1}, \underline{V_2}$

Double-click (or enter) to edit

```
Eval, Evec =eig(Cov_mat)
print(Eval)
print(Evec)

[2.83333333 8.5      ]
[[-0.85749293 -0.51449576]
 [ 0.51449576 -0.85749293]]
```

Get Original Data Projected to principal Components as new axis

```
Projected_data = Evec.T.dot(Scaled_Data.T)
print(Projected_data.T)

[[-9.71825316e-01  2.91547595e+00]
 [ 1.94365063e+00  1.11022302e-16]
 [-9.71825316e-01 -2.91547595e+00]]
```

```
from sklearn.decomposition import PCA
```

```
pca= PCA(n_components=2)
pca.fit_transform(Marks)

array([[ 2.91547595e+00, -9.71825316e-01],
       [-7.37588530e-16,  1.94365063e+00],
       [-2.91547595e+00, -9.71825316e-01]])
```

▼ variance explanation ratio by each PCA

```
pca.explained_variance_ratio_

array([0.75, 0.25])
```

```
PCDF=pd.DataFrame(data=pca.fit_transform(Marks),columns=['PC1','PC2'])
PCDF
```

	PC1	PC2
0	2.915476e+00	-0.971825
1	-7.375885e-16	1.943651
2	-2.915476e+00	-0.971825

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