

```

1 import numpy as np
2 import matplotlib
3 import matplotlib.pyplot as plt
4 from numpy import array
5 from numpy import diag
6 from numpy import dot
7 from numpy import zeros
8 from sklearn.decomposition import PCA
9 from numpy import dot
10 from numpy.linalg import inv
11 from sklearn.metrics import mean_squared_error

```

Generating data

```

1 X = np.array([3,2,1,2,4,5,1,2,3,0,2,5])
2 X = np.reshape(X,(4,3))
3 print(X)

```

```

↳ [[3 2 1]
    [2 4 5]
    [1 2 3]
    [0 2 5]]

```

Finding sample mean

```

1 mean = np.mean(X,axis = 0, dtype='float64')
2 print(f"Mean of the columns of X {mean}")

```

```

↳ Mean of the columns of X [1.5 2.5 3.5]

```

Zero centering of the samples

```

1 X = X - mean
2 print(X)

```

```

↳ [[ 1.5 -0.5 -2.5]
    [ 0.5  1.5  1.5]
    [-0.5 -0.5 -0.5]
    [-1.5 -0.5  1.5]]

```

PCA by Eigen value decomposition of covariance matrix

```

1 from numpy import cov
2 from numpy.linalg import eig
3 V = cov(X.T)
4 Evalues, Eectors = eig(V)
5 print(f"Eigen vectors = \n {Eectors}")
6 print(f"Eigen values = \n {Evalues}")

```

```

↳ Eigen vectors =
  [[-0.45056922 -0.66677184 -0.59363515]
   [ 0.19247228 -0.72187235  0.66472154]
   [ 0.87174641 -0.18524476 -0.45358856]]
Eigen values =
  [4.74888619 1.56450706 0.01994008]

```

```

1 # Converting Evalues to a diagonal matrix
2 Evalues_diag = zeros((X.shape[0], X.shape[1]))
3 Evalues_diag[:X.shape[1], :X.shape[1]] = diag(Evalues)
4 print(f"Diagonalized form of Evalues = \n {Evalues_diag}")

```

```

↳ Diagonalized form of Evalues =
  [[4.74888619 0.          0.          ]
   [0.          1.56450706 0.          ]
   [0.          0.          0.01994008]
   [0.          0.          0.          ]]

```

Projecting X using the Eigen vectors

```

1 k = 2
2 Eectors_k = Eectors[:,0:k]
3 proj = X.dot(Eectors_k)
4 print(f"Selecting 2 principal axes = \n {Eectors_k}")
5 print("\n")
6 print(f"Projected X using the above principal axes = \n {proj}")

```

```

↳ Selecting 2 principal axes =
  [[-0.45056922 -0.66677184]
   [ 0.19247228 -0.72187235]
   [ 0.87174641 -0.18524476]]

```

```

Projected X using the above principal axes =
  [[-2.95145599 -0.17610969]
   [ 1.37104342 -1.69406159]
   [-0.30682473  0.78694448]
   [ 1.8872373   1.0832268  ]]

```

Reconstruction of X

```

1 recon = proj.dot(Eectors_k.T)+mean
2 print(f"Reconstruction of X using the new basis = \n {recon}")

```

```

↳ Reconstruction of X using the new basis =
  [[ 2.94726021  2.05905526  0.95970224]
   [ 2.0118026   3.98678407  5.0090182  ]
   [ 1.11353336  1.87287129  3.0867493  ]
   [-0.07259617  2.08128939  4.94453025]]

```

Reconstruction error

```

1 print(mean_squared_error(X+mean, recon))

```

0.004985020477602166

An alternate way to perform PCA: PCA by singular value decomposition of data

```
1 U, S, VT = np.linalg.svd(X)
2
3 print(f"Unitary matrix = \n {U}")
4 print(f"Shape of unitary matrix = {U.shape}")
5 print("\n")
6 print(f"Diagonal matrix of singular values = \n {S}")
7 print(f"Shape of this matrix = {S.shape}")
8 print("\n")
9 print(f"Matrix of principal axes = \n {VT}")
10 print(f"Shape of this matrix = {VT.shape}")
11 print("\n")
12
13 # Converting S to a diagonal matrix
14 S_diag = zeros((X.shape[0], X.shape[1]))
15 S_diag[:X.shape[1], :X.shape[1]] = diag(S)
16 print(f"Diagonalized form of S = \n {S_diag}")
```

```
Unitary matrix =
[[-0.78195148 -0.08128939  0.36324086  0.5          ]
 [ 0.36324086 -0.78195148 -0.08128939  0.5          ]
 [-0.08128939  0.36324086 -0.78195148  0.5          ]
 [ 0.5          0.5          0.5          0.5          ]]
Shape of unitary matrix = (4, 4)
```

```
Diagonal matrix of singular values =
[3.77447461 2.1664536  0.24458178]
Shape of this matrix = (3,)
```

```
Matrix of principal axes =
[[-0.45056922  0.19247228  0.87174641]
 [-0.66677184 -0.72187235 -0.18524476]
 [ 0.59363515 -0.66472154  0.45358856]]
Shape of this matrix = (3, 3)
```

```
Diagonalized form of S =
[[3.77447461 0.          0.          ]
 [0.          2.1664536  0.          ]
 [0.          0.          0.24458178]
 [0.          0.          0.          ]]
```

- Eigen vectors are the columns of 'V' or rows of 'VT'.
- Eigen values are present in the diagonal matrix of S.

Reconstruction with minimum loss using first 2 components (k=2)

```
1 k = 2
```

```

2 U_k = U.T[0:k][0:k]
3 U_kT = U_k.T
4 S_diag_k = S_diag[0:2,0:2]
5 VT_k = VT[0:k]

```

PC scores or Projected X

```

1 projectedX = U_kT.dot(S_diag_k)
2 print(projectedX)

```

```

↳ [[-2.95145599 -0.17610969]
    [ 1.37104342 -1.69406159]
    [-0.30682473  0.78694448]
    [ 1.8872373   1.0832268  ]]

```

```

1 reconstruct_k = U_kT.dot(S_diag_k.dot(VT_k))
2 reconstruct_k = reconstruct_k + mean
3 print(reconstruct_k)

```

```

↳ [[ 2.94726021  2.05905526  0.95970224]
    [ 2.0118026   3.98678407  5.0090182  ]
    [ 1.11353336  1.87287129  3.0867493  ]
    [-0.07259617  2.08128939  4.94453025]]

```

Reconstruction error

```

1 print(mean_squared_error(X+mean, reconstruct_k))

```

```

↳ 0.0049850204776021615

```