# **PCA** Implementation

#### **Data**

Here is the set-up code to load in the data and import dependencies:

```
import numpy as np
from sklearn.preprocessing import StandardScaler

data = np.array([[0.2, -0.3], [-1.1, 2], [1, -2.2], [0.5, -1], [-0.6, 1]])
num_components = 1
print("data:\n", data)
```

Output:

```
[[ 0.2 -0.3]
[-1.1 2. ]
[ 1. -2.2]
[ 0.5 -1. ]
[-0.6 1. ]]
```

### Scaled data

The data is scaled using a standard scaler:

```
scaler = StandardScaler()
scaler.fit(data)
scaled_data = scaler.transform(data)
print("\nscaled:\n", scaled_data)
```

Output:

### **Covariance Matrix**

The covariance matrix of the scaled data is calculated as follows:

```
covariance_matrix = np.cov(scaled_data.T)
print("\ncovariance matrix:\n", covariance_matrix)
```

Output:

### **Eigenvalues and Eigenvectors**

The eigenvalues and eigenvectors of the covariance matrix are calculated as follows:

```
eigenvalues, eigenvectors = np.linalg.eig(covariance_matrix)
print("\neigenvalues:\n", eigenvalues)
print("\neigenvectors:\n", eigenvectors)
```

Output:

```
eigenvalues: [2.49591192 0.00408808]
eigenvectors: [[ 0.70710678  0.70710678]
[-0.70710678  0.70710678]]
```

### **Proportion of variance**

The proportion of variance is calculated as follows:

```
print("\nProportion of variance:\n", sum(eigenvalues[:num_components]) /
sum(eigenvalues))
```

Output:

```
0.99836476739648
```

Since the proportion of variance is so close to 1, the information lost is likely negligible.

## **Projection Matrix**

The projection matrix is formed from the eigenvectors:

```
projection_matrix = (eigenvectors.T[:][:num_components]).T
print("\nprojection matrix:\n", projection_matrix)
```

Output:

```
[[ 0.70710678]
[-0.70710678]]
```

### **PCA Data**

The data after applying PCA is:

```
data_pca = scaled_data.dot(projection_matrix)
print("\ndata_pca:\n", data_pca)
```

Output:

```
[[ 0.28286002]
[-2.03508324]
[ 1.94158854]
[ 0.8988913 ]
[-1.08825662]]
```