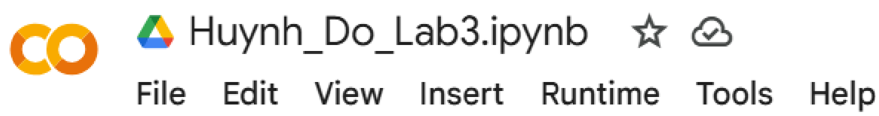
**Huynh Do Lab#3:**
**Objective**:
This lab assignment works with Principal Component Analysis (PCA) to expose how they can determine the best explained variance ratio. This is a statistical procedure that is used to reduce dimensionality




## 1. Import libraries

```
[5]  # Import required Python packages
     import matplotlib.pyplot as plt
     import pandas as pd
     import numpy as np
     import sklearn
     from sklearn.preprocessing import scale
     from sklearn.decomposition import PCA
     import seaborn as sns  # Optional for better visuals
     from google.colab import files
     from sklearn.preprocessing import StandardScaler
```

The code above imports several Python libraries commonly used in data analysis.

1. **matplotlib.pyplot** – Used to create basic graphs like scatter plots, line charts, and bar graphs.
2. **pandas** – Loads and manages tabular data (like CSVs) into an easy-to-use DataFrame.
3. **numpy** – Powers fast mathematical operations, especially with large arrays of numbers.
4. **sklearn** – Provides machine learning algorithms and data processing tools.
5. **scale** – Instantly standardizes your data to have a mean of 0 and variance of 1.
6. **PCA** – Reduces the number of variables while keeping the important patterns in your data.
7. **seaborn** – Makes fancier, cleaner-looking graphs with less code than plain matplotlib.
8. **google.colab.files** – Lets you upload and download files when working inside Google Colab.
9. **StandardScaler** – Another way to standardize data, but more control across train/test splits.

## 2. Upload file b5.csv

```python
# Upload 'b5.csv' file
uploaded = files.upload()

# Load the dataset
df = pd.read_csv("b5.csv")
df.head()
```

The above screen shot is used to upload and load a CSV file named **b5.csv** into a Pandas Data Frame in a Google Colab environment.

When upload is done:

```
Choose Files  b5.csv
• b5.csv(text/csv) - 1912084 bytes, last modified: 4/21/2025 - 100% done
Saving b5.csv to b5 (2).csv
```

| | E1 | E2 | E3 | E4 | E5 | E6 | E7 | E8 | E9 | E10 | ... | O1 | O2 | O3 | O4 | O5 | O6 | O7 | O8 | O9 | O10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 4 | 2 | 5 | 2 | 5 | 1 | 4 | 3 | 5 | 1 | ... | 4 | 1 | 3 | 1 | 5 | 1 | 4 | 2 | 5 | 5 |
| **1** | 2 | 2 | 3 | 3 | 3 | 3 | 1 | 5 | 1 | 5 | ... | 3 | 3 | 3 | 3 | 2 | 3 | 3 | 1 | 3 | 2 |
| **2** | 5 | 1 | 1 | 4 | 5 | 1 | 1 | 5 | 5 | 1 | ... | 4 | 5 | 5 | 1 | 5 | 1 | 5 | 5 | 5 | 5 |
| **3** | 2 | 5 | 2 | 4 | 3 | 4 | 3 | 4 | 4 | 5 | ... | 4 | 3 | 5 | 2 | 4 | 2 | 5 | 2 | 5 | 5 |
| **4** | 3 | 1 | 3 | 3 | 3 | 1 | 3 | 1 | 3 | 5 | ... | 3 | 1 | 1 | 1 | 3 | 1 | 3 | 1 | 5 | 3 |

5 rows × 50 columns

## 3. Process PCA

### Step 1

```python
# Step 1: Standardize the dataset
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df)
```

- **scaler = StandardScaler()** Creates a scaler object to standardize features (zero mean, unit variance).
- **df_scaled = scaler.fit_transform(df)** Fits the scaler to the dataset and transforms the data into a standardized form.

**Step 2**

```
[18] # Step 2: Calculate covariance matrix
     cov_matrix = np.cov(df_scaled.T)
```

- **cov_matrix = np.cov(df_scaled.T)** Calculates the covariance matrix by transposing the standardized data so features are treated as variables.

**Step 3**

```
[19] # Step 3: Compute eigenvalues and eigenvectors
     eigenvalues, eigenvectors = np.linalg.eigh(cov_matrix)
```

- **eigenvalues, eigenvectors = np.linalg.eigh(cov_matrix)** Computes the eigenvalues and eigenvectors of the covariance matrix to find directions and magnitudes of variance.

**Step 4**

```
[21]
     # Step 4: Sort eigenvalues and eigenvectors in descending order
     sorted_indices = np.argsort(eigenvalues)[::-1]
     eigenvalues_sorted = eigenvalues[sorted_indices]
     eigenvectors_sorted = eigenvectors[:, sorted_indices]
```

- **sorted_indices = np.argsort(eigenvalues)[::-1]** Finds indices that sort eigenvalues from largest to smallest.
- **eigenvalues_sorted = eigenvalues[sorted_indices]** Reorders eigenvalues in descending order.

**Step** 5

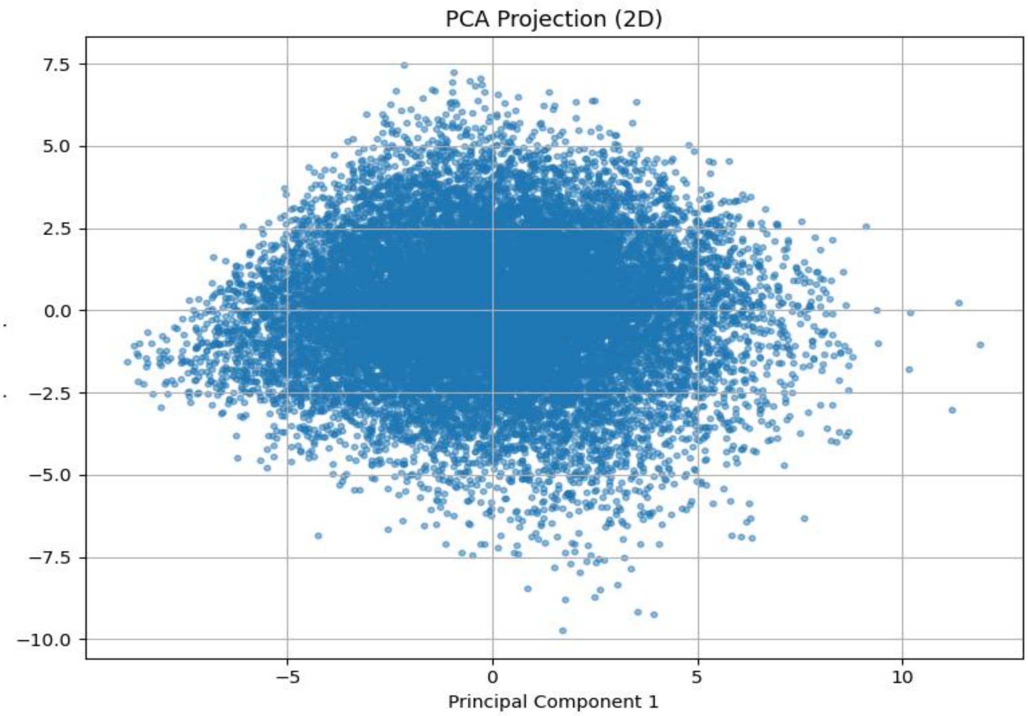
```
[22] # Step 5: Select top k eigenvectors and project the data (2D)
     k2 = 2
     top_k2_eigenvectors = eigenvectors_sorted[:, :k2]
     df_pca_2d = df_scaled.dot(top_k2_eigenvectors)
     df_pca_2d = pd.DataFrame(df_pca_2d, columns=[f'PC{i+1}' for i in range(k2)])
```

- **k2 = 2** Sets the number of principal components to keep at 2 for 2D projection.
- **top_k2_eigenvectors = eigenvectors_sorted[:, :k2]** Selects the first two sorted eigenvectors.
- **df_pca_2d = df_scaled.dot(top_k2_eigenvectors)** Projects the standardized data onto the 2D principal component space.
- **df_pca_2d = pd.DataFrame(df_pca_2d, columns=[f'PC{i+1}' for i in range(k2)])** Converts the projected data into a labeled DataFrame with PC1 and PC2.

**Step 6**

```
# Step 6: Visualize 2D PCA
plt.figure(figsize=(8, 6))
plt.scatter(df_pca_2d['PC1'], df_pca_2d['PC2'], alpha=0.5, s=10)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('PCA Projection (2D)')
plt.grid(True)
plt.tight_layout()
plt.show()
```

- **plt.figure(figsize=(8, 6))** Creates a new figure with specified size.
- **plt.scatter(df_pca_2d['PC1'], df_pca_2d['PC2'], alpha=0.5, s=10)** Plots the 2D PCA result as a scatter plot.
- **plt.xlabel('Principal Component 1')** Labels the x-axis.
- **plt.ylabel('Principal Component 2')** Labels the y-axis.
- **plt.title('PCA Projection (2D)')** Adds a title to the plot.
- **plt.grid(True)** Enables grid lines for better readability.




- Total summary

```python
# Total sum of all eigenvalues
total_variance = np.sum(eigenvalues_sorted)

# Variance explained by each principal component
variance_explained = eigenvalues_sorted / total_variance

# Print variance explained by PC1, PC2, PC3
for i in range(3):
    print(f"PC{i+1} explains {variance_explained[i]*100:.2f}% of the total variance.")
```

PC1 explains 16.10% of the total variance.
PC2 explains 9.25% of the total variance.
PC3 explains 7.53% of the total variance.