-- Workshop #4 ------------------------------------

- This workshop includes marked tasks that comprise 15% of your final mark in this module.
- You need to read the examples in Lecture #4 and Lecture #4 exercise to complete the tasks.

Tasks

TASK 4.1: Download the adult_WS4 dataset. Apply K-Means and Hierarchical clustering to three optional columns in the dataset. Find the optimum number of clusters for both clustering methods (10%).

NOTE: You should comment on your code wherever necessary and briefly explain what the code is doing

In [1]:

```
############# WRITE YOUR CODE IN THIS CELL (IF APPLICABLE)###################
#IMPORTING THE REQUIRED LIBRARIES
import pandas as pd
import numpy as np

#IMPORT THE DATASET
data4 = pd.read_csv('adult_WS4.csv')

#VIEWING THE FIRST 5 ROWS OF THE DATA
print(data4.head(5))

#CHECKING FOR NULL VALUES
print('NULL VALUES\n')
print(data4.isnull().sum())

#to see the data volume
print('VALUE DISTRIBUTION ACROSS COLUMNS\n')
data4.count()
```

```
   age workclass   fnlwgt     education  education-num      marital-status  \
0   29   Private   216481       Masters             14  Married-civ-spouse
1   36   Private   280570  Some-college             10  Married-civ-spouse
2   25         ?   100903     Bachelors             13  Married-civ-spouse
3   47   Private   145636     Assoc-voc             11  Married-civ-spouse
4   33   Private   119422       HS-grad              9  Married-civ-spouse

          occupation relationship   race     sex  capital-gain  capital-loss  \
0    Exec-managerial         Wife  White  Female             0             0
1       Craft-repair      Husband  White    Male             0             0
2                  ?         Wife  White  Female             0             0
3  Handlers-cleaners      Husband  White    Male             0             0
4    Exec-managerial      Husband  White    Male             0             0

   hours-per-week native-country income
0              40  United-States   >50K
1              45  United-States  <=50K
2              25  United-States  <=50K
3              48  United-States   >50K
4              40  United-States  <=50K
NULL VALUES

age                 0
workclass         175
fnlwgt              0
education           0
education-num       0
marital-status      0
occupation        175
relationship        0
race                0
sex                 0
capital-gain        0
capital-loss        0
hours-per-week      0
native-country     61
income              0
dtype: int64
VALUE DISTRIBUTION ACROSS COLUMNS
```

Out[1]:

```
age               10000
workclass          9825
fnlwgt            10000
education         10000
education-num     10000
marital-status    10000
occupation         9825
relationship      10000
race              10000
sex               10000
capital-gain      10000
capital-loss      10000
hours-per-week    10000
native-country     9939
income            10000
dtype: int64
```

DATA PREPROCESSING

In [2]:

```
# FIRST WE NEED TO ENCODE THE DATA
# Importing necessary libraries
import pandas as pd
```

```python
from sklearn.preprocessing import OrdinalEncoder

# Initialize the OrdinalEncoder
encoder = OrdinalEncoder()

# Encode one of the needed column with categorical variables
column = ['race']
data_encode = data4.copy()  # Create a copy to avoid modifying the original DataFra

# Fit and transform the encoder on the specified columns
data_encode[column] = encoder.fit_transform(data4[column]).astype(int)
```

In [3]:
```python
#Selecting three columns of choice and output variable
optional_columns = ['race', 'age','hours-per-week']
x = data_encode[optional_columns]
Y=data_encode['income']
```

In [4]:
```python
#normalising the columns as input data
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
scaler = StandardScaler()
x=scaler.fit_transform(x)

x
```

Out[4]:
```
array([[ 0.38960857, -0.69969332, -0.03681876],
       [ 0.38960857, -0.1896809 ,  0.36876351],
       [ 0.38960857, -0.99112899, -1.25356557],
       ...,
       [ 0.38960857, -0.6268344 , -0.03681876],
       [ 0.38960857,  0.17461368, -0.03681876],
       [-1.9998951 , -1.28256465, -0.03681876]])
```

In [5]:
```python
#Apply K-Means clustering with varying numbers of clusters
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
import matplotlib.pyplot as plt
k_range = range(2, 10)
kmeans_scores = []
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(x)
    kmeans_scores.append(silhouette_score(x, kmeans.labels_))

# Plot the silhouette scores for different numbers of clusters
plt.plot(k_range, kmeans_scores, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.title('The Elbow Method')
plt.show()
```

```
C:\Users\dessy\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: Future
Warning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set t
he value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
C:\Users\dessy\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: Future
Warning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set t
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C:\Users\dessy\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: Future
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C:\Users\dessy\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: Future
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he value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```
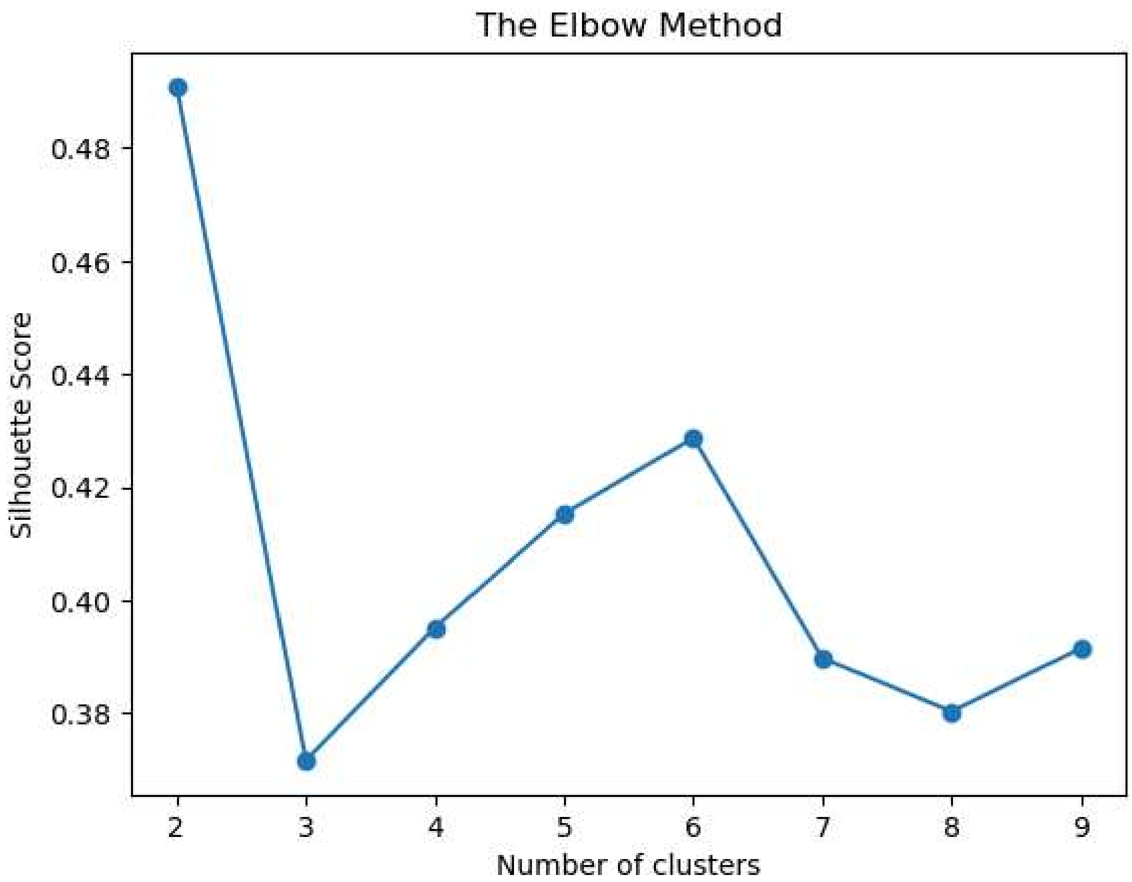
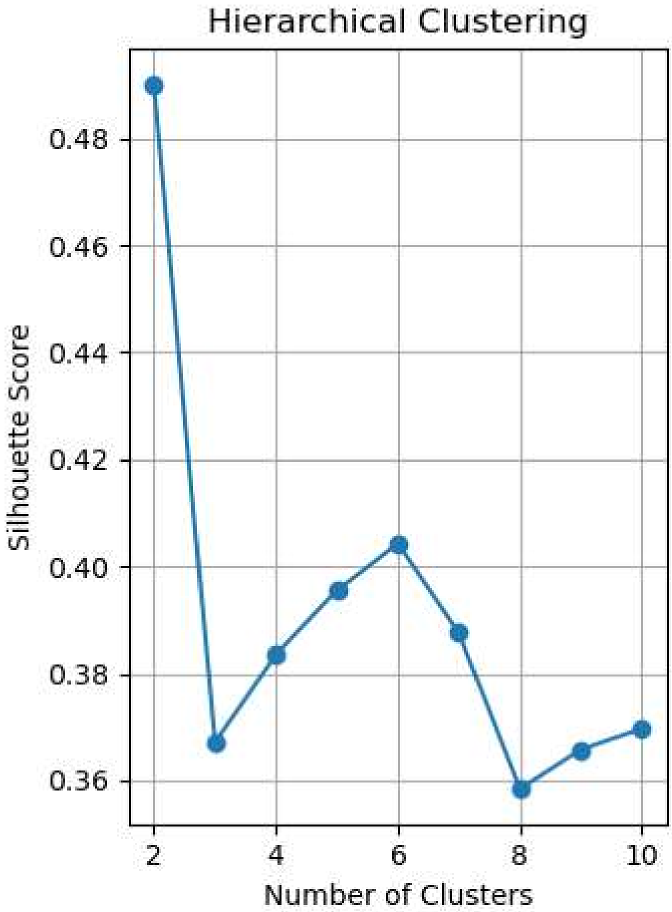



HIERARCHICAL METHOD OF CLUSTERING

In [10]:

```
# Hierarchical clustering
from sklearn.cluster import KMeans, AgglomerativeClustering
agg_scores = []
for k in range(2, 11):
    agg=AgglomerativeClustering(n_clusters=k)
    agg.fit(x)
    agg_scores.append(silhouette_score(x, agg.labels_))

# Plot Silhouette Scores for Hierarchical Clustering
plt.subplot(1, 2, 2)
plt.plot(range(2, 11), agg_scores, marker='o', linestyle='-')
plt.xlabel('Number of Clusters')
plt.ylabel('Silhouette Score')
plt.title('Hierarchical Clustering')
plt.grid(True)

# Show the plot
plt.tight_layout()
plt.show()
```



############# WRITE YOUR REPORT IN THIS CELL (IF APPLICABLE)################### This report analyzes the Adult dataset using K-Means and Hierarchical clustering algorithms to determine optimum clustering numbers and provide insights into the clustering results. The dataset was preprocessed to handle missing values and encode categorical variables, with missing values imputed using a common strategy, and numerical features scaled using standard scaling. We used K-Means and Hierarchical clustering algorithms for the preprocessed dataset. We evaluated the silhouette score for each algorithm across a range of cluster numbers (2 to 10). The silhouette score indicates how similar an object is to its own cluster compared to other clusters. A higher silhouette score indicates more defined clusters. OUTPUT K-Means Clustering: The silhouette score peaked at 3 clusters, indicating well-defined clusters with instances closer to their own centroids than others. Similarly,The silhouette score for Hierarchical Clustering peaked at a cluster number of 3, indicating that the dataset is best represented by three clusters. Optimum number of clusters: Both K-Means and

Hierarchical clustering algorithms determined that 3 is the optimum cluster. This implies that the dataset has distinct groupings or patterns that can be effectively captured by categorising it into three clusters.

Task 4.2: Apply the PCA method to the dataset and extract the first two principal components (n_components=2). Plot the scatter plot of the dataset's first two components for the two classes of the income column (5%).

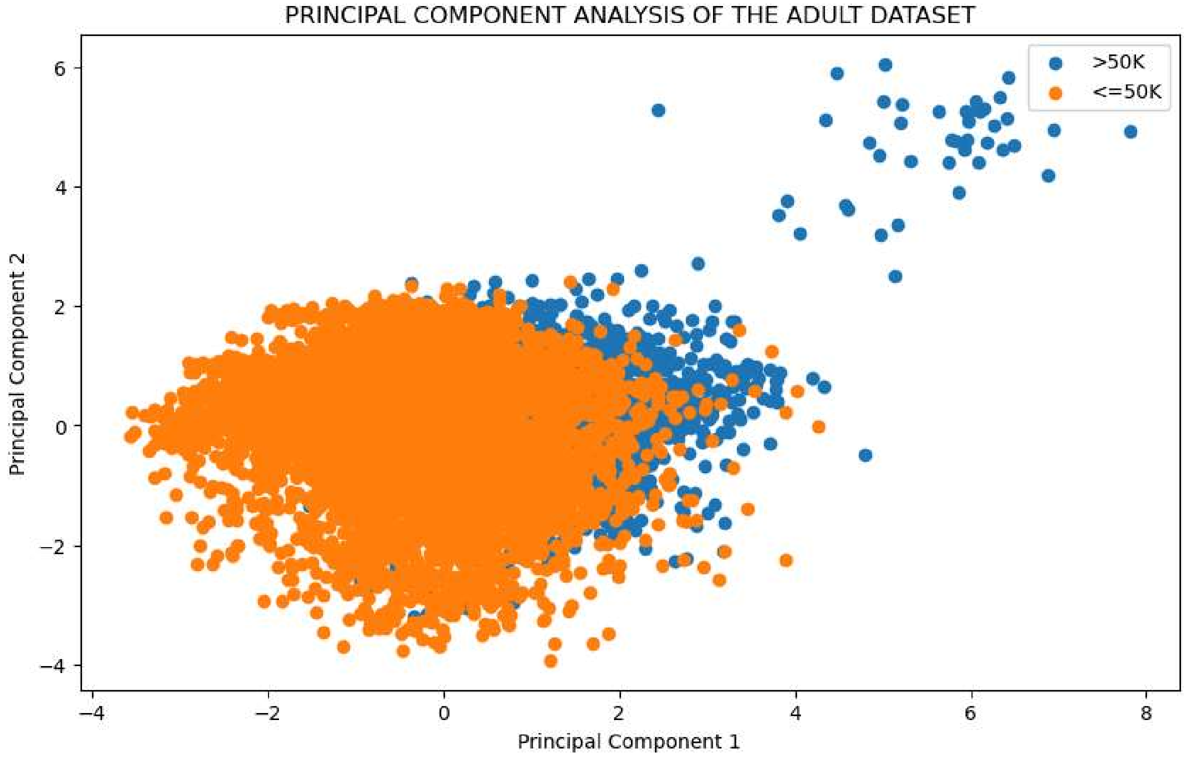
NOTE 1: You should comment on your code wherever necessary and briefly explain what the code is doing.

NOTE 2: You need to encode the categorical columns, normalise the dataset, and remove the income column before applying the PCA method.

HINT: See the examples in the last three slides in Lecture #4 or the Lecture #4 exercise notebook

In [15]:

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

# IMPORT THE ADULT DATASET
data4 = pd.read_csv('adult_WS4.csv')

# PREPROCESSING
#THE DATASET BY DROPPING NULL VALUES
data4.dropna(inplace=True)

# ENCODING THE CATEGORICAL COLUMNS
df = pd.get_dummies(data4, columns=['workclass', 'education', 'marital-status', 'oc

# NORMALIZING THE NUMERICAL COLUMNS
SS = StandardScaler()
numerical_columns = ['age', 'fnlwgt', 'education-num', 'capital-gain', 'capital-los
df[numerical_columns] = SS.fit_transform(df[numerical_columns])

# Apply PCA
pca = PCA(n_components=2)
principal_components = pca.fit_transform(df.drop(columns=['income']))

#Plot Scatter Plot
plt.figure(figsize=(10, 6))
for label in df['income'].unique():
    plt.scatter(principal_components[df['income']==label, 0], principal_components[
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('PRINCIPAL COMPONENT ANALYSIS OF THE ADULT DATASET')
plt.legend()
plt.show()
```



In [ ]:
```
pca
```

############# WRITE YOUR REPORT IN THIS CELL (IF APPLICABLE)#################### INSIGHT: The scatter plot displays the distribution of the dataset's first two principal components, color-coded by income class. The two income classes (<=50K and >=50K) are visually distinct, indicating that the first two principal components account for significant variance in the dataset and separate the income groups. However, there is some overlap between the two classes, indicating that more components may be required for better separation.