Practical No: 10

Distance methods with Prediction | K – Means Clustering.

10 A) Aim: Implement the different Distance methods (Euclidean) with Prediction, Test Score and Confusion Matrix.

Code and Output:

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
#Load the dataset
df = pd.read_csv("../dataset/Iris.csv")

#quick look into the data
print(df.head(5))
print("\n")
#Separate data and label
x = df.drop(['Species'], axis=1)
y = df['Species']
#Prepare data for classification process
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=0)
#Create a model , p = 2 => Euclidean Distance:
knn = KNeighborsClassifier(n_neighbors = 6, p = 2, metric='minkowski')
#Train the model
knn.fit(x_train, y_train)
# Calculate the accuracy of the model
print("Accuracy of Euclidean Distance model:-")
print(knn.score(x_test, y_test))
y_pred = knn.predict(x_test)
#confusion matrix
```

```
from sklearn.metrics import  confusion_matrix
cm=np.array(confusion_matrix(y_test,y_pred))
print("-"*50)
print("Confusion matrix:-")
print(cm)
print("\n")
#Create a model , p = 1 => Manhattan Distance
knn = KNeighborsClassifier(n_neighbors = 6, p = 1, metric='minkowski')
#Train the model
knn.fit(x_train, y_train)
# Calculate the accuracy of the model
print("-"*50)
print("Accuracy of Manhattan Distance model:-")
print(knn.score(x_test, y_test))
y_pred = knn.predict(x_test)
#confusion matrix
from sklearn.metrics import  confusion_matrix
cm=np.array(confusion_matrix(y_test,y_pred))
print("-"*50)
print("Confusion matrix:-")
print(cm)
print("\n")
#Create a model ,p = ∞, Chebychev Distance
#let ∞ = 10000
knn = KNeighborsClassifier(n_neighbors = 6, p = 10000, metric='minkowski')

#Train the model
knn.fit(x_train, y_train)
# Calculate the accuracy of the model
print("-"*50)
print("Accuracy of Chebychev Distance model:-")
print(knn.score(x_test, y_test))
y_pred = knn.predict(x_test)
#confusion matrix
```

```
from sklearn.metrics import  confusion_matrix
cm=np.array(confusion_matrix(y_test,y_pred))
print("-"*50)
print("Confusion matrix:-")
print(cm)
print("\n")
```

```
   SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm      Species
0            5.1           3.5            1.4           0.2  Iris-setosa
1            4.9           3.0            1.4           0.2  Iris-setosa
2            4.7           3.2            1.3           0.2  Iris-setosa
3            4.6           3.1            1.5           0.2  Iris-setosa
4            5.0           3.6            1.4           0.2  Iris-setosa

Accuracy of Euclidean Distance model:-
0.9777777777777777
--------------------------------------------------
Confusion matrix:-
[[16  0  0]
 [ 0 17  1]
 [ 0  0 11]]
```

```
--------------------------------------------------
Accuracy of Manhattan Distance model:-
0.9555555555555556
--------------------------------------------------
Confusion matrix:-
[[16  0  0]
 [ 0 17  1]
 [ 0  1 10]]
```

```
--------------------------------------------------
Accuracy of Chebychev Distance model:-
0.8
--------------------------------------------------
Confusion matrix:-
[[16  0  0]
 [ 0 18  0]
 [ 0  9  2]]
```

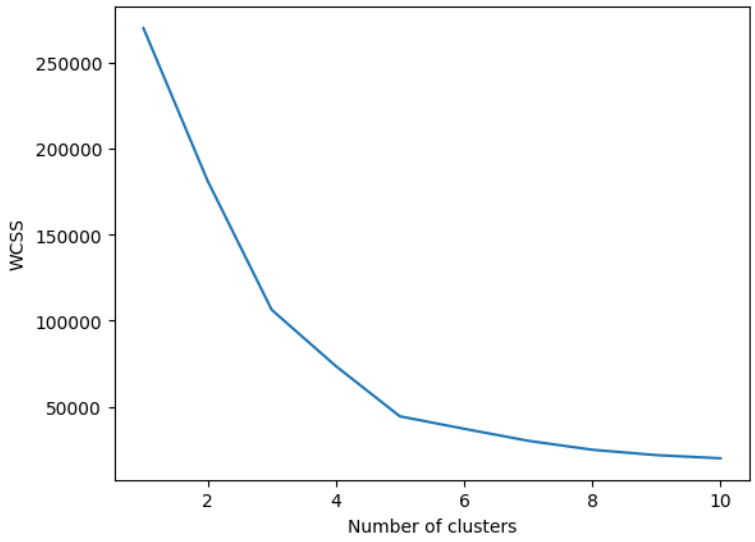
10B: AIM: Implement the classification model using K-means clustering with Prediction, Test score and Confusion Matrix.

Description:

K-Means Clustering is an unsupervised learning algorithm that is used to solve the clustering problems in machine learning or data science. In this topic, we will learn what is K-means clustering algorithm, how the algorithm works, along with the Python implementation of k-means clustering.

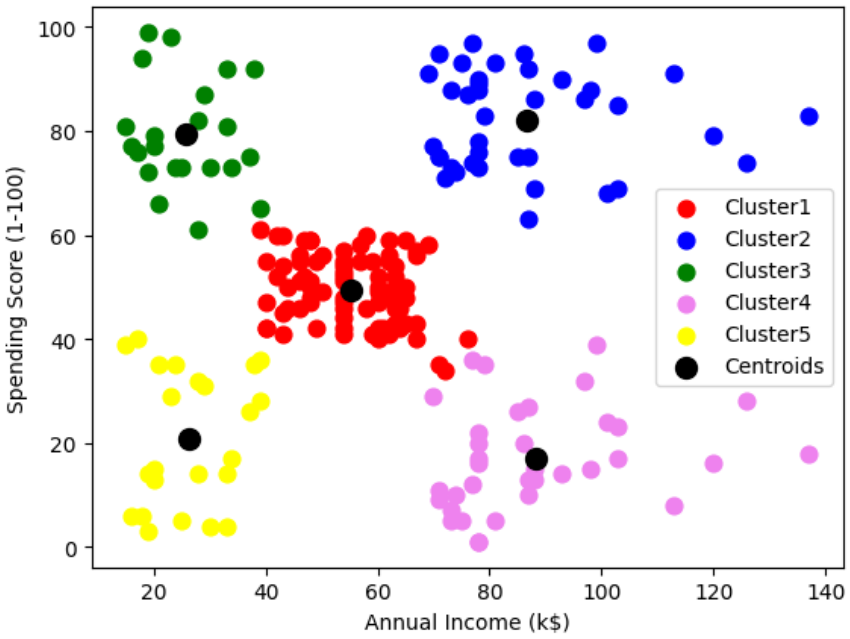
Code and output:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import sklearn
#Import the dataset and slice the important features
dataset = pd.read_csv('Mall_Customers.csv')
X = dataset.iloc[:, [3,4]].values
#Find the optimal k value for clustering the data.
from sklearn.cluster import KMeans
wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters=i, init='k-means++',random_state=42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.plot(range(1,11),wcss)
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



#The point at which the elbow shape is created is 5.

```
kmeans = KMeans(n_clusters=5,init="k-means++",random_state=42)
y_kmeans = kmeans.fit_predict(X)

plt.scatter(X[y_kmeans == 0,0], X[y_kmeans == 0,1], s = 60, c = 'red', label = 'Cluster1')
plt.scatter(X[y_kmeans == 1,0], X[y_kmeans == 1,1], s = 60, c = 'blue', label = 'Cluster2')
plt.scatter(X[y_kmeans == 2,0], X[y_kmeans == 2,1], s = 60, c = 'green', label = 'Cluster3')
plt.scatter(X[y_kmeans == 3,0], X[y_kmeans == 3,1], s = 60, c = 'violet', label = 'Cluster4')
plt.scatter(X[y_kmeans == 4,0], X[y_kmeans == 4,1], s = 60, c = 'yellow', label = 'Cluster5')
plt.scatter(kmeans.cluster_centers_[:,0],
kmeans.cluster_centers_[:,1],s=100,c='black',label='Centroids')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100')
plt.legend()
plt.show()
```



Learning:

This code snippet demonstrates the implementation of K-Means clustering on a Mall Customers dataset using Python's scikit-learn library. It first imports necessary modules and reads the dataset, selecting two key features – Annual Income and Spending Score. The optimal number of clusters (k) is determined by plotting the Within-Cluster-Sum-of-Squares (WCSS) against different k values. In this case, the elbow method suggests k=5. The K-Means algorithm is then applied, and the clusters are visualized with a scatter plot, showcasing distinct clusters based on customers' Annual Income and Spending Score. The black points represent cluster centroids, providing insights into customer segmentation for targeted business strategies.