In [1]: import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns import warnings warnings.filterwarnings("ignore") df=pd.read csv("Mall Customers.csv") df.head() In [3]: CustomerID Out[3]: Genre Age Annual Income (k\$) Spending Score (1-100) 0 Male 19 15 39 1 1 Male 21 15 81 2 20 3 Female 16 6 3 4 Female 23 16 77 4 17 40 5 Female 31 In [4]: df.shape (200, 5)Out[4]: In [5]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 200 entries, 0 to 199 Data columns (total 5 columns): # Column Non-Null Count Dtype CustomerID 200 non-null 0 int64 1 Genre 200 non-null object Age 200 non-null int64 Annual Income (k\$) int64 200 non-null 4 Spending Score (1-100) 200 non-null int64 dtypes: int64(4), object(1) memory usage: 7.9+ KB In [6]: df.describe() Out[6]: Age Annual Income (k\$) Spending Score (1-100) CustomerID 200.000000 200.000000 200.000000 200.000000 count 100.500000 38.850000 60.560000 50.200000 mean 57.879185 13.969007 26.264721 25.823522 std min 1.000000 18.000000 15.000000 1.000000 25% 50.750000 28.750000 41.500000 34.750000 **50%** 100.500000 36.000000 61.500000 50.000000 **75**% 150.250000 49.000000 78.000000 73.000000 200.000000 70.000000 137.000000 99.000000 max sns.pairplot(df) In [7]: <seaborn.axisgrid.PairGrid at 0x1fd30cb6ac0> Out[7]: 200 150 CustomerID 100 50 70 60 50 Age 30 20 140 120 Annual Income (k\$) 100 80 60 40 20 100 Spending Score (1-100) 80 60 40 20 100 50 100 50 100 150 25 75 0 CustomerID Age Annual Income (k\$) Spending Score (1-100) x=df.iloc[:,[3,4]]In [8]: Annual Income (k\$) Spending Score (1-100) Out[8]: 0 15 39 15 81 2 16 6 3 16 77 4 17 40 195 120 79 196 126 28 197 126 74 198 137 18 199 137 83 200 rows × 2 columns In [9]: **from** sklearn.cluster **import** KMeans wcss = []for i in range(1,11): Kmeans=KMeans(n clusters=i,random state=1) wcss.append (Kmeans.inertia) In [10]: wcss [269981.28, Out[10]: 181363.59595959593, 106348.37306211118, 73679.78903948836, 44448.45544793371, 37233.81451071001, 30566.45113025186, 25005.55037243283, 21996.523372372307, 19746.911957660894] In [11]: plt.plot(range(1,11),wcss,"o--") plt.title("The Elbow Method") plt.grid() plt.show() The Elbow Method 250000 200000 150000 100000 50000 Kmeans=KMeans(n_clusters=5, random_state=1) In [12]: ylabel=Kmeans.fit_predict(x) In [13]: Out[13]: Genre Age Annual Income (k\$) Spending Score (1-100) CustomerID 0 1 Male 19 15 39 21 15 81 Male 2 3 Female 20 16 6 3 23 16 77 Female 4 5 Female 31 17 40 195 196 Female 35 120 79 196 197 Female 45 126 28 197 198 32 126 74 Male 198 199 Male 32 137 18 199 200 Male 30 137 83 200 rows × 5 columns df["yKmeans"]=ylabel In [14]: df Out[14]: Genre Age Annual Income (k\$) Spending Score (1-100) yKmeans CustomerID 0 Male 19 15 39 4 1 Male 21 15 81 0 2 3 Female 16 6 4 3 23 16 77 0 4 Female 31 17 4 5 Female 195 196 Female 35 120 79 3 196 28 197 Female 45 126 197 198 126 74 3 Male 32 198 199 1 Male 32 137 199 200 137 83 3 Male 30 200 rows × 6 columns Kmeans.cluster_centers_ In [15]: array([[25.72727273, 79.36363636], Out[15]: , 17.11428571], [88.2 [55.2962963 , 49.51851852], [86.53846154, 82.12820513], [26.30434783, 20.91304348]]) df["yKmeans"].value_counts() In [16]: 81 Out[16]: 39 1 35 23 4 22 Name: yKmeans, dtype: int64 In [17]: y=df.iloc[:,-1] У 4 Out[17]: 0 2 4 3 0 4 4 195 3 196 1 197 3 198 1 199 3 Name: yKmeans, Length: 200, dtype: int32 In [18]: from sklearn.model_selection import train_test_split xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=1) In [19]: from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB from sklearn.neighbors import KNeighborsClassifier from sklearn.linear_model import LogisticRegression from sklearn.tree import DecisionTreeClassifier from sklearn.metrics import classification_report In [20]: def indmodel(model): model.fit(xtrain,ytrain) ypred=model.predict(xtest) train=model.score(xtrain,ytrain) test=model.score(xtest,ytest) print(f' Training Accuracy : {train} \n Testing Accuracy : {test} \n') print(classification_report(ytest,ypred)) return model In [21]: | gnb=indmodel(GaussianNB()) Training Accuracy: 0.9785/14285/14285 Testing Accuracy : 0.9833333333333333 precision recall f1-score support 1.00 1.00 1.00 1.00 0.89 1.00 1.00 0.98 1.00 0.94 0 1.00 8 1 1.00 11 0.95 2 21 3 1.00 11 1.00 4 9 0.98 60 accuracy 0.99 0.98 macro avg 0.98 60 0.98 weighted avg 0.98 0.98 60 In [22]: knn=indmodel(KNeighborsClassifier(n_neighbors=5)) Training Accuracy: 0.9714285714285714 precision recall f1-score support 1.00 1.00 1.00 1.00 0 1.00 8 1.00 11 0.98 2 0.95 1.00 21 1.00 0.94 1.00 3 1.00 11 0.89 1.00 9 0.98 60 accuracy 0.98 0.99 0.98 60 macro avg weighted avg 0.98 0.98 0.98 60 In [23]: logreg=indmodel(LogisticRegression()) Training Accuracy: 0.9928571428571429 Testing Accuracy: 0.95 precision recall f1-score support 0.93 0.95 0.93 1.00 0.94 0.88 0.91 1.00 8 1 1.00 1.00 11 0.88 21 3 1.00 11 0.89 1.00 9 accuracy 0.95 60 0.97 0.93 0.95 60 macro avg 0.96 weighted avg 0.95 0.95 60 In [24]: cladt=indmodel(DecisionTreeClassifier(random state=2)) Training Accuracy: 1.0 Testing Accuracy : 0.966666666666667 precision recall f1-score support 0.88 0.88 0.93 1.00 1.00 1.00 0.95 1.00 8 1 1.00 11 2 0.91 21 1.00 1.00 1.00 1.00 0.89 0.94 3 11 9 0.97 60 accuracy macro avg 0.98 0.95 0.97 60 weighted avg 0.97 0.97 0.97 60 In []: