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") In [2]: df.head() In [3]: Out[3]: CustomerID Genre Age Annual Income (k\$) Spending Score (1-100) 0 39 1 Male 19 15 1 Male 21 15 81 2 20 16 6 3 Female 3 23 77 4 Female 16 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 int64 0 CustomerID 200 non-null Genre 1 200 non-null object 2 Age 200 non-null int64 200 non-null int64 Annual Income (k\$) 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]: CustomerID Age Annual Income (k\$) Spending Score (1-100) 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 df.isna().sum() In [10]: CustomerID Out[10]: Genre Age 0 Annual Income (k\$) 0 Spending Score (1-100) dtype: int64 In [9]: sns.pairplot(df) <seaborn.axisgrid.PairGrid at 0x1ed83015cd0> Out[9]: 200 150 CustomerID 100 50 0 70 60 50 30 20 140 120 Annual Income (k\$) 100 80 60 40 20 100 Spending Score (1-100) 80 60 20 100 150 20 100 50 75 200 50 25 CustomerID Annual Income (k\$) Spending Score (1-100) Age x=df.iloc[:,[3,4]]Out[12]: Annual Income (k\$) Spending Score (1-100) 0 15 39 15 81 2 16 6 3 77 16 4 17 40 195 120 79 196 126 28 197 126 74 198 137 18 137 199 83 200 rows × 2 columns In [13]: **from** sklearn.preprocessing **import** StandardScaler sc=StandardScaler() x=sc.fit transform(x) In [15]: from scipy.cluster import hierarchy as hi lk=hi.linkage(x,method="ward") ddg=hi.dendrogram(lk) 16 14 12 10 8 6 4 2 from sklearn.cluster import AgglomerativeClustering In [16]: hc=AgglomerativeClustering(n_clusters=5) ylabel=hc.fit_predict(x) In [17]: df["hcy"]=ylabel df["hcy"].value_counts() In [18]: 85 Out[18]: 39 0 32 4 23 3 21 Name: hcy, dtype: int64 df[df.hcy==0].describe() In [19]: Out[19]: CustomerID Age Annual Income (k\$) Spending Score (1-100) hcy 32.0 count 32.000000 32.000000 32.000000 32.000000 166.250000 41.000000 89.406250 15.593750 0.0 mean std 21.005376 11.036596 16.612975 8.936548 0.0 min 129.000000 19.000000 71.000000 1.000000 0.0 25% 150.500000 34.000000 78.000000 9.750000 0.0 **50**% 168.000000 41.500000 86.500000 15.000000 0.0 **75**% 183.500000 47.000000 98.250000 20.500000 0.0 max 199.000000 59.000000 137.000000 39.000000 0.0 df[df.hcy==3].describe() In [20]: Annual Income (k\$) Spending Score (1-100) Out[20]: CustomerID hcy Age 21.000000 21.000000 21.000000 21.000000 21.0 count mean 22.000000 25.333333 25.095238 80.047619 3.0 12.409674 5.378971 7.133756 10.249274 0.0 std 2.000000 18.000000 15.000000 61.000000 3.0 min 25% 12.000000 21.000000 19.000000 73.000000 3.0 **50**% 22.000000 23.000000 24.000000 77.000000 3.0 **75**% 32.000000 30.000000 30.000000 87.000000 3.0 42.000000 35.000000 38.000000 99.000000 max 3.0 df.groupby("hcy")[["Annual Income (k\$)", "Spending Score (1-100)"]].mean() In [23]: Out[23]: Annual Income (k\$) Spending Score (1-100) hcy 0 89.406250 15.593750 1 86.538462 82.128205 2 55.811765 49.129412 3 25.095238 80.047619 4 26.304348 20.913043 In [24]: X array([[-1.73899919, -0.43480148],Out[24]: [-1.73899919, 1.19570407], [-1.70082976, -1.71591298],[-1.70082976, 1.04041783],[-1.66266033, -0.39597992],[-1.66266033, 1.00159627],[-1.62449091, -1.71591298],[-1.62449091, 1.70038436],[-1.58632148, -1.83237767],[-1.58632148, 0.84631002],[-1.58632148, -1.4053405],[-1.58632148, 1.89449216],[-1.54815205, -1.36651894],[-1.54815205, 1.04041783],[-1.54815205, -1.44416206],[-1.54815205, 1.11806095],[-1.50998262, -0.59008772],[-1.50998262, 0.61338066],[-1.43364376, -0.82301709],[-1.43364376, 1.8556706],[-1.39547433, -0.59008772],[-1.39547433, 0.88513158],[-1.3573049 , -1.75473454], [-1.3573049, 0.88513158],[-1.24279661, -1.4053405],[-1.24279661, 1.23452563],[-1.24279661, -0.7065524],[-1.24279661, 0.41927286],[-1.20462718, -0.74537397],[-1.20462718, 1.42863343], [-1.16645776, -1.7935561],[-1.16645776, 0.88513158], [-1.05194947, -1.7935561],[-1.05194947, 1.62274124], [-1.05194947, -1.4053405],[-1.05194947, 1.19570407],[-1.01378004, -1.28887582],[-1.01378004, 0.88513158],[-0.89927175, -0.93948177],[-0.89927175, 0.96277471],[-0.86110232, -0.59008772],[-0.86110232, 1.62274124], [-0.82293289, -0.55126616],[-0.82293289, 0.41927286],[-0.82293289, -0.86183865],[-0.82293289, 0.5745591],[-0.78476346, 0.18634349],[-0.78476346, -0.12422899],[-0.78476346, -0.3183368],[-0.78476346, -0.3183368],[-0.70842461, 0.06987881],[-0.70842461, 0.38045129],[-0.67025518, 0.14752193],[-0.67025518, 0.38045129],[-0.67025518, -0.20187212],[-0.67025518, -0.35715836],[-0.63208575, -0.00776431],[-0.63208575, -0.16305055],[-0.55574689, 0.03105725],[-0.55574689, -0.16305055],[-0.55574689, 0.22516505],[-0.55574689, 0.18634349],[-0.51757746, 0.06987881],[-0.51757746, 0.34162973],[-0.47940803, 0.03105725],[-0.47940803, 0.34162973],[-0.47940803, -0.00776431],[-0.47940803, -0.08540743],[-0.47940803, 0.34162973],[-0.47940803, -0.12422899],[-0.4412386, 0.18634349],[-0.4412386, -0.3183368],[-0.40306917, -0.04658587],[-0.40306917, 0.22516505],[-0.25039146, -0.12422899],[-0.25039146, 0.14752193],[-0.25039146, 0.10870037],[-0.25039146, -0.08540743],[-0.25039146, 0.06987881],[-0.25039146, -0.3183368],[-0.25039146, 0.03105725],[-0.25039146, 0.18634349],[-0.25039146, -0.35715836],[-0.25039146, -0.24069368],[-0.25039146, 0.26398661],[-0.25039146, -0.16305055],[-0.13588317, 0.30280817],[-0.13588317, 0.18634349],[-0.09771374, 0.38045129],[-0.09771374, -0.16305055],[-0.05954431, 0.18634349],[-0.05954431, -0.35715836],[-0.02137488, -0.04658587],[-0.02137488, -0.39597992],[-0.02137488, -0.3183368],[-0.02137488, 0.06987881],[-0.02137488, -0.12422899],[-0.02137488, -0.00776431],[0.01679455, -0.3183368], [0.01679455, -0.04658587], [0.05496398, -0.35715836],[0.05496398, -0.08540743], [0.05496398, 0.34162973], [0.05496398, 0.18634349], [0.05496398, 0.22516505], [0.05496398, -0.3183368], [0.09313341, -0.00776431], [0.09313341, -0.16305055],[0.09313341, -0.27951524],[0.09313341, -0.08540743],[0.09313341, 0.06987881], [0.09313341, 0.14752193], [0.13130284, -0.3183368], [0.13130284, -0.16305055], [0.16947227, -0.08540743], [0.16947227, -0.00776431], [0.16947227, -0.27951524], [0.16947227, 0.34162973], [0.24581112, -0.27951524],[0.24581112, 0.26398661], [0.24581112, 0.22516505], [0.24581112, -0.39597992],[0.32214998, 0.30280817], [0.32214998, 1.58391968], [0.36031941, -0.82301709],[0.36031941, 1.04041783], [0.39848884, -0.59008772],[0.39848884, 1.73920592], [0.39848884, -1.52180518],[0.39848884, 0.96277471], [0.39848884, -1.5994483],[0.39848884, 0.96277471], [0.43665827, -0.62890928],[0.43665827, 0.80748846], [0.4748277 , -1.75473454], [0.4748277 , 1.46745499], [0.4748277 , -1.67709142], [0.4748277 , 0.88513158], [0.51299713, -1.56062674],[0.51299713, 0.84631002], [0.55116656, -1.75473454], [0.55116656, 1.6615628], [0.58933599, -0.39597992], [0.58933599, 1.42863343], [0.62750542, -1.48298362], [0.62750542, 1.81684904], [0.62750542, -0.55126616], [0.62750542, 0.92395314], [0.66567484, -1.09476801], [0.66567484, 1.54509812], [0.66567484, -1.28887582], [0.66567484, 1.46745499], [0.66567484, -1.17241113], [0.66567484, 1.00159627], [0.66567484, -1.32769738], [0.66567484, 1.50627656], [0.66567484, -1.91002079],[0.66567484, 1.07923939], [0.66567484, -1.91002079],[0.66567484, 0.88513158], [0.70384427, -0.59008772],[0.70384427, 1.27334719], [0.78018313, -1.75473454], [0.78018313, 1.6615628], [0.93286085, -0.93948177], [0.93286085, 0.96277471], [0.97103028, -1.17241113],[0.97103028, 1.73920592], [1.00919971, -0.90066021], [1.00919971, 0.49691598], [1.00919971, -1.44416206], [1.00919971, 0.96277471], [1.00919971, -1.56062674], [1.00919971, 1.62274124], [1.04736914, -1.44416206], [1.04736914, 1.38981187], [1.04736914, -1.36651894], [1.04736914, 0.72984534], [1.23821628, -1.4053405], [1.23821628, 1.54509812], [1.390894 , -0.7065524], [1.390894 , 1.38981187], [1.42906343, -1.36651894], [1.42906343, 1.46745499], [1.46723286, -0.43480148], [1.46723286, 1.81684904], [1.54357172, -1.01712489], [1.54357172, 0.69102378], [1.61991057, -1.28887582], [1.61991057, 1.35099031], [1.61991057, -1.05594645], [1.61991057, 0.72984534], [2.00160487, -1.63826986], [2.00160487, 1.58391968], [2.26879087, -1.32769738], [2.26879087, 1.11806095], [2.49780745, -0.86183865], [2.49780745, 0.92395314], [2.91767117, -1.25005425], [2.91767117, 1.27334719]]) In [34]: plt.scatter(x[ylabel==0,0],x[ylabel==0,1],s=100,c="red",label="Cluster1") plt.scatter(x[ylabel==1,0],x[ylabel==1,1],s=100,c="green",label="Cluster2") plt.scatter(x[ylabel==2,0],x[ylabel==2,1],s=100,c="blue",label="Cluster3") $\verb|plt.scatter(x[ylabel==3,0],x[ylabel==3,1],s=100,c="yellow",label="Cluster4")|\\$ plt.scatter(x[ylabel==4,0],x[ylabel==4,1],s=100,c="cyan",label="Cluster5") plt.xlabel("Annual Income") plt.xlabel("Spending Score") plt.xlabel("Clustering of Customer") plt.legend() plt.show() 2.0 1.5 1.0 Cluster1 0.5 Cluster2 Cluster3 0.0 Cluster4 -0.5Cluster5 -1.0-1.5-2.00 -1Clustering of Customer y=df.iloc[:,-1] In [28]: У 4 Out[28]: 3 2 4 3 3 4 4 195 1 196 0 197 1 198 0 199 1 Name: hcy, Length: 200, dtype: int64 In [29]: 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 [30]: from sklearn.tree import DecisionTreeClassifier from sklearn.metrics import classification_report def indmodel(model): In [31]: 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 [32]: cladt=indmodel(DecisionTreeClassifier(random_state=2)) Training Accuracy: 1.0 Testing Accuracy: 0.95 precision recall f1-score support 0 0.90 0.90 0.90 10 1 0.92 1.00 0.96 11 2 1.00 0.95 0.98 22 3 1.00 0.88 0.93 8 0.90 9 1.00 0.95 0.95 60 accuracy 0.94 0.95 0.95 0.95 0.94 0.95 60 macro avg 60 weighted avg In []: