Machine Learning (Assignment # 6)

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link: https://github.com/SindhuRajanala/ML_Assignment_6

1.(Provide only mathematical solutions for this question) Six points with the following attributes are given, calculate and find out clustering representations and dendrogram using Single, complete, and average link proximity function in hierarchical clustering technique.

Given:

point	x coordinate	y coordinate
p1	0.4005	0.5306
p2	0.2148	0.3854
p3	0.3457	0.3156
p4	0.2652	0.1875
p5	0.0789	0.4139
p6	0.4548	0.3022

Table : X-Y coordinates of six points.

	p1	p2	p3	p4	p5	p6
p1	0.0000	0.2357	0.2218	0.3688	0.3421	0.2347
p2	0.2357	0.0000	0.1483	0.2042	0.1388	0.2540
p3	0.2218	0.1483	0.0000	0.1513	0.2843	0.1100
p4	0.3688	0.2042	0.1513	0.0000	0.2932	0.2216
p5	0.3421	0.1388	0.2843	0.2932	0.0000	0.3921
p6	0.2347	0.2540	0.1100	0.2216	0.3921	0.0000

Table : Distance Matrix for Six Points

Single Linkage: **the distance between two clusters as the minimum distance between any single data point in the first cluster and any single data point in the second cluster**.
We see the points P3, P6 has the least distance “0.1100”. So, we will first merge those into a cluster

Re-compute the distance matrix after forming a cluster

Update the distance between the cluster (P3, P6) to P1= Min (dist(P3, P6), P1)) -> Min(dist(P3, P1),dist(P6,P1))

	P1	P2	P3, P6	P4	P5
P1	**0**				
P2	0.2357	**0**			
P3, P6	0.2218	0.1483	**0**		
P4	0.3688	0.2042	0.1513	**0**	
P5	0.3421	0.1388	0.2843	0.2932	**0**

Merging – P2 and P5 – (P2, P5)

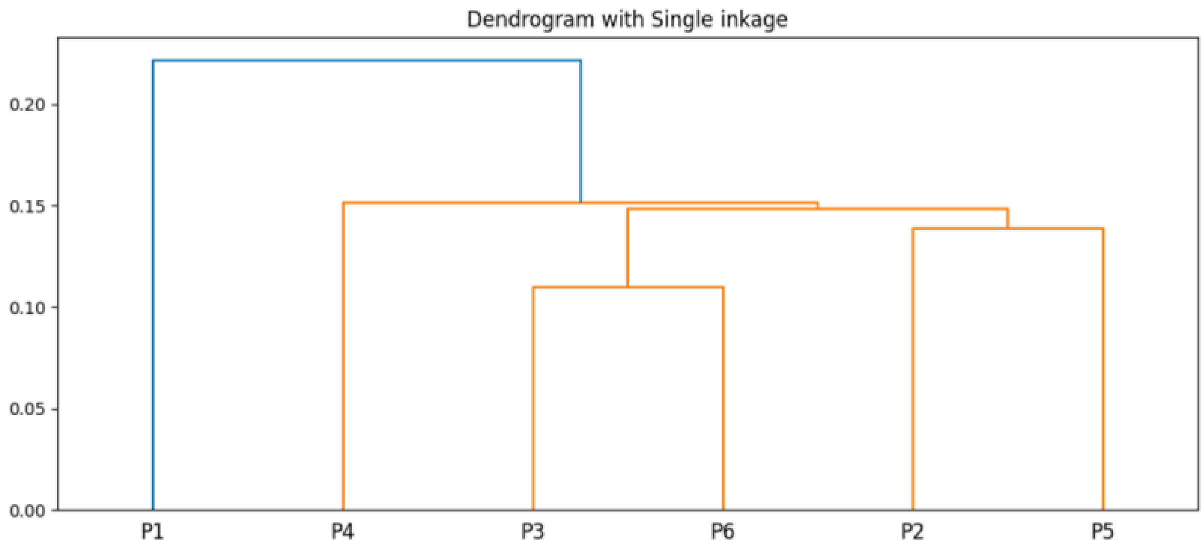
	P1	P2, P5	P3, P6	P4
P1	**0**			
P2, P5	0.2357	**0**		
P3, P6	0.2218	0.1483	**0**	
P4	0.3688	0.2042	0.1513	**0**

Merging – (P2, P5) and (P3, P6) – (P2, P5, P3, P6)

	P1	P2, P5, P3, P6	P4
P1	**0**		
P2, P5, P3, P6	0.2357	**0**	
P4	0.2218	0.1513	**0**

Merging – P1 and (P2, P5, P3, P6, P4)

	P1	P2, P5, P3, P6, P4
P1	**0**	
P2, P5, P3, P6, P4	0.2218	**0**



In Complete Linkage, the distance between two clusters is the maximum distance between members of the two clusters.
We see the points P3, P6 has the least distance “0.1100”. So, we will first merge those into a cluster.

Recompute the distance matrix after forming a cluster

Update the distance between the cluster (P3, P6) to P1= Max (distance(P3, P6), P1)) -> Max(distance(P3,P1),distance(P6,P1)), Applying same logic over the distance matrix will result as below.

	P1	P2	P3, P6	P4	P5
P1	**0**				
P2	0.2357	**0**			
P3, P6	0.2347	0.2540	**0**		
P4	0.3688	0.2042	0.2216	**0**	
P5	0.3421	0.1388	0.3921	0.2932	**0**

Merging – P2 and P5 – (P2, P5)

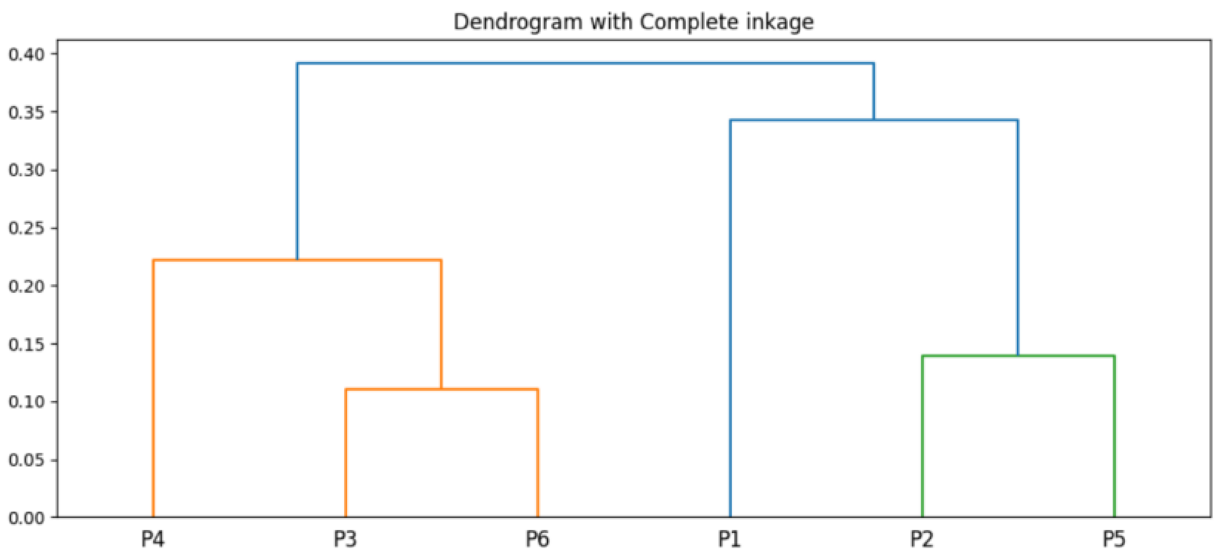
	P1	P2, P5	P3, P6	P4
P1	**0**			
P2, P5	0.3421	**0**		
P3, P6	0.2347	0.3921	**0**	
P4	0.3688	0.2932	0.2216	**0**

Merging – P4 and P3, P6 – (P4, P3, P6)

	P1	P2, P5	P4, P3, P6
P1	**0**		
P2, P5	0.3421	**0**	
P4, P3, P6	0.3688	0.3921	**0**

Merging P1 and (P2, P5) – (P1, P2, P5)

	P1, P2, P5	P4, P3, P6
P1, P2, P5	**0**	
P4, P3, P6	0.3921	**0**



In Average Linkage, the distance between two clusters is the average of all distances between members of the two clusters.

We see the points P3, P6 has the least distance "0.1100". So, we will first merge those into a cluster.

Recompute the distance matrix after forming a cluster.

Update the distance between the cluster (P3, P6) to P1= Avg (distance(P3, P6), P1)) -> Avg(distance(P3,P1),distance(P6,P1)), Applying same logic over the distance matrix will result as below.

	P1	P2	P3, P6	P4	P5
P1	**0**				
P2	0.2357	**0**			
P3, P6	0.2282	0.2011	**0**		
P4	0.3688	0.2042	0.1864	**0**	
P5	0.3421	0.1388	0.3382	0.2932	**0**

Merging – P2 and P5 – (P2, P5)

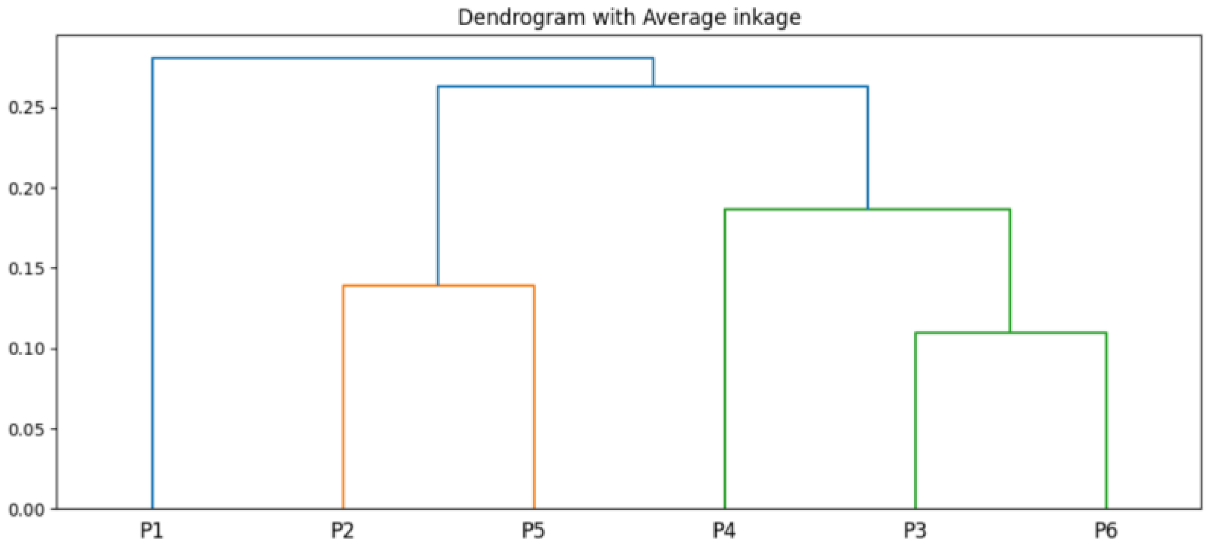
	P1	P2, P5	P3, P6	P5
P1	**0**			
P2, P5	0.2889	**0**		
P3, P6	0.2282	0.2696	**0**	
P5	0.3421	0.2487	0.1864	**0**

Merging – P4 and (P3, P6)

	P1	P2, P5	P4, P3, P6
P1	**0**		
P2, P5	0.2889	**0**	
P4, P3, P6	0.2851	0.2591	**0**

Merging – (P2, P5) and (P3, P4, P6)

	P1	P2, P5, P3, P6, P4
P1	**0**	
P2, P5, P3, P6, P4	0.2870	**0**



2) Use CC_GENERAL.csv given in the folder and apply:

a) Preprocess the data by removing the categorical column and filling the missing values.

```
import numpy as num
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn import preprocessing
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score
import seaborn as sns
sns.set(style="white", color_codes=True)
import warnings
warnings.filterwarnings("ignore")
df = pd.read_csv("CC GENERAL.csv")
df.info()
```

```python
import numpy as num
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn import preprocessing
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score
import seaborn as sns
sns.set(style="white", color_codes=True)
import warnings
warnings.filterwarnings("ignore")
```

```python
df = pd.read_csv("CC GENERAL.csv")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8950 entries, 0 to 8949
Data columns (total 18 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   CUST_ID                           8950 non-null   object 
 1   BALANCE                           8950 non-null   float64
 2   BALANCE_FREQUENCY                 8950 non-null   float64
 3   PURCHASES                         8950 non-null   float64
 4   ONEOFF_PURCHASES                  8950 non-null   float64
 5   INSTALLMENTS_PURCHASES            8950 non-null   float64
 6   CASH_ADVANCE                      8950 non-null   float64
 7   PURCHASES_FREQUENCY               8950 non-null   float64
 8   ONEOFF_PURCHASES_FREQUENCY        8950 non-null   float64
 9   PURCHASES_INSTALLMENTS_FREQUENCY  8950 non-null   float64
 10  CASH_ADVANCE_FREQUENCY            8950 non-null   float64
 11  CASH_ADVANCE_TRX                  8950 non-null   int64  
 12  PURCHASES_TRX                     8950 non-null   int64  
 13  CREDIT_LIMIT                      8949 non-null   float64
 14  PAYMENTS                          8950 non-null   float64
 15  MINIMUM_PAYMENTS                  8637 non-null   float64
 16  PRC_FULL_PAYMENT                  8950 non-null   float64
 17  TENURE                            8950 non-null   int64  
dtypes: float64(14), int64(3), object(1)
memory usage: 1.2+ MB
```

df.head()
dataframe = df.drop(["CUST_ID"],axis=1)
dataframe.head()
dataframe.isnull().any()

```
df.head()
```

]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FRE
0	C10001	40.900749	0.818182	95.40	0.00	95.4	0.000000	
1	C10002	3202.467416	0.909091	0.00	0.00	0.0	6442.945483	
2	C10003	2495.148862	1.000000	773.17	773.17	0.0	0.000000	
3	C10004	1666.670542	0.636364	1499.00	1499.00	0.0	205.788017	
4	C10005	817.714335	1.000000	16.00	16.00	0.0	0.000000	

```
dataframe = df.drop(["CUST_ID"],axis=1)
dataframe.head()
```

]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY
0	40.900749	0.818182	95.40	0.00	95.4	0.000000	0.166667
1	3202.467416	0.909091	0.00	0.00	0.0	6442.945483	0.000000
2	2495.148862	1.000000	773.17	773.17	0.0	0.000000	1.000000
3	1666.670542	0.636364	1499.00	1499.00	0.0	205.788017	0.083333
4	817.714335	1.000000	16.00	16.00	0.0	0.000000	0.083333

```
dataframe.isnull().any()
```

```
]: BALANCE                             False
BALANCE_FREQUENCY                   False
PURCHASES                           False
ONEOFF_PURCHASES                    False
INSTALLMENTS_PURCHASES              False
CASH_ADVANCE                        False
PURCHASES_FREQUENCY                 False
ONEOFF_PURCHASES_FREQUENCY          False
PURCHASES_INSTALLMENTS_FREQUENCY    False
CASH_ADVANCE_FREQUENCY              False
CASH_ADVANCE_TRX                    False
PURCHASES_TRX                       False
CREDIT_LIMIT                         True
PAYMENTS                            False
MINIMUM_PAYMENTS                     True
PRC_FULL_PAYMENT                    False
TENURE                              False
dtype: bool
```

dataframe.fillna(df.mean(), inplace=True)
dataframe. isnull().any()

```
dataframe.fillna(df.mean(), inplace=True)
dataframe.isnull().any()
```

```
]: BALANCE                             False
BALANCE_FREQUENCY                   False
PURCHASES                           False
ONEOFF_PURCHASES                    False
INSTALLMENTS_PURCHASES              False
CASH_ADVANCE                        False
PURCHASES_FREQUENCY                 False
ONEOFF_PURCHASES_FREQUENCY          False
PURCHASES_INSTALLMENTS_FREQUENCY    False
CASH_ADVANCE_FREQUENCY              False
CASH_ADVANCE_TRX                    False
PURCHASES_TRX                       False
CREDIT_LIMIT                        False
PAYMENTS                            False
MINIMUM_PAYMENTS                    False
PRC_FULL_PAYMENT                    False
TENURE                              False
dtype: bool
```

dataframe.corr().style.background_gradient(cmap="Reds")

```
dataframe.corr().style.background_gradient(cmap="Reds")
```

]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_A
BALANCE	1.000000	0.322412	0.181261	0.164350	0.126469	
BALANCE_FREQUENCY	0.322412	1.000000	0.133674	0.104323	0.124292	
PURCHASES	0.181261	0.133674	1.000000	0.916845	0.679896	
ONEOFF_PURCHASES	0.164350	0.104323	0.916845	1.000000	0.330622	
INSTALLMENTS_PURCHASES	0.126469	0.124292	0.679896	0.330622	1.000000	
CASH_ADVANCE	0.496692	0.099388	-0.051474	-0.031326	-0.064244	
PURCHASES_FREQUENCY	-0.077944	0.229715	0.393017	0.264937	0.442418	
ONEOFF_PURCHASES_FREQUENCY	0.073166	0.202415	0.498430	0.524891	0.214042	
PURCHASES_INSTALLMENTS_FREQUENCY	-0.063186	0.176079	0.315567	0.127729	0.511351	
CASH_ADVANCE_FREQUENCY	0.449218	0.191873	-0.120143	-0.082628	-0.132318	
CASH_ADVANCE_TRX	0.385152	0.141555	-0.067175	-0.046212	-0.073999	
PURCHASES_TRX	0.154338	0.189626	0.689561	0.545523	0.628108	
CREDIT_LIMIT	0.531267	0.095795	0.356959	0.319721	0.256496	
PAYMENTS	0.322802	0.065008	0.603264	0.567292	0.384084	
MINIMUM_PAYMENTS	0.394282	0.114249	0.093515	0.048597	0.131687	
PRC_FULL_PAYMENT	-0.318959	-0.095082	0.180379	0.132763	0.182569	
TENURE	0.072692	0.119776	0.086288	0.064150	0.086143	

Description:
To process the CC_GENERAL.csv data we declare df = pd.read_csv (“”) file then to get information we use info() and to display what are the columns available we use head() and to check null values we have used isnull().any().

b) Apply StandardScaler() and normalize() functions to scale and normalize raw input data.

x= dataframe.iloc[:,0:-1]
y= dataframe.iloc[:,-1]
scaler = preprocessing.StandardScaler()
scaler.fit(x)
X_scaled_array = scaler.transform(x)
X_scaled_dataframe = pd.DataFrame(X_scaled_array,columns = x.columns)
X_normalized = preprocessing.normalize(X_scaled_dataframe)
X_normalized = pd.DataFrame(X_normalized)

```
x= dataframe.iloc[:,0:-1]
y= dataframe.iloc[:,-1]
scaler = preprocessing.StandardScaler()
scaler.fit(x)
X_scaled_array = scaler.transform(x)
X_scaled_dataframe = pd.DataFrame(X_scaled_array,columns = x.columns )
```

```
X_normalized = preprocessing.normalize(X_scaled_dataframe)
X_normalized = pd.DataFrame(X_normalized)
```

Description:
We have used Standardscaler() and normalization() to the raw data.

c) Use PCA with K=2 to reduce the input dimensions to two features.

pca =PCA(n_components=2)
pc = pca.fit_transform(X_normalized)
pdf = pd.DataFrame(data = pc, columns = ['p1','p2'])
fdf = pd.concat([pdf,df[['TENURE']]],axis= 1)
fdf.head()


```
pca =PCA(n_components=2)
pc = pca.fit_transform(X_normalized)
pdf = pd.DataFrame(data = pc, columns = ['p1','p2'])
fdf = pd.concat([pdf,df[['TENURE']]],axis= 1)
fdf.head()
```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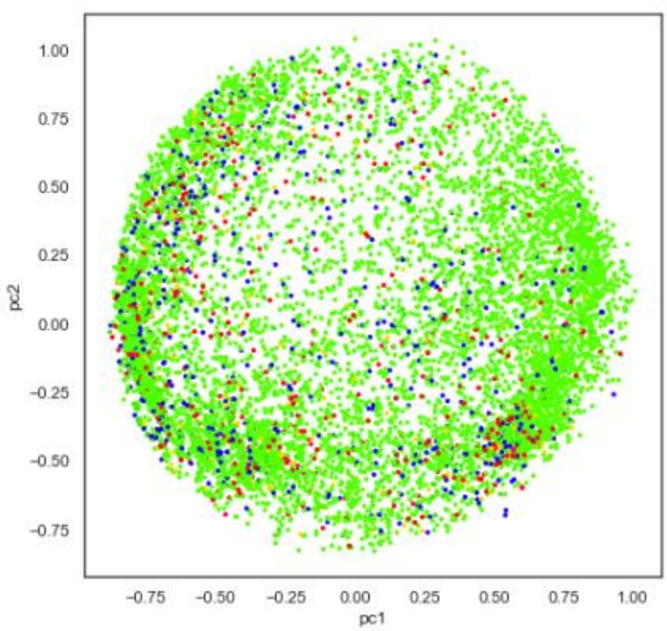
	p1	p2	TENURE
0	-0.488186	-0.677233	12
1	-0.517294	0.556075	12
2	0.334384	0.287313	12
3	-0.486616	-0.080780	12
4	-0.562175	-0.474770	12

plt.figure(figsize=(7,7))
plt.scatter(fdf['p1'],fdf['p2'],c=fdf['TENURE'],cmap='prism',s=5)
plt.xlabel('pc1')
plt.ylabel('pc2')


```
plt.figure(figsize=(7,7))
plt.scatter(fdf['p1'],fdf['p2'],c=fdf['TENURE'],cmap='prism',s=5)
plt.xlabel('pc1')
plt.ylabel('pc2')
```


0]: Text(0, 0.5, 'pc2')

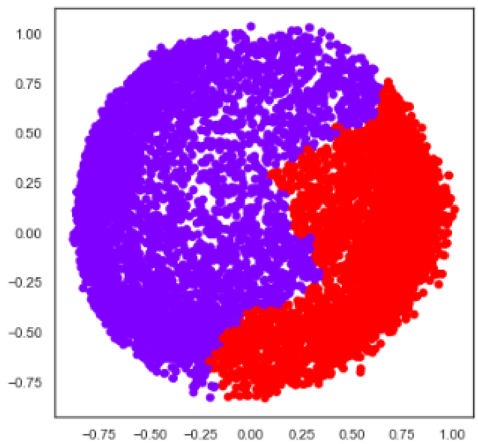


Description:
After performing Standardscaler and normalization method we have used PCA where the k value is 2.

d) Apply Agglomerative Clustering with k=2,3,4 and 5 on reduced features and visualize result for each k value using scatter plot.

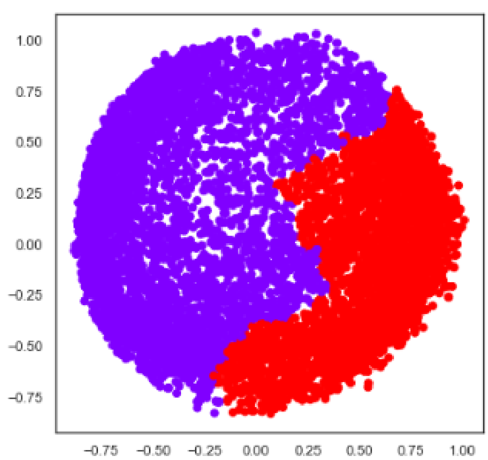
ac = AgglomerativeClustering(n_clusters= 2)
plt.figure(figsize = (6,6))
plt.scatter(pdf['p1'],pdf['p2'],c=ac.fit_predict(pdf),cmap = 'rainbow')
plt.show()

```
ac = AgglomerativeClustering(n_clusters= 2)
plt.figure(figsize = (6,6))
plt.scatter(pdf['p1'],pdf['p2'],c=ac.fit_predict(pdf),cmap = 'rainbow')
plt.show()
```



ac1 = AgglomerativeClustering(n_clusters= 3)
plt.figure(figsize = (6,6))
plt.scatter(pdf['p1'],pdf['p2'],c=ac.fit_predict(pdf),cmap = 'rainbow')
plt.show()

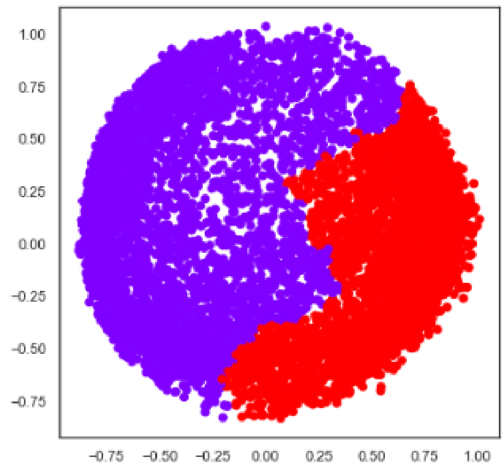
```
ac1 = AgglomerativeClustering(n_clusters= 3)
plt.figure(figsize = (6,6))
plt.scatter(pdf['p1'],pdf['p2'],c=ac.fit_predict(pdf),cmap = 'rainbow')
plt.show()
```



ac2 = AgglomerativeClustering(n_clusters= 4)
plt.figure(figsize = (6,6))
plt.scatter(pdf['p1'],pdf['p2'],c=ac.fit_predict(pdf),cmap = 'rainbow')

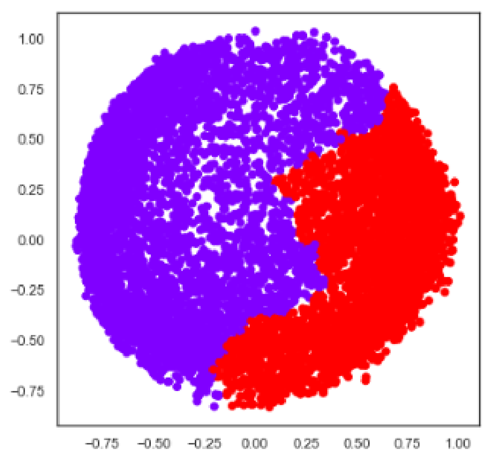
plt.show()

```
ac2 = AgglomerativeClustering(n_clusters= 4)
plt.figure(figsize = (6,6))
plt.scatter(pdf['p1'],pdf['p2'],c=ac.fit_predict(pdf),cmap = 'rainbow')
plt.show()
```



ac3 = AgglomerativeClustering(n_clusters= 5)
plt.figure(figsize = (6,6))
plt.scatter(pdf['p1'],pdf['p2'],c=ac.fit_predict(pdf),cmap = 'rainbow')
plt.show()

```
ac3 = AgglomerativeClustering(n_clusters= 5)
plt.figure(figsize = (6,6))
plt.scatter(pdf['p1'],pdf['p2'],c=ac.fit_predict(pdf),cmap = 'rainbow')
plt.show()
```

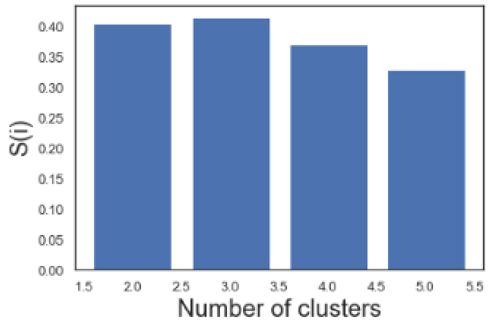


e) Evaluate different variations using Silhouette Scores and Visualize results with a bar chart.

k=[2,3,4,5]
silhouette_scores = []
silhouette_scores.append(silhouette_score(pdf,ac.fit_predict(pdf)))
silhouette_scores.append(silhouette_score(pdf,ac1.fit_predict(pdf)))
silhouette_scores.append(silhouette_score(pdf,ac2.fit_predict(pdf)))

silhouette_scores.append(silhouette_score(pdf,ac3.fit_predict(pdf)))
plt.bar(k, silhouette_scores)
plt.xlabel('Number of clusters', fontsize=20)
plt.ylabel('S(i)',fontsize=20)
plt.show()

```
k=[2,3,4,5]
silhouette_scores = []
silhouette_scores.append(silhouette_score(pdf,ac.fit_predict(pdf)))
silhouette_scores.append(silhouette_score(pdf,ac1.fit_predict(pdf)))
silhouette_scores.append(silhouette_score(pdf,ac2.fit_predict(pdf)))
silhouette_scores.append(silhouette_score(pdf,ac3.fit_predict(pdf)))
plt.bar(k, silhouette_scores)
plt.xlabel('Number of clusters', fontsize=20)
plt.ylabel('S(i)',fontsize=20)
plt.show()
```



Description:
We have used silhouette score to calculate and display the bar graph.