Assignment 5

Problem Statement:

Implement Agglomerative hierarchical clustering algorithm using appropriate dataset.

Objective:

- Evaluate and analyse retrieved information using Page Ranking algorithm.
- To study Random Walk.

Theory:

Prerequisites:
Agglomerative Clustering Agglomerative Clustering is one of the most common hierarchical clustering techniques.
Dataset – Credit Card Dataset.

Assumption: The clustering technique assumes that each data point is similar enough to the other data points that the data at the starting can be assumed to be clustered in 1 cluster.

Step 1: Importing the required libraries

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.decomposition import PCA

from sklearn.cluster import AgglomerativeClustering

from sklearn.preprocessing import StandardScaler, normalize

from sklearn.metrics import silhouette_score

import scipy.cluster.hierarchy as shc
```

Step 2: Loading and Cleaning the data

- Python3

```
# Changing the working location to the location of the file

cd C:\Users\Dev\Desktop\Kaggle\Credit_Card

 X = pd.read_csv('CC_GENERAL.csv')

 # Dropping the CUST_ID column from the data

X = X.drop('CUST_ID', axis = 1)
```

```
# Handling the missing values
X.fillna(method ='ffill', inplace = True)
```

Step 3: Preprocessing the data

- Python3

```
# Scaling the data so that all the features become comparable
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
# Normalizing the data so that the data approximately
# follows a Gaussian distribution
X_normalized = normalize(X_scaled)
# Converting the numpy array into a pandas DataFrame
X_normalized = pd.DataFrame(X_normalized)
```

Step 4: Reducing the dimensionality of the Data

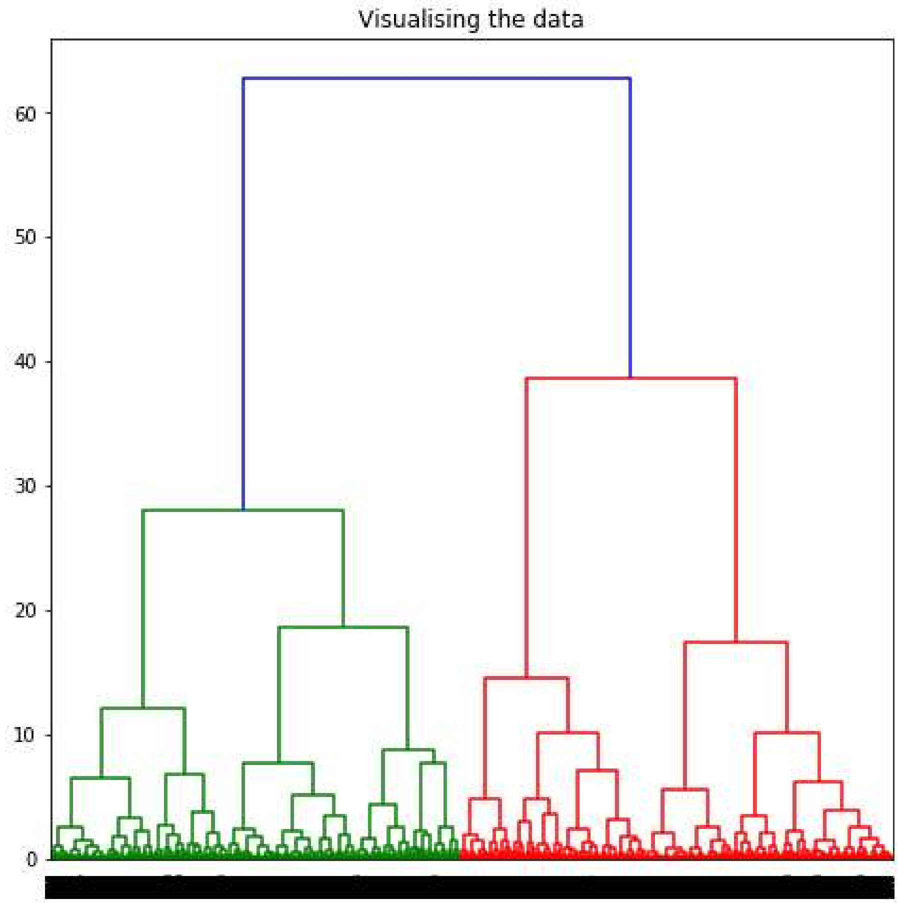
- Python3

```
pca = PCA(n_components = 2)
X_principal = pca.fit_transform(X_normalized)
X_principal = pd.DataFrame(X_principal)
X_principal.columns = ['P1', 'P2']
```

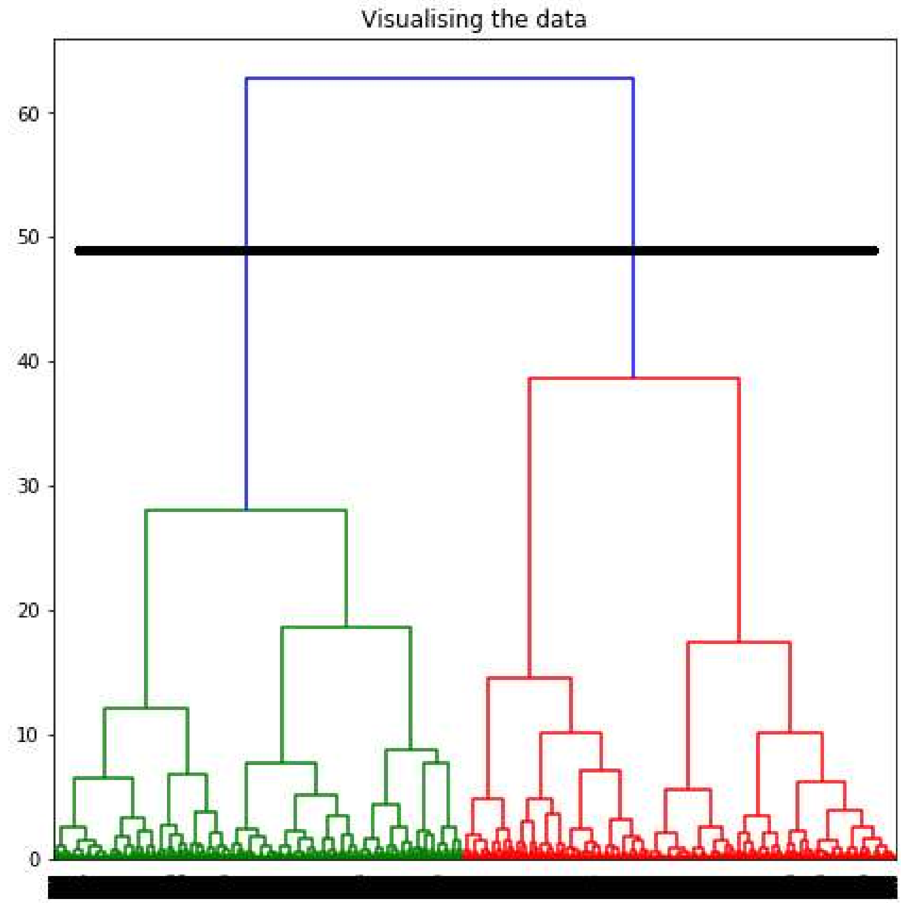
Dendrograms are used to divide a given cluster into many different clusters. **Step 5: Visualizing the working of the Dendrograms**

- Python3

```
plt.figure(figsize =(8, 8))
plt.title('Visualising the data')
Dendrogram = shc.dendrogram((shc.linkage(X_principal, method ='ward')))
```



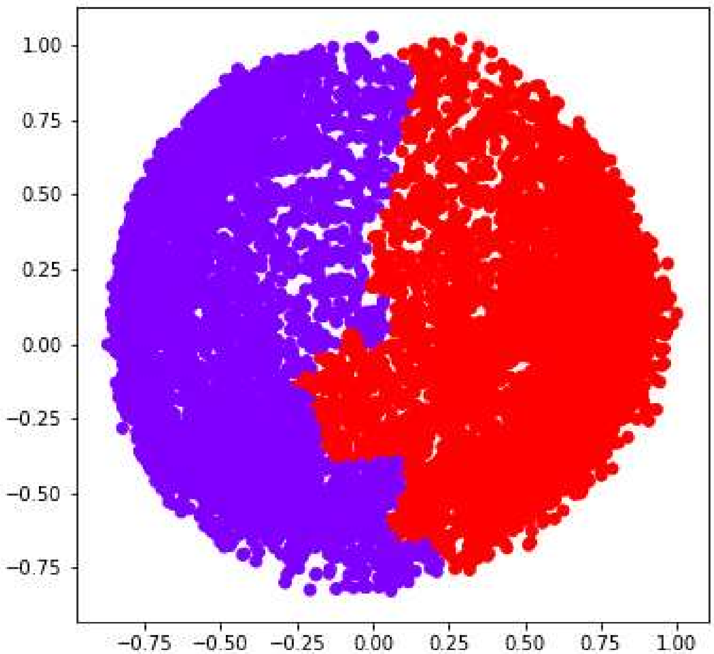
To determine the optimal number of clusters by visualizing the data, imagine all the horizontal lines as being completely horizontal and then after calculating the maximum distance between any two



The above image shows that the optimal number of clusters should be 2 for the given data. **Step 6: Building and Visualizing the different clustering models for different values of k** a) **k = 2**

- Python3

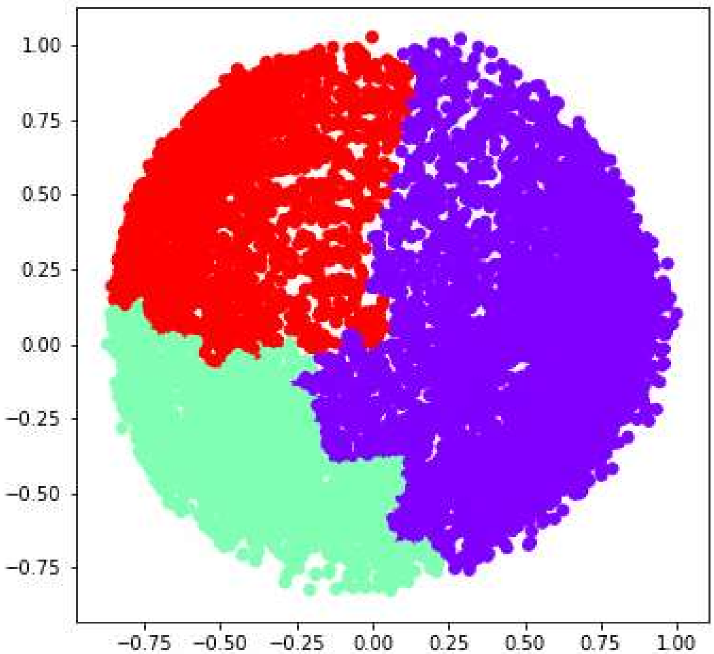
```
ac2 = AgglomerativeClustering(n_clusters = 2)

 # Visualizing the clustering

plt.figure(figsize =(6, 6))

plt.scatter(X_principal['P1'], X_principal['P2'],

           c = ac2.fit_predict(X_principal), cmap ='rainbow')

plt.show()
```



b) **k = 3**

- Python3

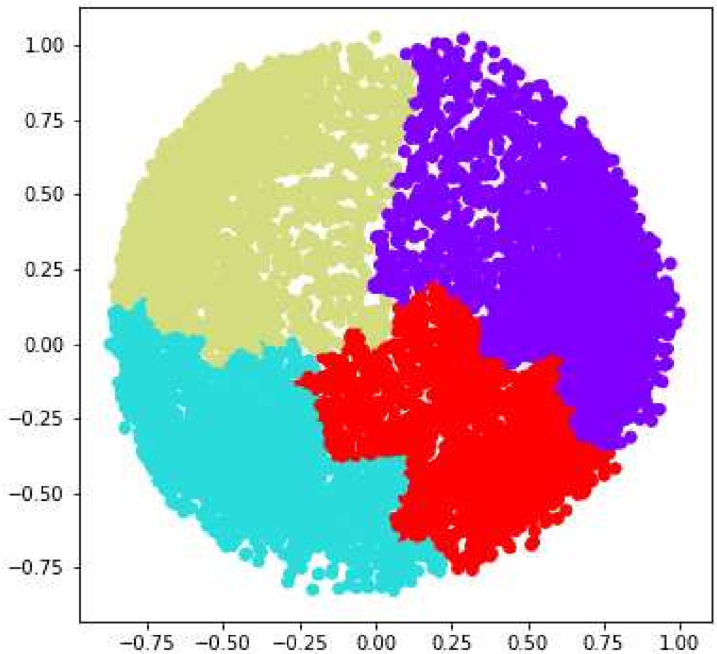
```
ac3 = AgglomerativeClustering(n_clusters = 3)


plt.figure(figsize =(6, 6))
plt.scatter(X_principal['P1'], X_principal['P2'],
           c = ac3.fit_predict(X_principal), cmap ='rainbow')
plt.show()
```



c) **k = 4**

- Python3

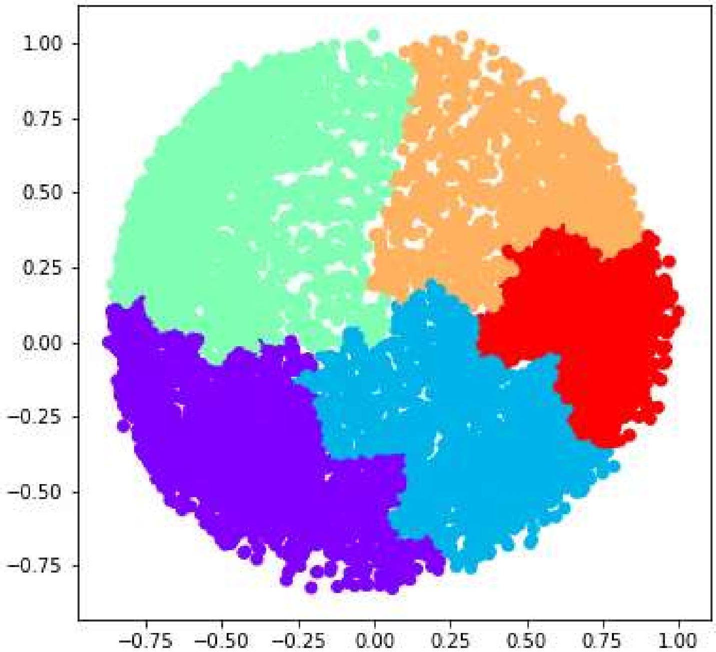
```
ac4 = AgglomerativeClustering(n_clusters = 4)


plt.figure(figsize =(6, 6))
plt.scatter(X_principal['P1'], X_principal['P2'],
            c = ac4.fit_predict(X_principal), cmap ='rainbow')
plt.show()
```



d) **k = 5**

- Python3

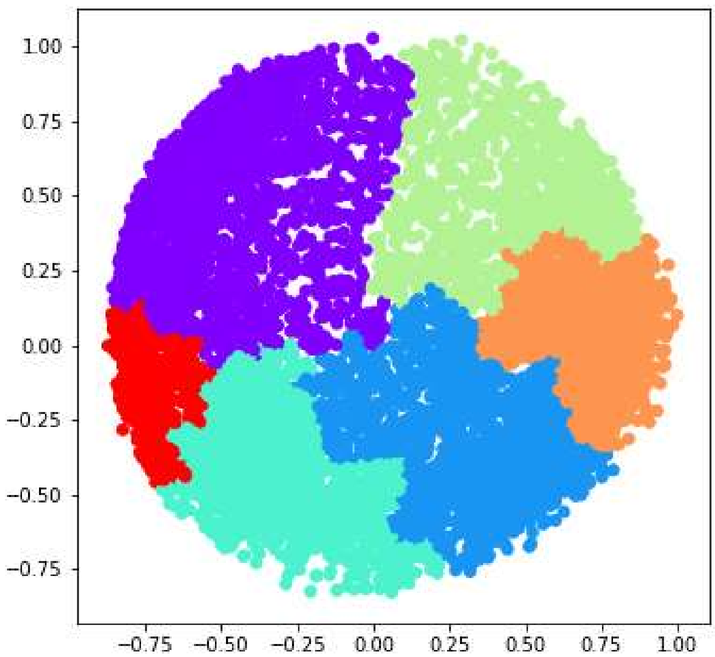
```
ac5 = AgglomerativeClustering(n_clusters = 5)


plt.figure(figsize =(6, 6))

plt.scatter(X_principal['P1'], X_principal['P2'],

           c = ac5.fit_predict(X_principal), cmap ='rainbow')

plt.show()
```



e) **k = 6**

- Python3

```
ac6 = AgglomerativeClustering(n_clusters = 6)


plt.figure(figsize =(6, 6))

plt.scatter(X_principal['P1'], X_principal['P2'],

          c = ac6.fit_predict(X_principal), cmap ='rainbow')

plt.show()
```



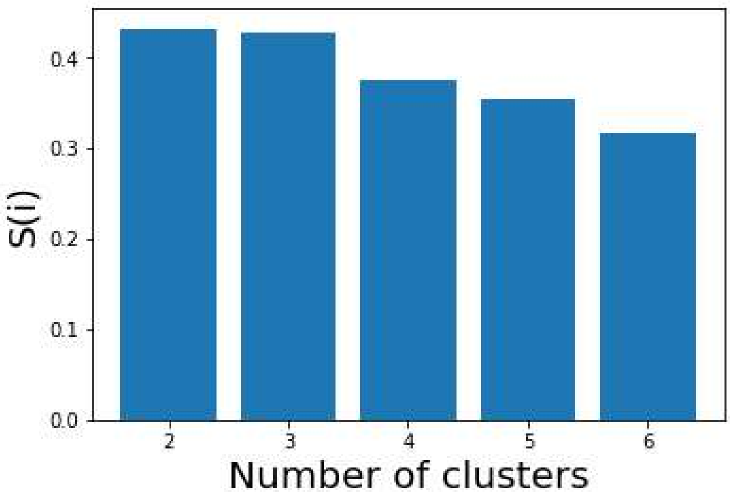
We now determine the optimal number of clusters using a mathematical technique. Here, We will use the **Silhouette Scores** for the purpose.

Step 7: Evaluating the different models and Visualizing the results.

- Python3

```
k = [2, 3, 4, 5, 6]


# Appending the silhouette scores of the different models to the list

silhouette_scores = []

silhouette_scores.append(

    silhouette_score(X_principal, ac2.fit_predict(X_principal)))

silhouette_scores.append(

    silhouette_score(X_principal, ac3.fit_predict(X_principal)))

silhouette_scores.append(

    silhouette_score(X_principal, ac4.fit_predict(X_principal)))

silhouette_scores.append(

    silhouette_score(X_principal, ac5.fit_predict(X_principal)))

silhouette_scores.append(
```

```
    silhouette_score(X_principal, ac6.fit_predict(X_principal)))


# Plotting a bar graph to compare the results
plt.bar(k, silhouette_scores)
plt.xlabel('Number of clusters', fontsize = 20)
plt.ylabel('S(i)', fontsize = 20)
plt.show()
```



Thus, with the help of the silhouette scores, it is concluded that the optimal number of clusters for the given data and clustering technique is 2.

Conclusion:

In this way, we have successfully completed implementation of Agglomerative hierarchical clustering algorithm using appropriate dataset.

Oral Questions:

1. What is mean by Agglomerative hierarchical clustering algorithm?
2. Which is the readymade function available to build Agglomerative hierarchical clustering algorithm?
3. Tell me the steps to implement Agglomerative hierarchical clustering algorithm.
4. Applications of Agglomerative hierarchical clustering algorithm.