Week 11 Lab (Hierarchical Clustering)

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About The Data

We'll be using the Credit Card Dataset from kaggle for this lab, but feel free to follow along with your own dataset. We will develop a customer segmentation to define marketing strategy. The sample Dataset summarizes the usage behavior of about 9000 active credit card holders during the last 6 months. The file is at a customer level with 18 behavioral variables:

- CUSTID : Identification of Credit Card holder (Categorical)
- BALANCE : Balance amount left in their account to make purchases (
- BALANCEFREQUENCY : How frequently the Balance is updated, score between 0 and 1 (1 = frequently updated, 0 = not frequently updated)
- PURCHASES : Amount of purchases made from account
- ONEOFFPURCHASES : Maximum purchase amount done in one-go
- INSTALLMENTSPURCHASES : Amount of purchase done in installment
- CASHADVANCE : Cash in advance given by the user
- PURCHASESFREQUENCY : How frequently the Purchases are being made, score between 0 and 1 (1 = frequently purchased, 0 = not frequently purchased)
- ONEOFFPURCHASESFREQUENCY : How frequently Purchases are happening in one-go (1 = frequently purchased, 0 = not frequently purchased)
- PURCHASESINSTALLMENTSFREQUENCY : How frequently purchases in installments are being done (1 = frequently done, 0 = not frequently done)
- CASHADVANCEFREQUENCY : How frequently the cash in advance being paid
- CASHADVANCETRX : Number of Transactions made with "Cash in Advanced"
- PURCHASESTRX : Numbe of purchase transactions made
- CREDITLIMIT : Limit of Credit Card for user
- PAYMENTS : Amount of Payment done by user
- MINIMUM_PAYMENTS : Minimum amount of payments made by user
- PRCFULLPAYMENT : Percent of full payment paid by user
- TENURE : Tenure of credit card service for user

About Hierarchical clustering

Hierarchical clustering is a method which seeks to build a hierarchy of clusters. Strategies for hierarchical clustering generally fall into two types:

- Agglomerative : This is a "bottom-up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy.
- Divisive : This is a "top-down" approach: all observations start in one cluster, and splits are performed recursively as one moves down the hierarchy.

In general, the merges and splits are determined in a greedy manner, and the results of hierarchical clustering are usually presented in a dendrogram.

Agglomerative Clustering

The algorithm goes as follows:

- Compute the proximity matrix
- Let each data point be a cluster
- Repeat: Merge two closest clusters and update the proximity matrix until 1/ K cluster remains

For example, say we have six data points {a,b,c,d,e,f}

- In the initial step, we consider all the six data points as individual clusters as shown in the image below.

The first step is to determine which elements to merge in a cluster. Usually, we want to take the two closest elements, according to the chosen distance.We construct a distance matrix at this stage, where the number in the i-th row j-th column is the distance between the i-th and j-th elements. Then, as clustering progresses, rows and columns are merged as the clusters are merged and the distances updated.

Computation of Proximity/Distance Matrix

To calculate the proximity between two clusters, we need to define the distance between them. Usually the distance is one of the following:

- The maximum distance between elements of each cluster (also called complete-linkage clustering)
- The minimum distance between elements of each cluster (also called single-linkage clustering)
- The mean distance between elements of each cluster (also called average linkage clustering)
- The sum of all intra-cluster variance.

Note: Euclidean, Manhattan, Mahalanobis, etc. distance formulas can be used when calculating distances for each of the above.

Implementation

Similarly to the K Means lab, we'll skip the data exploration portion and jump to implementation, but you're welcome to explore this data, or your own if working with a different dataset.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
from matplotlib import rcParams
rcParams['figure.figsize'] = 15, 5
sns.set_style('darkgrid')
```

Let's first load the data into a pandas DataFrame. MINIMUM_PAYMENTS and CREDIT_LIMIT are missing a few values, so we'll go ahead and fill them with their respective column mean. We'll also go ahead and drop CUST_ID while we're at it since it serve's us no valuable information.

In [3]:
```
cc_df = pd.read_csv('cc.csv')
cc_df.drop('CUST_ID', axis = 1, inplace=True)
cc_df['MINIMUM_PAYMENTS'].fillna(value=cc_df['MINIMUM_PAYMENTS'].mean(), inplace = True)
cc_df['CREDIT_LIMIT'].fillna(value=cc_df['CREDIT_LIMIT'].mean(), inplace = True)
cc_df.head()
```

Out[3]:

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

Checking to see that there are no more missing values:

In [5]:
```
cc_df.isnull().sum()
```

Out[5]:
```
BALANCE                             0
BALANCE_FREQUENCY                   0
PURCHASES                           0
ONEOFF_PURCHASES                    0
INSTALLMENTS_PURCHASES              0
CASH_ADVANCE                        0
PURCHASES_FREQUENCY                 0
ONEOFF_PURCHASES_FREQUENCY          0
PURCHASES_INSTALLMENTS_FREQUENCY    0
CASH_ADVANCE_FREQUENCY              0
CASH_ADVANCE_TRX                    0
PURCHASES_TRX                       0
CREDIT_LIMIT                        0
PAYMENTS                            0
MINIMUM_PAYMENTS                    0
PRC_FULL_PAYMENT                    0
TENURE                              0
dtype: int64
```

We'll now standardize and normalize the data as follows:

In [6]:
```
from sklearn.preprocessing import StandardScaler, normalize

scaler = StandardScaler()
scaled_df = scaler.fit_transform(cc_df)

normalized_df = normalize(scaled_df)

# Converting the scaled data back into a pandas DataFrame
normalized_df = pd.DataFrame(data=normalized_df)
```

Next (optional, but recommended), we will reduce the dimensions of the data using PCA

In [10]:
```
from sklearn.decomposition import PCA

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

X_principal.head()
```

Out[10]:

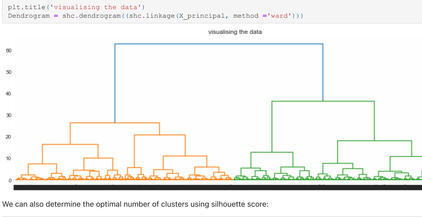
	P1	P2
0	-0.489826	-0.679678
1	-0.518791	0.545010
2	0.330885	0.268980
3	-0.482374	-0.092114
4	-0.563289	-0.481914

Next, we'll use a dendrogram to visualize the linkage of the reduced data (X_principal) using ***method='ward'***.

Note: The cell below might take a while to run.

In [11]:
```
import scipy.cluster.hierarchy as shc

plt.title('visualising the data')
Dendrogram = shc.dendrogram((shc.linkage(X_principal, method ='ward')))
```



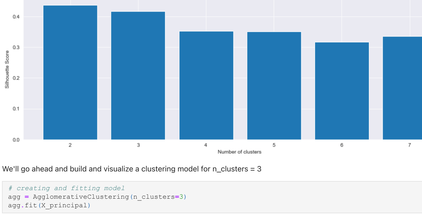
We can also determine the optimal number of clusters using silhouette score:

In [12]:
```
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score

# where we'll save scores for later plotting
silhouette_scores = []

# testing different cluster values in range [2,8)
for n_cluster in range(2, 8):
    silhouette_scores.append(silhouette_score(X_principal,
                                              AgglomerativeClustering(n_clusters = n_cluster).fit_predict(X_

# Creating bar graph to compare the results. You can use a line plot if you prefer (similar to K Means lab)
plt.bar(x=range(2, 8), height=silhouette_scores)
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.show()
```

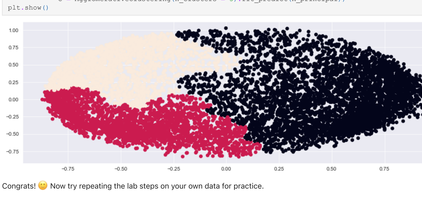


We'll go ahead and build and visualize a clustering model for n_clusters = 3

In [13]:
```
# creating and fitting model
agg = AgglomerativeClustering(n_clusters=3)
agg.fit(X_principal)
```

Out[13]:
```
AgglomerativeClustering(n_clusters=3)
```

In [14]:
```
# Visualizing the clustering
plt.scatter(X_principal['P1'], X_principal['P2'],
            c = AgglomerativeClustering(n_clusters = 3).fit_predict(X_principal))
plt.show()
```



Congrats! 😀 Now try repeating the lab steps on your own data for practice.