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# MALL CUSTOMER SEGMENTATION USING CLUSTERING ALGORITHM



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USE/2017/OCT/0045

Lanka Nippon BizTech Institute

March 2021

### **Declaration**

I declare that this report is my own work and has not been submitted in any form for another degree or diploma at any university or other institution of higher education. Information derived from the published or unpublished work of others has been acknowledged in the text and a list of references is given.

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Janith Perera

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Date:

### **Acknowledgement**

*I would like to express my special thanks of gratitude to our lecturer “Janith Perera” who gave us the golden opportunity to do this wonderful project on the “MALL CUSTOMER SEGMENTATION USING CLUSTERING ALGORITHM”, which also helped me in doing a lot of Research and I came to know about so many new things I am really thankful to him. Secondly, I would also like to thank my parents and friends who helped me a lot in finalizing this project within the limited time frame.*

## **Abstract**

Customer segmentation is a separation of a market into multiple distinct groups of consumers who share the similar characteristics. Segmentation of market is an effective way to define and meet customer needs. Unsupervised Machine Learning Techniques, K-Means Clustering Algorithm, Minibatch K-Means and Hierarchical Clustering are used to perform Market Basket Analysis. Market Basket Analysis is carried out to predict the target customers who can be easily converged, among all the customers. In order to allow the marketing team to plan the strategy to market the new products to the target customers which are similar to their interests.

Key words: Target Customers, Clusters, Unsupervised Learning, K-Means, Minibatch K-Means, Hierarchical Clustering Segmentation, Market Basket Analysis

## Table of Contents

Abstract.....	4
Introduction .....	8
Literature Review .....	9
Customer Segmentation .....	9
Clustering and K-Means Algorithm .....	10
Proposed System .....	10
General View of Data.....	10
Methodology.....	11
Clustering .....	11
K Means Clustering Algorithm .....	11
Minibatch K-Means Clustering Algorithm.....	12
Hierarchical Clustering Segmentation .....	13
Elbow Method.....	13
General View of Data.....	13
Reason to use Unsupervised Learning Algorithms .....	14
K-Means .....	18
MiniBatch K-Means.....	21
Hierarchical Clustering Segmentation .....	22
Comparison of Results .....	23
K-Means model .....	24
K-Means model conclusion .....	27
MiniBatch K-Means model.....	27
MiniBatch K-Means model conclusion .....	32
Hierarchical Clustering Segmentation model .....	32
Hierarchical Clustering Segmentation model conclusion .....	36
References .....	36

Figure 1:K Means Clustering Algorithm	12
Figure 2:Minibatch K-Means Clustering Algorithm	12
Figure 3:Hierarchical Clustering Segmentation	13
Figure 4:Elbow Method	13
Figure 5: importing libraries	15
Figure 6: read csv file	15
Figure 7:df.head()	16
Figure 8:df.info()	16
Figure 9: df.describe()	17
Figure 10: remove null values	17
Figure 11: remove unnecessary columns	18
Figure 12: outliers	18
Figure 13: clear dataset last	18
Figure 14:kmeans elbow method	19
Figure 15: kmeans Davies Bouldin	20
Figure 16:kmeans model clustering	20
Figure 17:kmeans diagram	21
Figure 18: MiniBatch K-Means	21
Figure 19: MiniBatch K-Means diagram code	21
Figure 20: MiniBatch K-Means	22
Figure 21:Hierarchical Clustering Segmentation1	22
Figure 22:Hierarchical Clustering Segmentation2	22
Figure 23:Hierarchical Clustering Segmentation diagram	23
Figure 24:comparison of results	23
Figure 25:kmeans number of clusters	24
Figure 26:understand behaviours or labels of customers.	24
Figure 27:kmeans values fo clusters	24
Figure 28:kmeans balance	24
Figure 29:kmeans balance frequency	25
Figure 30:kmeans purchases frequency	25
Figure 31: kmeans cash advance frequency	25
Figure 32:kmeans purchases_trx	26
Figure 33:kmeans credit limit	26
Figure 34:kmeans tenure	26
Figure 35:MiniBatch K-Means number of clusters	27
Figure 36:MiniBatch K-Means cluster mean	28
Figure 37:MiniBatch K-Means cluster characteristics	28
Figure 38: label generating code	28
Figure 39:MiniBatch K-Means balance	29
Figure 40:MiniBatch K-Means balance frequency	29
Figure 41:MiniBatch K-Means purchases frequency	30
Figure 42:MiniBatch K-Means purchase installment frequency	30
Figure 43:MiniBatch K-Means cash advance frequency	30

Figure 44:MiniBatch K-Means purchases frequency _____	31
Figure 45:MiniBatch K-Means credit limit _____	31
Figure 46:MiniBatch K-Means tenure _____	31
Figure 47:Hierarchical Clustering Segmentation model clustering _____	32
Figure 48:Hierarchical Clustering Segmentation model characteristics _____	33
Figure 49:Hierarchical Clustering Segmentation model label diagram _____	33
Figure 50:Hierarchical Clustering Segmentation model balance _____	33
Figure 51:Hierarchical Clustering Segmentation model balance frequency _____	34
Figure 52:Hierarchical Clustering Segmentation model purchases frequency _____	34
Figure 53:Hierarchical Clustering Segmentation model purchases instalment frequency _____	34
Figure 54:Hierarchical Clustering Segmentation model cash advance frequency _____	35
Figure 55:Hierarchical Clustering Segmentation model credit limit _____	35
Figure 56:Hierarchical Clustering Segmentation model tenure _____	35



## **Introduction**

Management and maintain of customer relationship have always played a vital role to provide business intelligence to organizations to build, manage and develop valuable long term customer relationships. The importance of treating customers as an organizations main asset is increasing in value in present day and era. Organizations have an interest to invest in the development of customer acquisition, maintenance and development strategies. The business intelligence has a vital role to play in allowing companies to use technical expertise to gain better customer knowledge and Programs for outreach. By using clustering techniques like k-means, customers with similar means are clustered together. Customer segmentation helps the marketing team to recognize and expose different customer segments that think differently and follow different purchasing strategies. Customer segmentation helps in figuring out the customers who vary in terms of preferences, expectations, desires and attributes. The main purpose of performing customer segmentation is to group people, who have similar interest so that the marketing team can converge in an effective marketing plan. Clustering is an iterative process of knowledge discovery from vast amounts of raw and unorganized data. Clustering is a type of exploratory data mining that is used in many applications, such as machine learning, classification and pattern recognition.

## **Literature Review**

### **Customer Segmentation**

Over the years, as there is very strong competition in the business world, the organizations have to enhance their profits and business by satisfying the demands of their customers and attract new customers according to their needs. The identification of customers and satisfying the demands of each customer is a very complex task. This is because customers may be different according to their demands, desires, preferences and so on. Instead of “one-size-fits-all” approach, customer segmentation clusters the customers into groups sharing the same properties or behavioural characteristics. According to, [1] customer segmentation is a strategy of dividing the market into homogenous groups. The data used in customer segmentation technique that divides the customers into groups depends on various factors like, demographical conditions, data geographical conditions and economic conditions as well as behavioural patterns. The customer segmentation technique allows the business to make better use of their marketing budgets, gain a competitive edge over their rival companies, demonstrating the better knowledge of the needs of the customer. It also helps an organization in, increasing their marketing efficiency, plan the marketing budget, determining new market opportunities, making better brand strategy, identifying customers retention.

According to [1], Decision makers use many variables to segment customers. Demographic variables such as age, gender, family, education level and income are the easiest and common variables for segmentation. Socio- cultural, geographic, psychographic and behavioural variables are the other major variables that are used for segmentation.

[2], presented various clustering algorithms taking into account the characteristics of Big Data such as size, noise, dimensionality, algorithm calculations, cluster shape and presented a brief overview of the various clustering algorithms grouped under partitioning, hierarchical, density, grid-based and model-based algorithms.

[4] explored the necessity of segmentation of the customers using clustering algorithms as the core functionality of CRM. The mostly used K-Means and Hierarchical Clustering were studied and the advantages and disadvantages of these techniques were highlighted. At last, the idea of creating a hybrid approach is addressed by integrating the above two strategies with the potential to surpass the individual designs.

[5], Merged clustering of fuzzy c-means and genetic algorithms to cluster, steel industry customers, by using the LRFM variables (length, recency, frequency, monetary value) system, customers were divided into two clusters

## Clustering and K-Means Algorithm

Clustering algorithms generates clusters such that within the clusters are similar based on some characteristics. Similarity is defined in terms of how close the objects are in space.

According to [1], K-means algorithm is one of the most popular centroid based algorithms. Suppose data set,  $D$ , contains  $n$  objects in space. Partitioning methods distribute the objects in  $D$  into  $k$  clusters,  $C_1, \dots, C_k$ , that is,  $C_i \subset D$  and  $C_i \cap C_j = \emptyset$  for  $(1 \leq i, j \leq k)$ . A centroid-based partitioning technique uses the centroid of a cluster,  $C_i$ , to represent that cluster. Conceptually, the centroid of a cluster is its centre point. The difference between an object  $p \in C_i$  and  $c_i$ , the representative of the cluster, is measured by  $\text{dist}(p, c_i)$ , where  $\text{dist}(x, y)$  is the Euclidean distance between two points  $x$  and  $y$ .

**Algorithm:** The k-means algorithm for partitioning, where each cluster's centre is represented by the mean value of the objects in the cluster. Input:  $k$ : the number of clusters,  $D$ : a data set containing  $n$  objects. Output: A set of  $k$  clusters. Method: (1) arbitrarily choose  $k$  objects from  $D$  as the initial cluster centres; (2) repeat (3) (re)assigns each object to the cluster to which the object is the most similar, based on the mean value of the objects in the cluster; (4) update the cluster means, that is, calculate the mean value of the objects for each cluster; (5) until no change.

## Proposed System

We are going to aim to cluster a data set that is about behaviour of the customers having credit card using many unsupervised algorithms.

**Our research question is "How many clusters can we distinguish the customers according to their transactions or behaviours?"**

### General View of Data

The data set has 8950 transactions or information about account that belong to customers.

### Features

CUSTID: Identification of Credit Card holder (Categorical)

BALANCE: Balance amount left in their account to make purchases

BALANCE FREQUENCY: How frequently the Balance is updated, score between 0 and 1 (1 = frequently updated, 0 = not frequently updated)

PURCHASES: Number of purchases made from account

ONE OFF PURCHASES: Maximum purchase amount done in one-go

INSTALLMENTS PURCHASES: Amount of purchase done in installment

CASH ADVANCE: Cash in advance given by the user

**PURCHASES FREQUENCY:** How frequently the Purchases are being made, score between 0 and 1 (1 = frequently purchased, 0 = not frequently purchased)

**ONE OFF PURCHASES FREQUENCY:** How frequently Purchases are happening in one-go (1 = frequently purchased, 0 = not frequently purchased)

**PURCHASES INSTALLMENTS FREQUENCY:** How frequently purchases in installments are being done (1 = frequently done, 0 = not frequently done)

**CASH ADVANCE FREQUENCY:** How frequently the cash in advance being paid

**CASH ADVANCE TRX:** Number of Transactions made with "Cash in Advanced"

**PURCHASES TRX:** Number of purchase transactions made

**CREDIT LIMIT:** Limit of Credit Card for user

**PAYMENTS:** Amount of Payment done by user

**MINIMUM PAYMENTS:** Minimum number of payments made by user

**PRC FULL PAYMENT:** Percent of full payment paid by user

**TENURE:** Tenure of credit card service for user

## **Methodology**

### **Clustering**

Clustering is one of the most common methods used in exploring data to obtain a clear understanding of the data structure. It can be characterized as the task of finding the subtitles and subgroups in the complete dataset. Similar data is clustered in many subgroups. A cluster refers to a collection of aggregated data points due to some similarities. Clustering is used in Market basket analysis used to segment the customers based on their behaviours and transactions.

### **K Means Clustering Algorithm**

K Means Clustering is the most common and simplest Machine learning algorithm and it follows an iterative approach which attempts to partition the dataset into different “k” number of predefined and non-overlapping subgroups where each data point belongs to only one subgroup according to their similar qualities.

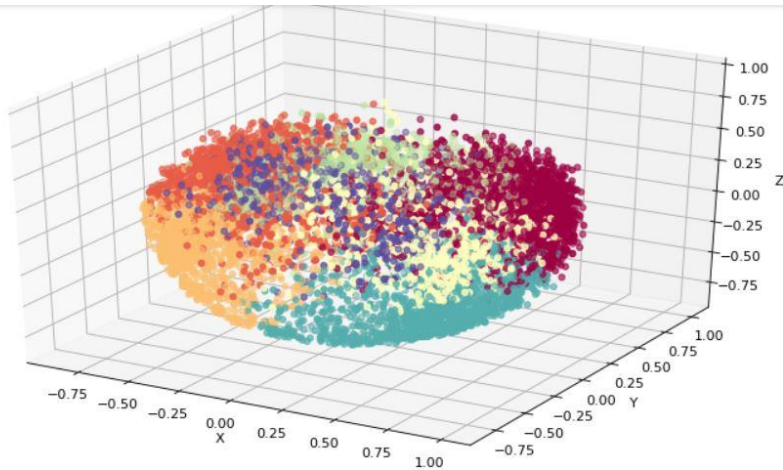


Figure 1: K Means Clustering Algorithm

### Minibatch K-Means Clustering Algorithm

Mini Batch K-means algorithm [6] main idea is to use small random batches of data of a fixed size, so they can be stored in memory. Each iteration a new random sample from the dataset is obtained and used to update the clusters and this is repeated until convergence. Each mini batch updates the clusters using a convex combination of the values of the prototypes and the data, applying a learning rate that decreases with the number of iterations. This learning rate is the inverse of the number of data assigned to a cluster during the process. As the number of iterations increases, the effect of new data is reduced, so convergence can be detected when no changes in the clusters occur in several consecutive iterations.

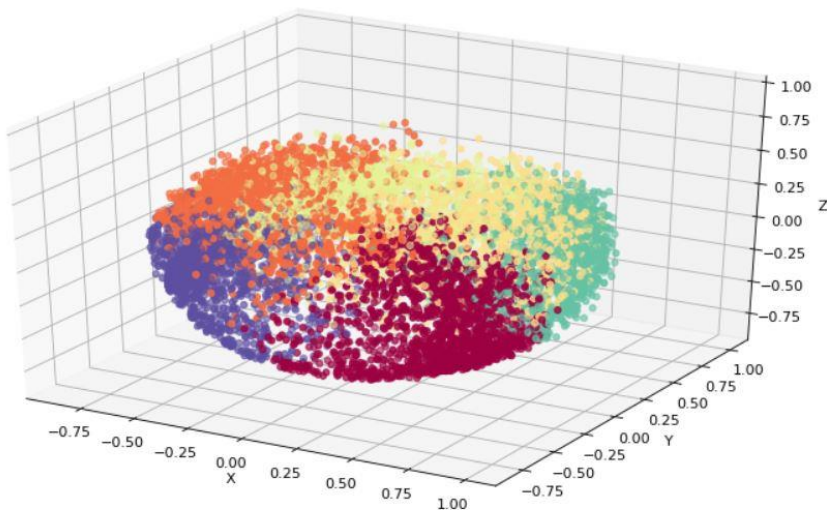


Figure 2: Minibatch K-Means Clustering Algorithm

## Hierarchical Clustering Segmentation

[7]The output of this model is a set of visualized clusters, where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other in features.

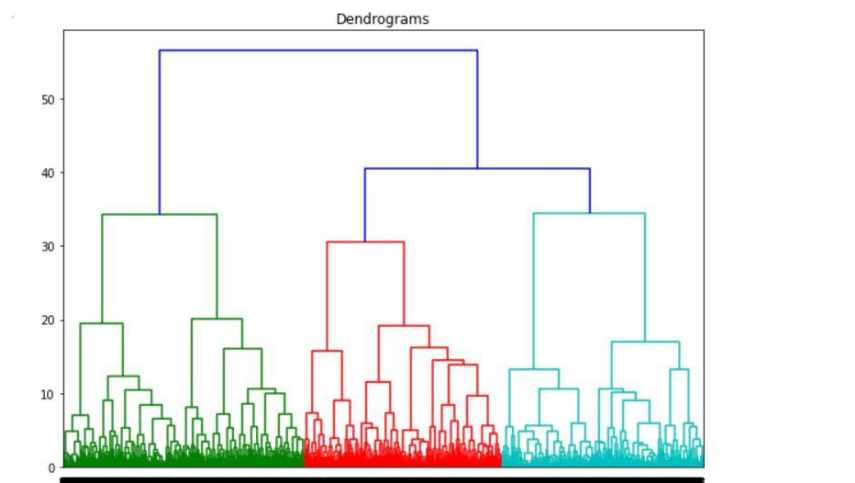


Figure 3: Hierarchical Clustering Segmentation

## Elbow Method

Elbow method is a tool used for analysing the clusters formed from our dataset and helps to interpret the appropriate number of optimal clusters in dataset. From this method the optimal number of clusters for our dataset is found to be seven.

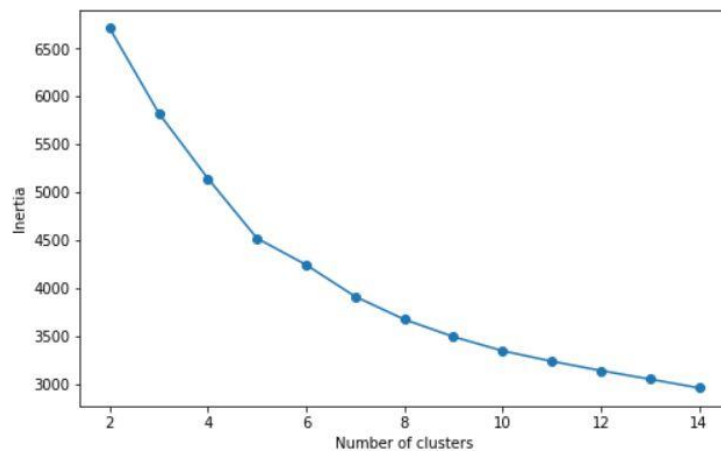


Figure 4: Elbow Method

## General View of Data

The data set has 8950 transactions or information about account that belong to customers.

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PRC FULL PAYMENT: Percent of full payment paid by user

TENURE: Tenure of credit card service for user

### **Reason to use Unsupervised Learning Algorithms**

Unlike Supervised Learning, Unsupervised Learning has only independent variables and no corresponding target variable. The data is unlabelled. The aim of unsupervised learning is to model the underlying structure or distribution in the data in order to learn more about the data.

We are going to examine a dataset that is about credit card users for segmentation. There is no any feature about label of customers. That is to say, we don't have information about customer's characteristics. We are going to try clustering clients through identifying similarities with machine learning algorithms. Segmentation of customers has a pretty significant position for companies in new marketing disciplines. Firms must reach to the right target audiences with right approaches because of costs.

we have started with data pre-processing such as filling the missing values, standardization etc. First of all, we have to import all necessary libraries

```
[ ]
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

from sklearn.preprocessing import StandardScaler, normalize
from sklearn.cluster import KMeans
from sklearn.cluster import MiniBatchKMeans
from sklearn.cluster import AgglomerativeClustering
import scipy.cluster.hierarchy as shc
from sklearn.cluster import DBSCAN
from sklearn.mixture import GaussianMixture
from sklearn.cluster import MeanShift
from sklearn.cluster import estimate_bandwidth
from sklearn import metrics

from sklearn.decomposition import PCA

import warnings
warnings.filterwarnings('ignore')
```

Figure 5: importing libraries

After that, we have to mount Jupiter notebook in to drive with destination folder and save the dataset inside folder.

We can use following code to read data from .csv file.

```
[ ]
from google.colab import drive
drive.mount('/content/gdrive')

Mounted at /content/gdrive

[ ]
df=pd.read_csv('/content/drive/MyDrive/Colab Notebooks/data/Marketing_data.csv')
df.head()
```

Figure 6: read csv file



We can use `df.head()` to see first 5 data records from dataset.

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_F
0	C10001	40.900749	0.818182	95.40	0.00	95.4	0.000000	0.166667	0.000000	
1	C10002	3202.467416	0.909091	0.00	0.00	0.0	6442.945483	0.000000	0.000000	
2	C10003	2495.148862	1.000000	773.17	773.17	0.0	0.000000	1.000000	1.000000	
3	C10004	1666.670542	0.636364	1499.00	1499.00	0.0	205.788017	0.083333	0.083333	
4	C10005	817.714335	1.000000	16.00	16.00	0.0	0.000000	0.083333	0.083333	

Figure 7: `df.head()`

We can use following code to get information regarding dataset.

`df.shape[0]` gives number of rows and `df.shape[1]` gives number of columns regarding dataset.

To get information regarding each column, we can use `df.info()` as follows.

```
[ ] print('This data set has {} rows and {} columns.\n'.format(df.shape[0],df.shape[1]))
df.info()
```

This data set has 8950 rows and 18 columns.

```
<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
```

Figure 8: `df.info()`

```
[ ] df.describe()
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	ONEOFF_PURCHASES_FREQUENCY	PURCH
count	8950.000000	8950.000000	8950.000000	8950.000000	8950.000000	8950.000000	8950.000000	8950.000000	8950.000000
mean	1564.474828	0.877271	1003.204834	592.437371	411.067645	978.871112	0.490351	0.202458	
std	2081.531879	0.236904	2136.634782	1659.887917	904.338115	2097.163877	0.401371	0.298336	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	128.281915	0.888889	39.635000	0.000000	0.000000	0.000000	0.083333	0.000000	
50%	873.385231	1.000000	361.280000	38.000000	89.000000	0.000000	0.500000	0.083333	
75%	2054.140036	1.000000	1110.130000	577.405000	468.637500	1113.821139	0.916667	0.300000	
max	19043.138560	1.000000	49039.570000	40761.250000	22500.000000	47137.211760	1.000000	1.000000	

Figure 9: df.describe()

df.describe() use to get mathematical information about each columns' data.

Ex: count, mean, std, min,25%,50%,75% of each column.

From now on, we have to prepare dataset for clustering. Before enter dataset as input to the clustering model, we have to clean the dataset. It means that we are fixing if there is any null values or errors.

Following code describes, if there is missing values or not in dataset,

```
[ ]
# Lets check the missing values and fill them with appropriate method.
def null_values(df):
    nv=pd.DataFrame(df.isnull().sum()).rename(columns={0:'Missing_Records'})
    return nv[nv.Missing_Records>0].sort_values('Missing_Records', ascending=False)
null_values(df)
```

Missing_Records	
MINIMUM_PAYMENTS	313
CREDIT_LIMIT	1

Figure 10: remove null values

if we want to remove unnecessary columns from dataset, following code can used. Before use data set for clustering, we have to remove customer\_Id column.

```
[ ] # Actually we can drop the "CUST_ID" columns because we will not use it.
    df=df.drop('CUST_ID',axis=1)
```

Figure 11: remove unnecessary columns

There are lots of outliers in columns but we will not apply winsorize or other methods to them.

```
# There are lots of outliers in columns but we will not apply winsorize or another methods to them.Because we may have information loss.
# They may represent another clusters.
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
((df[df.columns] < (Q1 - 1.5 * IQR)) | (df[df.columns] > (Q3 + 1.5 * IQR))).sum()
```

BALANCE	695
BALANCE_FREQUENCY	1493
PURCHASES	808
ONEOFF_PURCHASES	1013
INSTALLMENTS_PURCHASES	867
CASH_ADVANCE	1030
PURCHASES_FREQUENCY	0
ONEOFF_PURCHASES_FREQUENCY	782
PURCHASES_INSTALLMENTS_FREQUENCY	0
CASH_ADVANCE_FREQUENCY	525
CASH_ADVANCE_TRX	804
PURCHASES_TRX	766
CREDIT_LIMIT	248
PAYMENTS	808
MINIMUM_PAYMENTS	774
PRC_FULL_PAYMENT	1474
TENURE	1366

dtype: int64

Figure 12: outliers

Because we may have information loss. They may represent another clusters.

```
[ ] # StandardScaler performs the task of Standardization. Usually a dataset contains variables that are
    scaler=StandardScaler()
    df_scl=scaler.fit_transform(df)

[ ] # Normalization refers to rescaling real valued numeric attributes into the range 0 and 1.
    # It is useful to scale the input attributes for a model that relies on the magnitude of values, such
    norm=normalize(df_scl)

[ ] # We can apply both (StandardScaler and Normalize) on our data before clustering.
    df_norm=pd.DataFrame(norm)
```

Figure 13: clear dataset last

Now our dataset is ready to use clustering algorithm model.

## K-Means

K Means Clustering is the most common and simplest Machine learning algorithm and it follows an iterative approach which attempts to partition the dataset into different “k” number of

predefined and non-overlapping subgroups where each data point belongs to only one subgroup according to their similar qualities.

```
scores = []
for k in range(2,15):
    km = KMeans(n_clusters=k,random_state=123)
    km = km.fit(df_norm)
    scores.append(km.inertia_)
dfk = pd.DataFrame({'Cluster':range(2,15), 'Score':scores})
plt.figure(figsize=(8,5))
plt.plot(dfk['Cluster'], dfk['Score'], marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()
```

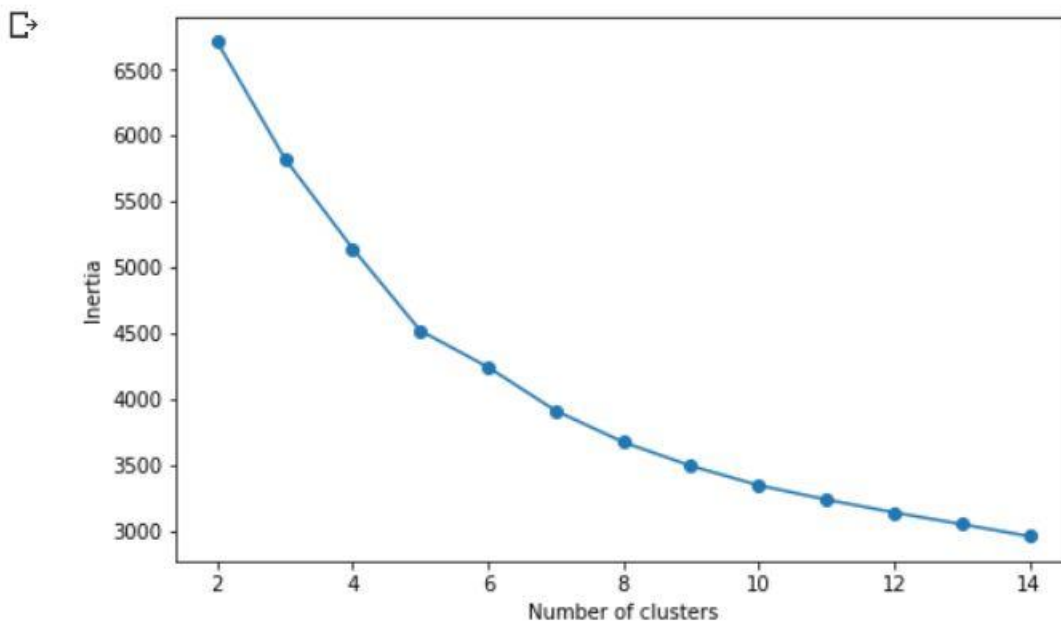


Figure 14:kmeans elbow method

The silhouette value measures how similar a point is to its own cluster (cohesion) compared to other clusters (separation).

```
[ ] for i in range(5,11):
    kmeans_labels=KMeans(n_clusters=i,random_state=123).fit_predict(df_norm)
    print("Silhouette score for {} clusters k-means : {}".format(i,metrics.silhouette_score(df_norm,kmeans_labels, metric='euclidean').round(3)))

Silhouette score for 5 clusters k-means : 0.229
Silhouette score for 6 clusters k-means : 0.222
Silhouette score for 7 clusters k-means : 0.238
Silhouette score for 8 clusters k-means : 0.239
Silhouette score for 9 clusters k-means : 0.219
Silhouette score for 10 clusters k-means : 0.217
```

```
[ ] for i in [6,7,8]:
    kmeans_labels=KMeans(n_clusters=i,random_state=123).fit_predict(df_norm)
    print('Davies Bouldin Score:'+str(metrics.davies_bouldin_score(df_norm,kmeans_labels).round(3)))

Davies Bouldin Score:1.465
Davies Bouldin Score:1.354
Davies Bouldin Score:1.415
```

Figure 15: kmeans Davies Bouldin

The values of silhouette score are close to each other in range 6 to 8. In the circumstances, Let's look at another metric. The metric is Davies Bouldin that is defined as the average similarity measure of each cluster with its most similar cluster, where similarity is the ratio of within-cluster distances to between-cluster distances. The minimum score is zero, with lower values indicating better clustering.

Unlike Davies Bouldin, we want to be high of Silhouette score. Hence, when we evaluate both Elbow technique and Silhouette score, optimal cluster numbers are 7 according to K-Means Algorithm. So, I have determined 7 as the k values of the K-means model.

In [0]:

```
[ ] kmeans_labels=KMeans(n_clusters=7,random_state=123).fit_predict(df_norm)
```

```
[ ]
pca = PCA(n_components=3).fit_transform(df_norm)
fig = plt.figure(figsize=(12, 7), dpi=80, facecolor='w', edgecolor='k')
ax = plt.axes(projection="3d")
ax.scatter3D(pca.T[0],pca.T[1],pca.T[2],c=kmeans_labels,cmap='Spectral')

xLabel = ax.set_xlabel('X')
yLabel = ax.set_ylabel('Y')
zLabel = ax.set_zlabel('Z')
```

Figure 16:kmeans model clustering

Now, Let's visualize "CC GENERAL" dataset in three-dimensional space. Hence, we should apply PCA before.



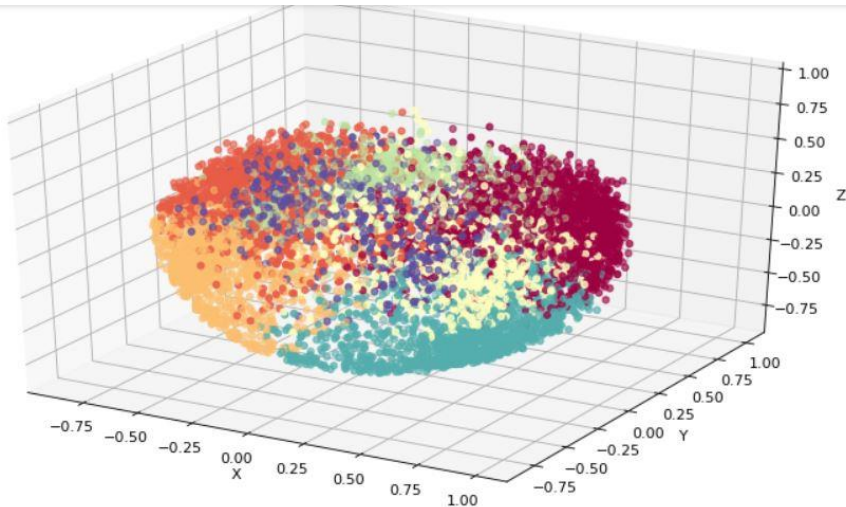


Figure 17:kmeans diagram

## MiniBatch K-Means

```
[ ]
for i in range(5,11):
    minikm_labels = MiniBatchKMeans(n_clusters=i,init='random',batch_size=100000).fit_predict(df_norm)
    print("Silhouette score for {} clusters MiniBatch k-means : {}".format(i,metrics.silhouette_score(df_norm, minikm_labels, metric='euclidean')).round(3)))

Silhouette score for 5 clusters MiniBatch k-means : 0.236
Silhouette score for 6 clusters MiniBatch k-means : 0.232
Silhouette score for 7 clusters MiniBatch k-means : 0.236
Silhouette score for 8 clusters MiniBatch k-means : 0.199
Silhouette score for 9 clusters MiniBatch k-means : 0.24
Silhouette score for 10 clusters MiniBatch k-means : 0.18

[ ] for i in [6,7,8,10]:
    minikm_labels = MiniBatchKMeans(n_clusters=i,init='random',batch_size=100000).fit_predict(df_norm)
    print("Davies Bouldin Score: "+str(metrics.davies_bouldin_score(df_norm,minikm_labels).round(3)))

Davies Bouldin Score:1.575
Davies Bouldin Score:1.716
Davies Bouldin Score:1.392
Davies Bouldin Score:1.59
```

Figure 18: MiniBatch K-Means

```
[ ] minikm_labels = MiniBatchKMeans(n_clusters=6,init='random',batch_size=100000).fit_predict(df_norm)

[ ]
fig = plt.figure(figsize=(12, 7), dpi=80, facecolor='w', edgecolor='k')
ax = plt.axes(projection="3d")
ax.scatter3D(pca.T[0],pca.T[1],pca.T[2],c=minikm_labels,cmap='Spectral')

xLabel = ax.set_xlabel('X')
yLabel = ax.set_ylabel('Y')
zLabel = ax.set_zlabel('Z')
```

Figure 19: MiniBatch K-Means diagram code

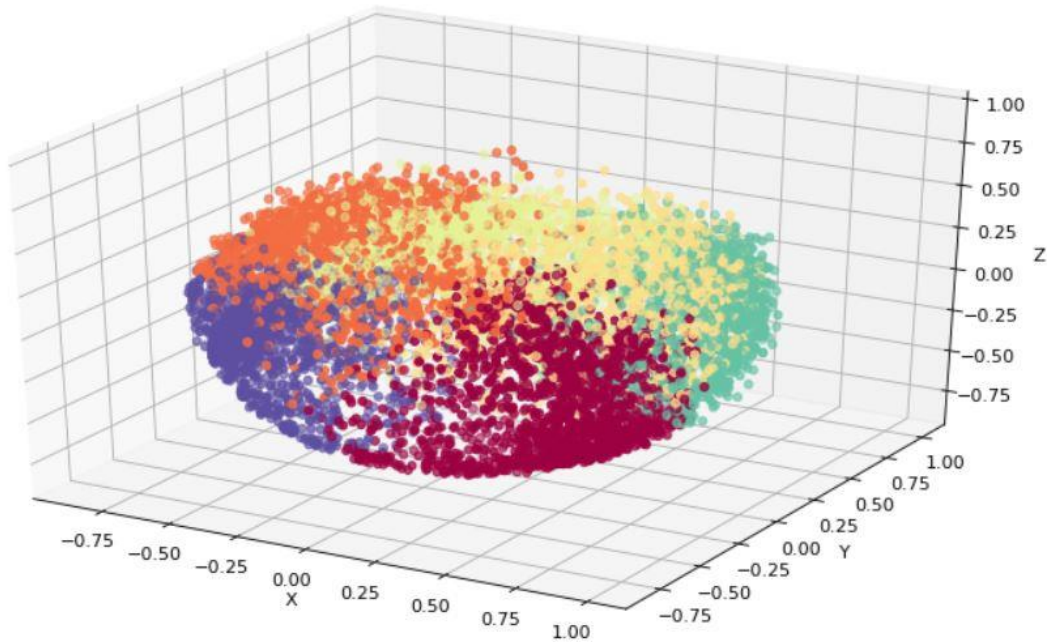


Figure 20: MiniBatch K-Means

## Hierarchical Clustering Segmentation

```
[ ]
plt.figure(figsize=(10, 7))
plt.title("Dendrograms")
dend = shc.dendrogram(shc.linkage(df_norm, method='ward'))
```

Figure 21: Hierarchical Clustering Segmentation1

```
[ ] hcluster = AgglomerativeClustering(n_clusters=3, affinity='euclidean', linkage='ward')
hcp=hcluster.fit_predict(df_norm)
print('Silhouette Score for Hieararchial Clustering:'+str(metrics.silhouette_score(df_norm,hcp,metric='euclidean')))
print('Davies Bouldin Score:'+str(metrics.davies_bouldin_score(df_norm,hcp)))
```

Silhouette Score for Hieararchial Clustering:0.16269232126810304  
Davies Bouldin Score:2.0178566980982713

```
[ ] fig = plt.figure(figsize=(12, 7), dpi=80, facecolor='w', edgecolor='k')
ax = plt.axes(projection="3d")
ax.scatter3D(pca.T[0],pca.T[1],pca.T[2],c=hcp,cmap='Spectral')

xlabel = ax.set_xlabel('X')
ylabel = ax.set_ylabel('Y')
zlabel = ax.set_zlabel('Z')
```

Figure 22: Hierarchical Clustering Segmentation2

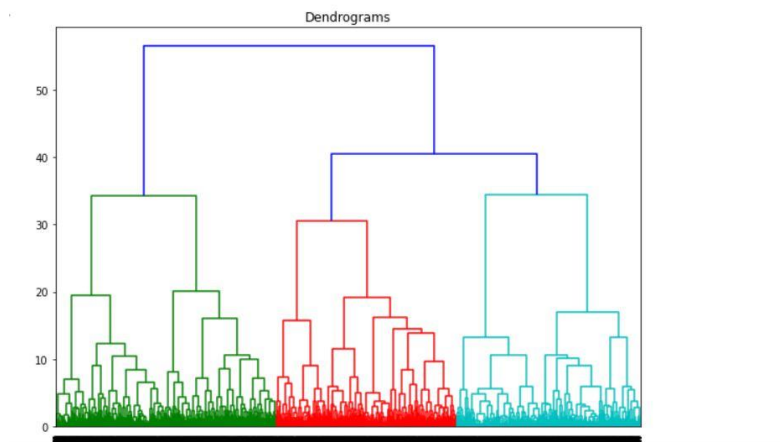


Figure 23: Hierarchical Clustering Segmentation diagram

## Comparison of Results

```
[ ] algorithms=["K-Means","MiniBatch K-Means","Hierarchical Clustering"]

[ ] # Silhouette Score
ss=[metrics.silhouette_score(df_norm,kmeans_labels),metrics.silhouette_score(df_norm,minikm_labels)
,metrics.silhouette_score(df_norm,hcp)]

# Davies Bouldin Score
db=[metrics.davies_bouldin_score(df_norm,kmeans_labels),metrics.davies_bouldin_score(df_norm,minikm_labels)
,metrics.davies_bouldin_score(df_norm,hcp)]

[ ] comprsn={"Algorithms":algorithms,"Davies Bouldin":db,"Silhouette Score":ss}
compdf=pd.DataFrame(comprsn)
display(compdf.sort_values(by=["Silhouette Score"], ascending=False))
```

	Algorithms	Davies Bouldin	Silhouette Score
0	K-Means	1.354108	0.237578
1	MiniBatch K-Means	1.628938	0.218182
2	Hierarchical Clustering	2.017857	0.162692

Figure 24: comparison of results

Finally, we have tried three algorithms. K-Means has the best Silhouette and Hierarchical has best Davies Bouldin score.

However, we are going to 3 algorithms for make conclusion separately.



## K-Means model

```
[ ] df['Clusters']=list(kmeans_labels)
customers=pd.DataFrame(df['Clusters'].value_counts()).rename(columns={'Clusters':'Number of Customers'})
customers.T
```

	2	0	4	5	1	3	6
Number of Customers	1865	1653	1554	1307	1147	771	653

Figure 25:kmeans number of clusters

we have 7 customer types. Let's try to understand behaviours or labels of customers.

```
[ ] means=pd.DataFrame(df.describe().loc['mean'])
means.T.iloc[:,[0,1,6,8,9,11,12,16]].round(1)
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	CASH_ADVANCE_FREQUENCY	PURCHASES_TRX	CREDIT_LIMIT	TENURE
mean	1564.5	0.9	0.5	0.4	0.1	14.7	4494.4	11.5

Figure 26:understand behaviours or labels of customers.

```
[ ] df.set_index('Clusters')
grouped=df.groupby(by='Clusters').mean().round(1)
grouped.iloc[:,[0,1,6,8,9,11,12,16]]
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	CASH_ADVANCE_FREQUENCY	PURCHASES_TRX	CREDIT_LIMIT	TENURE	
Clusters									
0	2020.6	1.0	0.9		0.6	0.1	44.6	7003.0	11.9
1	131.0	0.4	0.2		0.2	0.0	4.0	3811.0	11.8
2	1259.7	1.0	0.1		0.0	0.1	2.2	2780.2	11.9
3	99.6	0.9	0.8		0.7	0.0	16.6	4123.0	11.7
4	4044.3	1.0	0.2		0.2	0.4	5.8	6744.0	11.7
5	947.0	1.0	0.9		0.8	0.0	18.4	2906.6	11.9
6	862.4	0.8	0.4		0.3	0.2	5.1	2504.2	7.4

Figure 27:kmeans values fo clusters

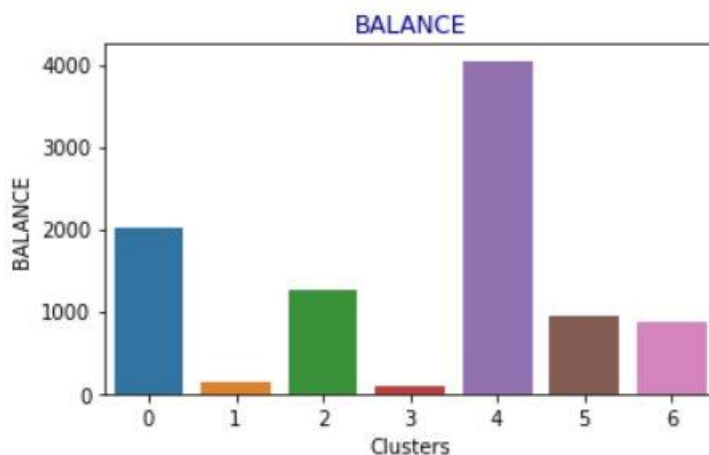


Figure 28:kmeans balance

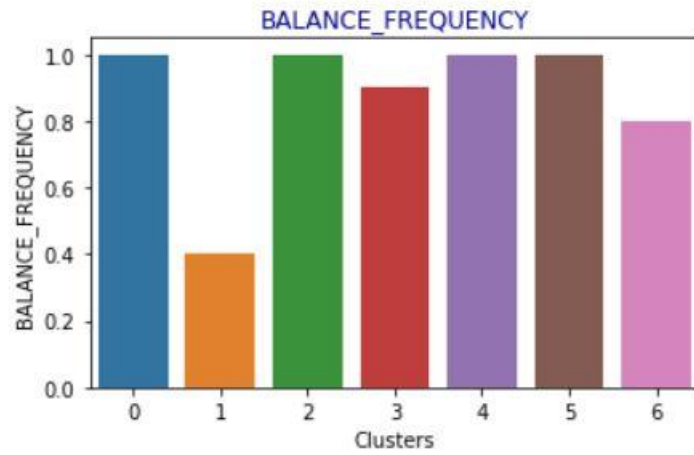


Figure 29:kmeans balance frequency

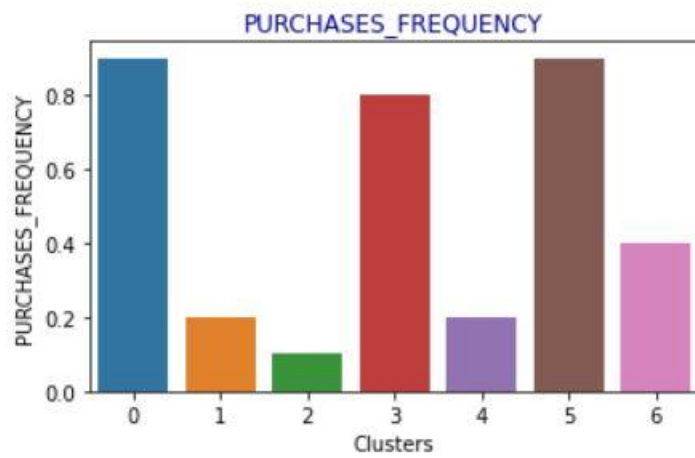


Figure 30:kmeans purchases frequency

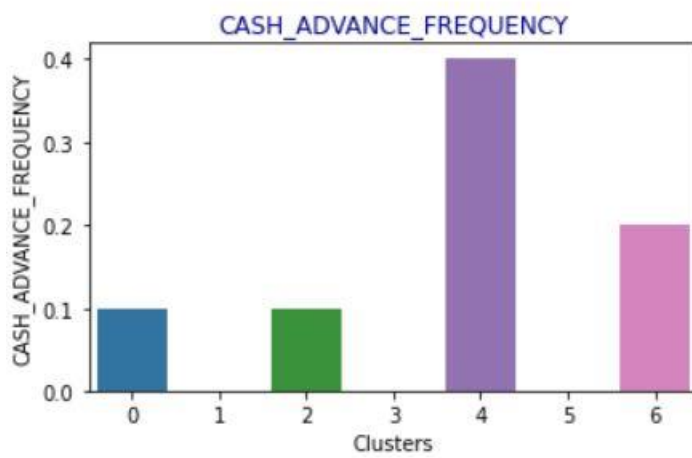


Figure 31: kmeans cash advance frequency

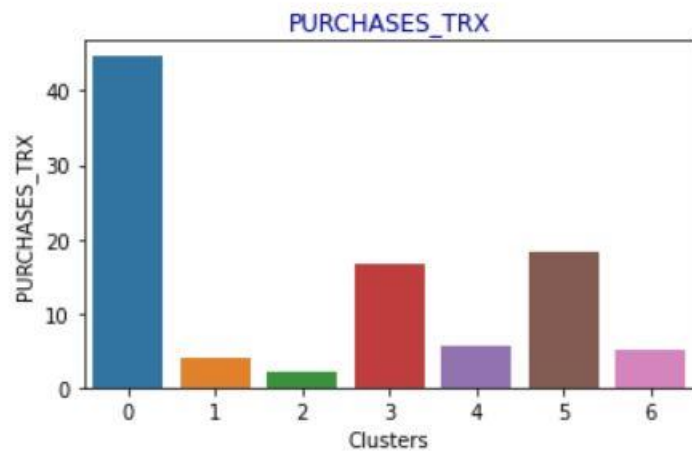


Figure 32:kmeans purchases\_trx

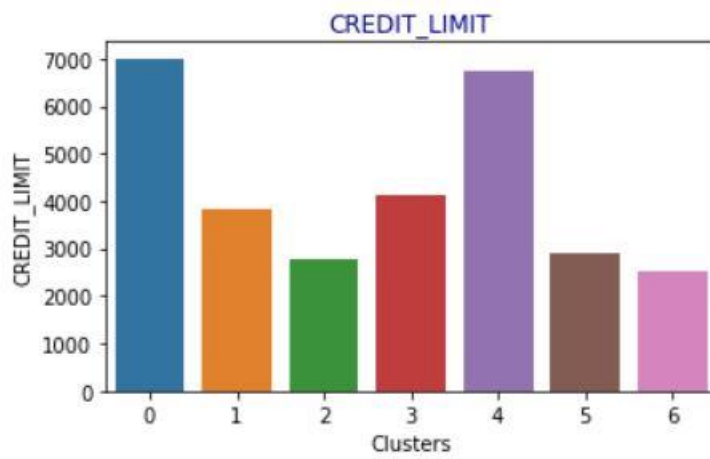


Figure 33:kmeans credit limit

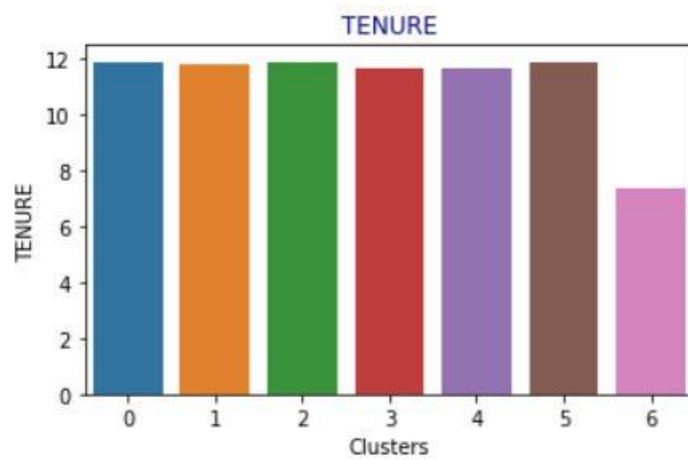


Figure 34:kmeans tenure

We have chosen some columns that are significant to identify the clusters.

### K-Means model conclusion

Cluster 0: The highest purchase frequency which tend to pay in instalment, that is higher credit limit and long duration customers.

Cluster 1: Pretty low balance and purchase frequency. They rarely use credit card and also, they have lower credit limit.

Cluster 2: This group is having the highest number of customers and lowest usage of cards. Inactive customers, also long duration customers.

Cluster 3: High tendency of payment instalment, higher purchase frequency and their tenure time is above average.

Cluster 4: The highest balance amount but purchase frequency is not that good. Tend to cash in advance, higher credit limit than others. They don't like spending money.

Cluster 5: Second highest purchase frequency and also higher tendency payment in instalment. They are long duration customers.

Cluster 6: The least quantity of customer is in this group which are below average of purchase frequency and a shortly duration customers.

Firstly, we have started with data pre-processing. Then, we applied clustering algorithms. After comparing these clustering models than, we decided to use K-Means as the first model. Then, we divided the data into seven clusters, because seven clusters can be easily used to determine the behaviours of customers. However, each of the clusters have their own characteristics.

### MiniBatch K-Means model

```
[ ] df['clusters']=list(minikm_labels)
customersMINIKM=pd.DataFrame(df['clusters'].value_counts()).rename(columns={'clusters':'Number of Customers'})
customersMINIKM.T
```

	5	0	3	1	2	4
Number of Customers	1946	1723	1688	1406	1119	1068

Figure 35: MiniBatch K-Means number of clusters

we have 6 customer types. Let's try to understand behaviours or labels of customers.

```
[ ] means=pd.DataFrame(df.describe().loc['mean'])
means.T.iloc[:,[0,1,6,8,9,11,12,16]].round(1)
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	CASH_ADVANCE_FREQUENCY	PURCHASES_TRX	CREDIT_LIMIT	TENURE
mean	1564.5	0.9	0.5	0.4	0.1	14.7	4494.4	11.5

Figure 36:MiniBatch K-Means cluster mean

```
[ ] df.set_index('Clusters')
grouped=df.groupby(by='Clusters').mean().round(1)
grouped.iloc[:,[0,1,6,8,9,11,12,16]]
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	CASH_ADVANCE_FREQUENCY	PURCHASES_TRX	CREDIT_LIMIT	TENURE
Clusters								
0	488.6	1.0	0.9	0.8	0.0	15.4	2695.0	11.4
1	131.9	0.4	0.3	0.2	0.0	4.2	3703.7	11.3
2	1076.9	1.0	0.8	0.3	0.0	26.8	5547.1	11.7
3	3681.4	1.0	0.2	0.1	0.4	4.8	6224.7	11.2
4	2894.8	1.0	0.9	0.9	0.1	53.7	7735.4	11.9
5	1266.1	1.0	0.1	0.0	0.1	2.0	2774.2	11.7

Figure 37:MiniBatch K-Means cluster characteristics

```
[ ] features=["BALANCE","BALANCE_FREQUENCY","PURCHASES_FREQUENCY","PURCHASES_INSTALLMENTS_FREQUENCY","CASH_ADVANCE_FREQUE
plt.figure(figsize=(15,10))
for i,j in enumerate(features):
    plt.subplot(3,3,i+1)
    sns.barplot(grouped.index,grouped[j])
    plt.title(j,fontdict={'color':'darkblue'})
plt.tight_layout()
plt.show()
```

Figure 38: label generating code

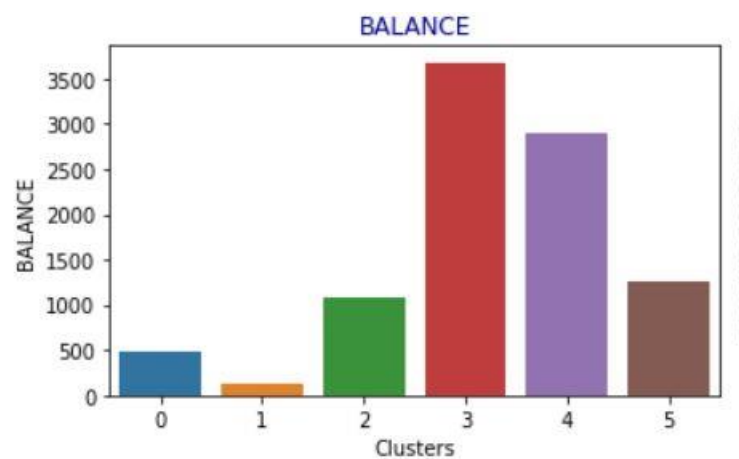


Figure 39: MiniBatch K-Means balance

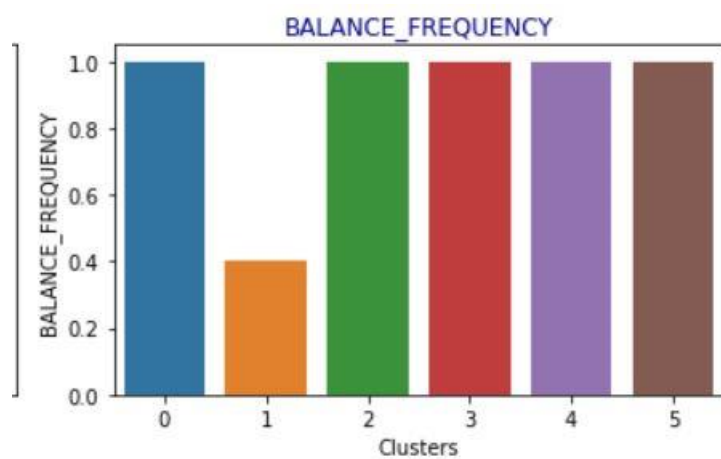


Figure 40: MiniBatch K-Means balance frequency

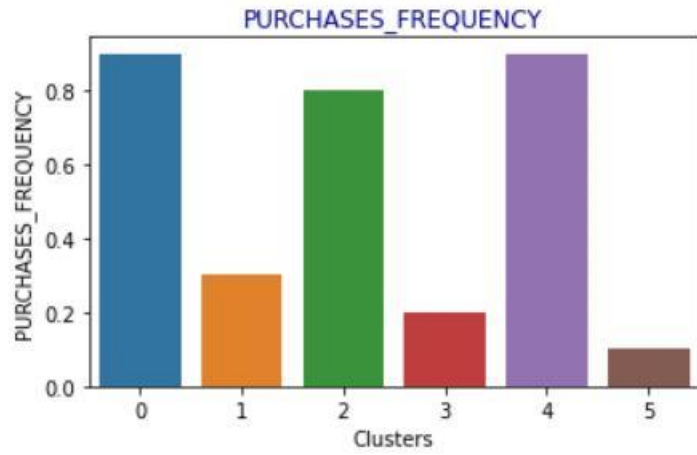


Figure 41: MiniBatch K-Means purchases frequency

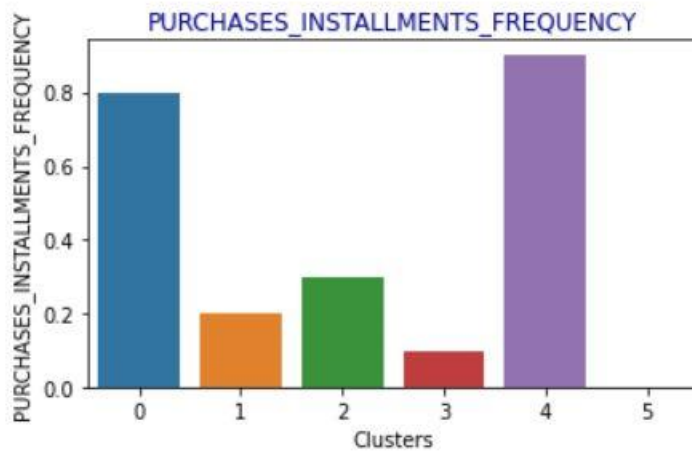


Figure 42: MiniBatch K-Means purchase installment frequency

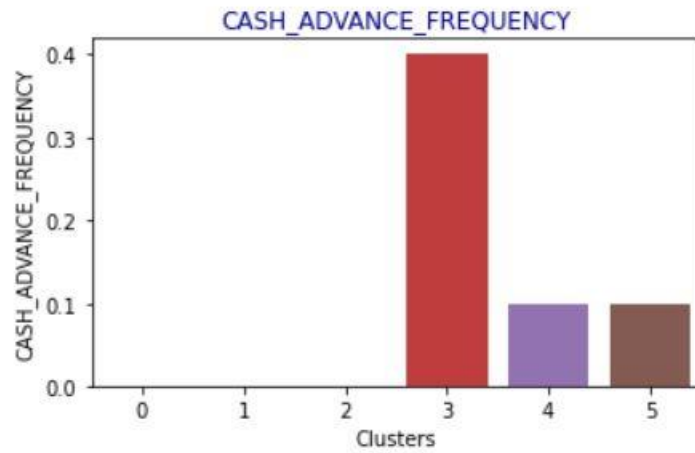


Figure 43: MiniBatch K-Means cash advance frequency

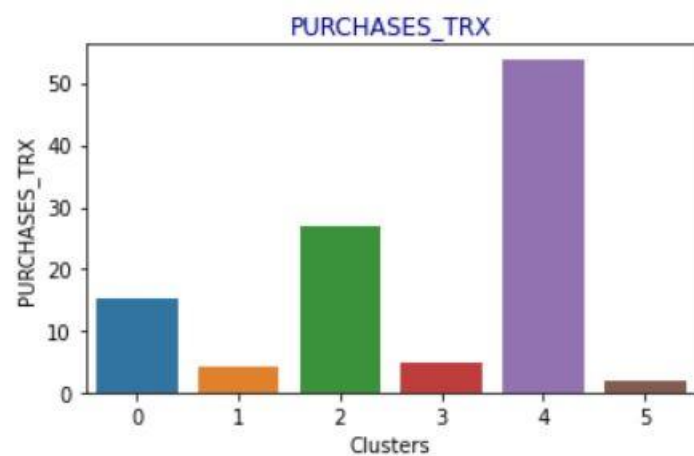


Figure 44: MiniBatch K-Means purchases frequency

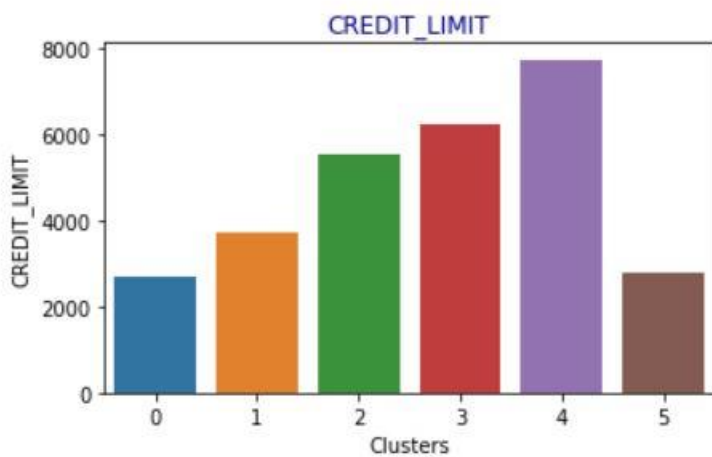


Figure 45: MiniBatch K-Means credit limit

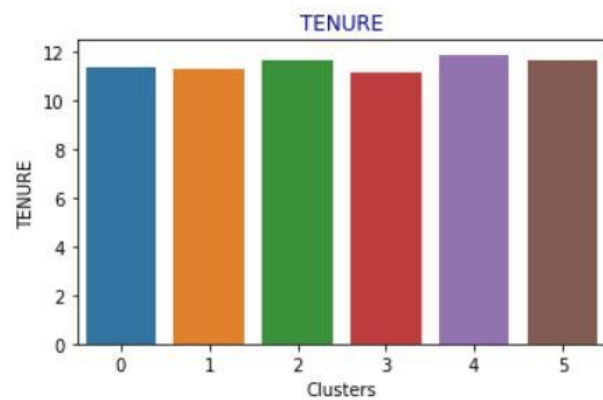


Figure 46: MiniBatch K-Means tenure



We have chosen some columns that are significant to identify the clusters.

### MiniBatch K-Means model conclusion

Cluster 0: Second highest purchase frequency which tend to pay in instalment, that is lower credit limit and long duration customers.

Cluster 1: Pretty low balance and purchase frequency. They rarely use credit card and also, they have lower credit limit.

Cluster 2: This group is having the highest number of customers and lowest usage of cards. Inactive customers, also long duration customers.

Cluster 3: High tendency of payment instalment, higher purchase frequency and their tenure time is above average.

Cluster 4: The highest balance amount but purchase frequency is not that good. Tend to cash in advance, higher credit limit than others. They don't like spending money.

Cluster 5: Second highest purchase frequency and also higher tendency payment in instalment. They are long duration customers.

Firstly, we have started with data pre-processing. Then, we applied clustering algorithms. After comparing these clustering models than, we decided to use MiniBatch K-Means as the second model. Then, we divided the data into six clusters, because six clusters can be easily used to determine the behaviours of customers. However, each of the clusters have their own characteristics.

### Hierarchical Clustering Segmentation model

```
[ ] df['clusters']=list(hcp)
customersHCP=pd.DataFrame(df['clusters'].value_counts()).rename(columns={'clusters':'Number of Customers'})
customersHCP.T
```

	1	0	2
Number of Customers	3380	2802	2768

Figure 47: Hierarchical Clustering Segmentation model clustering

we have 3 customer types. Let's try to understand behaviours or labels of customers.

```
df.set_index('Clusters')
grouped=df.groupby(by='Clusters').mean().round(1)
grouped.iloc[:,[0,1,6,8,9,11,12,16]]
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	CASH_ADVANCE_FREQUENCY	PURCHASES_TRX	CREDIT_LIMIT	TENURE
Clusters								
0	577.1		0.7	0.2	0.1	0.1	3.8	3227.9
1	1341.7		1.0	0.9	0.7	0.0	30.5	5023.3
2	2836.1		0.9	0.3	0.2	0.3	6.4	5130.8

Figure 48: Hierarchical Clustering Segmentation model characteristics

```
featuresHC=["BALANCE", "BALANCE_FREQUENCY", "PURCHASES_FREQUENCY", "PURCHASES_INSTALLMENTS_FREQUENCY", "CASH_ADVANCE_FREQUENCY", "PURCHASES_TRX", "CREDIT_LIMIT", "TENURE"]
plt.figure(figsize=(15,10))
for i,j in enumerate(featuresHC):
    plt.subplot(3,3,i+1)
    sns.barplot(grouped.index,grouped[j])
    plt.title(j,fontdict={'color': 'darkblue'})
plt.tight_layout()
plt.show()
```

Figure 49: Hierarchical Clustering Segmentation model label diagram

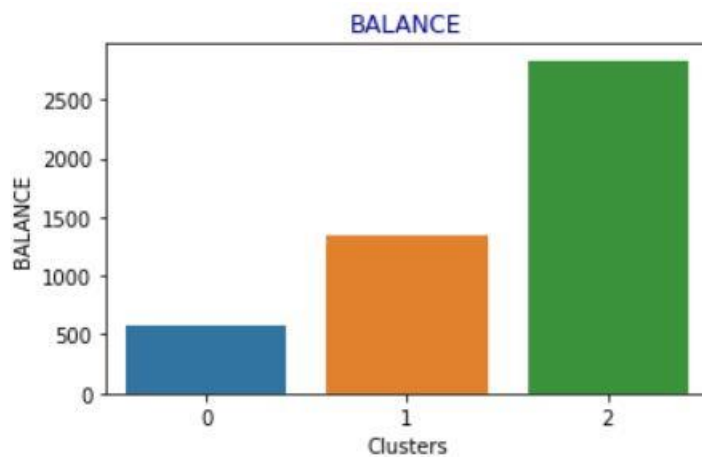


Figure 50: Hierarchical Clustering Segmentation model balance

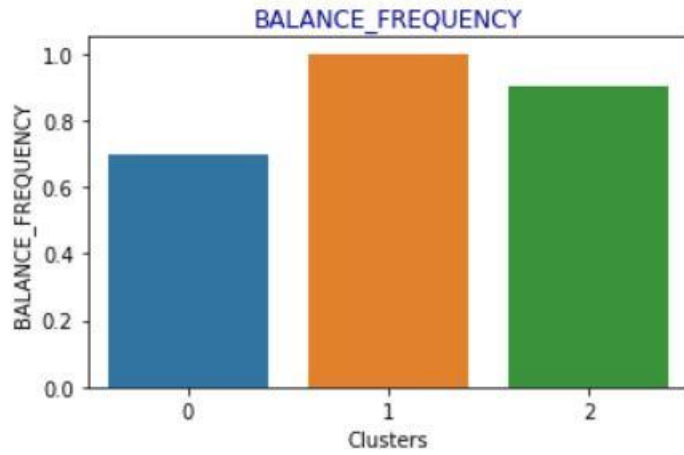


Figure 51: Hierarchical Clustering Segmentation model balance frequency

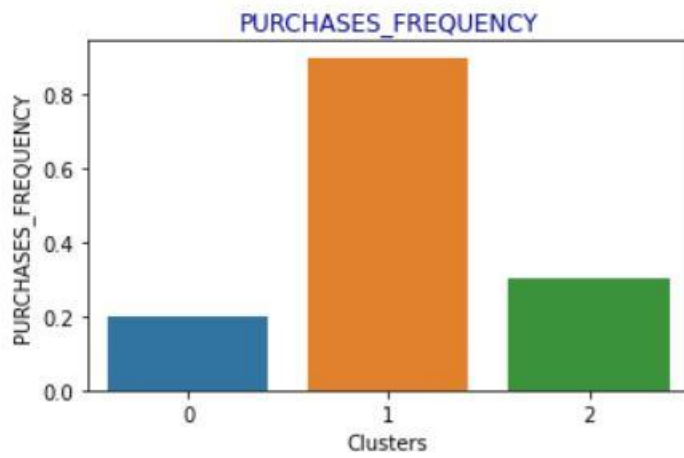


Figure 52: Hierarchical Clustering Segmentation model purchases frequency

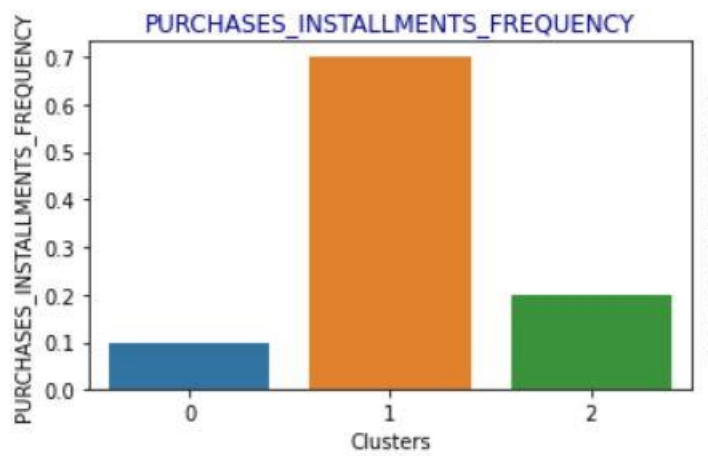


Figure 53: Hierarchical Clustering Segmentation model purchases instalment frequency

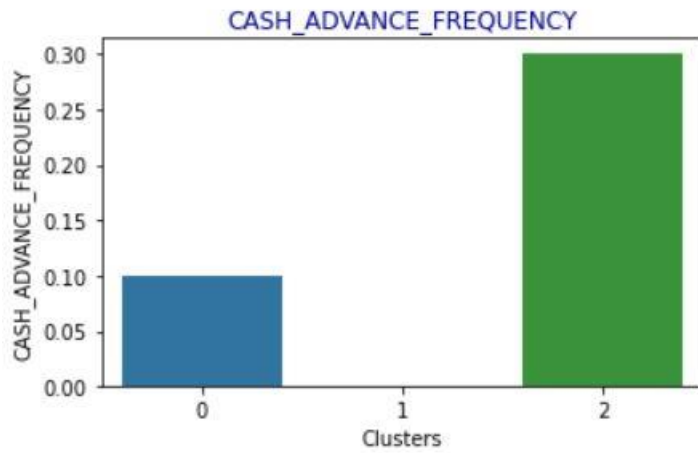


Figure 54: Hierarchical Clustering Segmentation model cash advance frequency

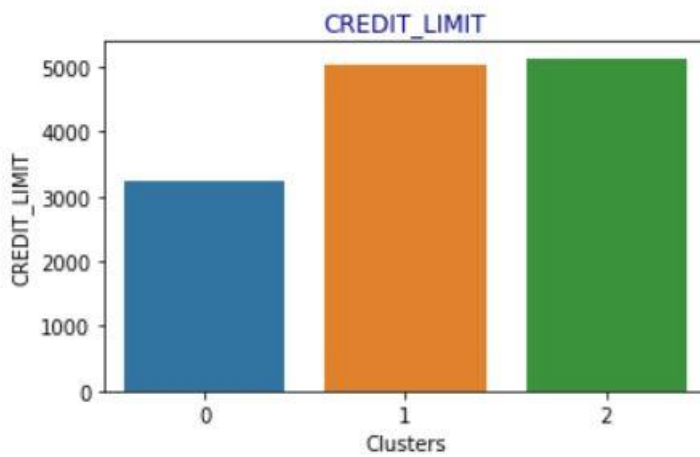


Figure 55: Hierarchical Clustering Segmentation model credit limit

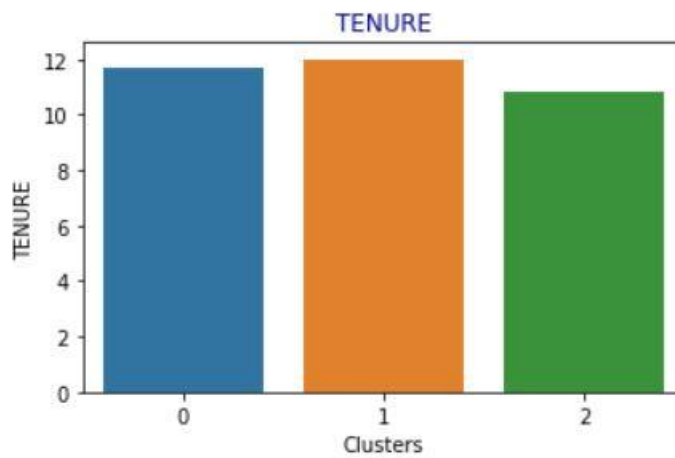


Figure 56: Hierarchical Clustering Segmentation model tenure

We have chosen some columns that are significant to identify the clusters.

### **Hierarchical Clustering Segmentation model conclusion**

Cluster 0: The lowest purchase frequency which tend to pay in instalment, that is one of lower credit limit and long duration customers.

Cluster 1: The highest purchase frequency which tend to pay in instalment mostly, that is one of higher credit limit and long duration customers.

Cluster 2: This group is having the highest balance and second highest purchase frequency .

## **References**

- [1] D. P. Yash Kushwaha, “Customer Segmentation using K-Means Algorithm,” 8th Semester Student of B.tech in Computer Science and Engineering.
- [2] E. A. Onur DOĞAN1, “CUSTOMER SEGMENTATION BY USING RFM”.
- [3] C. M. S. R. a. K. V. N. T. Sajana, “A Survey on,” in *Indian Journal of Science and Technology*, Volume 9, Issue 3,, Jan 2016..
- [4] A. B. P. E. Shreya Tripathi, “Approaches to,” in *International Journal of Engineering and Technology*, Volume 7, 2018.
- [5] A. R. Azarnoush Ansari, ““Customer Clustering Using a,” in *International Journal of Business and Management*, Volume 11, Issue 7,, 2016.
- [6] “mini-batch-k-means-clustering-algorithm,” [Online]. Available: <https://www.geeksforgeeks.org/ml-mini-batch-k-means-clustering-algorithm/>.
- [7] “/hierarchical-clustering-customer-segmentation,” [Online]. Available: <https://www.coursera.org/projects/hierarchical-clustering-customer-segmentation>.