Abstract

Project 2
Customer Segmentation

An UK – retail store has been in the business for quite some time and is now trying to roll out a loyalty campaign for customers who are very valuable to them. The store needs to understand who their valuable customers are and then roll out the campaign to them.

Tools / Skills Used

1. Python Programming
2. Jupyter Notebook
3. Pandas
4. Numpy
5. Matplotlib
6. Seaborn
7. Exploratory Data Analysis
8. Data Visualization
9. Scikitlearn
10. Machine Learning

Introduction to project 2

Problem Statement:

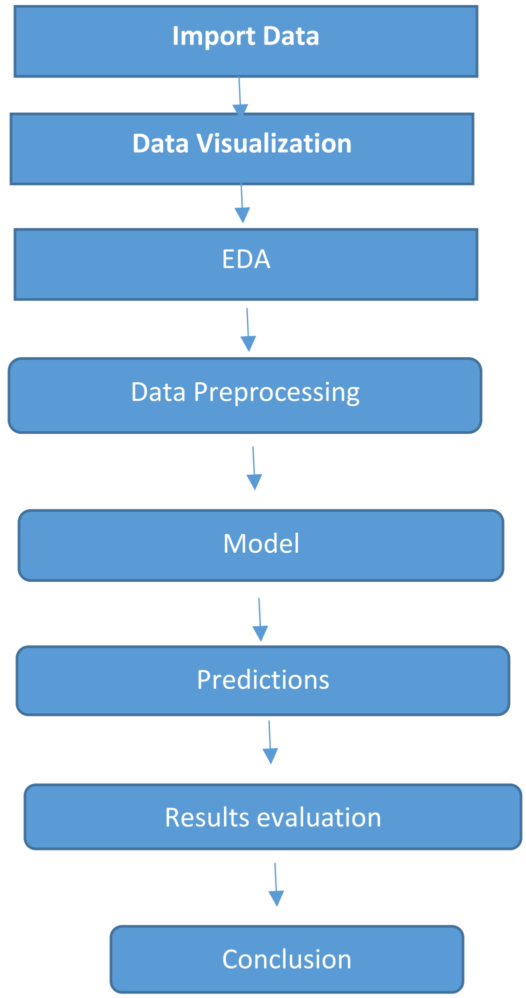
Customer Segmentation:

- Identify different customer segments
- Identify most valuable customer segments

So that, the US retail store can determine which customers to focus on and determine appropriate target strategies for different customer segments

Implementation

Workflow:



Modelling:

1. **K-means clustering**: **K-means clustering** is unsupervised machine learning algorithms. In the **K-means algorithm** identifies **k** number of centroids, and then allocates every data point to the nearest **cluster**, while keeping the centroids as small as possible. The first group of randomly selected centroids, which are used as the beginning points for every cluster, and then performs iterative (repetitive) calculations to optimize the positions of the centroid. It halts creating and optimizing clusters when either:

- The centroids have stabilized — there is no change in their values because the clustering has been successful.
- The defined number of iterations has been achieved.

2. **Agglomerative clustering** is the most common type of hierarchical clustering used to group objects in clusters based on their similarity. It's also known as *AGNES* (*Agglomerative Nesting*). The algorithm starts by treating each object as a singleton cluster. Next, pairs of clusters are successively merged until all clusters have been merged into one big cluster containing all objects. The result is a tree-based representation of the objects, named *dendrogram*.

Code Snippets:

Importing libraries

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

from sklearn.model_selection import train_test_split

from scipy.special import expit
from sklearn.metrics import confusion_matrix
from sklearn import svm
import datetime
```

In [2]:
```
os.chdir('C:/Users/soumya/Desktop/BI/Soumya - Projects')
df = pd.read_csv('Customer Segmentation.csv', encoding = "unicode_escape")
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  object
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
None
```

In [3]:
```
df = df.drop_duplicates()
df.dropna(inplace=True)
df.shape
```

Out[3]: (401604, 8)

]:
```
print(df.isna().sum())
```

```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

]:
```
df['CustomerID'] = df['CustomerID'].astype('category')
```

]:
```
df.head()
```

]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom

]:
```
df.describe().T
```

]:

	count	mean	std	min	25%	50%	75%	max
Quantity	401604.0	12.183273	250.283037	-80995.0	2.00	5.00	12.00	80995.0
UnitPrice	401604.0	3.474064	69.764035	0.0	1.25	1.95	3.75	38970.0

In [9]:
```
df.drop(df[df['Quantity'] > 6000].index, inplace=True)
df.drop(df[df['UnitPrice'] > 6000].index, inplace=True)
#df.drop(df[df['Quantity'] < 0].index, inplace=True)
df.drop(df[df['UnitPrice'] < 0].index, inplace=True)
df.shape
```

Out[9]:
```
(401597, 8)
```

In [10]:
```
df.nunique()
```

Out[10]:
```
InvoiceNo      22183
StockCode       3684
Description     3896
Quantity         433
InvoiceDate    20453
UnitPrice        617
CustomerID      4371
Country           37
dtype: int64
```

In [11]:
```
print(df.isna().sum())
```

```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

Converting into appropriate dtypes and bivariate analysis ¶

2]:
```
df['InvoiceDate']= pd.to_datetime(df['InvoiceDate'])
df['Month'] = pd.DatetimeIndex(df['InvoiceDate']).month
df['Day'] = pd.DatetimeIndex(df['InvoiceDate']).day
df['Hours'] = pd.DatetimeIndex(df['InvoiceDate']).hour
```

ANALYSING TOP CUSTOMERS

Invoice- wise

In [18]:
```
Total_order=df.groupby('InvoiceNo')['InvoiceNo'].agg('count')
a = Total_order.unique().sum()
print('Total orders made by customers are', a)
```

```
Total orders made by customers are 23275
```

Quantity- wise

In [19]:
```
Total_order=df.groupby('Quantity')['Quantity'].agg('count')
b = Total_order.unique().sum()
print('Total quaintity ordered made by customers are', b)
```

```
Total quaintity ordered made by customers are 398413
```

Net sales

In [20]:
```
df_returns = df[df['Quantity'] < 0]
Total_order_returned=df_returns.groupby('Quantity')['Quantity'].agg('count')
r = Total_order_returned.unique().sum()
print('Total quaintity ordered returned by customers are', r)
print('net sales', b-r)
```

```
Total quaintity ordered returned by customers are 8572
net sales 389841
```

Returns

21]:
```
cust_return = df[df['Total_purchase'] < 0]
Cost = cust_return.groupby(["CustomerID"])["Total_purchase"].agg("sum").nsmallest(5)
Cost
```

21]:
```
CustomerID
16446.0   -168469.6
12346.0    -77183.6
15749.0    -22998.4
16029.0    -12609.4
12744.0    -12158.9
Name: Total_purchase, dtype: float64
```

Top 5 customers

22]:
```
top_five_customer = df.groupby(["CustomerID"])["Quantity"].agg("count").nlargest(5)
print('top five customers are', top_five_customer)
```

```
top five customers are CustomerID
17841.0    7812
14911.0    5898
14096.0    5128
12748.0    4459
14606.0    2759
Name: Quantity, dtype: int64
```

Total money spent

23]:
```
Total_money_spent = (df.UnitPrice*df.Quantity).sum()
print('The total money spent by all customers is', Total_money_spent)
```

```
The total money spent by all customers is 8078766.224
```

Creating a pivot table with Total_purchase, times_bought, last_bought

4]:
```
cust_data_purchase = df.groupby('CustomerID')['Total_purchase'].sum().reset_index()
cust_data_purchase.head()
```

4]:

	CustomerID	Total_purchase
0	12346.0	-77183.60
1	12347.0	4310.00
2	12348.0	1797.24
3	12349.0	1757.55
4	12350.0	334.40

5]:
```
cust_data_freq = df.groupby('CustomerID')['InvoiceNo'].count().reset_index().rename(columns={'CustomerID':'CustomerID','InvoiceN
cust_data_freq.head()
```

5]:

	CustomerID	times_bought
0	12346.0	1
1	12347.0	182
2	12348.0	31
3	12349.0	73
4	12350.0	17

```
cust_data_quant = df.groupby('CustomerID')['Quantity'].sum().reset_index()
cust_data_quant.head()
```

	CustomerID	Quantity
0	12346.0	-74215
1	12347.0	2458
2	12348.0	2341
3	12349.0	631
4	12350.0	197

```
df['last_purchase'] =  max(df['InvoiceDate']) - df['InvoiceDate']
cust_data_pur = df.groupby('CustomerID') ['last_purchase'].min().reset_index()
cust_data_pur['last_purchase'] = cust_data_pur['last_purchase'].dt.days
cust_data_pur.head()
```

	CustomerID	last_purchase
0	12346.0	325.0
1	12347.0	1.0
2	12348.0	74.0
3	12349.0	18.0
4	12350.0	309.0

```
cust_total_1 = pd.merge(cust_data_purchase,cust_data_freq , on = "CustomerID", how = "inner")
cust_total =  pd.merge(cust_total_1,cust_data_pur , on = "CustomerID", how = "inner")
cust_total['last_purchase'].fillna(0, inplace = True)

cust_total.head()
```

	CustomerID	Total_purchase	times_bought	last_purchase
0	12346.0	-77183.60	1	325.0
1	12347.0	4310.00	182	1.0
2	12348.0	1797.24	31	74.0
3	12349.0	1757.55	73	18.0
4	12350.0	334.40	17	309.0

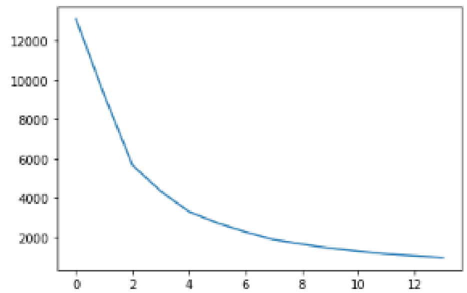
standard scaling

```
from sklearn.preprocessing import StandardScaler


cust_total_df = cust_total[['Total_purchase','times_bought','last_purchase']]

scaler = StandardScaler()

df_scaled = scaler.fit_transform(cust_total_df)
#df_scaled = pd.DataFrame(df_scaled)
#df_scaled.columns = ['Purchase', 'Freqency','Quantity', 'last_purchase']
#df_scaled['last_purchase'].fillna(0, inplace = True)
```

Kmeans clustering

```
30]: from sklearn.cluster import KMeans
ssd = []
range_of_cluster = range(1,15)
for optimal_num_cluster in range_of_cluster:
    kmeans = KMeans(n_clusters = optimal_num_cluster , max_iter = 500)
    kmeans.fit(df_scaled)

    ssd.append(kmeans.inertia_)

plt.plot(ssd)
```

```
30]: [<matplotlib.lines.Line2D at 0x1b36a7de490>]
```




```
31]: kmeans = KMeans(n_clusters=3, random_state=108, max_iter = 1000).fit(df_scaled)
Clusters = kmeans.labels_
```

```
cust_total_new = cust_total
cust_total_new['cust_total_df'] = kmeans.labels_
cust_total_new.columns = ['CustomerID','Purchase', 'Freqency', 'last_purchase','Cluster']

cust_total_new.head()
```

	CustomerID	Purchase	Freqency	last_purchase	Cluster
0	12346.0	-77183.60	1	325.0	2
1	12347.0	4310.00	182	1.0	1
2	12348.0	1797.24	31	74.0	1
3	12349.0	1757.55	73	18.0	1
4	12350.0	334.40	17	309.0	2

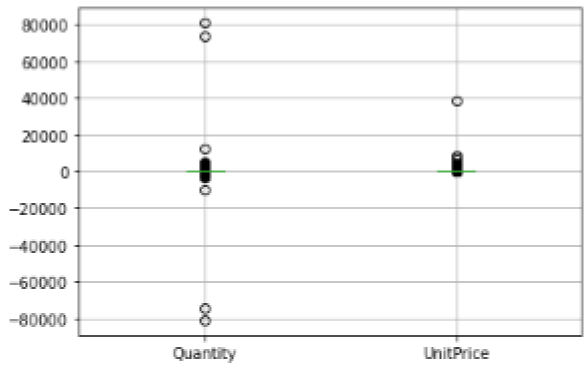
```
cust_total_new['Cluster'].value_counts()
```

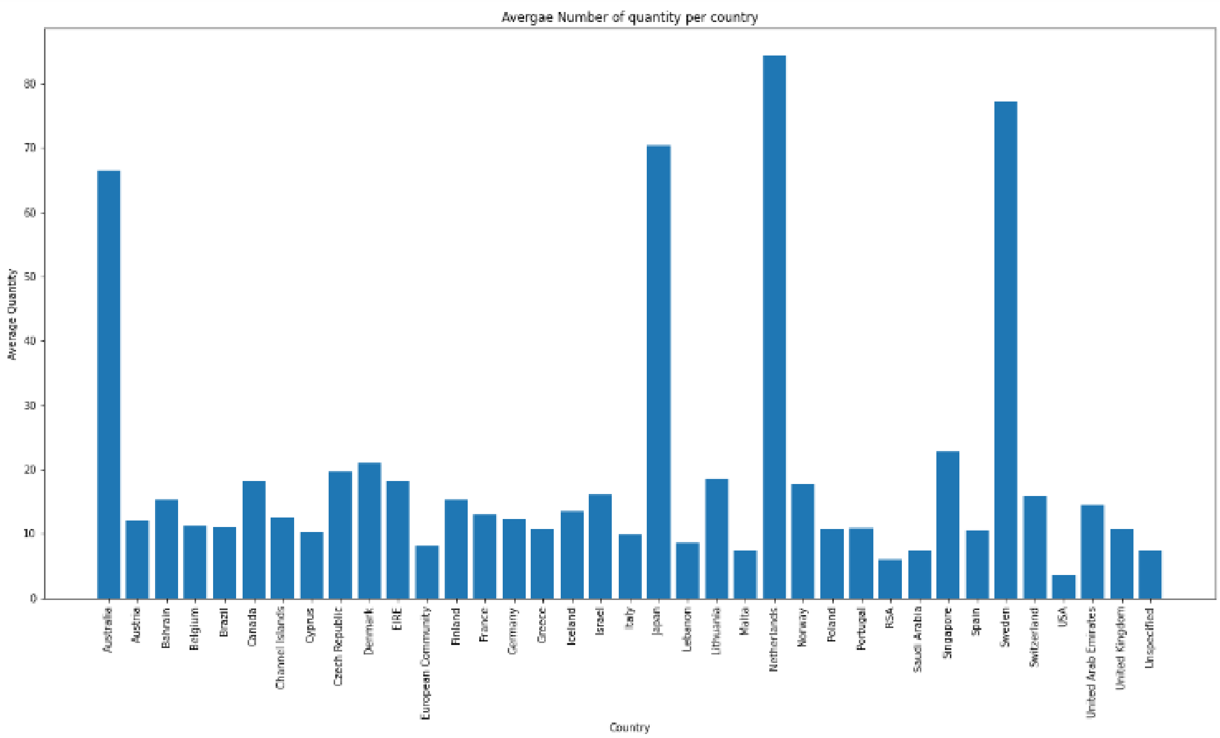
```
1    3260
2    1098
0      14
Name: Cluster, dtype: int64
```

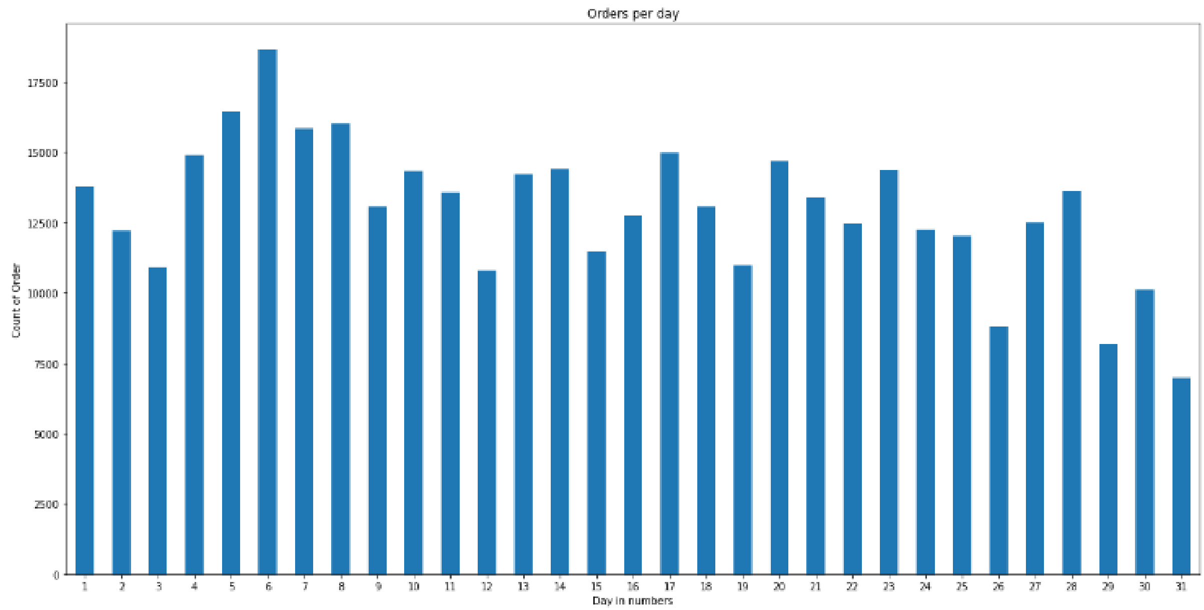
AgglomerativeClustering

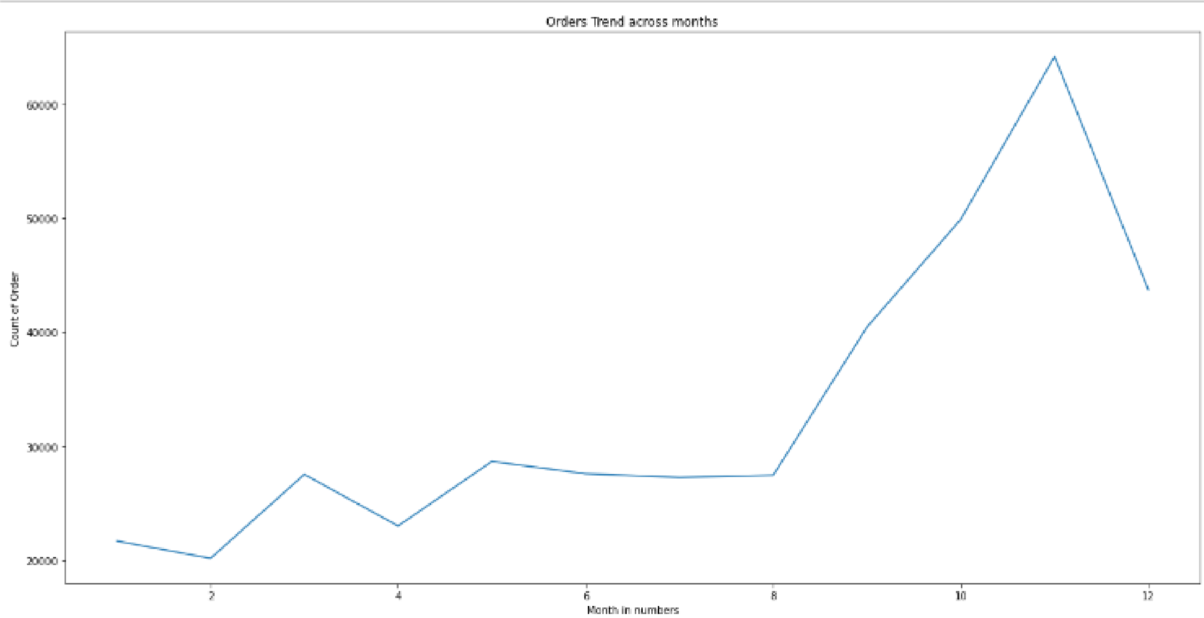
```
[43]: from sklearn.cluster import AgglomerativeClustering

hierarch_model = AgglomerativeClustering(n_clusters=3)

hierarch_label = hierarch_model.fit_predict(df_scaled)

cust_total['hierarch_label'] = hierarch_label
```

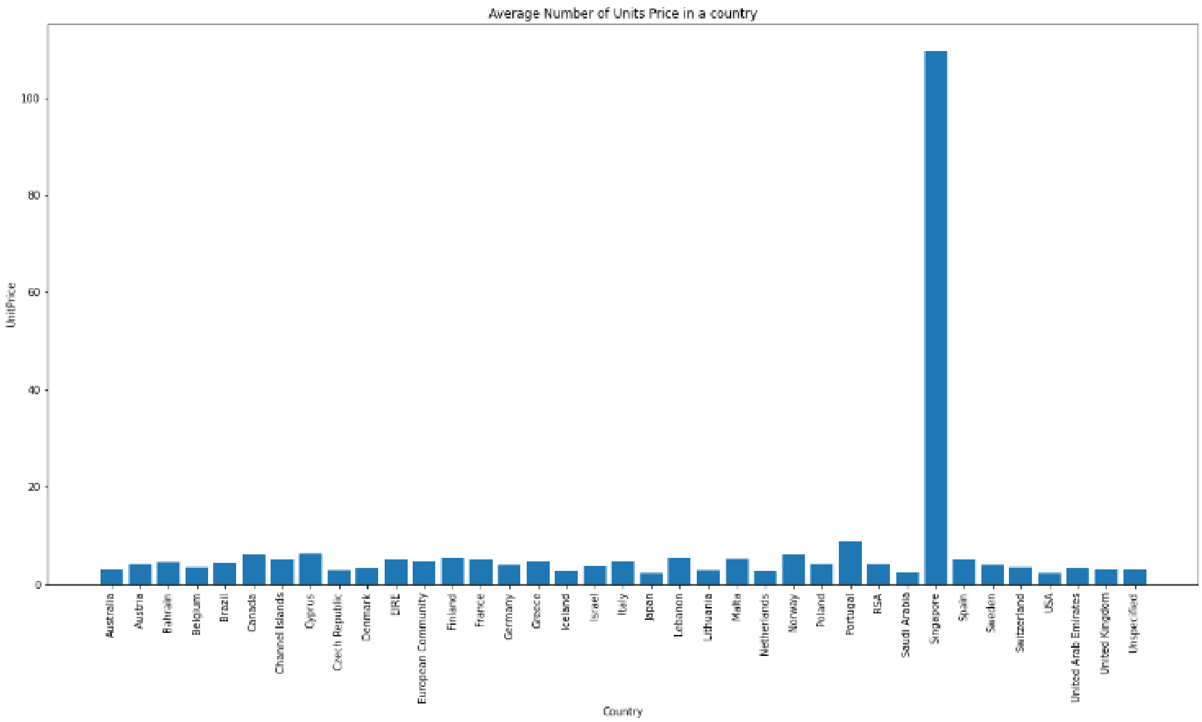
Visualization Snippets:

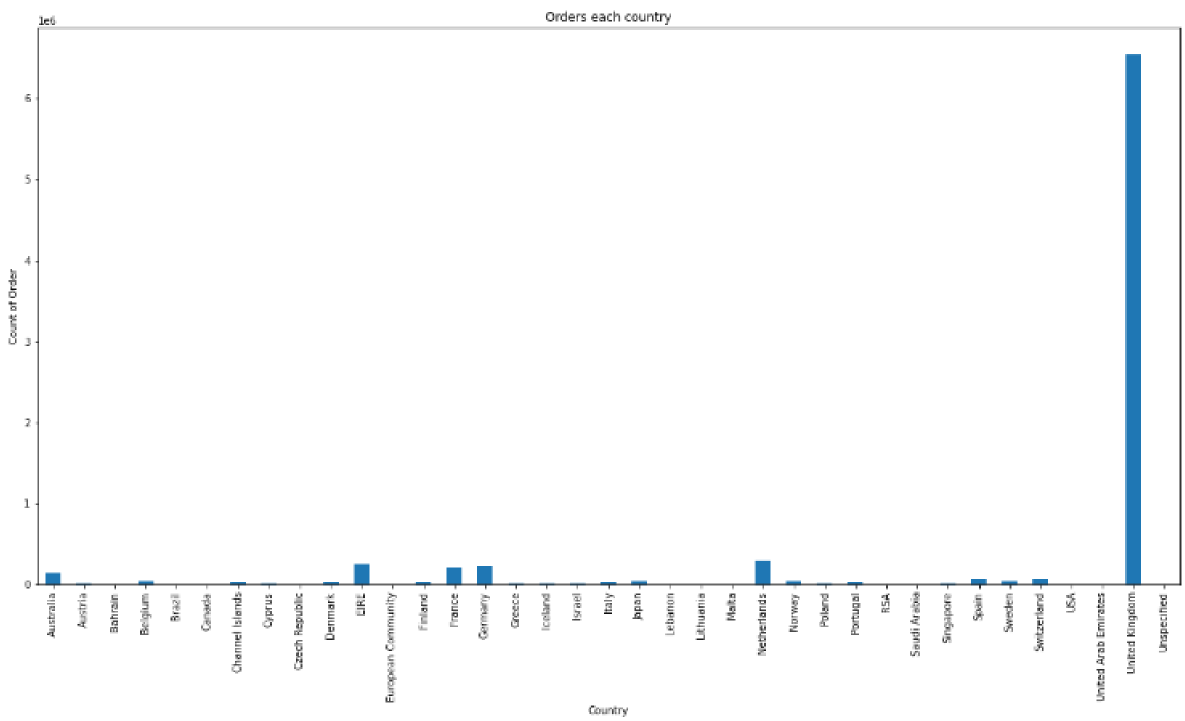





Orders per day
Count of Order
Day in numbers

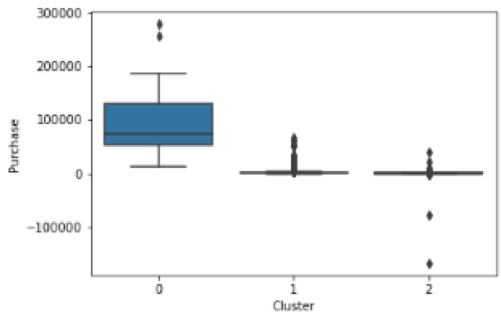

Orders Trend across months
Count of Order
Month in numbers


Average Number of Units Price in a country
UnitPrice
Country
Australia
Austria
Bahrain
Belgium
Brazil
Canada
Channel Islands
Cyprus
Czech Republic
Denmark
EIRE
European Community
Finland
France
Germany
Greece
Iceland
Israel
Italy
Japan
Lebanon
Lithuania
Malta
Netherlands
Norway
Poland
Portugal
RSA
Saudi Arabia
Singapore
Spain
Sweden
Switzerland
USA
United Arab Emirates
United Kingdom
Unspecified

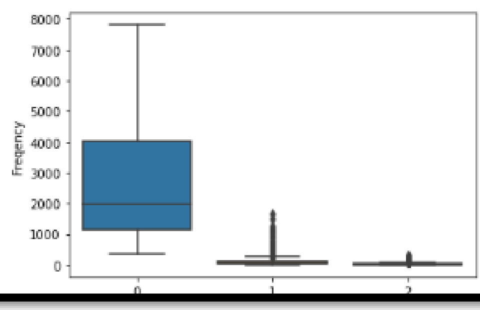

Orders each country
1e6
Count of Order
Country
Australia
Austria
Bahrain
Belgium
Brazil
Canada
Channel Islands
Cyprus
Czech Republic
Denmark
EIRE
European Community
Finland
France
Germany
Greece
Iceland
Israel
Italy
Japan
Lebanon
Lithuania
Malta
Netherlands
Norway
Poland
Portugal
RSA
Saudi Arabia
Singapore
Spain
Sweden
Switzerland
USA
United Arab Emirates
United Kingdom
Unspecified

Analaysing segments

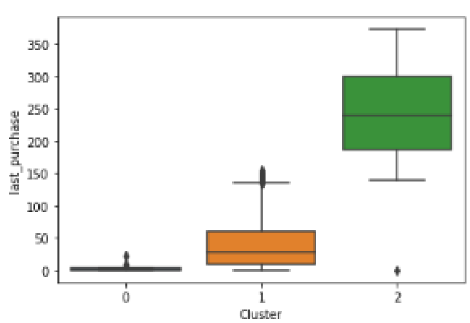
```
]: sns.boxplot(x= "Cluster" , y = "Purchase", data = cust_total )
]: <matplotlib.axes._subplots.AxesSubplot at 0x1b36a44a880>
```



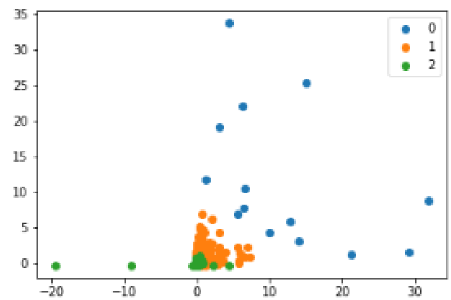

```
]: sns.boxplot(x= "Cluster" , y = "Freqency", data = cust_total )
]: <matplotlib.axes._subplots.AxesSubplot at 0x1b36b8c2fd0>
```

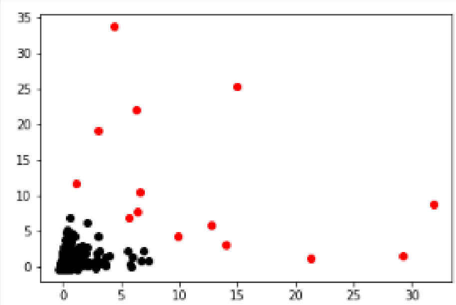



```
]: sns.boxplot(x= "Cluster" , y = "last_purchase", data = cust_total )
]: <matplotlib.axes._subplots.AxesSubplot at 0x1b36e32fe50>
```

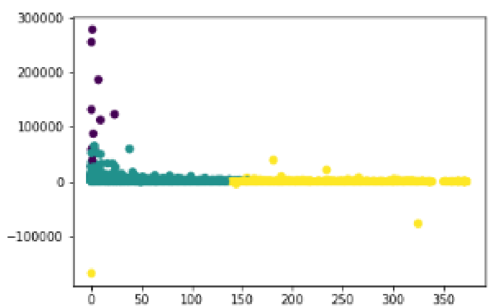


```
label = kmeans.labels_
u_labels = np.unique(label)

#plotting the results:

for i in u_labels:
    plt.scatter(df_scaled[label == i , 0] , df_scaled[label == i , 1] , label = i)
plt.legend()
plt.show()
```

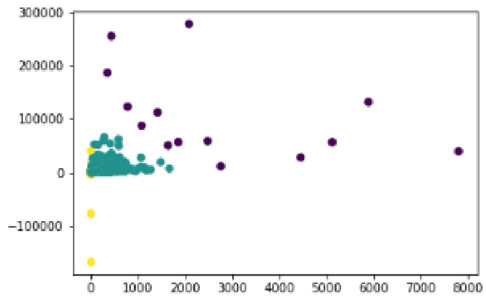




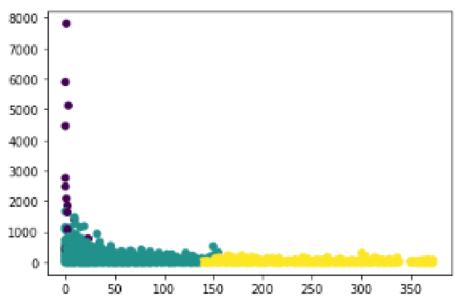
```
plt.scatter(cust_total['last_purchase'], cust_total['Purchase'], c = cust_total['Cluster'])
plt.show()
```



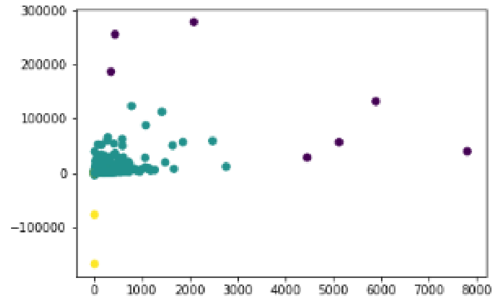
```
]: plt.scatter(cust_total['Freqency'], cust_total['Purchase'], c = cust_total['Cluster'])
   plt.show()
```



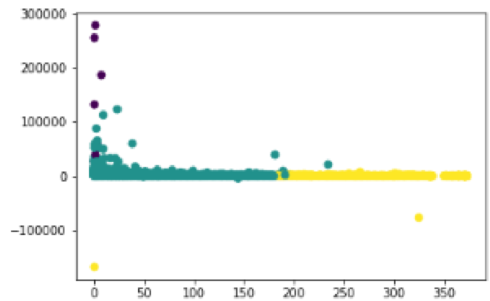

```
]: plt.scatter(cust_total['last_purchase'], cust_total['Freqency'], c = cust_total['Cluster'])
   plt.show()
```



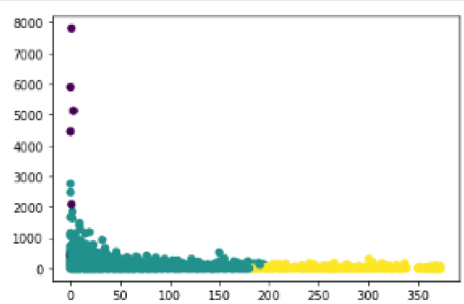
```
plt.scatter(cust_total['Freqency'], cust_total['Purchase'], c = cust_total['hierarch_label'])
plt.show()
```




```
plt.scatter(cust_total['last_purchase'], cust_total['Purchase'], c = cust_total['hierarch_label'])
plt.show()
```




```
plt.scatter(cust_total['last_purchase'], cust_total['Freqency'], c = cust_total['hierarch_label'])
plt.show()
```

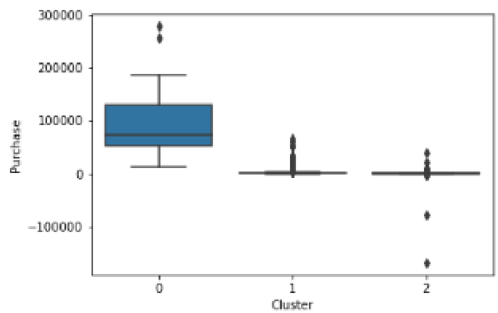



```
cust_total['hierarch_label'].value_counts()
```

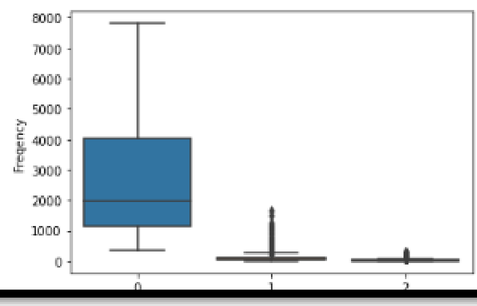
```
1    3525
2     840
0       7
Name: hierarch_label, dtype: int64
```

Analaysing segments

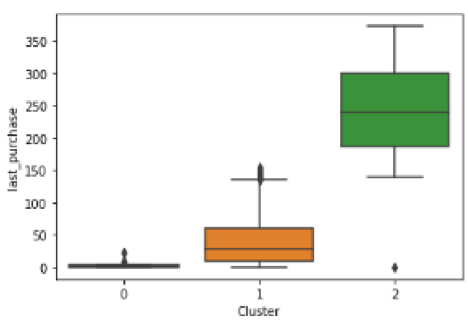
```
8]: sns.boxplot(x= "Cluster" , y = "Purchase", data = cust_total )
8]: <matplotlib.axes._subplots.AxesSubplot at 0x1b36ea02520>
```




```
9]: sns.boxplot(x= "Cluster" , y = "Freqency", data = cust_total )
9]: <matplotlib.axes._subplots.AxesSubplot at 0x1b36e4e63d0>
```




```
]: sns.boxplot(x= "Cluster" , y = "last_purchase", data = cust_total )
]: <matplotlib.axes._subplots.AxesSubplot at 0x1b36e494850>
```



Results

From visualization:

- Netherland, Japan, Sweden, Australia are supplied higher number quantity.
- November and December have high number of product sold
- Most expensive per unit products are sold in Singapore
- UK contributes to majority of purchase
- Total revenue is 8633412.944

From Models:

- **Kmeans clustering**

Cluster 1 (3260 customers) – Purchase amount is moderate. Purchase frequency is moderate. Buy regular ly.

Cluster 0 (14 customers) – Purchase amount is highest. Purchase frequency is high. Buy regularly

Cluster 2 (1098 customers) – Purchase amount is low. In this segment, the products return is also seen. P urchase frequency is low. Did not buy recently from the superstore

- **Agglomerative clustering**

Cluster 1 (3525 customers) – similar to cluster 1 of Kmeans

Cluster 2 (840 customers) – similar to cluster 2 of Kmeans

Cluster 0 (7 customers) **-** similar to cluster 0 of Kmeans

Conclusion

Cluster 0 are our loyal customers and store need to roll out loyalty / membership programs for them.
Cluster 1 store need to offer more discounts and offers to increase their buying spent and increase their frequency of buy.
Cluster 2 can be ignored.

Future Scope

In future, the models can be upgraded with some better techniques in terms of getting higher and better metrics.