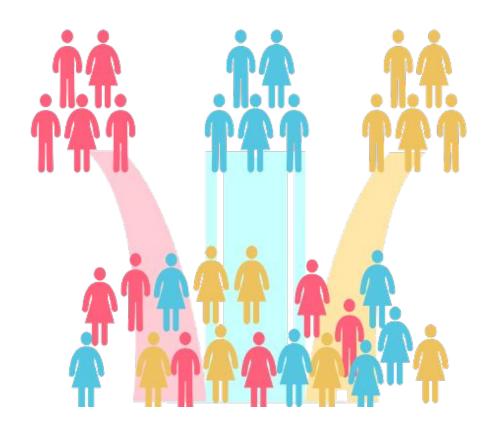


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UNSUPERVISED LEARNING CAPSTONE PROJECT

Customer Segmentation Analysis









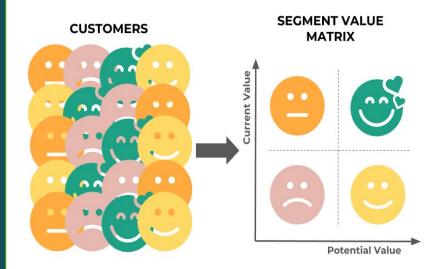
Contents:

- Introduction and Problem Statement
- Data Preview
- Data Summary , Null Values
- Cohort Retention Analysis
- > EDA
- RFM Modeling
- Transforming and Scaling
- Clustering
- > Conclusion

Introduction



Customer segmentation is the process of separating customers into groups on the basis of their shared behavior or other attributes. The groups should homogeneous within themselves and should also be heterogeneous to each other. The overall aim of this process is to identify high-value customer base i.e. customers that have the highest growth potential or are the most profitable.







Problem Description

In this project, our task is to identify major customer segments on a transnational which contains set data the transactions occurring between 01/12/2010 and 09/12/2011 UK-based and registered non-store online retail. The company mainly sells unique all-occasion gifts. Many customers of the company are wholesalers.

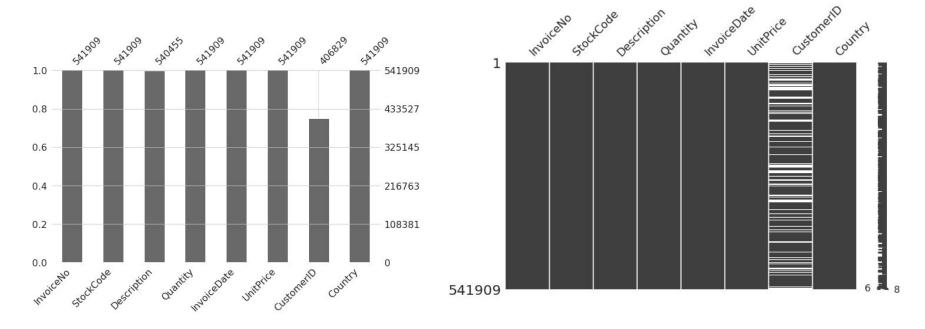
Dataset Preview:



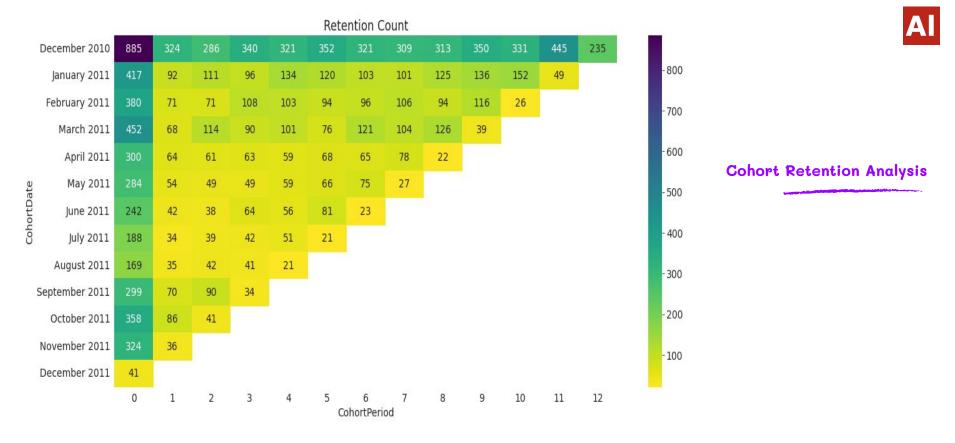
- InvoiceNo: Invoice number. Nominal, a 6-digit integral number uniquely assigned to each transaction. If this code starts with letter 'c', it indicates a cancellation.
- **Stock Code:** Product (item) code. Nominal, a 5-digit integral number uniquely assigned to each distinct product.
- Description: Product (item) name. Nominal.
- Quantity: The quantities of each product (item) per transaction. Numeric.
- InvoiceDate: Invoice Date and time. Numeric, the day and time when each transaction was generated.
- Unit Price: Unit price. Numeric, Product price per unit in sterling.
- **CustomerID:** Customer number. Nominal, a 5-digit integral number uniquely assigned to each customer.
- **Country:** Country name. Nominal, the name of the country where each customer resides



Looking for missing values



- White line in heatmap represent the position of null values in dataframe.
- Almost 25 percent of the data in Customer ID are missing and Description have only 0.27 percent of missing data.
- ❖ After removing the null values, there are 5225 duplicate observation in dataframe.



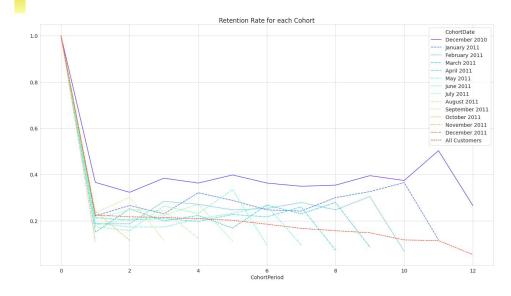
- Rows represent the activity, ie month of acquisition.
- ▶ Columns represent the retention, ie. month since acquisition.
- ▶ On December 2010 there were 885 new customers out of which 334 customers which is 36.6% of 885 remains in next month and so on..

| | | Retention Rate | | | | | | | | | | | | |
|------------|------------|----------------|-------|-------|-------|-------|--------|-----------------|---------|-------|-------|-------|-------|-------|
| Dece | mber 2010 | 100.0% | | 32.3% | | | 39.8% | | | | | | 50.3% | 26.6% |
| Jan | nuary 2011 | 100.0% | 22.1% | 26.6% | 23.0% | | 28.8% | 24.7% | 24.2% | | 32.6% | 36.5% | 11.8% | |
| Febr | ruary 2011 | 100.0% | 18.7% | 18.7% | 28.4% | 27.1% | 24.7% | 25.3% | 27.9% | 24.7% | 30.5% | 6.8% | | |
| M | March 2011 | 100.0% | 15.0% | 25.2% | 19.9% | 22.3% | 16.8% | 26.8% | 23.0% | 27.9% | 8.6% | | | |
| | April 2011 | 100.0% | 21.3% | 20.3% | 21.0% | 19.7% | 22.7% | 21.7% | 26.0% | 7.3% | | | | |
| | May 2011 | 100.0% | 19.0% | 17.3% | 17.3% | 20.8% | 23.2% | 26.4% | 9.5% | | | | | |
| Date | June 2011 | 100.0% | 17.4% | 15.7% | 26.4% | 23.1% | 33.5% | 9.5% | | | | | | |
| CohortDate | July 2011 | 100.0% | 18.1% | 20.7% | 22.3% | 27.1% | 11.2% | | | | | | | |
| | ugust 2011 | 100.0% | 20.7% | 24.9% | 24.3% | 12.4% | | | | | | | | |
| Septe | mber 2011 | 100.0% | 23.4% | 30.1% | 11.4% | | | | | | | | | |
| Oct | tober 2011 | 100.0% | 24.0% | 11.5% | | | | | | | | | | |
| Nove | mber 2011 | 100.0% | 11.1% | | | | | | | | | | | |
| Dece | mber 2011 | 100.0% | | | | | | | | | | | | |
| All | Customers | 100.0% | 22.5% | 21.7% | 21.4% | 20.9% | 20.2% | 18.5% | 16.7% | 15.7% | 14.8% | 11.7% | 11.4% | 5.4% |
| | | 0 | 1 | 2 | 3 | 4 | 5 C | 6 ohortPerio | 7 od | 8 | 9 | 10 | 11 | 12 |

Retention rate for all users is monotonically decreasing, while the graph for cohort dates from December 2010 to September 2011 is not monotonic in nature.



Customer corresponds to December 2010 (as their first month of purchase) have highest retention rate among all customers.





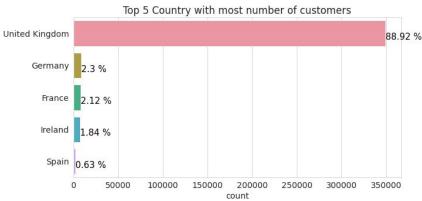




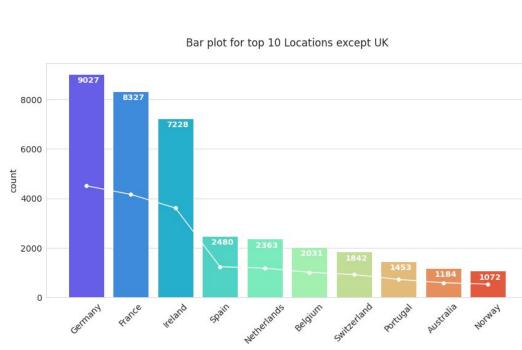
Exploratory Data Analysis



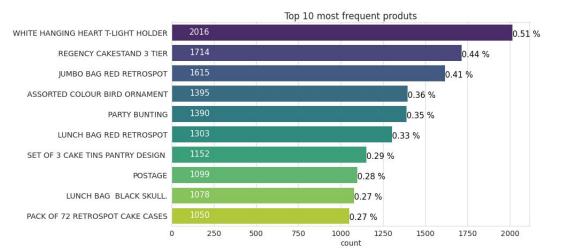




Since the company is based in the UK, most of its customers are from that country, followed by the top countries were also from Europe.

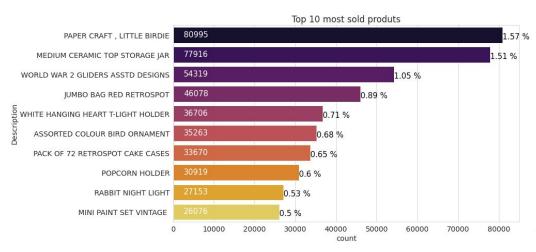


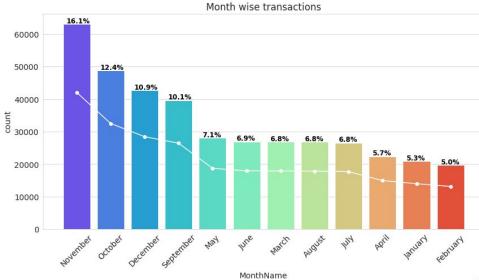




Frequent

Sold product



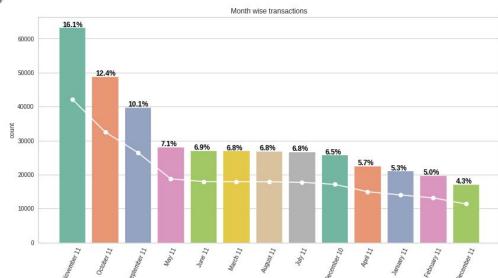


Most numbers of customers have purchased the gifts in the month of November, October and Septrmber. As we all know they have festive season in end of the year as well new year to celebrate so we have highest numbers of transaction in november, october, december as company have most of the customer wholesales who are keeping stocks for festive season.

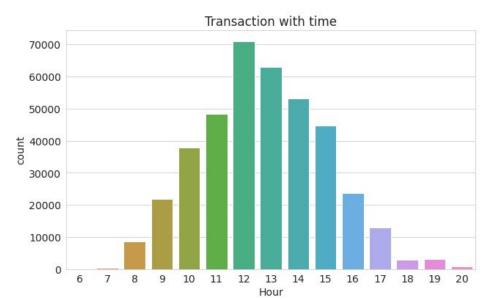
Least numbers of purchasing are in the month of December 2011 and February.



With Month



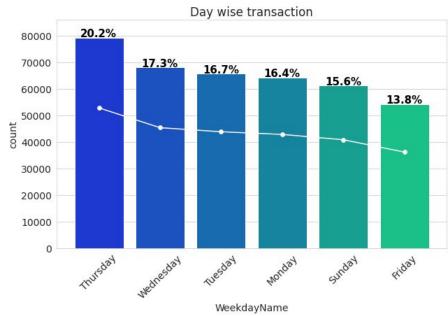
MonthYear



 From the above graph we can say that most numbers of purchasing is done between 10am to 3pm, and at 12 pm transaction is at its peak.

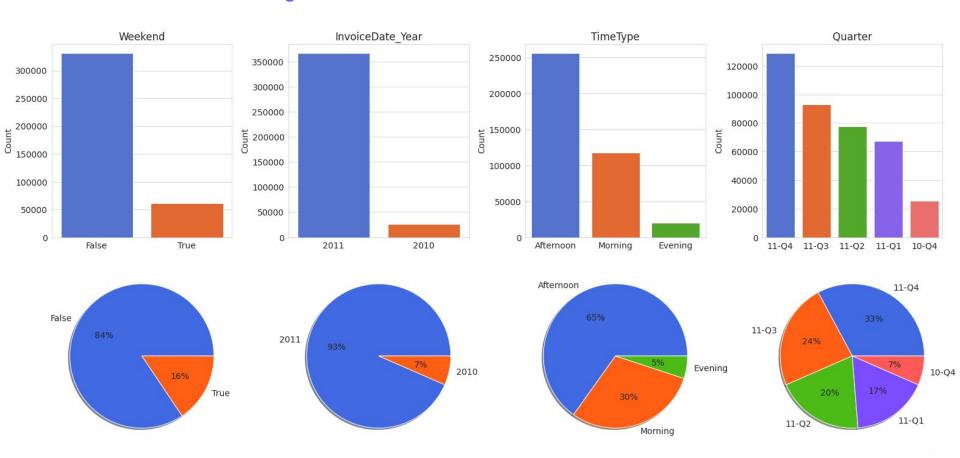


With Hour and WeekDay

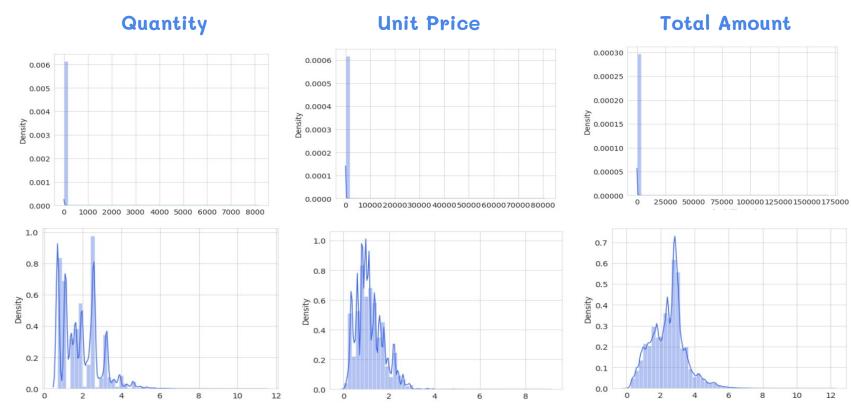




With other Categorical variable

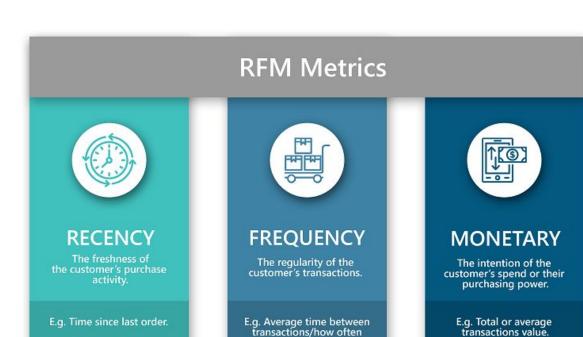






Logarithm





transactions/how often they place orders.

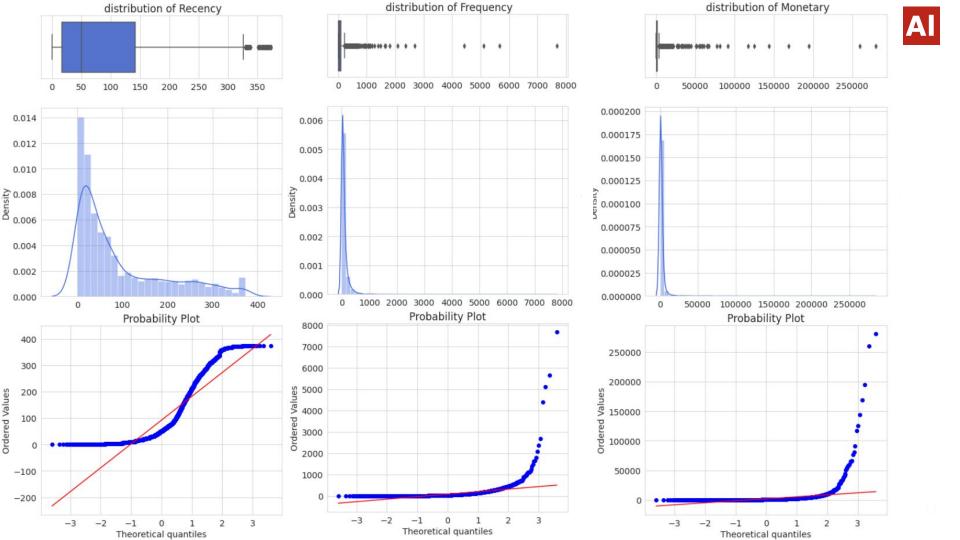
| | Recency | Frequency | Monetary |
|------------|---------|-----------|----------|
| CustomerID | | | |
| 12346.0 | 325 | 1 | 77183.60 |
| 12347.0 | 2 | 182 | 4310.00 |
| 12348.0 | 75 | 31 | 1797.24 |
| 12349.0 | 18 | 73 | 1757.55 |
| 12350.0 | 310 | 17 | 334.40 |
| | | | |

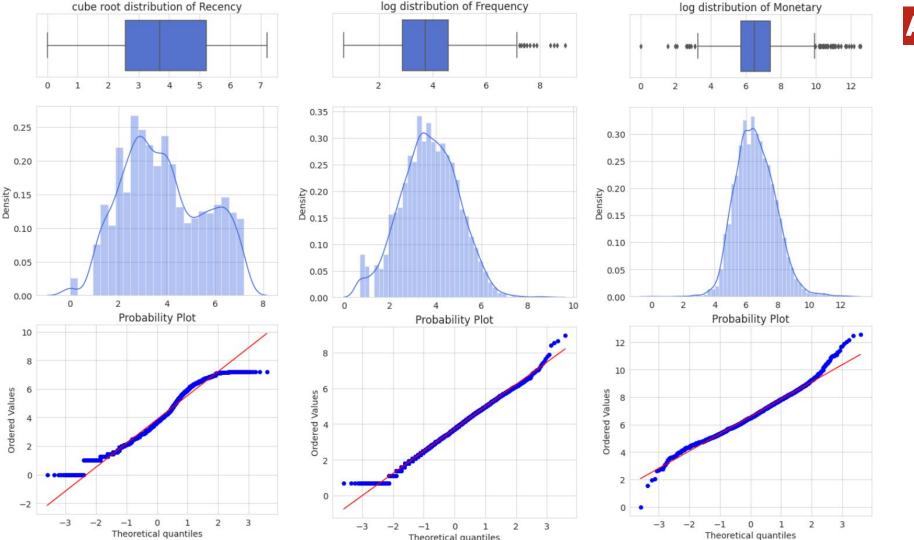
RFM is a method used for analyzing customer value. It is commonly used in database marketing and direct marketing and has received particular attention in retail and professional services industries. RFM stands for the three dimensions:

Recency – How recently did the customer purchase?

Frequency – How often do they purchase?

Monetary – How much do they spend?









After getting the RFM values, a common practice is to create group on each of the metrics and assigning the required order. For example, suppose that we divide each metric into 5 cuts. For the recency metric, the highest value 5 will be assigned to the customers with the least recency value (since they are the most recent customers). For the frequency and monetary metric, the highest value, 5, will be assigned to the customers with the Top 20% frequency and monetary values, respectively. After dividing the metrics into quartiles, we can collate the metrics into a single column (like a string of characters {like '213'}) to create classes of RFM values for our customers. We can divide the RFM metrics into lesser or more cuts depending on our requirements

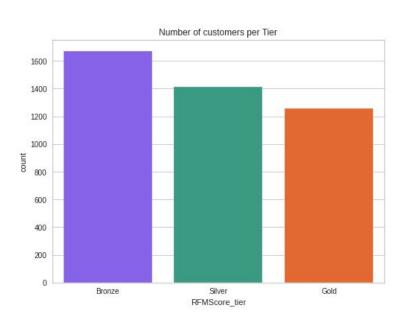
| | Recency | Frequency | Monetary | Recency_cbrt | Frequency_log | Monetary_log | R | F | M | RFMGroup | RFMScore | RFMScore_tier |
|------------|---------|-----------|----------|--------------|---------------|--------------|---|---|---|----------|----------|---------------|
| CustomerID | | | | | | | | | | | | |
| 12346.0 | 325 | 1 | 77183.60 | 6.875344 | 0.693147 | 11.253955 | 1 | 1 | 5 | 115 | 7 | Bronze |
| 12347.0 | 2 | 182 | 4310.00 | 1.259921 | 5.209486 | 8.368925 | 5 | 5 | 5 | 555 | 15 | Gold |
| 12348.0 | 75 | 31 | 1797.24 | 4.217163 | 3.465736 | 7.494564 | 2 | 3 | 4 | 234 | 9 | Silver |
| 12349.0 | 18 | 73 | 1757.55 | 2.620741 | 4.304065 | 7.472245 | 4 | 4 | 4 | 444 | 12 | Gold |
| 12350.0 | 310 | 17 | 334.40 | 6.767899 | 2.890372 | 5.815324 | 1 | 2 | 2 | 122 | 5 | Bronze |

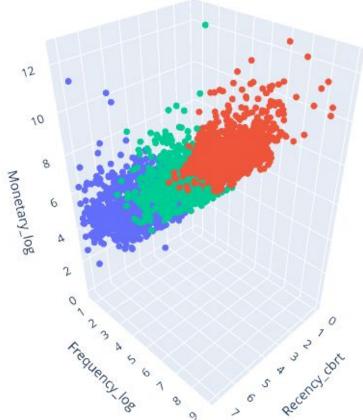




Based on the RFM score I divide the customers into three tiers which help us to differentiate the customers.

- ➤ Gold
- > Silver
- Bronze





RFMScore_tier

- Bronze
- Gold
- Silver

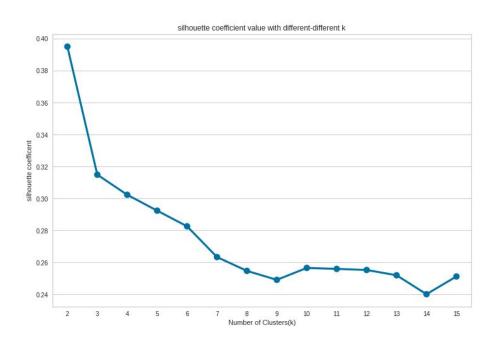
K-Means Clustering



Silhouette score method:

The Silhouette Coefficient is calculated using the mean intra-cluster distance (a) and the mean nearest-cluster distance (b) for each sample is a metric used to calculate the goodness of a clustering technique. Its value ranges from -1 to 1.

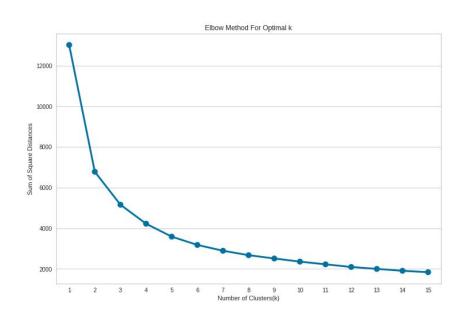
$$S = \frac{(b-a)}{max(a,b)}$$

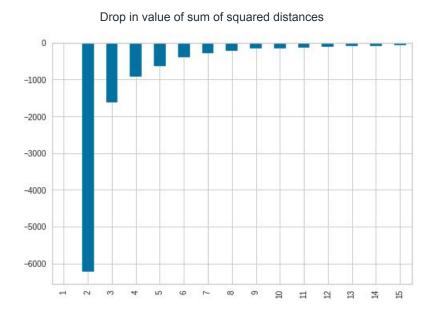


for K = 2 the value of silhouette coefficient is maximum which is 0.3951



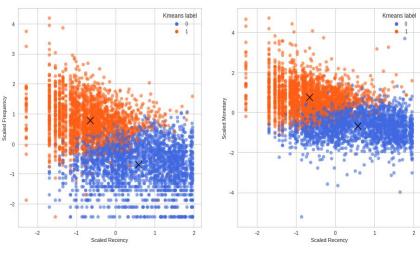
Elbow Method:

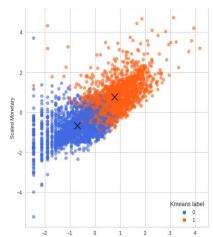




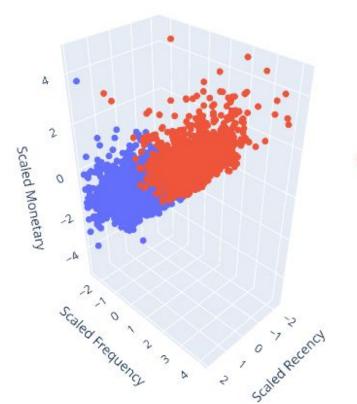
From the elbow method, it is clearly understood that, 2 clusters are performing best. Hence, 2 clusters will be selected to build the K Means model and classify the customers.







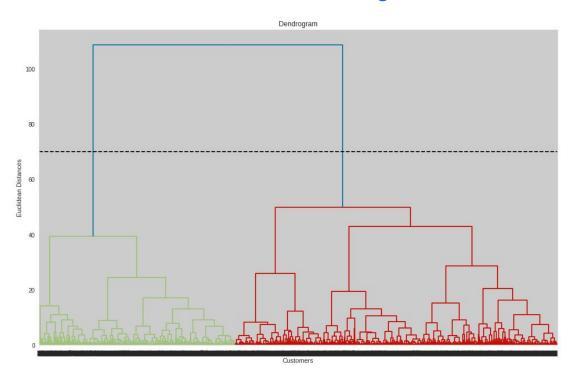
Scatter Plot using k-means clustering



Kmeans label

- 0
- 1

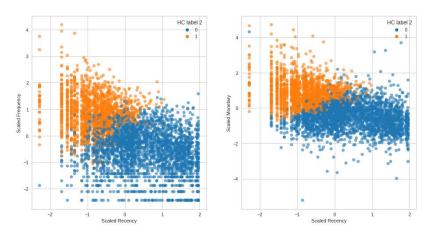
Hierarchical clustering

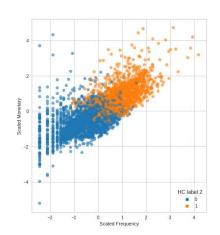


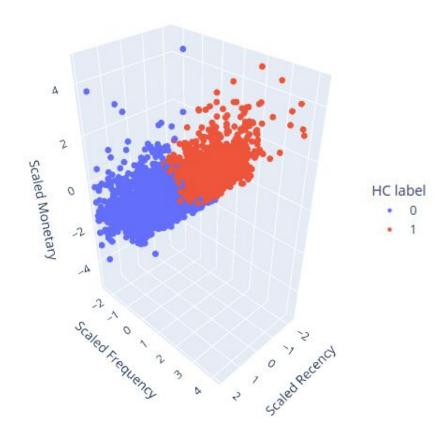
- Here, we can see No. of Clusters = 2 could be a good choice,
- 5 cluster would be my 2nd choice. 2 from green three from red.



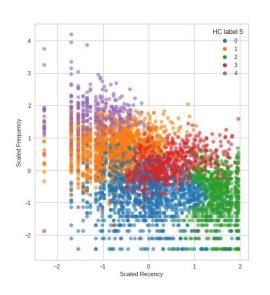


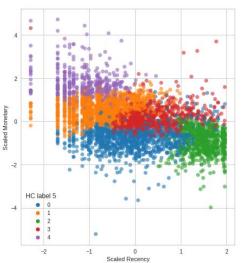


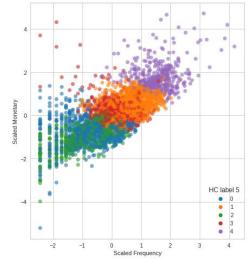








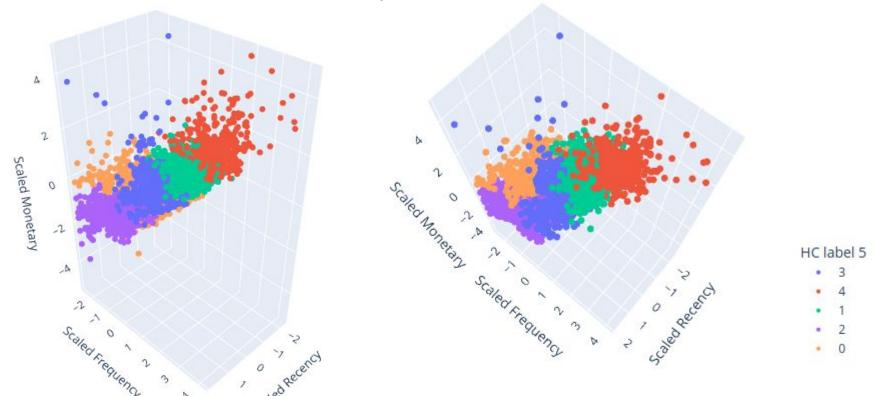




| | | Recency | Frequency | Monetary | RFMScore |
|---|----------|------------|------------|--------------|-----------|
| 5 | clusters | | | | |
| | 2 | 265.793243 | 19.041892 | 280.588838 | 4.454054 |
| | 0 | 72.107460 | 20.183837 | 344.038553 | 6.498224 |
| | 3 | 103.231047 | 54.672684 | 1472.102144 | 8.868833 |
| | 1 | 25.000000 | 112.841334 | 1737.637112 | 12.222945 |
| | 4 | 12.053269 | 415.978208 | 11945.067433 | 14.460048 |



3-D Scatter plot with 5 -clusters





Since this is an unsupervised learning approach, there is no 100% correct answer, number of clusters will vary depending on the company's requirement.



