CAPSTONE PROJECT
CUSTOMER SEGMENTATION

Team Members

Sanjaya Kumar Khadanga

Bibhuti Bhusan Sahu

Balaram Panigrahy

CONTENT

- BUSINESS UNDERSTANDING
- DATA SUMMARY
- FEATURE ANALYSIS
- EXPLORATORY DATA ANALYSIS
- DATA PREPROCESSING
- IMPLEMENTING ALGORITHMS
- CHALLENGES
- CONCLUSIONS

BUSINESS UNDERSTANDING

- Customer segmentation is the practice of dividing a company's customers into groups that reflect similarity among customers in each group. The goal of segmenting customers is to decide how to relate to customers in each segment in order to maximize the value of each customer to the business.
- Customer segmentation has the potential to allow marketers to address each customer in the most effective way. Using the large amount of data available on customers (and potential customers), a customer segmentation analysis allows marketers to identify discrete groups of customers with a high degree of accuracy based on demographic, behavioral and other indicators.
- Given the dataset, the objective is to build a clustering model that would perform customer segmentation.

DATA SUMMARY

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

- **Total Rows : 541909**
- **Total Column: 8**
- **A transnational data set with transactions occurring between 1st December 2010 and 9th December 2011 for a UK-based online retailer.**
- **Many customers of the company are wholesalers.**

FEATURE SUMMARY

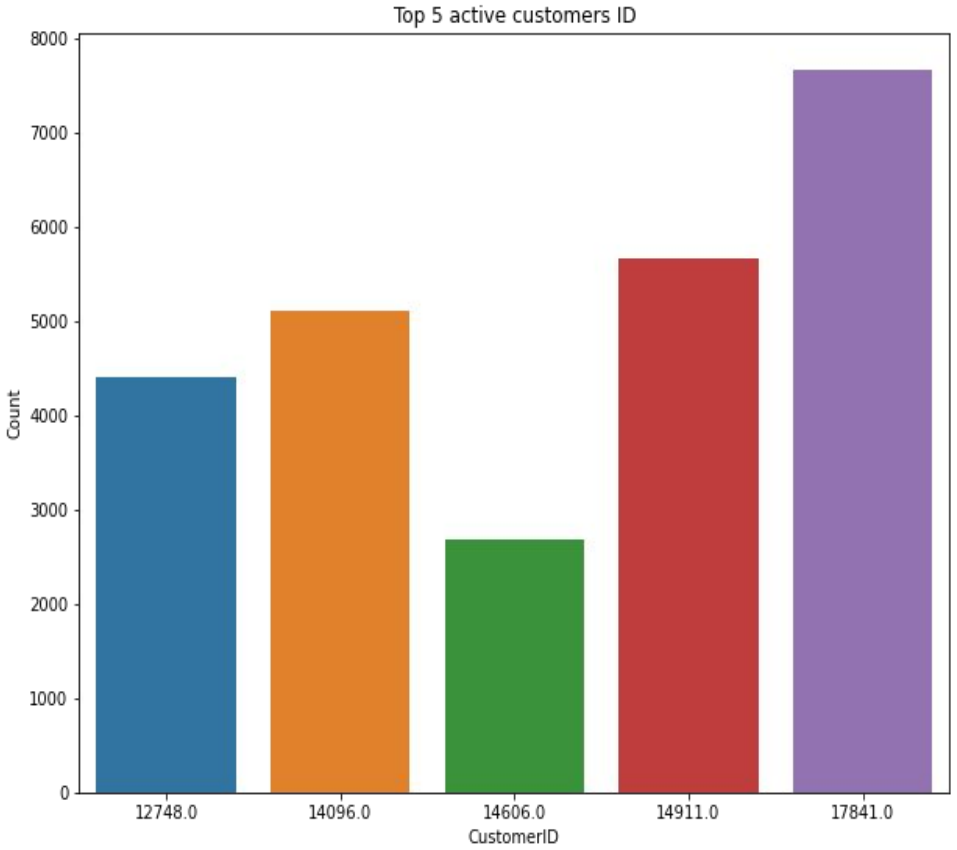
- The contents of the data had features such as:
- InvoiceNo: Invoice number. Nominal, a 6-digit integral number uniquely assigned to each transaction. If this code starts with letter 'c', it indicates a cancellation.
- StockCode: Product (item) code. Nominal, a 5-digit integral number uniquely assigned 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.

INSIGHTS FROM OUR DATASET

- This Dataset is from the UK
- In our data set there are 541909 rows, 8 columns
- Four categorical features ‘InvoiceNo’, ‘Stock Code’, & ‘Description’, ‘ Country’.
- There are Missing Values present on Description & CustomerID columns, Removed null values
- There are Duplicate values present, Removed duplicates
- One Datetime[ns] features ‘InvoiceDate’.
- Outliers present only in “Quantity” & “Unit Price”column.
- Removed cancelled orders.
- Added new features from datetime column such as months, days, hours.
- Added Total Amount
- Converted data types

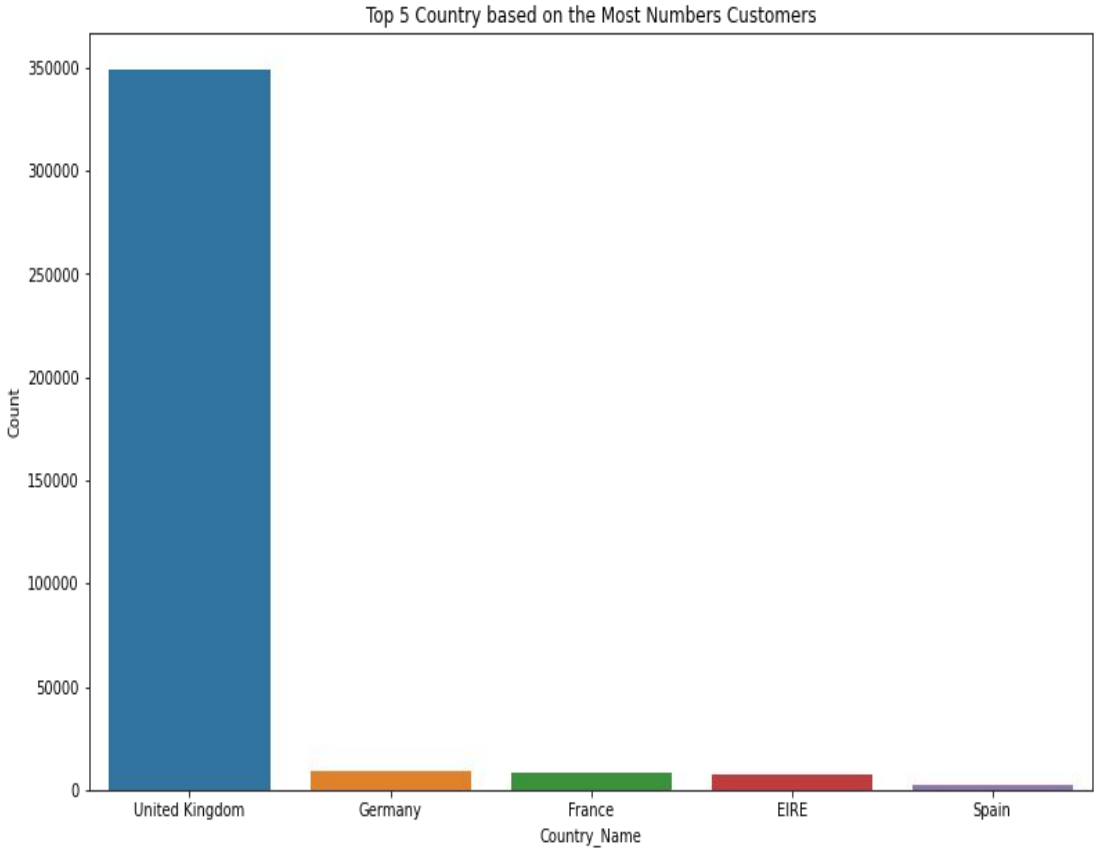
ANALYSIS ON CUSTOMER ID

- 4339 unique customer IDs.
- Id 17841 was the most active customer



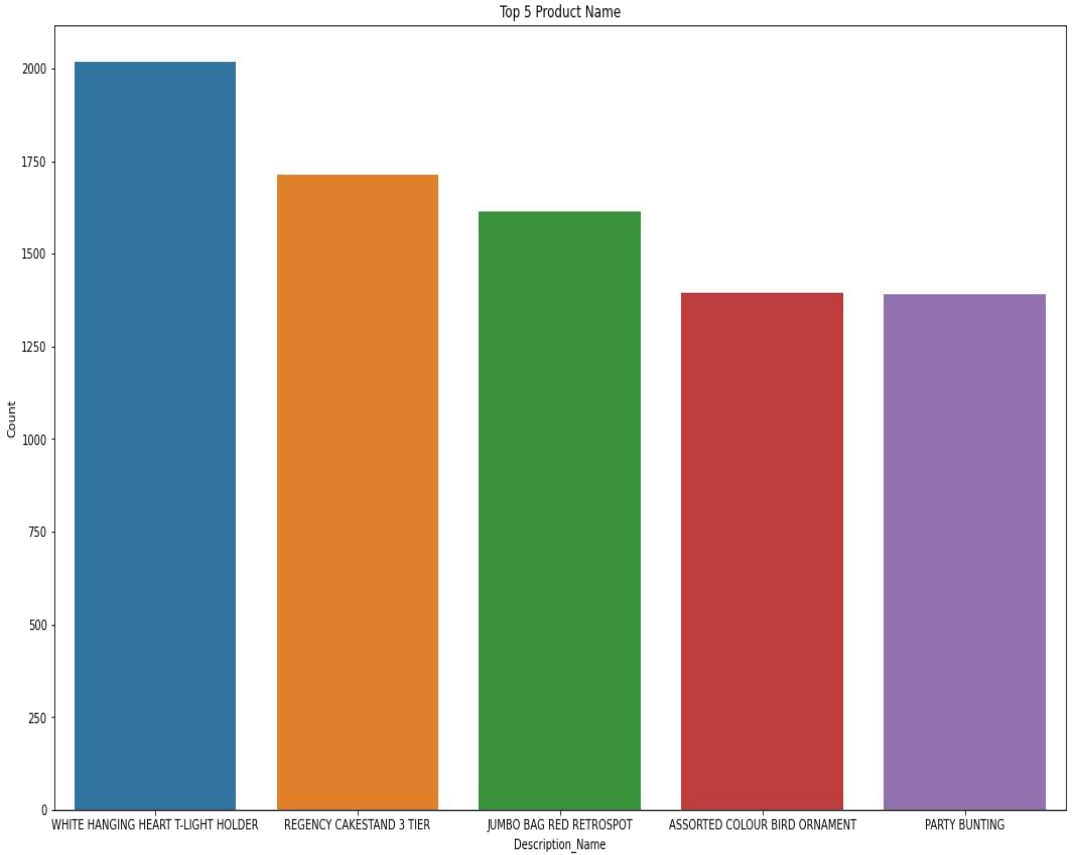
ANALYSIS ON COUNTRY

- UK, Germany, France were top countries having more no. of customers.
- Since data belonged to UK based company, UK had majority of customers



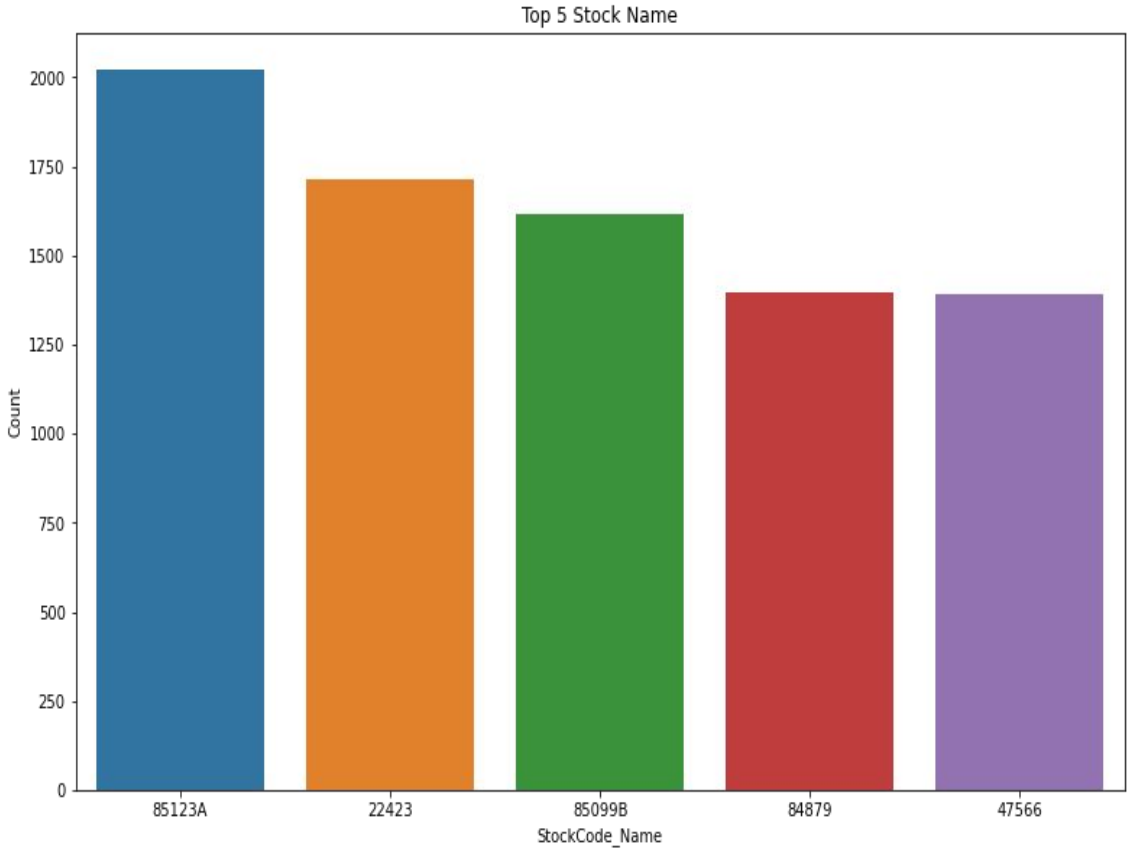
ANALYSIS ON DESCRIPTION

	Description_Name	Count
0	WHITE HANGING HEART T-LIGHT HOLDER	2016
1	REGENCY CAKESTAND 3 TIER	1714
2	JUMBO BAG RED RETROSPOT	1615
3	ASSORTED COLOUR BIRD ORNAMENT	1395
4	PARTY BUNTING	1390

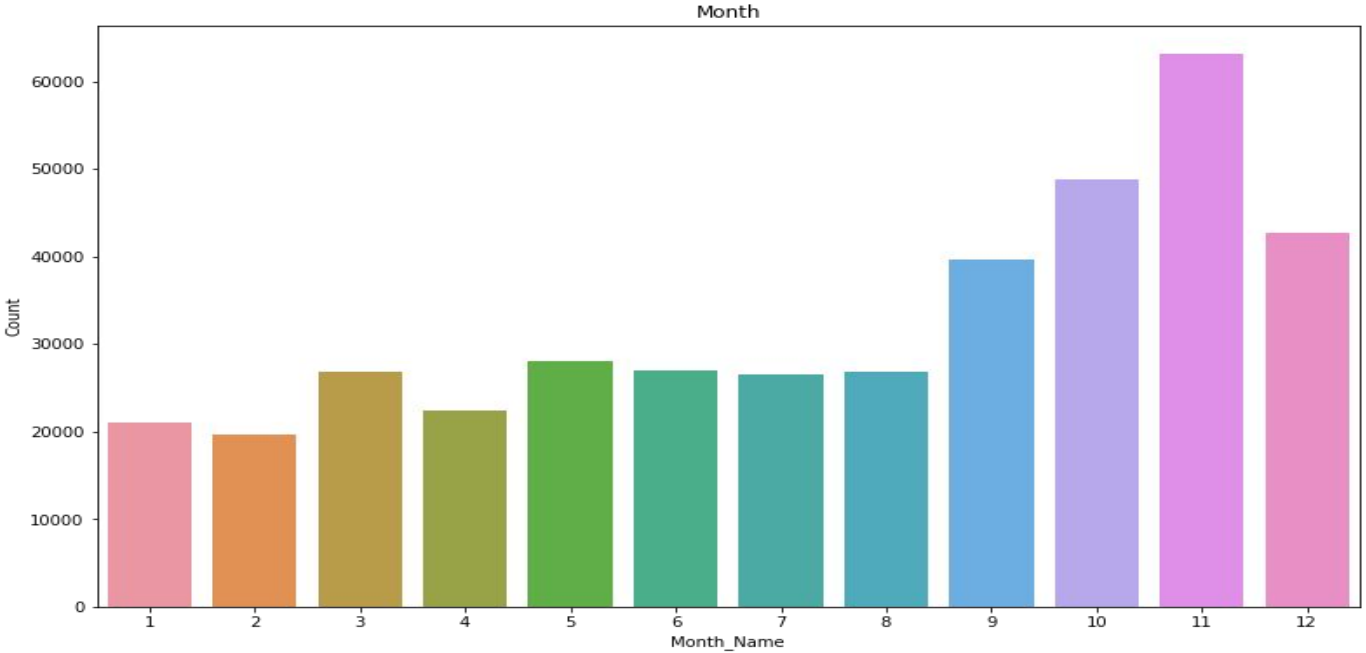


ANALYSIS ON STOCK CODE

	StockCode_Name	Count
0	85123A	2023
1	22423	1714
2	85099B	1615
3	84879	1395
4	47566	1390

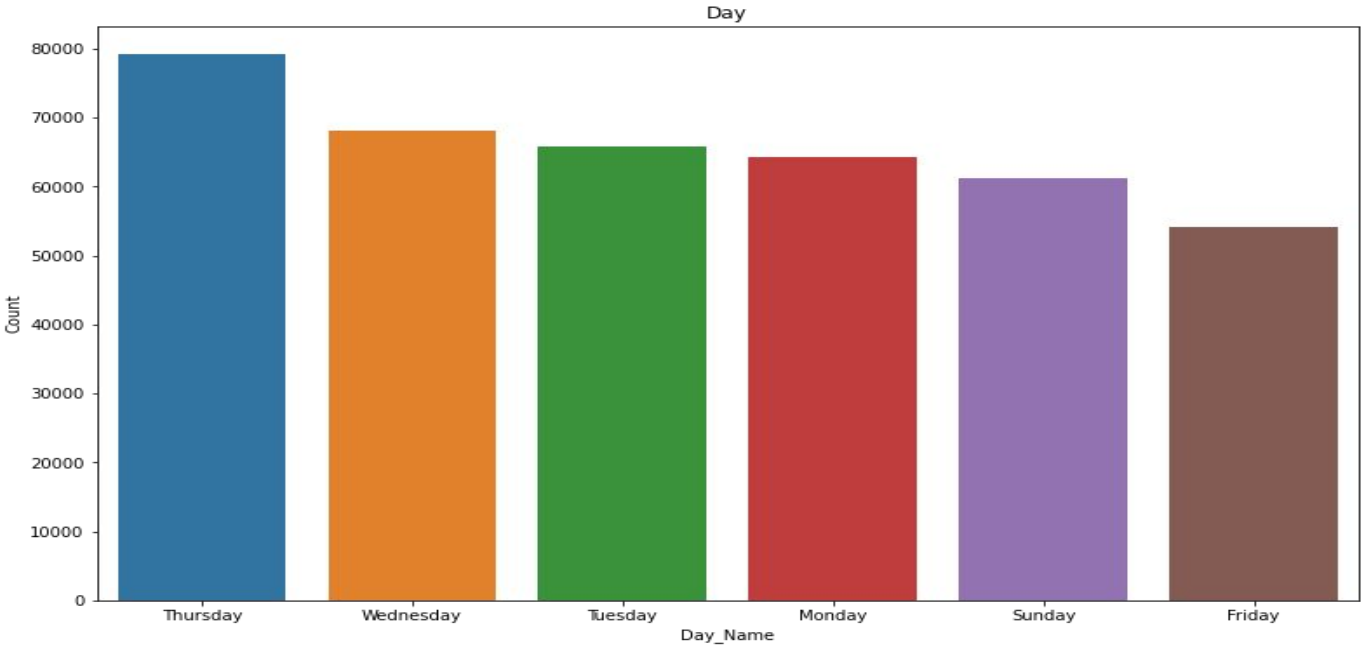


ANALYSIS MONTH WISE



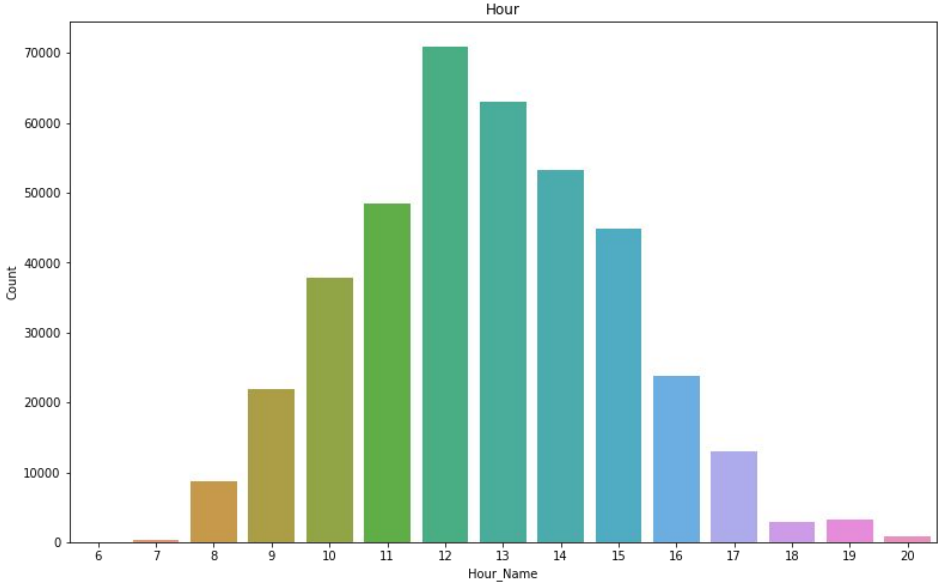
- **October, November and December could be the months with highest sales in anticipation of Christmas**

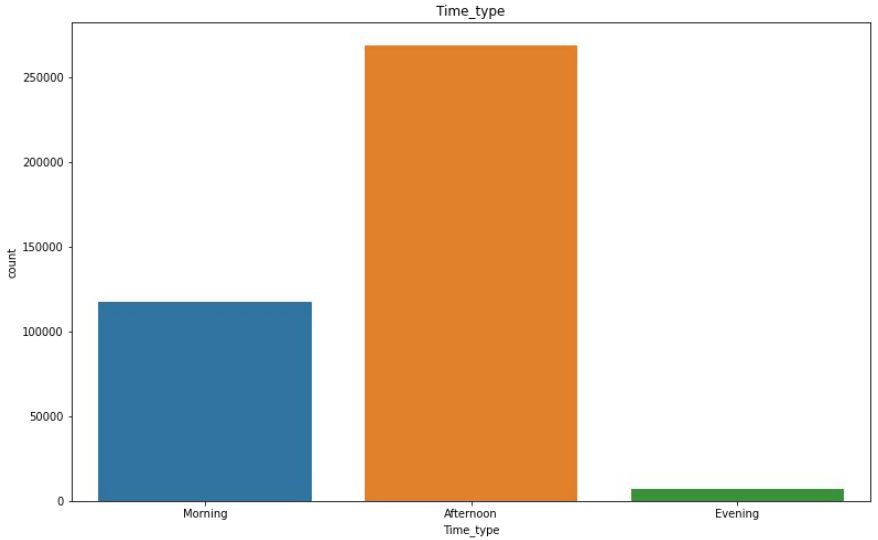
ANALYSIS DAY WISE



- **Most of the customers have purchased the items in Thursday, Wednesday and Tuesday**

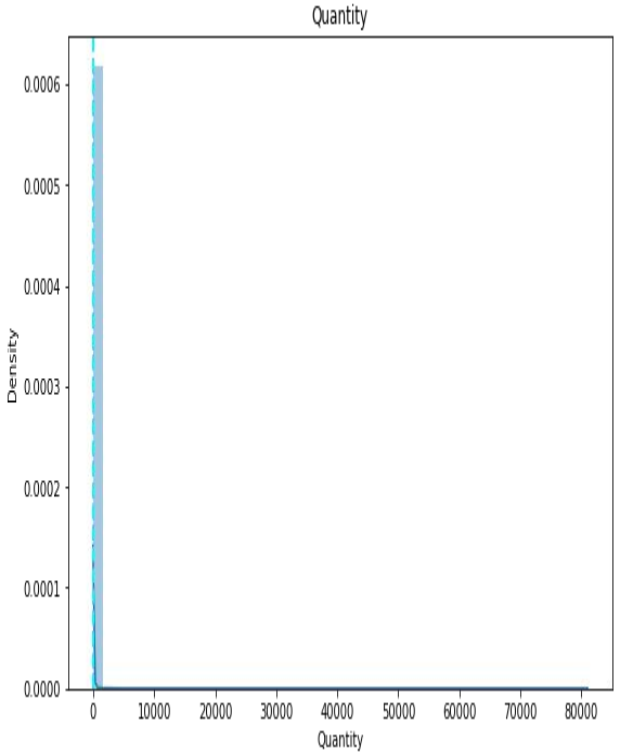
ANALYSIS HOUR WISE

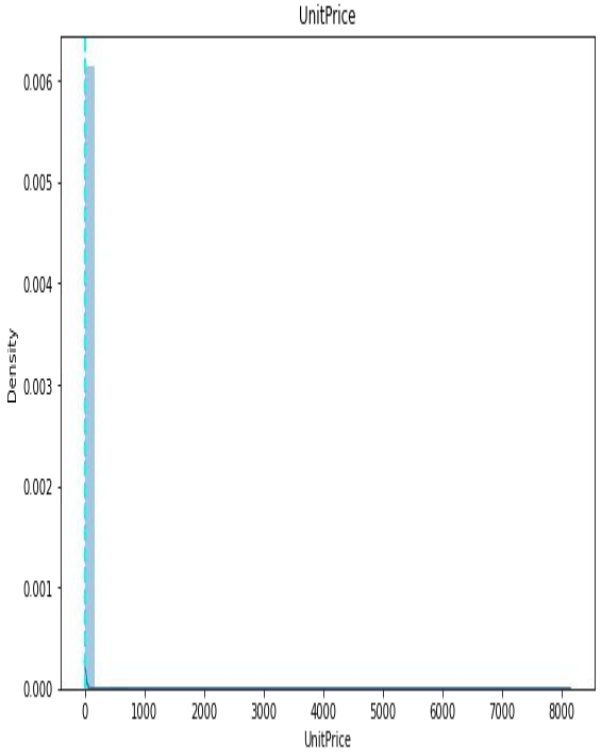


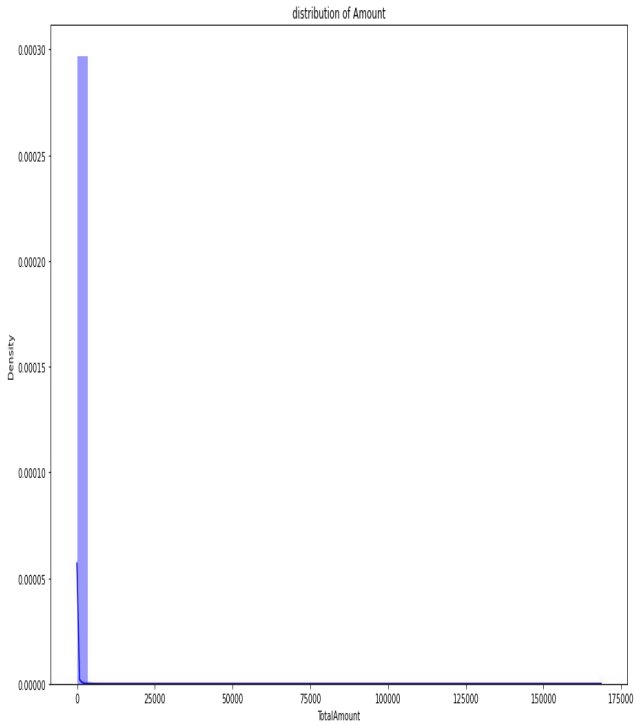


- **Working hours witnessing the highest sales could be attributed to the fact that a large part of the dataset is Wholesalers' data.**

ANALYSIS NUMERICAL VARIABLE



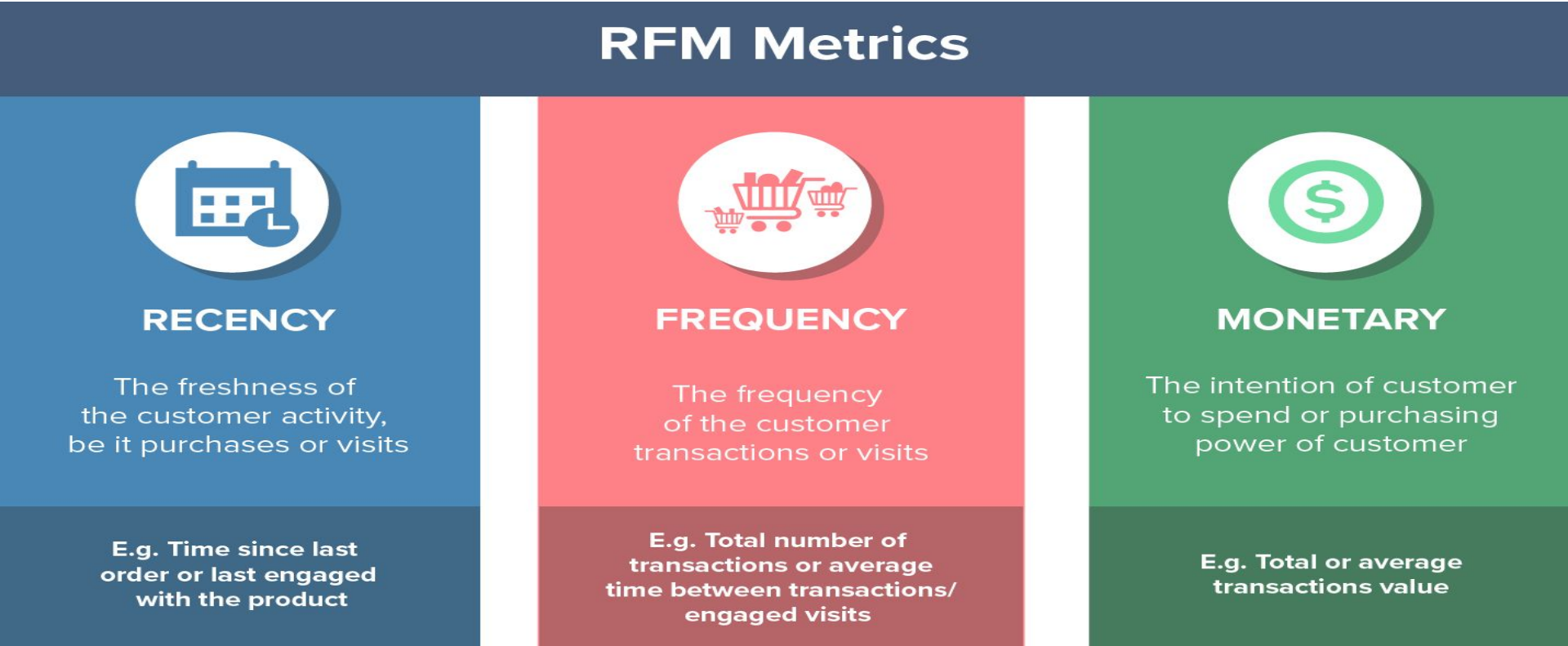




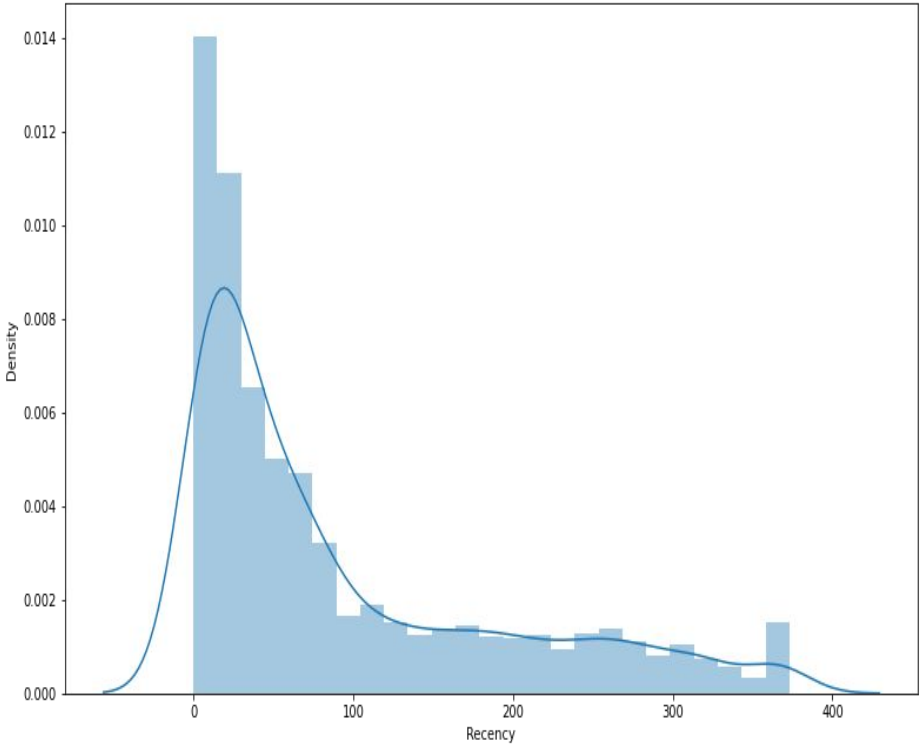
➢ **Highly positively skewed, need to do log transformation**

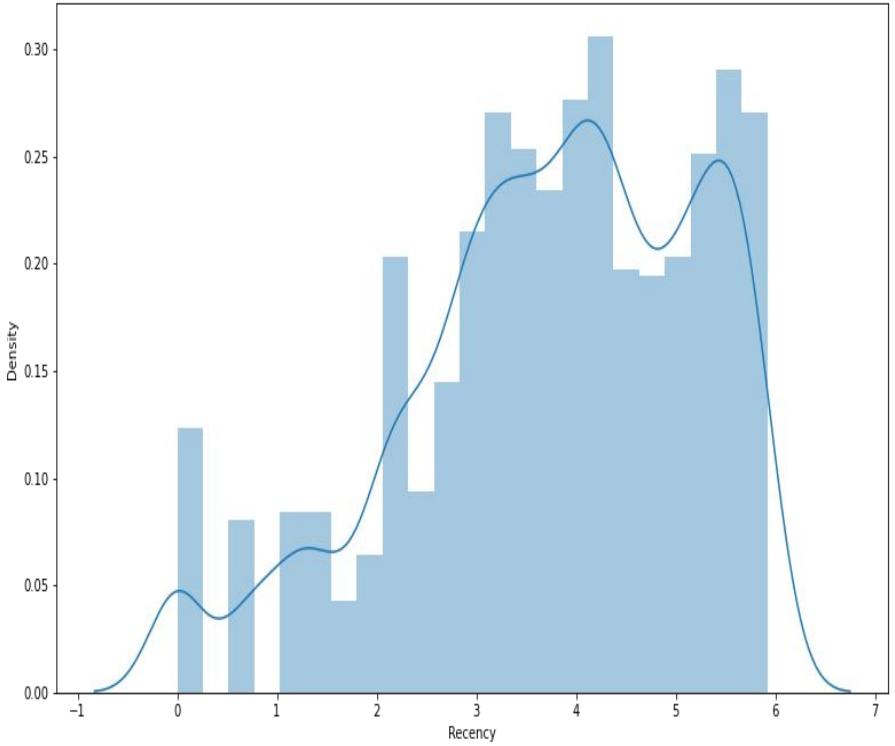
RFM MODEL

- **Created features such as recency, frequency and monetary**

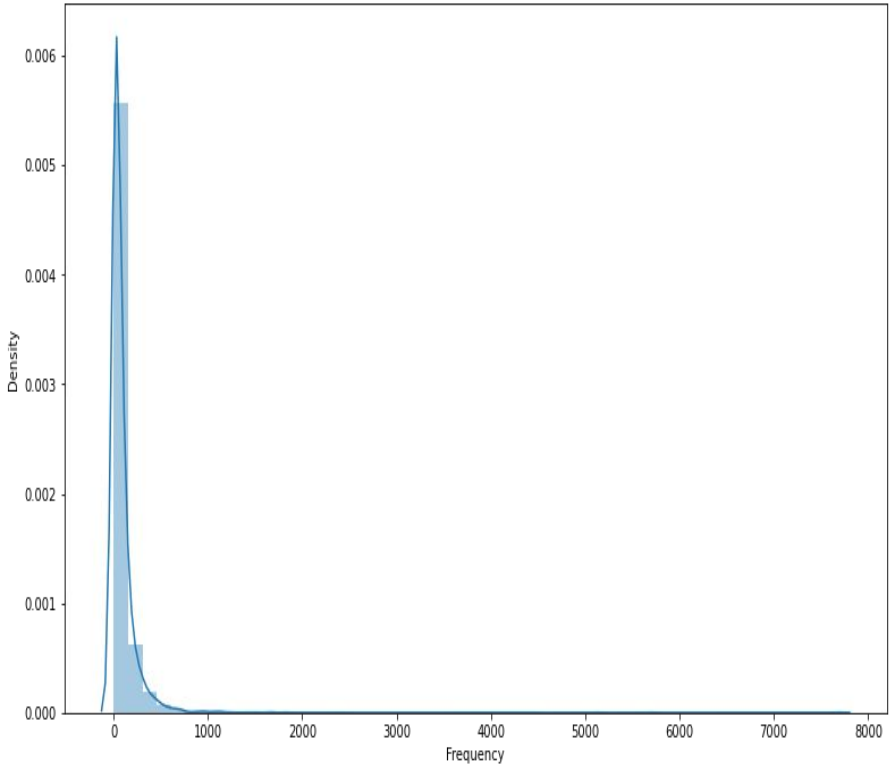


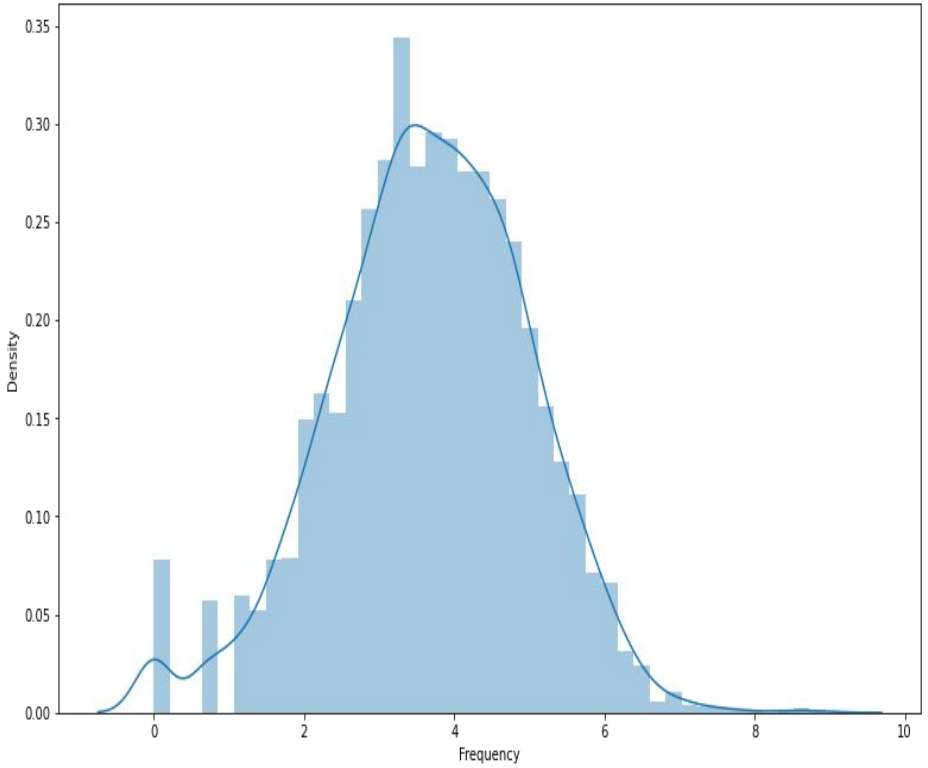
RECENCY


Density
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
0
100
200
300
400
Recency

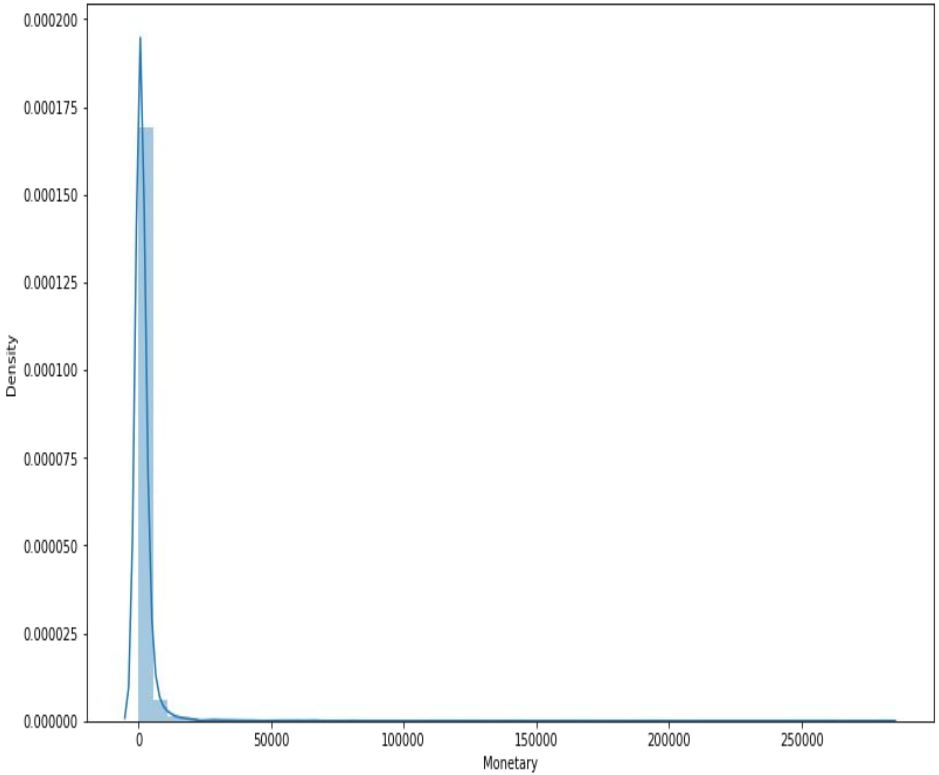

Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7
Recency

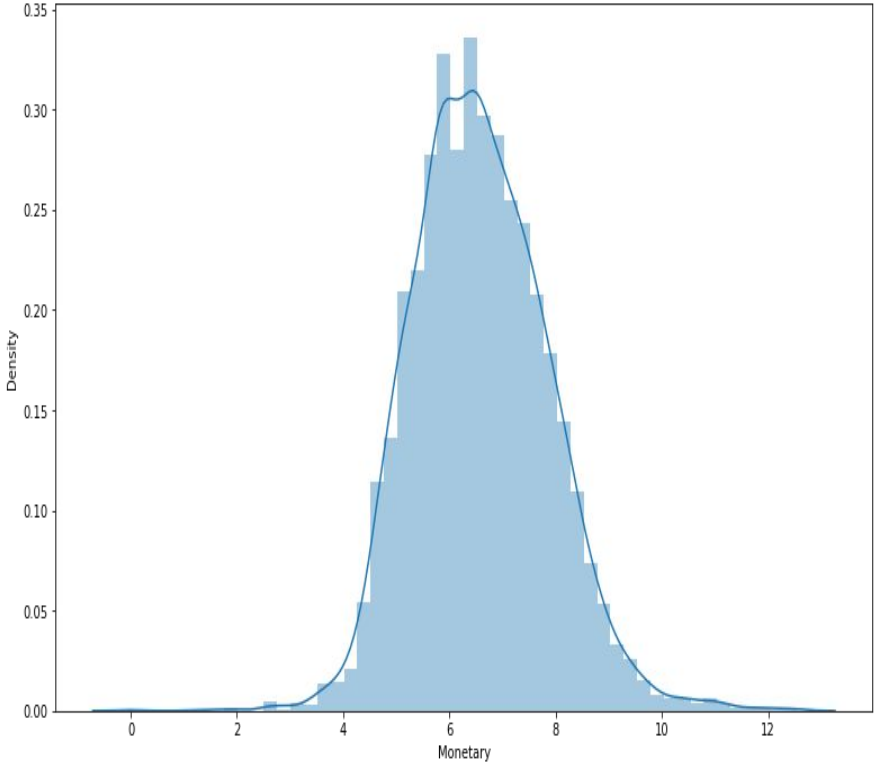
FREQUENCY


Density
0.006
0.005
0.004
0.003
0.002
0.001
0.000
0
1000
2000
3000
4000
5000
6000
7000
8000
Frequency

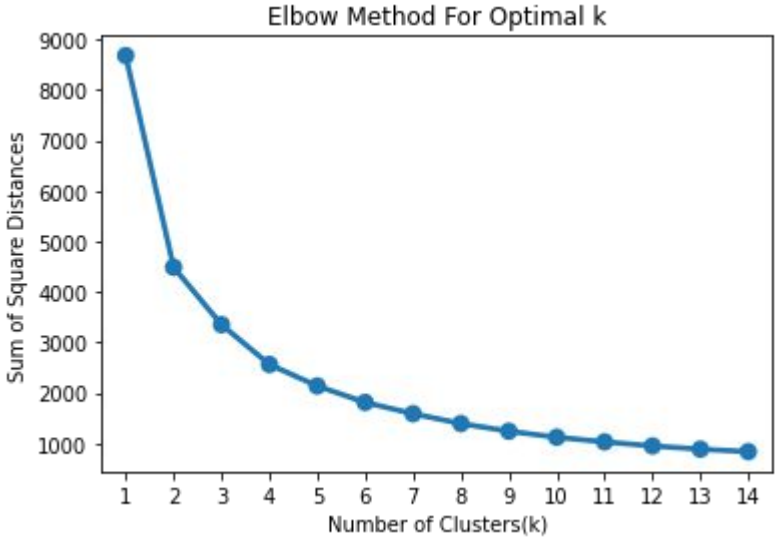

Density
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
10
Frequency

MONETARY

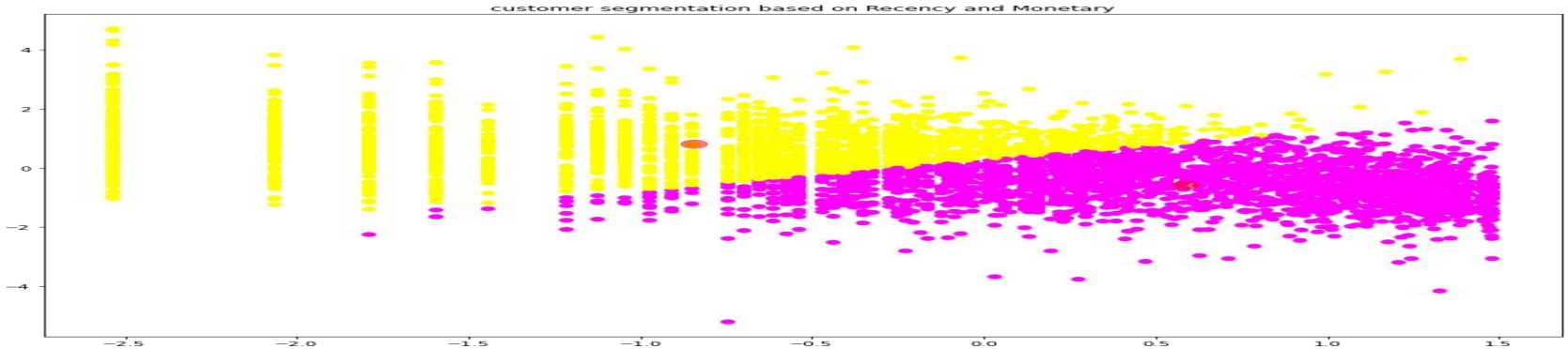

Density
0.000200
0.000175
0.000150
0.000125
0.000100
0.000075
0.000050
0.000025
0.000000
0
50000
100000
150000
200000
250000
Monetary


Density
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
10
12
Monetary

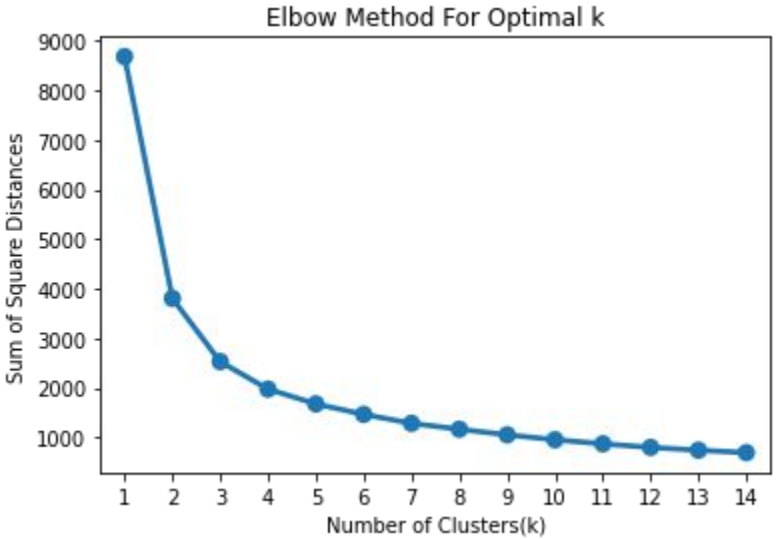
SILHOUETTE SCORE AND ELBOW METHOD ON R&M



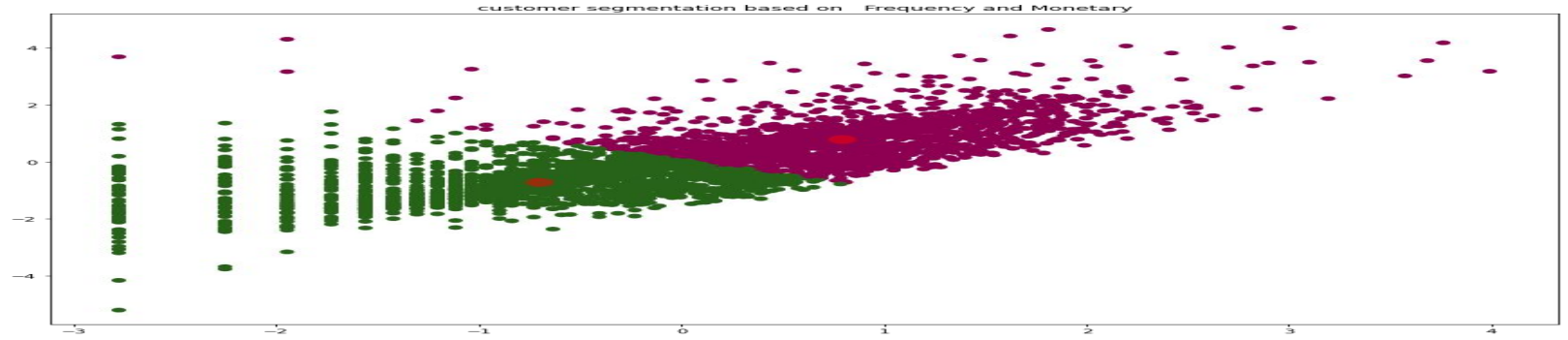

```
For n_clusters = 2, silhouette score is 0.42047430853642515
For n_clusters = 3, silhouette score is 0.34263694998026195
For n_clusters = 4, silhouette score is 0.36471463504091317
For n_clusters = 5, silhouette score is 0.3373938872753767
For n_clusters = 6, silhouette score is 0.34314878344616223
For n_clusters = 7, silhouette score is 0.34497773349086586
For n_clusters = 8, silhouette score is 0.33799261511793943
For n_clusters = 9, silhouette score is 0.34607062536188865
For n_clusters = 10, silhouette score is 0.3475247420875672
For n_clusters = 11, silhouette score is 0.33693656579850056
For n_clusters = 12, silhouette score is 0.3373606876306994
For n_clusters = 13, silhouette score is 0.3389910656356672
For n_clusters = 14, silhouette score is 0.34138143812594274
For n_clusters = 15, silhouette score is 0.33827205107215497
```



SILHOUETTE SCORE AND ELBOW METHOD ON F&M



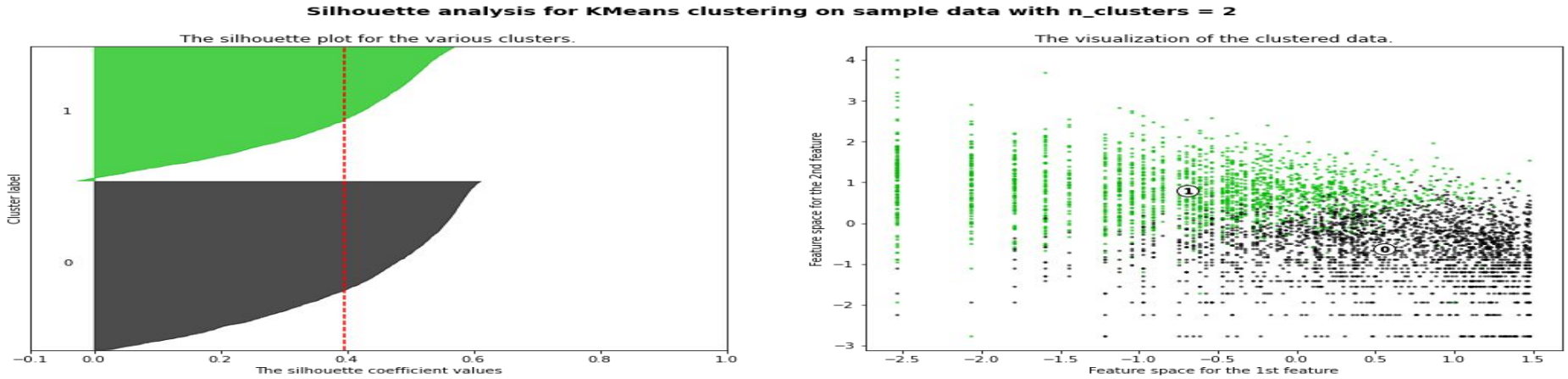

```
For n_clusters = 2, silhouette score is 0.4784099179679686
For n_clusters = 3, silhouette score is 0.40773549715950697
For n_clusters = 4, silhouette score is 0.37231818810915773
For n_clusters = 5, silhouette score is 0.3466695882675493
For n_clusters = 6, silhouette score is 0.36216641752478196
For n_clusters = 7, silhouette score is 0.3388444115986888
For n_clusters = 8, silhouette score is 0.3502006422275672
For n_clusters = 9, silhouette score is 0.3463581243091397
For n_clusters = 10, silhouette score is 0.359712396199174
For n_clusters = 11, silhouette score is 0.3667563841808519
For n_clusters = 12, silhouette score is 0.35450579287148154
For n_clusters = 13, silhouette score is 0.3522388459765374
For n_clusters = 14, silhouette score is 0.3656296509855817
For n_clusters = 15, silhouette score is 0.3387892798152116
```

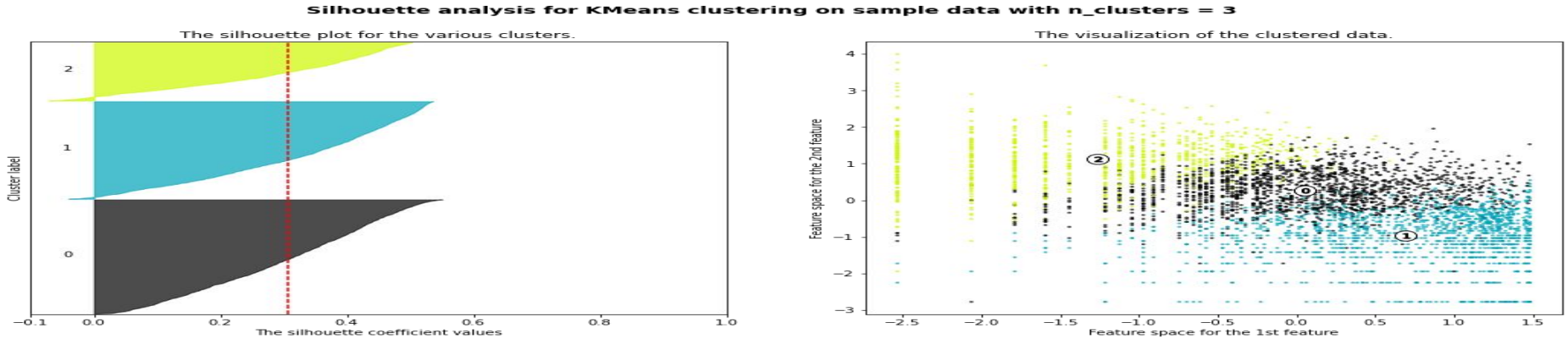


SILHOUETTE ANALYSIS ON R, F AND M

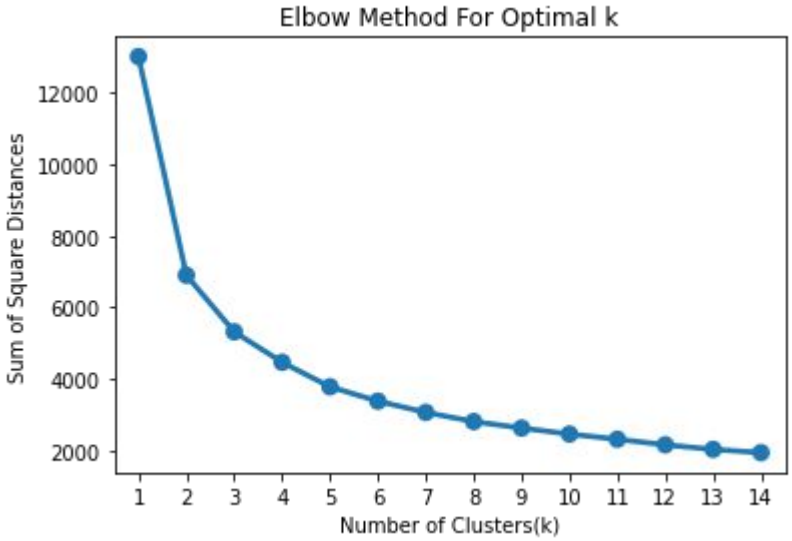
```
For n_clusters = 2 The average silhouette_score is : 0.3953473255895671
For n_clusters = 3 The average silhouette_score is : 0.3056346992700891
For n_clusters = 4 The average silhouette_score is : 0.30270317426951315
For n_clusters = 5 The average silhouette_score is : 0.279287144278932
For n_clusters = 6 The average silhouette_score is : 0.2791427508121517
For n_clusters = 7 The average silhouette_score is : 0.2624688625487521
For n_clusters = 8 The average silhouette_score is : 0.2641439272039239
For n_clusters = 9 The average silhouette_score is : 0.25335269919725206
For n_clusters = 10 The average silhouette_score is : 0.25957414651642013
For n_clusters = 11 The average silhouette_score is : 0.26311930659289096
For n_clusters = 12 The average silhouette_score is : 0.2678852371616394
For n_clusters = 13 The average silhouette_score is : 0.26266378048976555
For n_clusters = 14 The average silhouette_score is : 0.26201930714854194
For n_clusters = 15 The average silhouette_score is : 0.258239015178865
```

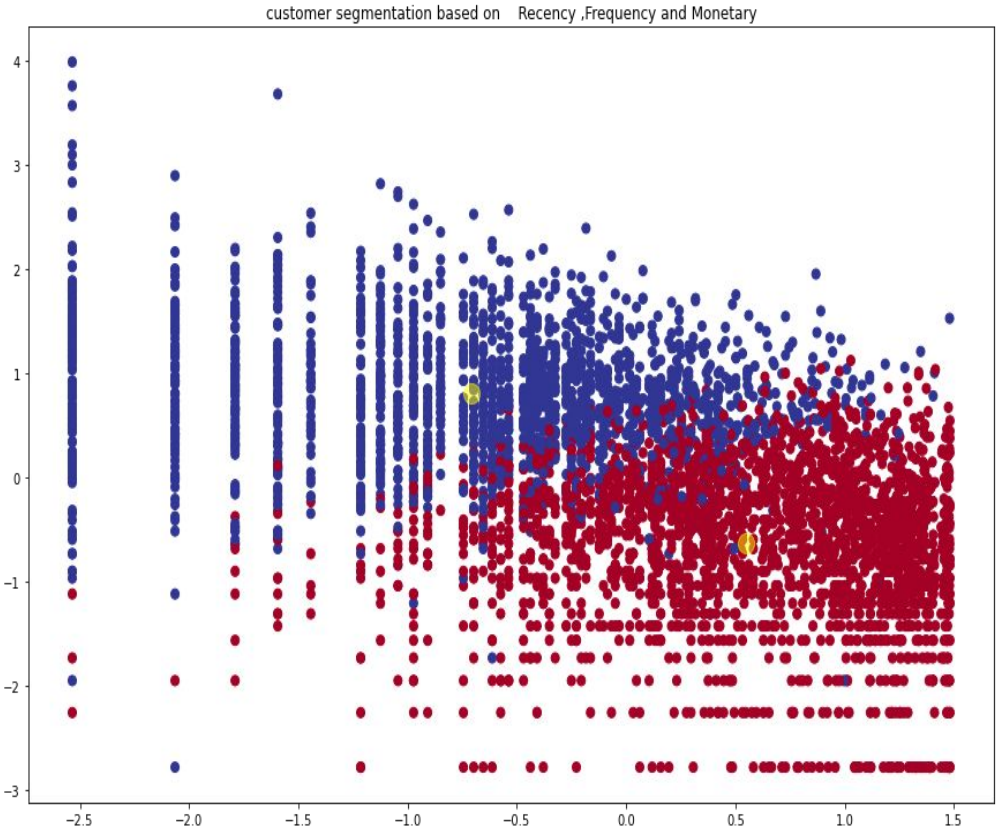
SILHOUETTE ANALYSIS ON R, F AND M





ELBOW METHOD AND CLUSTER CHART ON RFM

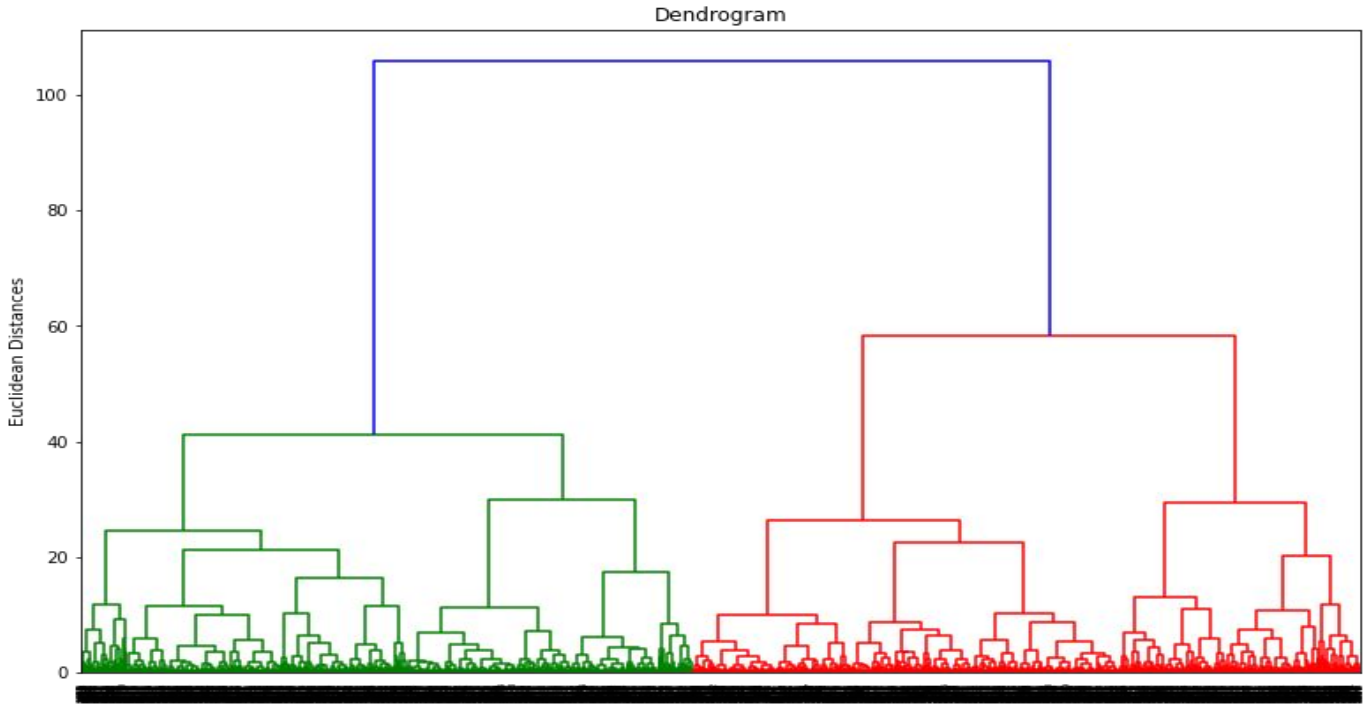




RFM ANALYSIS

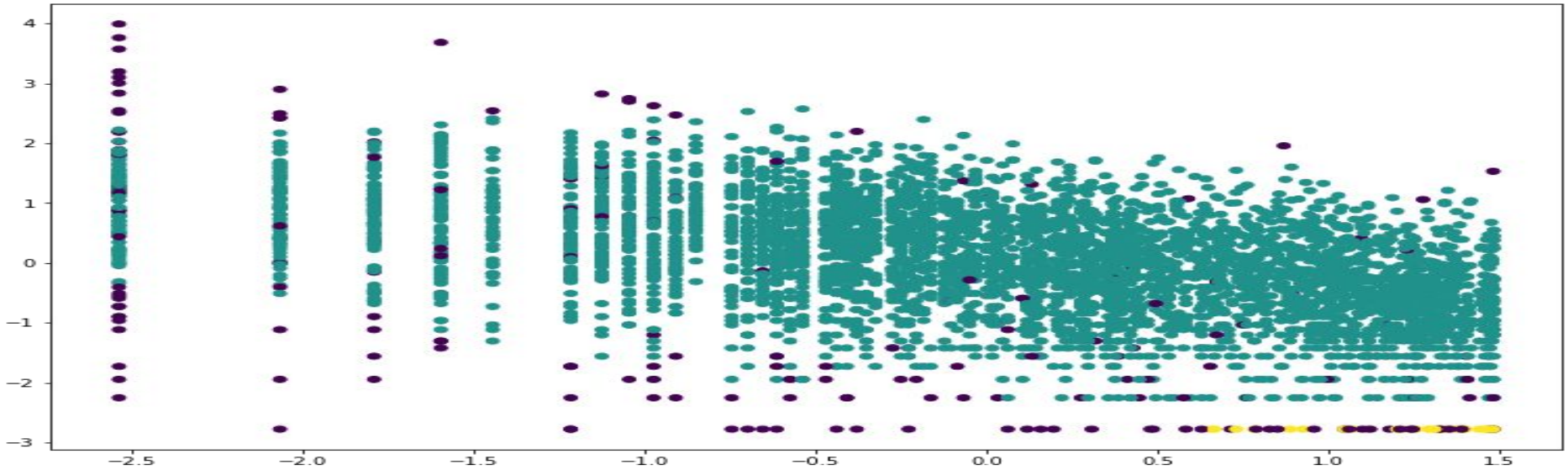
CustomerID	Recency	Frequency	Monetary	R	F	M	RFMGroup	RFMScore	Recency_log	Frequency_log	Monetary_log	Cluster
12346.0	325	1	77183.60	4	4	1	441	9	5.783825	0.000000	11.253942	1
12347.0	2	182	4310.00	1	1	1	111	3	0.693147	5.204007	8.368693	0
12348.0	75	31	1797.24	3	3	1	331	7	4.317488	3.433987	7.494007	1
12349.0	18	73	1757.55	2	2	1	221	5	2.890372	4.290459	7.471676	0
12350.0	310	17	334.40	4	4	3	443	11	5.736572	2.833213	5.812338	1
12352.0	36	85	2506.04	2	2	1	221	5	3.583519	4.442651	7.826459	0
12353.0	204	4	89.00	4	4	4	444	12	5.318120	1.386294	4.488636	1
12354.0	232	58	1079.40	4	2	2	422	8	5.446737	4.060443	6.984161	1
12355.0	214	13	459.40	4	4	3	443	11	5.365976	2.564949	6.129921	1
12356.0	22	59	2811.43	2	2	1	221	5	3.091042	4.077537	7.941449	0

HIERARCHICAL CLUSTERING



- The number of clusters will be the number of vertical lines which are being intersected by the line drawn using the threshold=90
- No. of Cluster = 2

DBSCAN TO RECENCY ,FREQUENCY AND MONETARY



- **Density-based spatial clustering of applications with noise** (DBSCAN)
- **we see that ,Customers are well separate when we cluster them by Recency ,Frequency and Monetary and optimal number of cluster is equal to 3**

CHALLENGES

- Large Dataset to handle.
- Needs to plot lot of Graphs to analyse.
- Lot of NaN values.
- Continuous Runtime and RAM Crash due to large dataset.
- Right number of ‘K’ for clusters

CONCLUSION

- Throughout the analysis we went through various steps to perform customer segmentation. We started with data wrangling in which we tried to handle null values, duplicates and performed feature modifications. Next we did some exploratory data analysis and tried to draw observations from the features we had in the dataset.
- Next we formulated some quantitative factors such as recency, frequency and monetary known as rfm model for each of the customers. We implemented K-Means clustering algorithm on these features. We also performed silhouette and elbow method analysis to determine the optimal no. of clusters which was 2.
- We saw customers having high recency and low frequency and monetary values were part of one cluster and customers having low recency and high frequency, monetary values were part of another cluster.
- We saw higher values of frequency, monetary and low values of recency is deciding one class and low values of frequency, monetary and high values of recency is deciding other class.

Q & A

THANK YOU