UNSUPERVISED MACHINE LEARNING (CUSTOMER SEGMENTATION) ONLINE RETAIL

INTRODUCTION

AI

1. The main goal is to identify customers that are most profitable and the ones who churned out to prevent further loss of customer by redefining company policies.

2. CLUSTER ANALYSIS: Statistically Segment Customers into groups Observation by using the features given below

Data Description

Attribute	Data Type	Description
Invoice Number	Nominal	6-digit unique number / code starts with letter 'c', it indicates a cancellation
Stock Code	Nominal	a 5-digit unique number assigned to each distinct product.
Description	Nominal	Product (item) name
Quantity	Numeric	Quantities of each product (item) per transaction
Invoice Date	Numeric	Date and time when each transaction was generated
Unit Price	Numeric	Product price per unit in sterling.
CustomerID	Nominal	5-digit unique number for Customer
Country	Nominal	the name of the country where each customer resides.

IMPORTING AND INSPECTING DATASET

Data set Name:- Online Retail

No of Observation:541908 (shape=8x541908)

dtypes: datetime=(1), float64=(2), int64=(1), object=(4) 1+2+1+4 = 8 columns

Data Cleaning

Checking Missing data

1. 25 % of items (i.e 135080)purchased are not assigned to Customers
2. CustomerID – 24.93
3. Description (0.27% Missing Values)

No use of this data it can be dropped

Checking duplicates

5268 data points were duplicated

Dropped duplicates

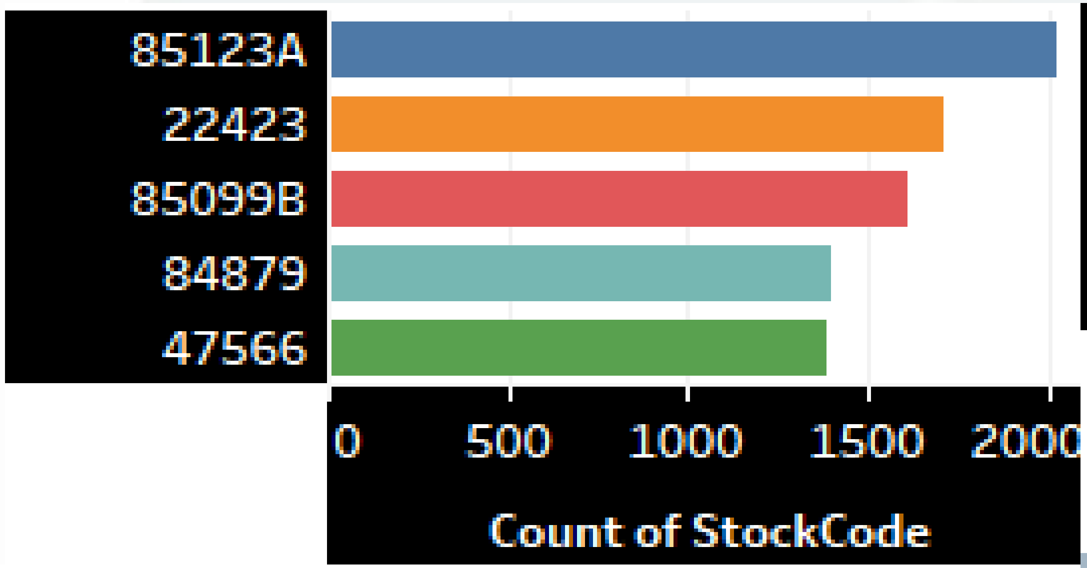
Total data points left

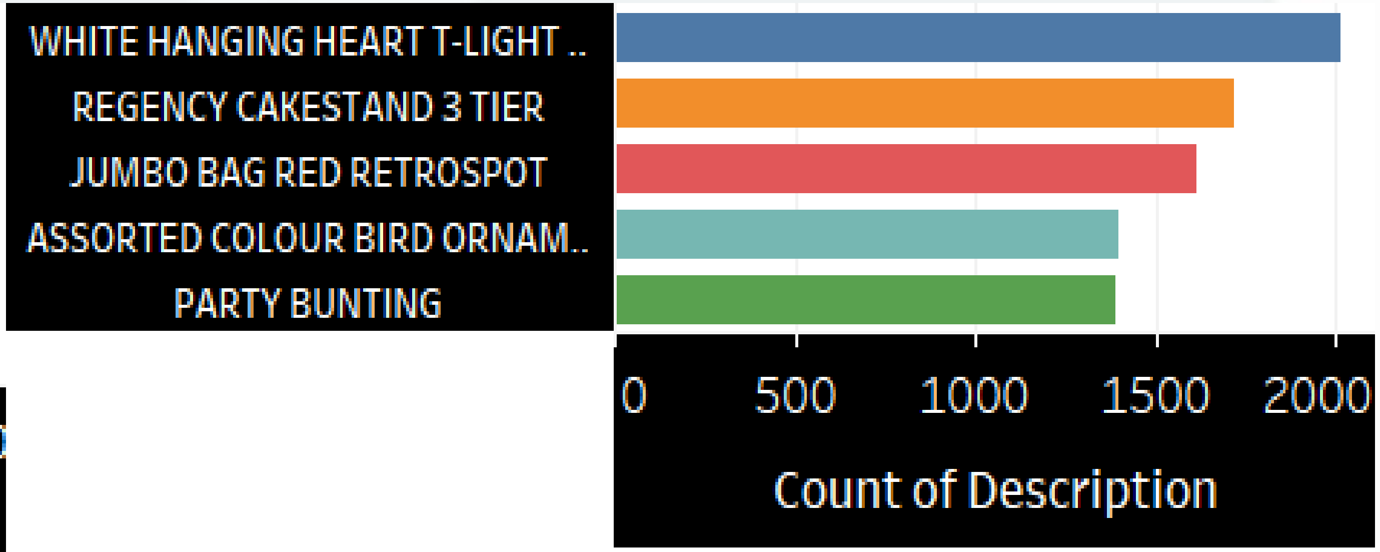
No of Observation left :401604 (shape=8x 401604)

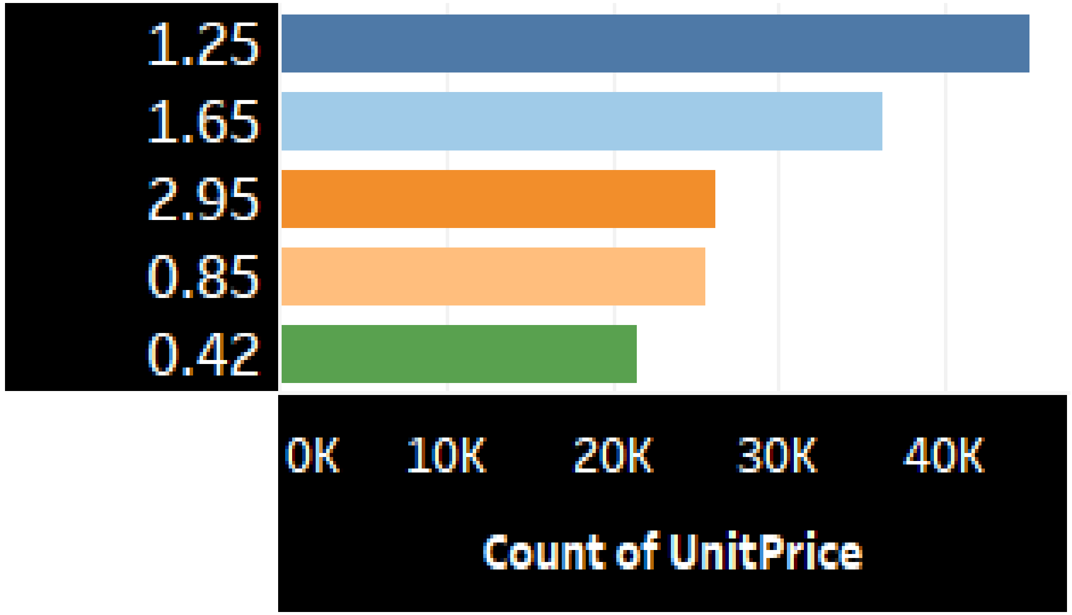
FEATURE ENGINEERING

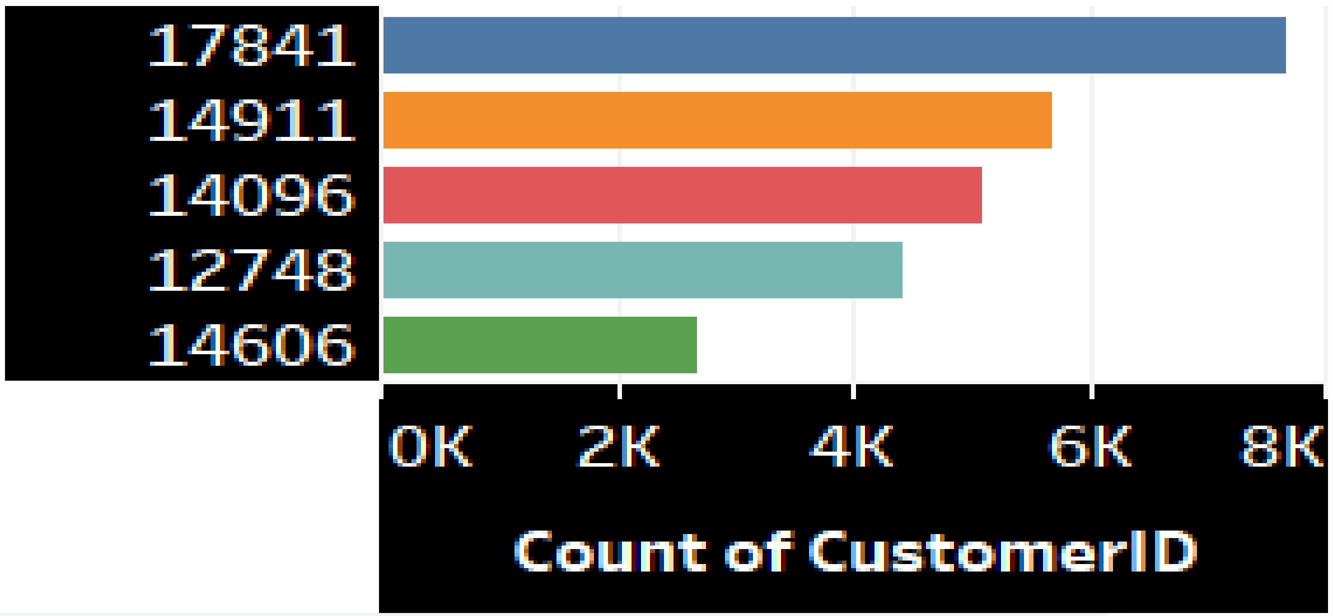
- Extracting year Date and Month from Invoice Date
- **Added Feature 'TotalAmount'** by multiplying values from the **Quantity** and **UnitPrice** column.(Sterling)
- **Added feature 'TimeType'** based on hours to define whether its Morning, Afternoon, or Evening
- Dropping InvoiceNo starting with 'C' that represents cancellation

MOST FREQUENT VALUES

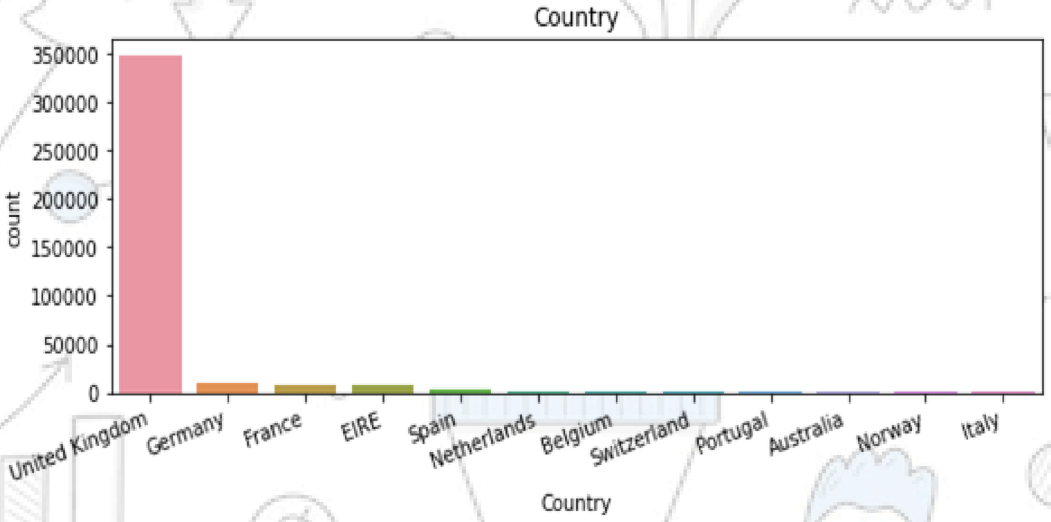


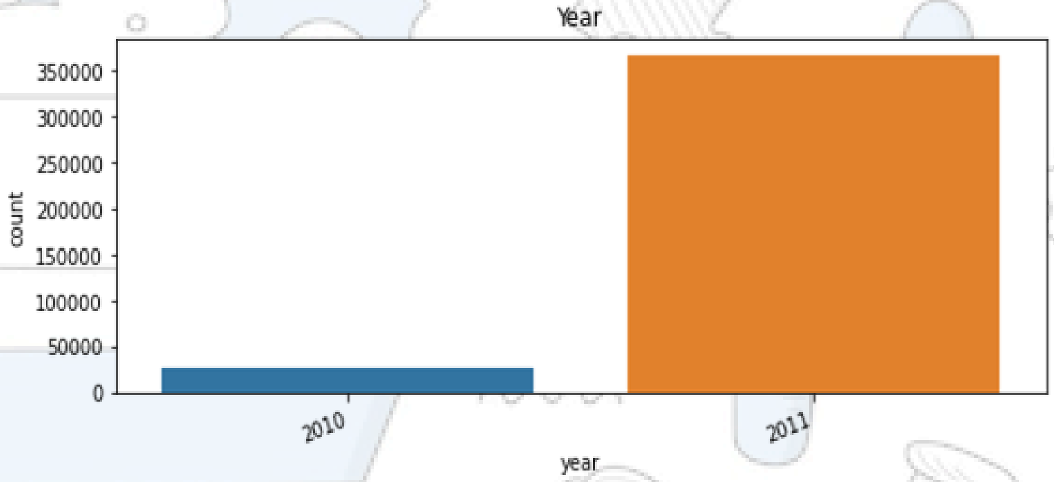


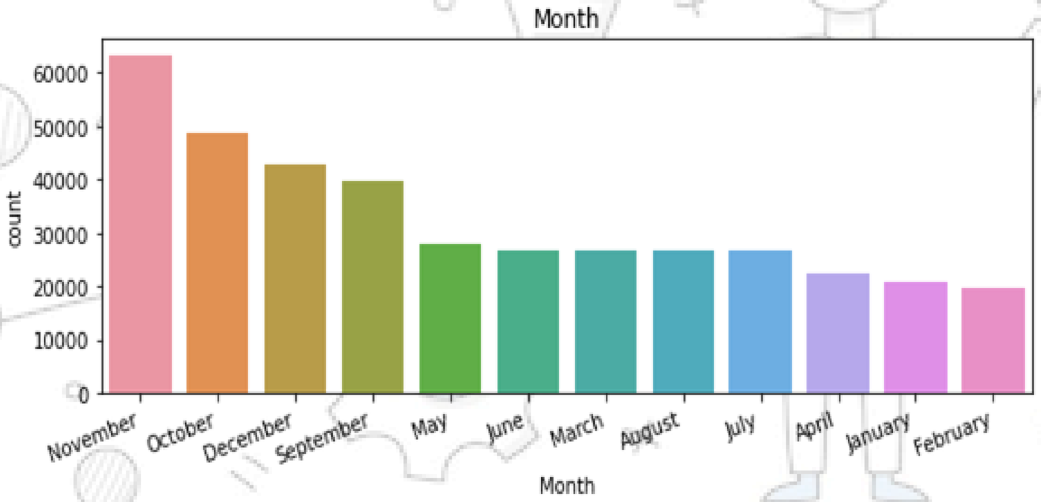


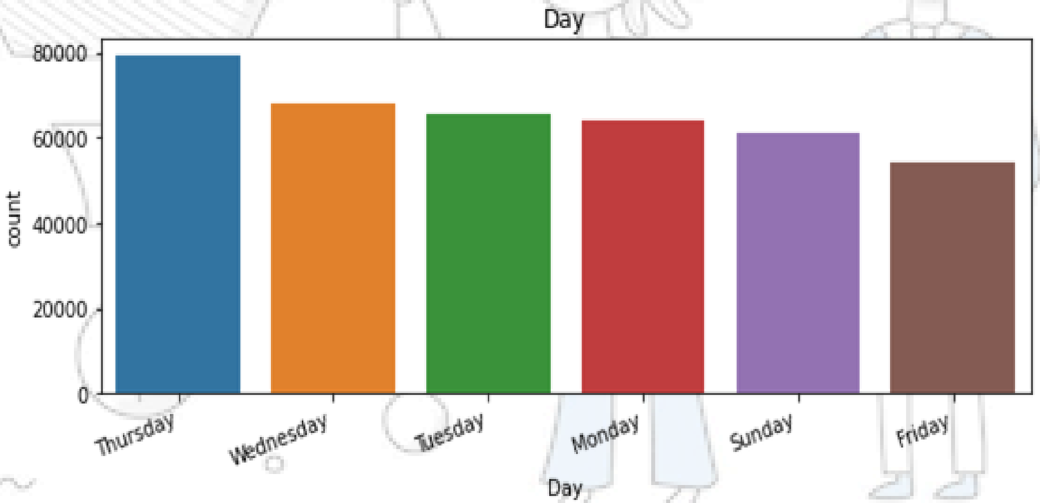


MOST FREQUENT VALUES









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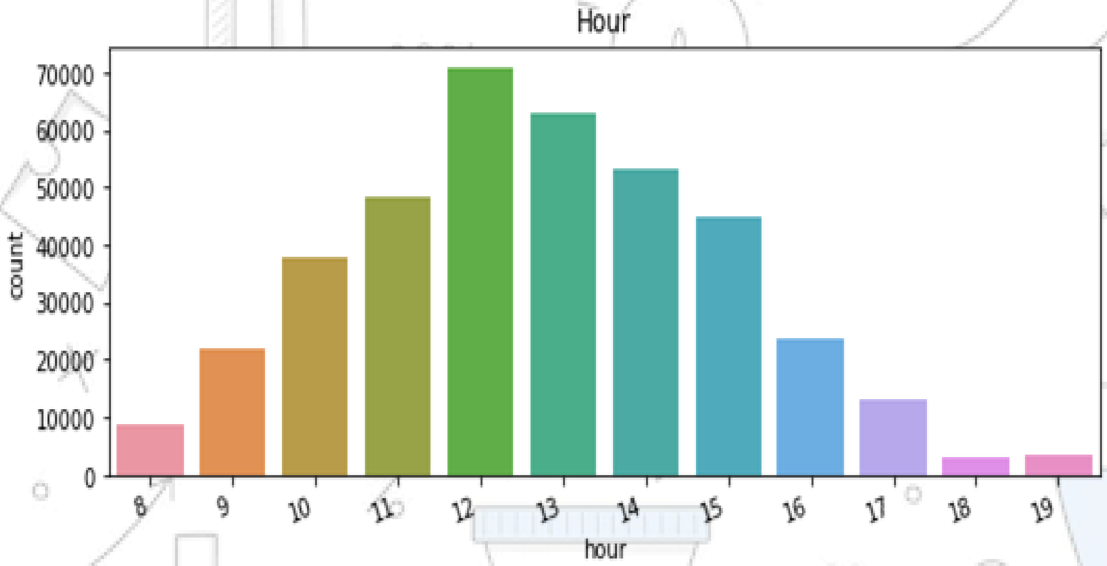
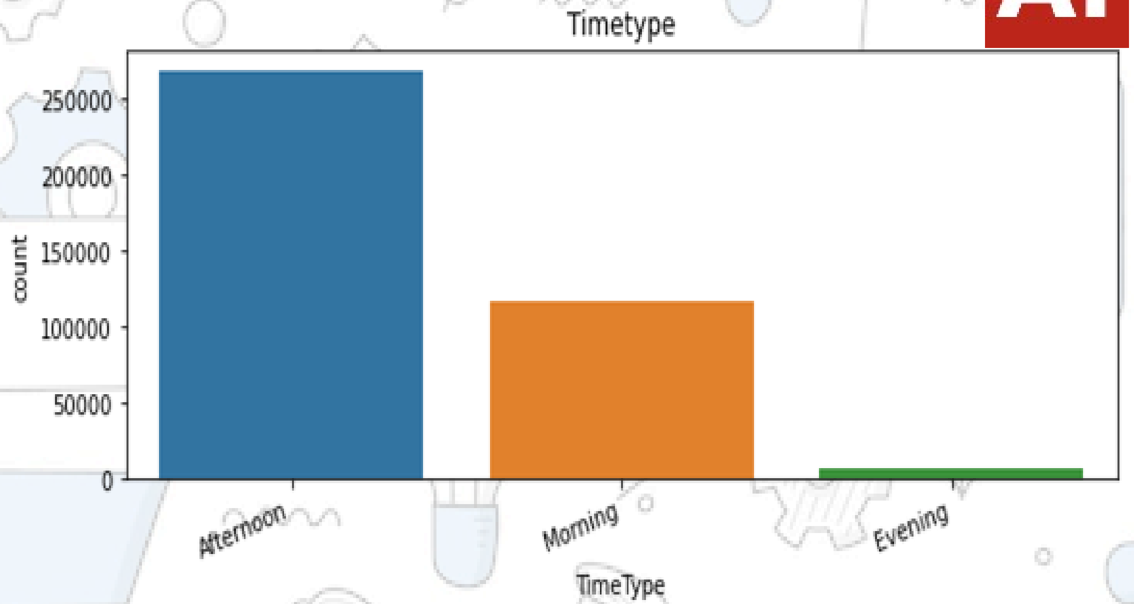




Observations/Hypothesis

1. Most Customers are from the United Kingdom. A considerable number of customers are also from Germany, France, EIRE and Spain.

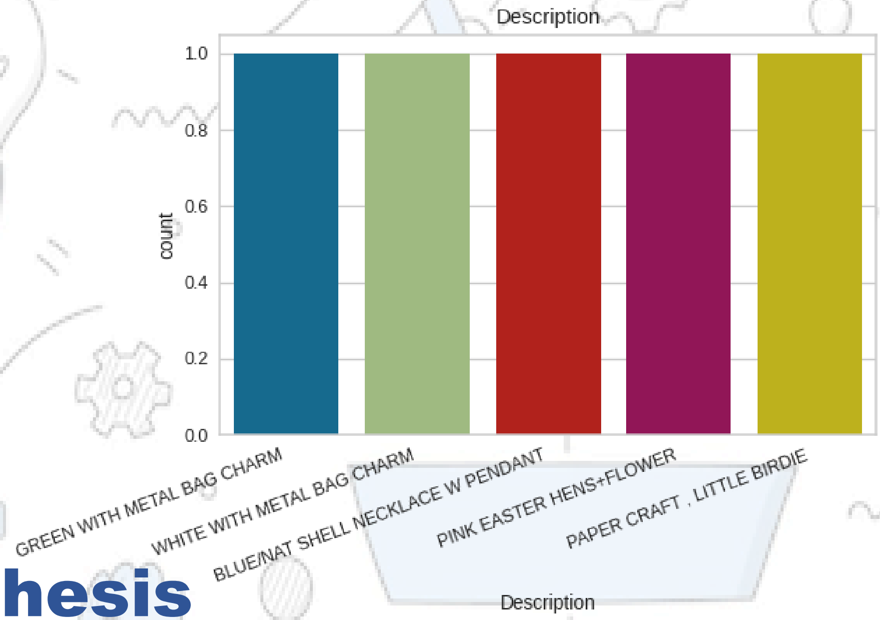
2. There are no orders placed on Saturdays. Looks like it’s a non-working day for the retailer.

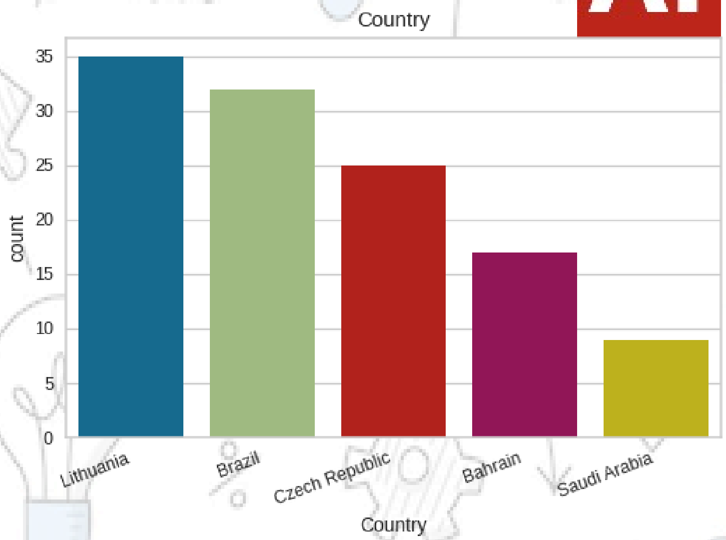
3. Most of the customers have purchased gifts in the month of November, October, December, and September. Less number of customers have purchased the gifts in the month of April, January, and February.

4. Most of the customers have purchased the items in the Afternoon, moderate numbers of customers have purchased the items in Morning and the least in the Evening.

5. WHITE HANGING HEART T-LIGHT HOLDER, REGENCY CAKESTAND 3 TIER, JUMBO BAG RED RETRO SPOT are the most ordered products

LESS FREQUENT VALUES



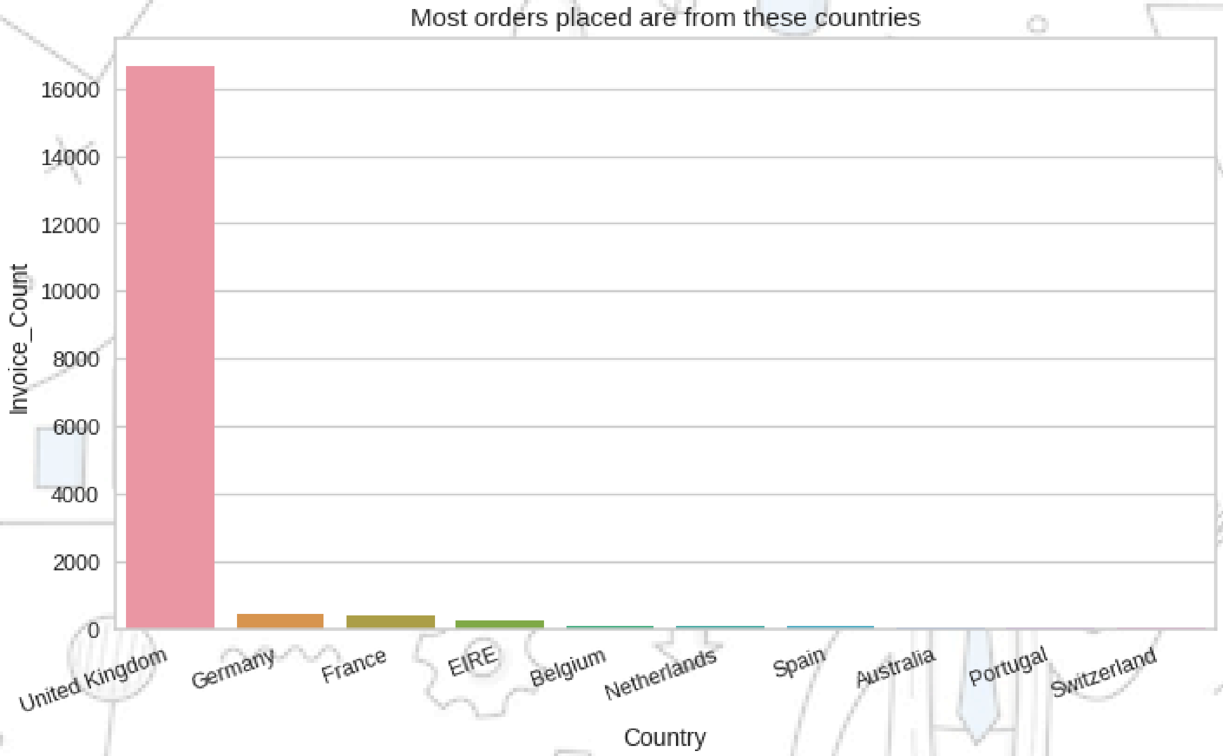


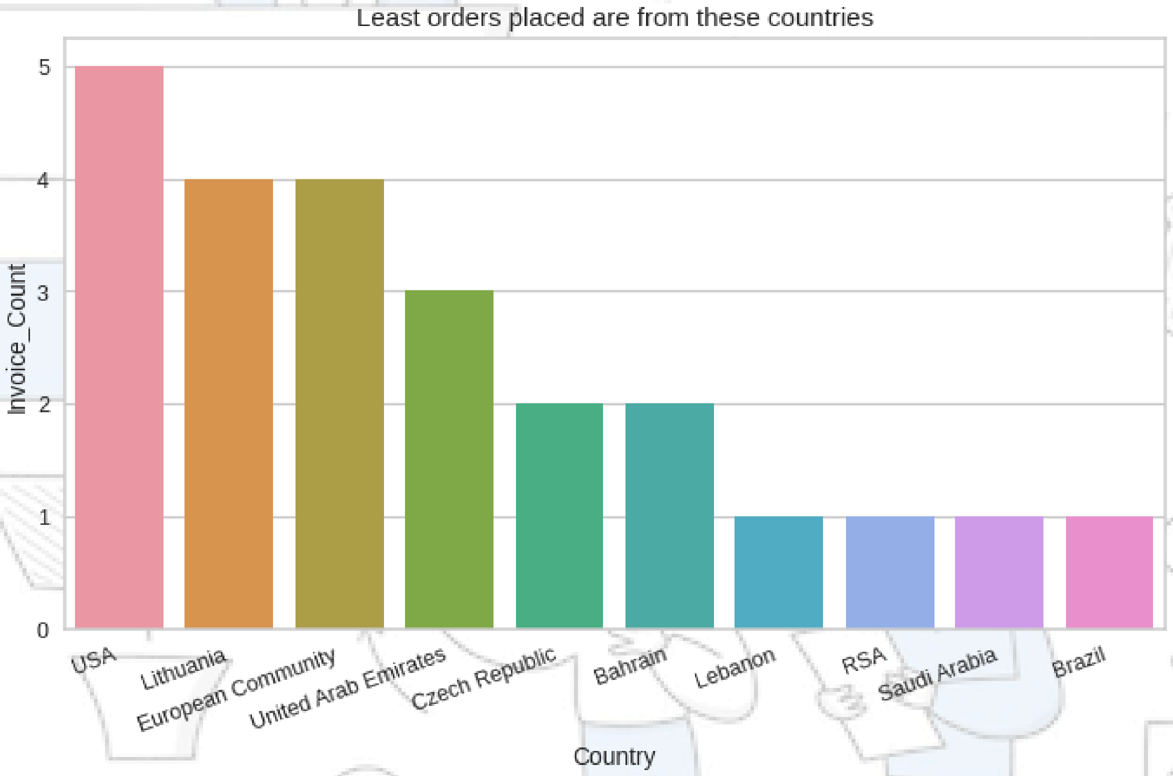
Observations/Hypothesis

1. Saudi Arabia, Bahrain, the Czech Republic, Brazil, and Lithuania has the least number of customers

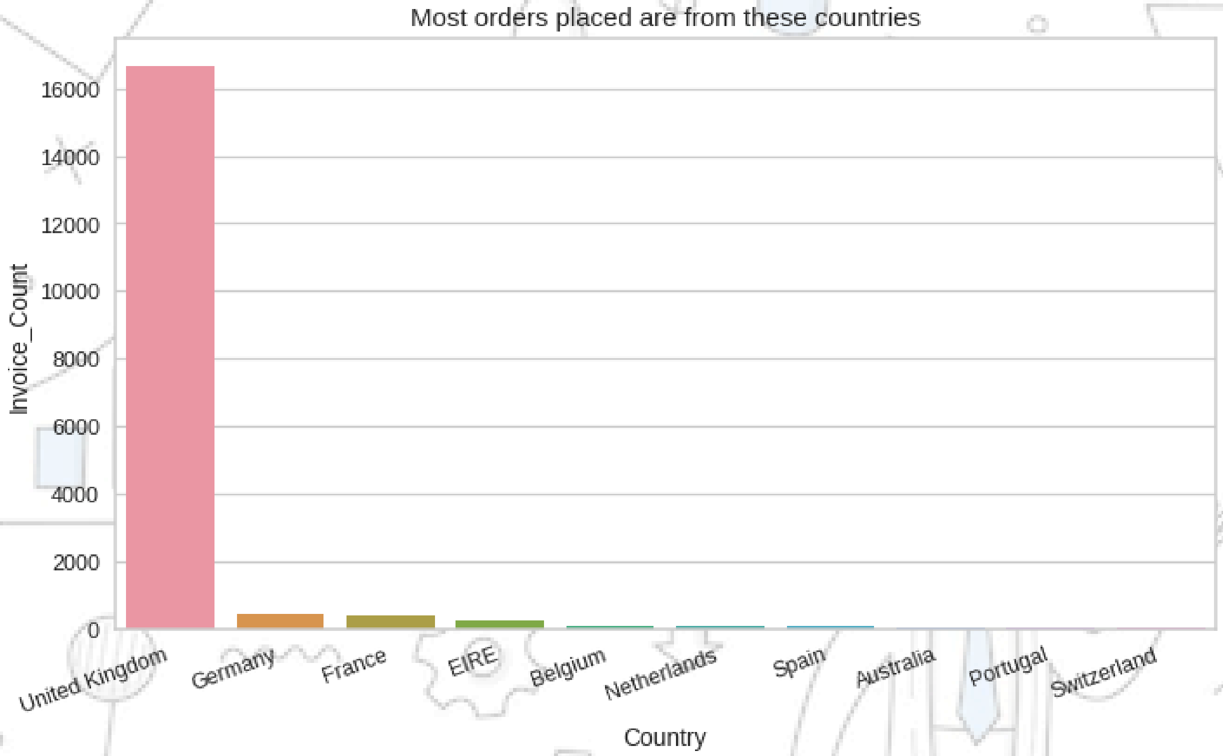
2. GREEN WIT METAL BAG CHARM, WHITE WITH METAL BAG CHARM, BLUE/NAT SELL NECLACE W PENDENT, PINK EASTER ENS FLOWER, PAPER CRAFT LITTLE BIRDIE are some of the least sold products.

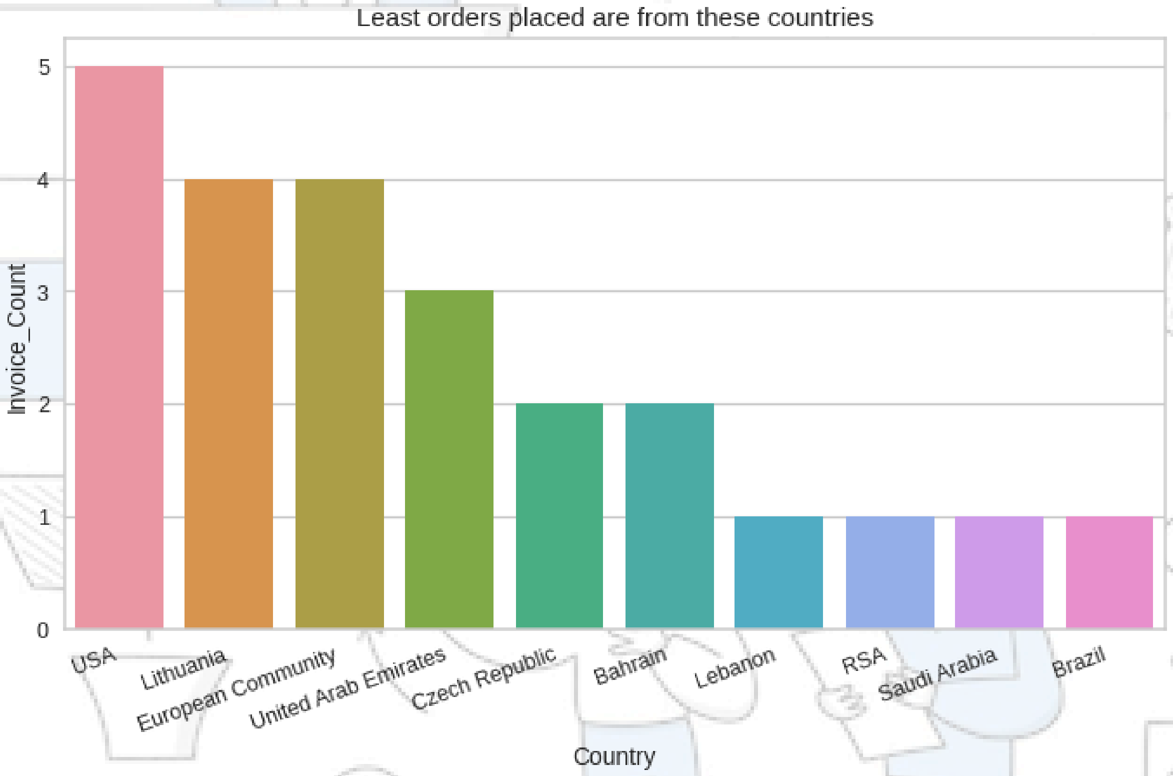
COUNTRY WISE ORDERS



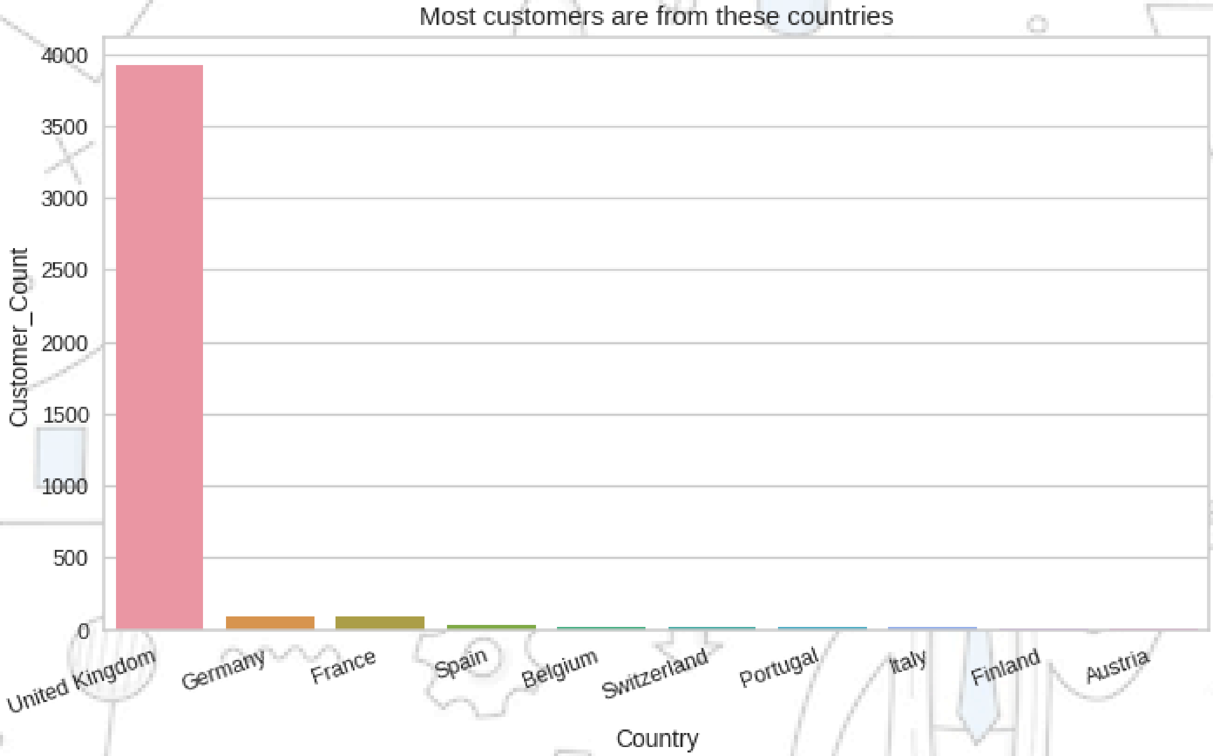


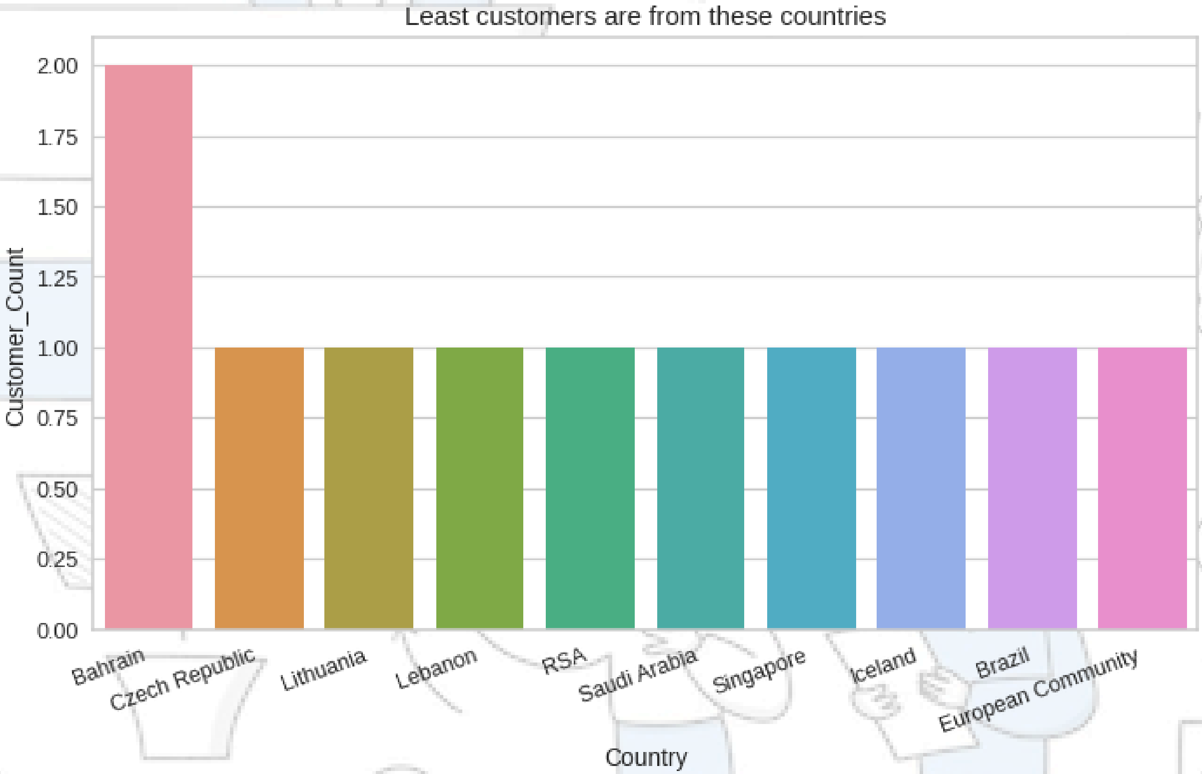
COUNTRY WISE ORDERS



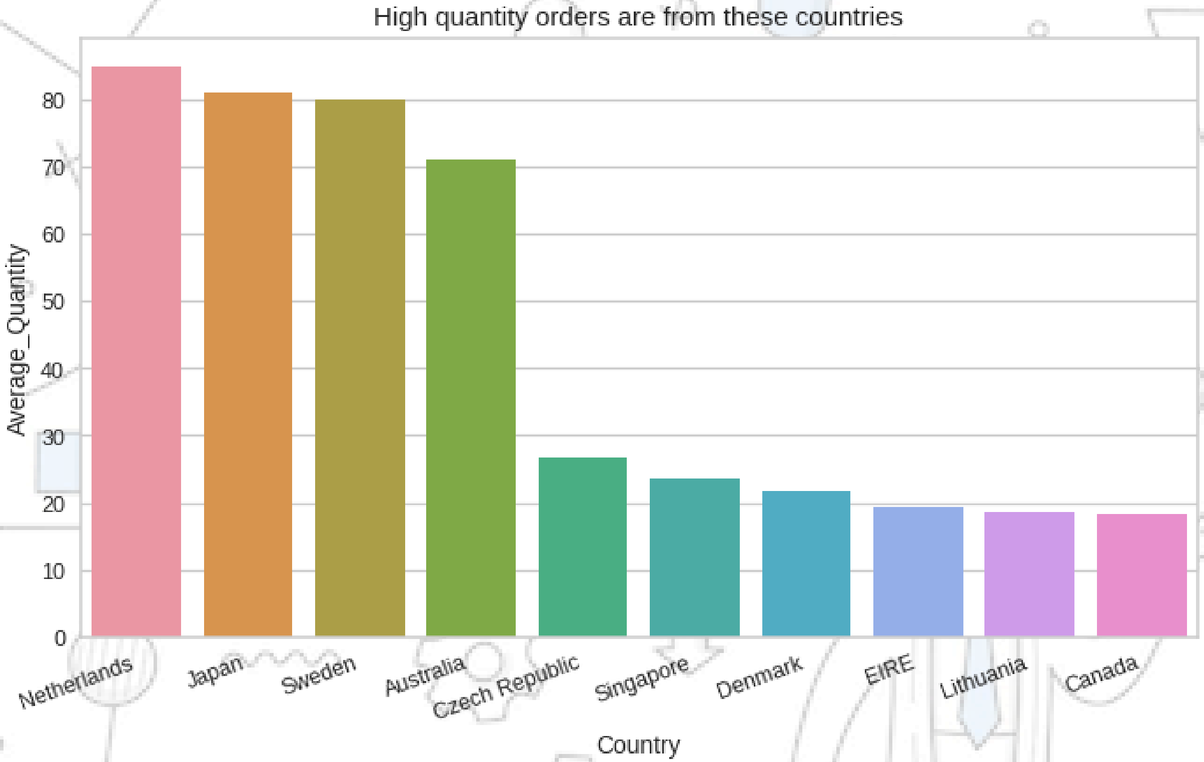


COUNTRY WISE CUSTOMERS

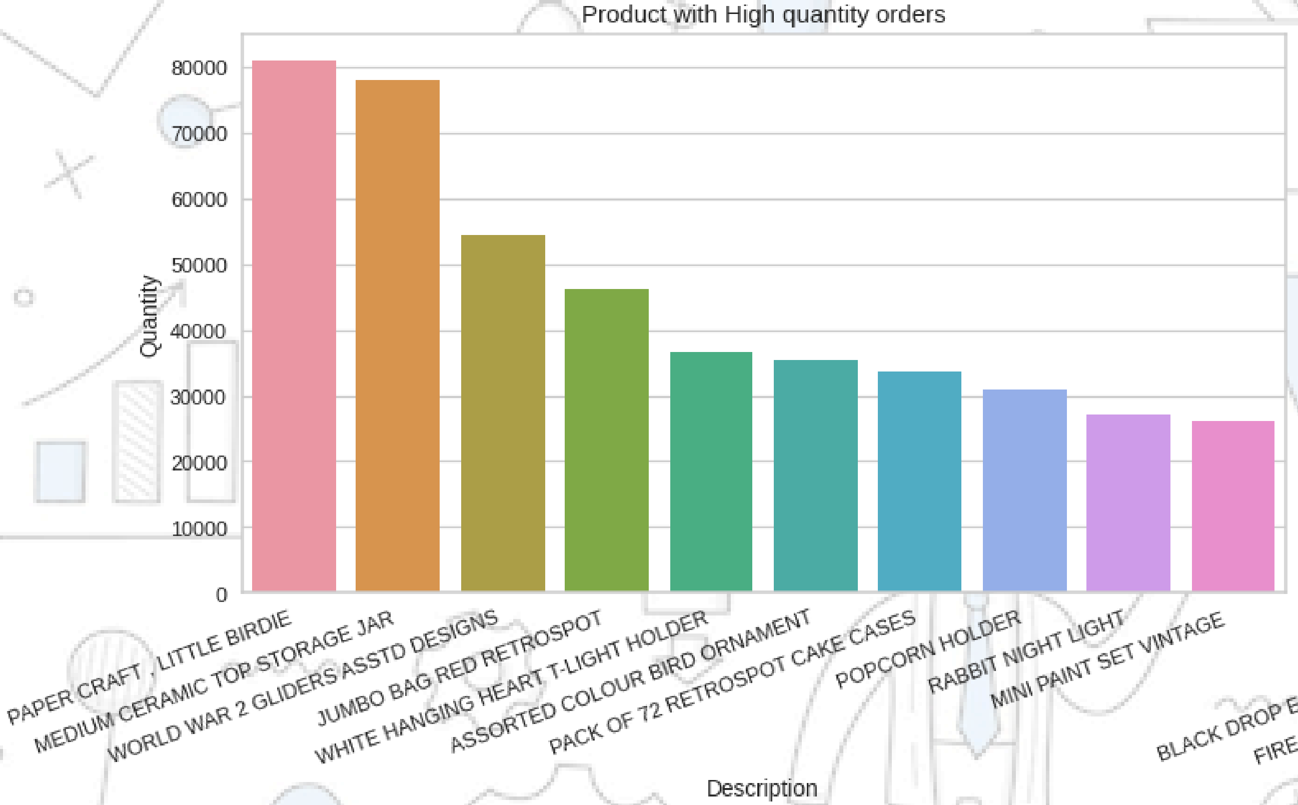


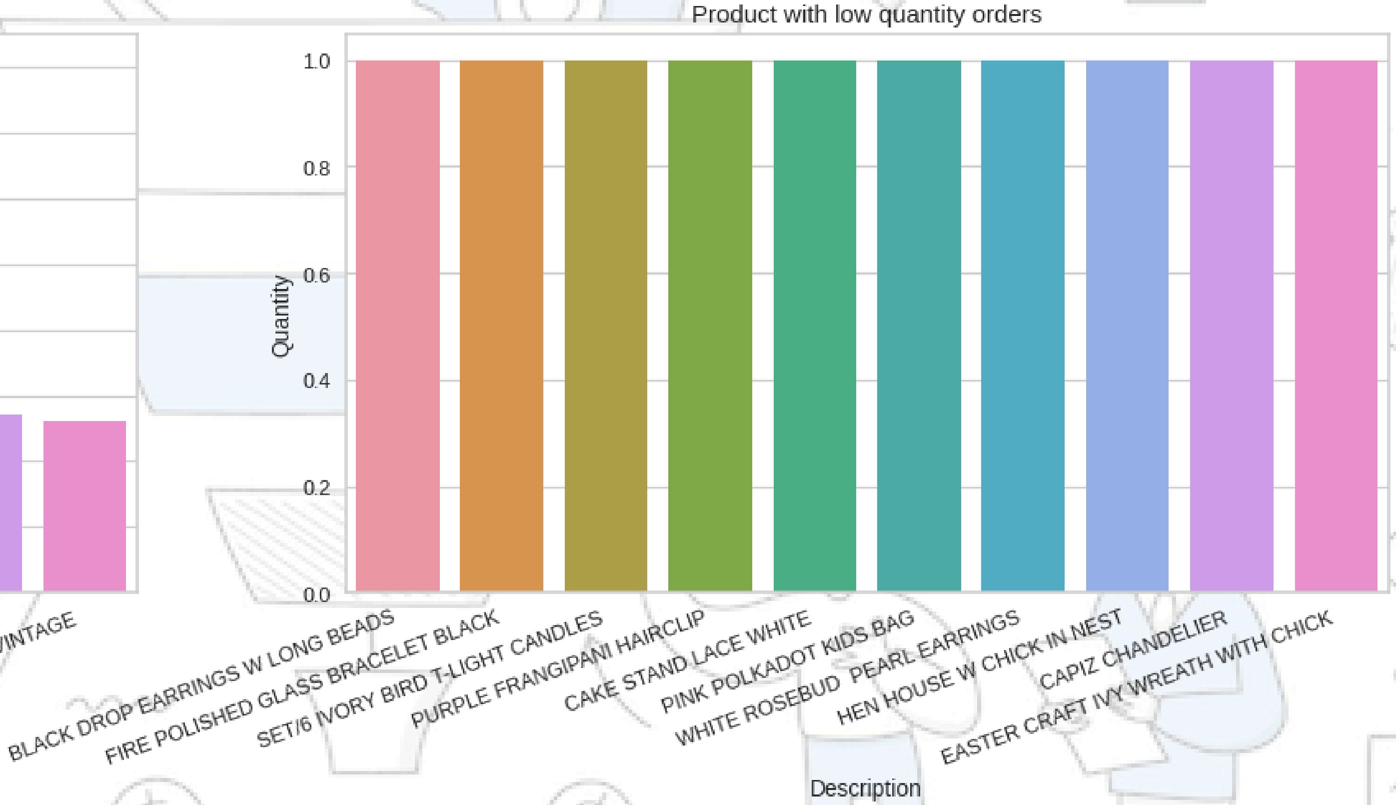


COUNTRY WISE PURCHASE QUANTITY

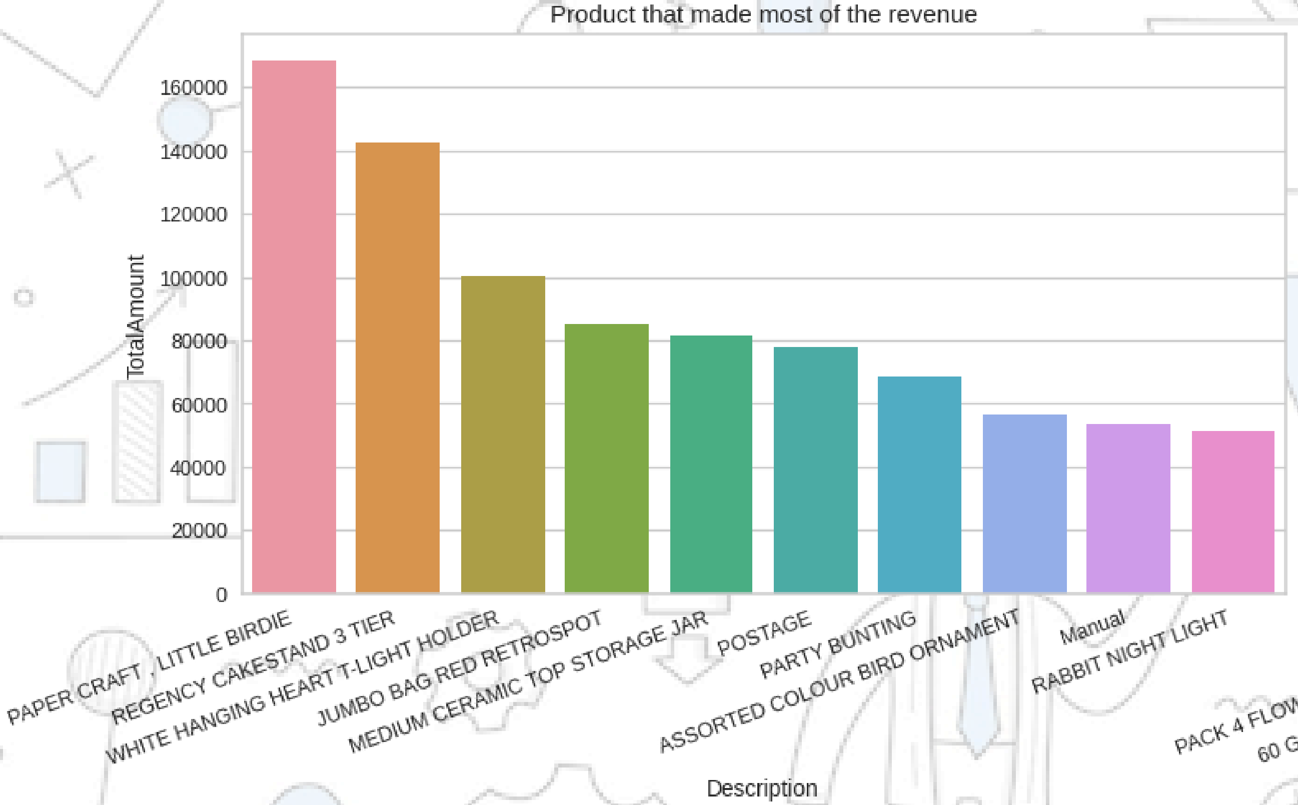


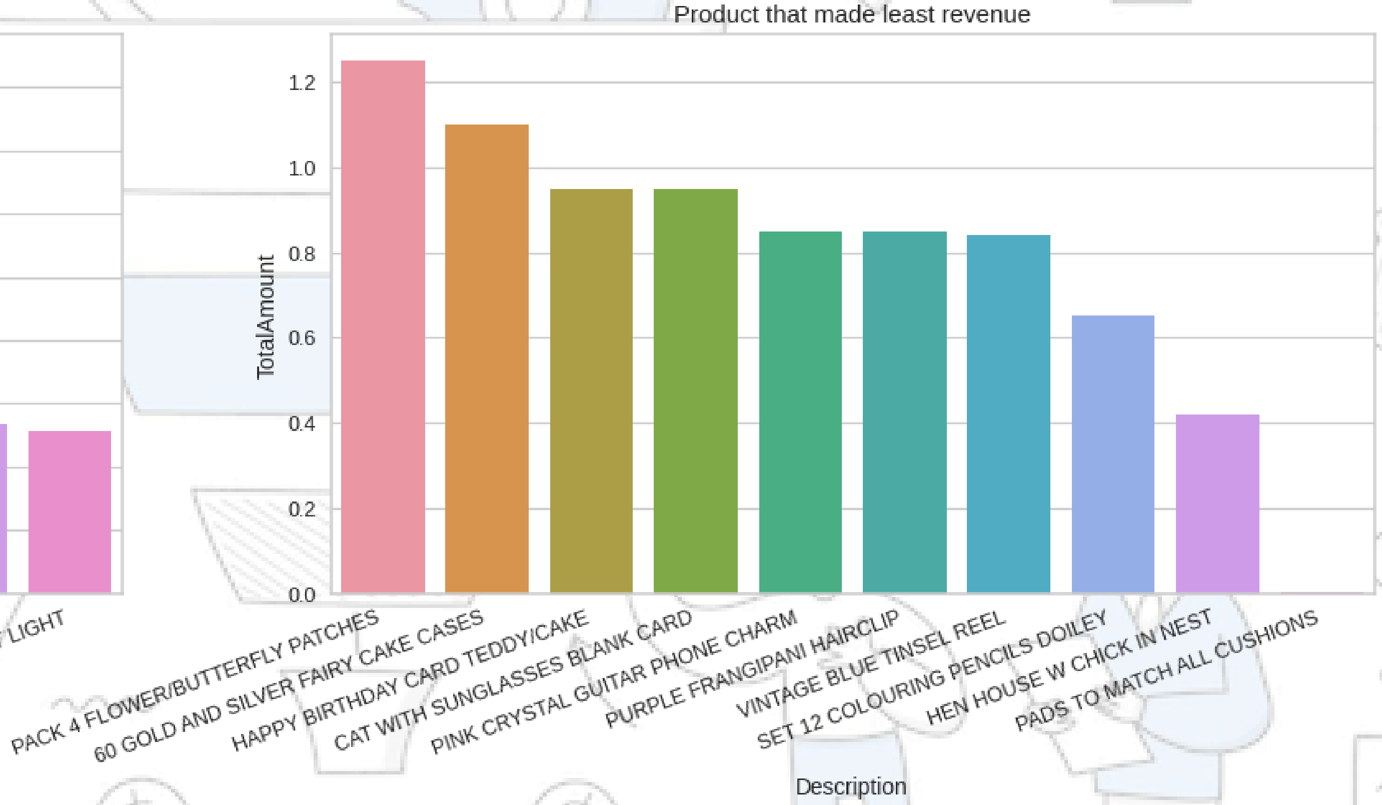
PRODUCT WISE PURCHASE QUANTITY



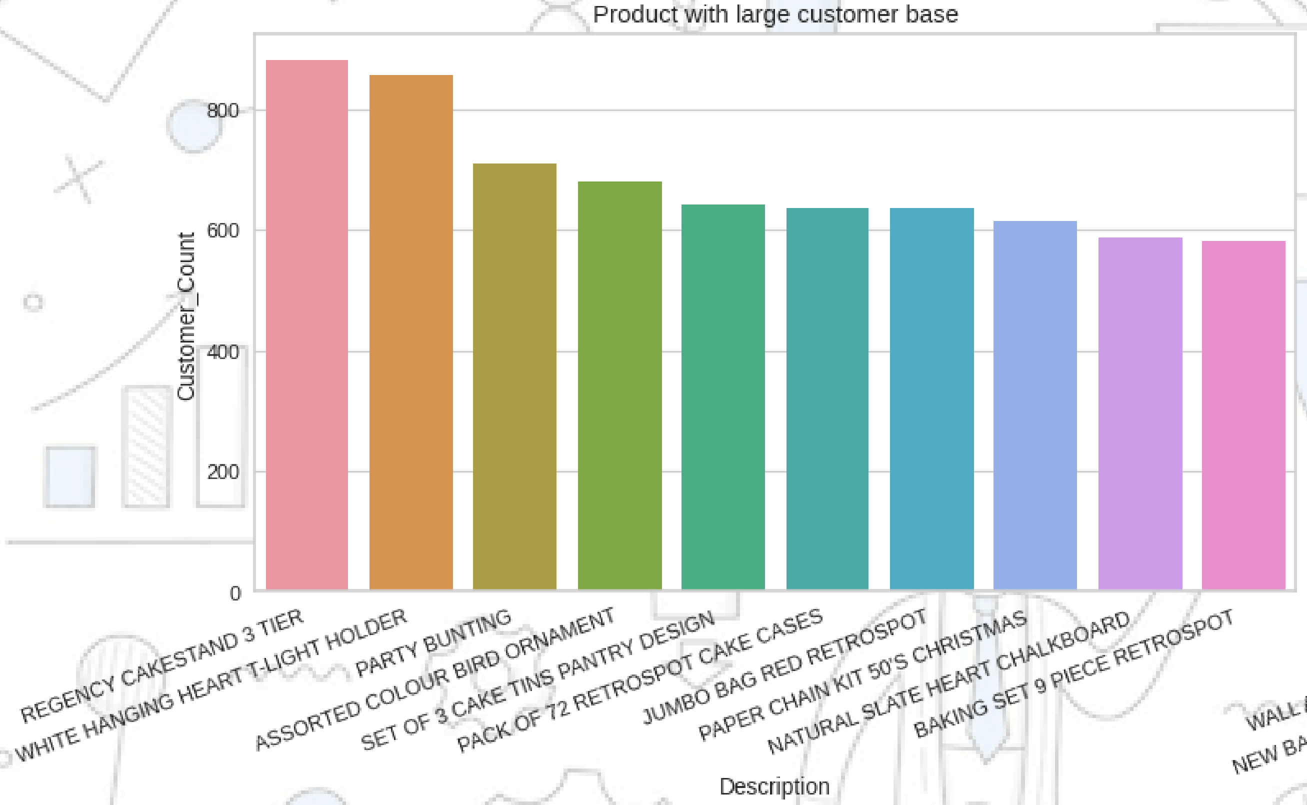


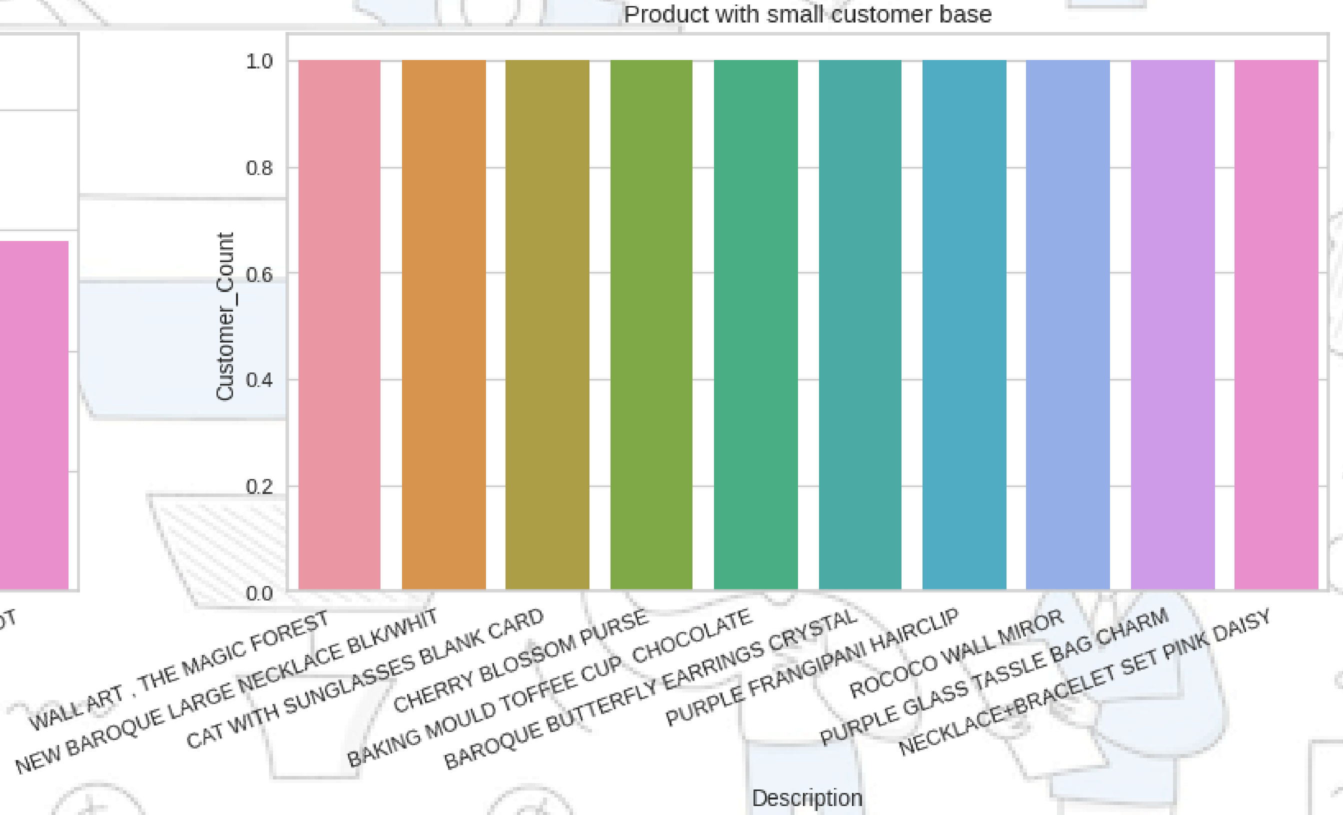
PRODUCT WISE REVENUE



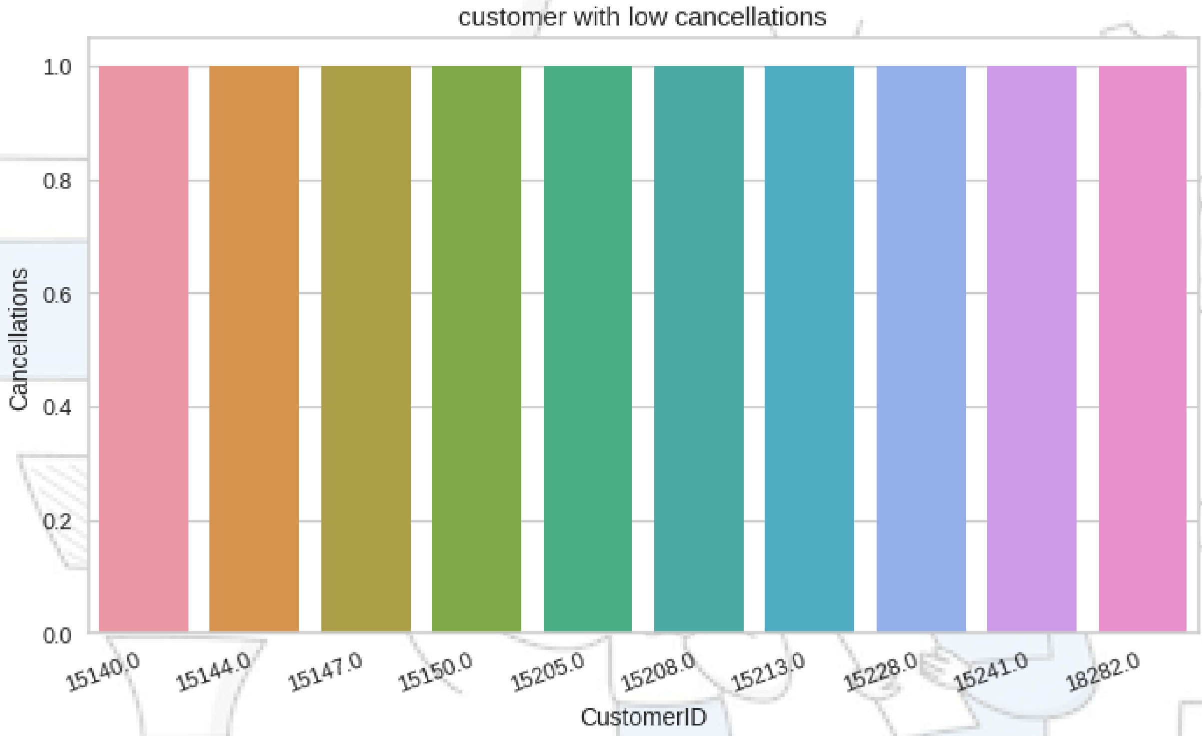


PRODUCT WISE CUSTOMERS

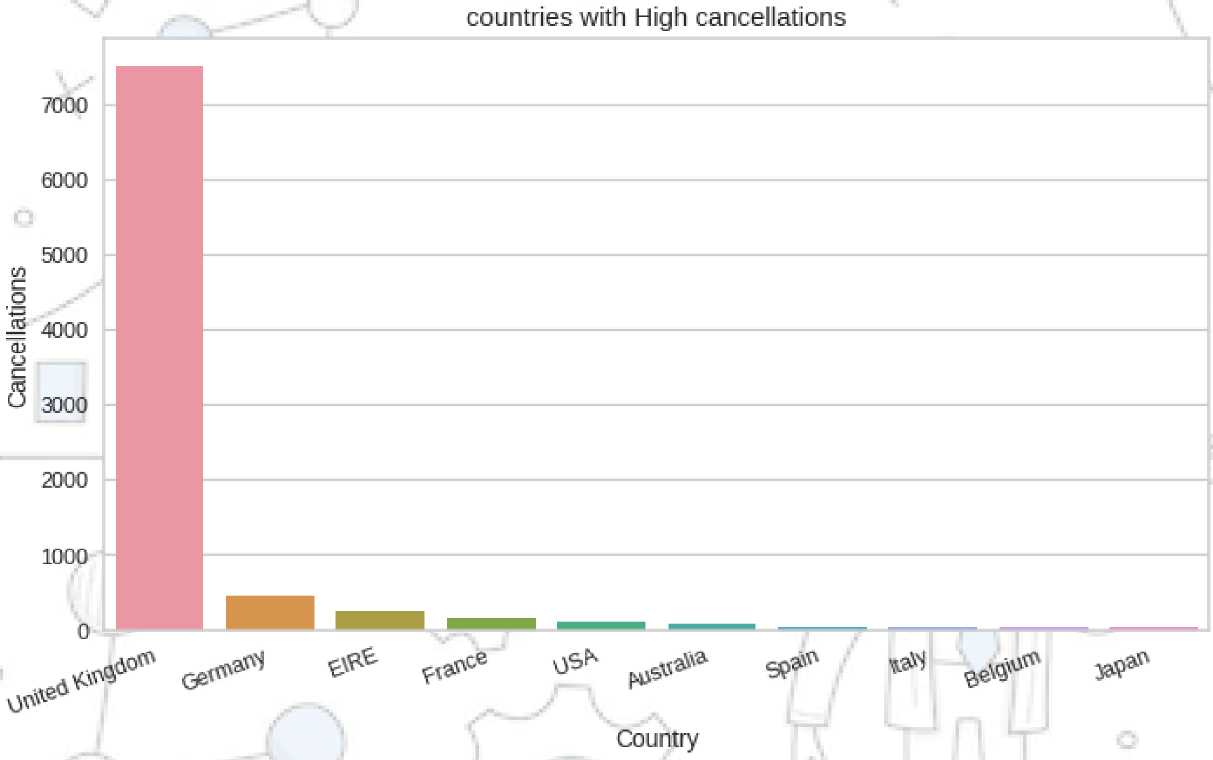


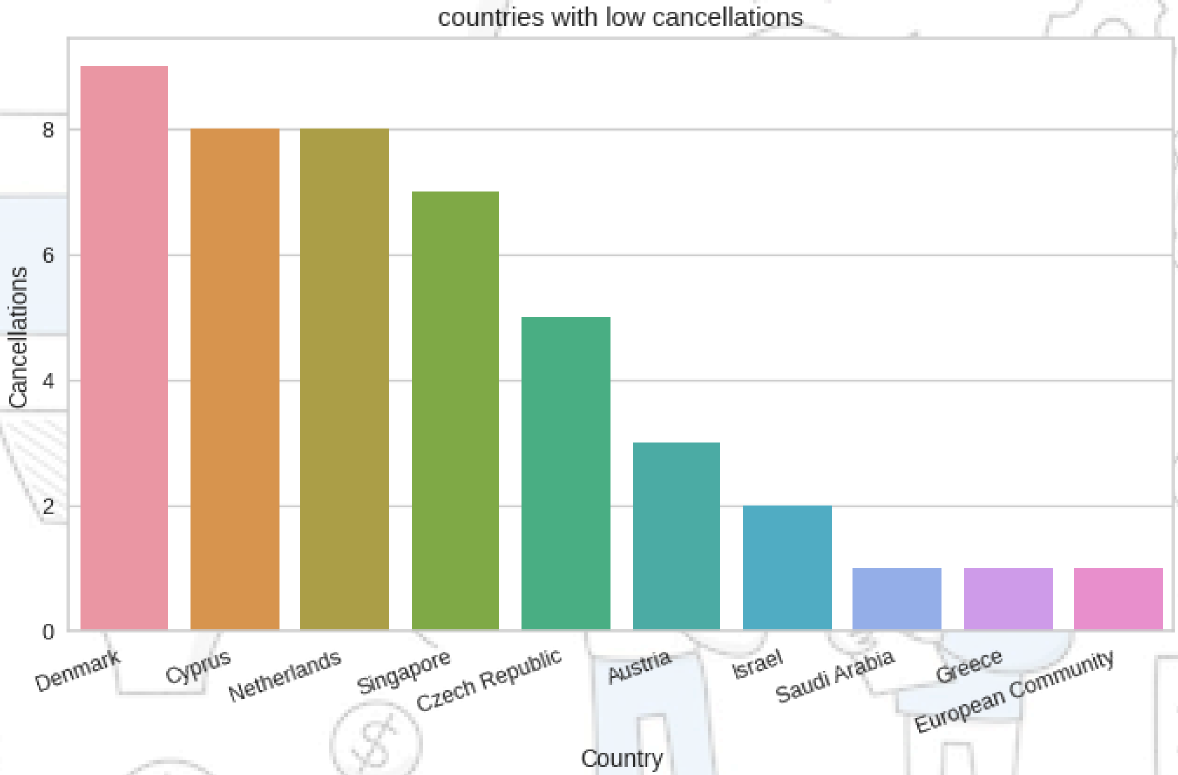


CUSTOMER WISE CANCELLATIONS

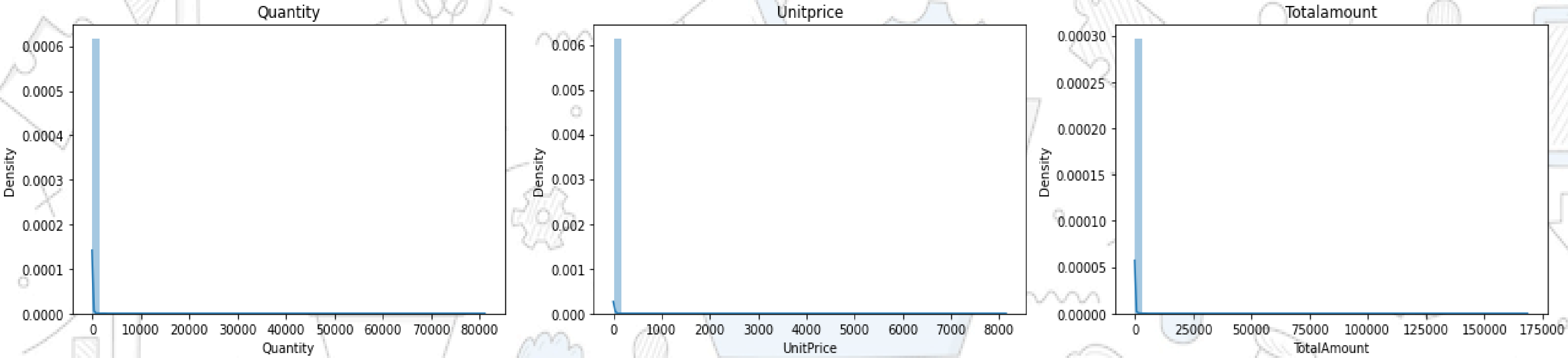


COUNTRY WISE CANCELLATIONS





VISUALIZING DISTRIBUTIONS

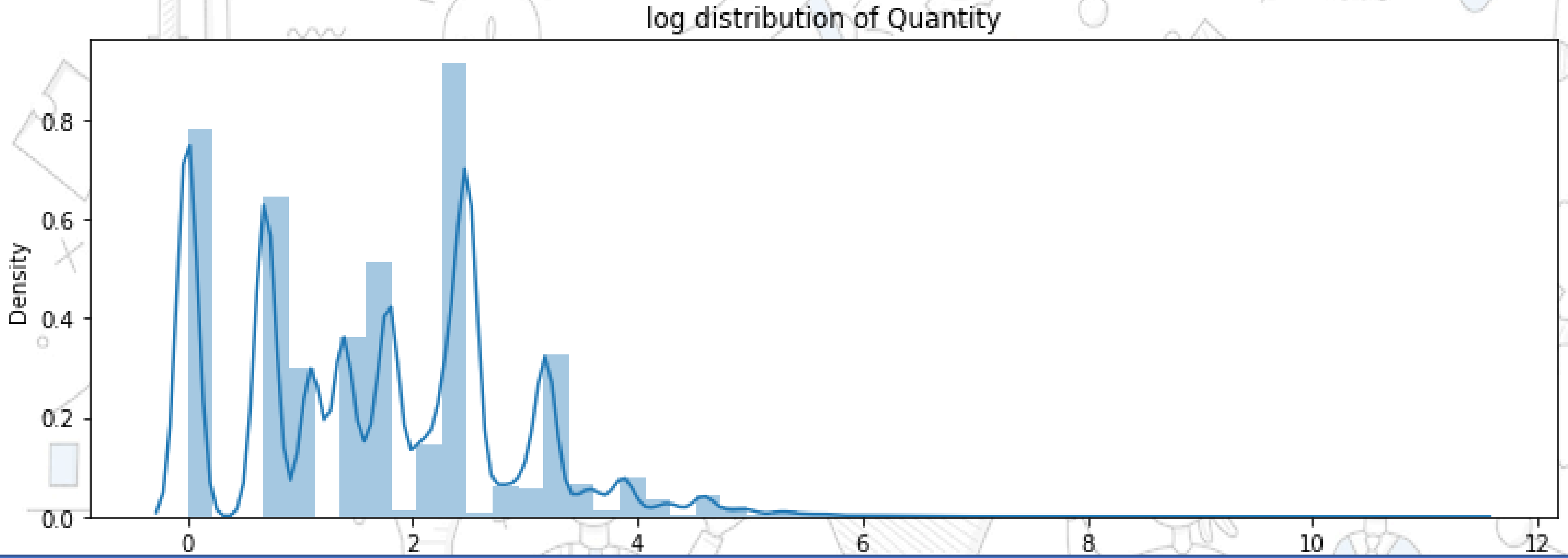


1. Visualizing the distribution of quantity, unitprice and total amount columns

2. It shows a positively skewed distribution because most of the values are clustered around the left side of the distribution while the right tail of the distribution is longer, which means mean>median>mode

3. For symmetric graph mean=median=mode.

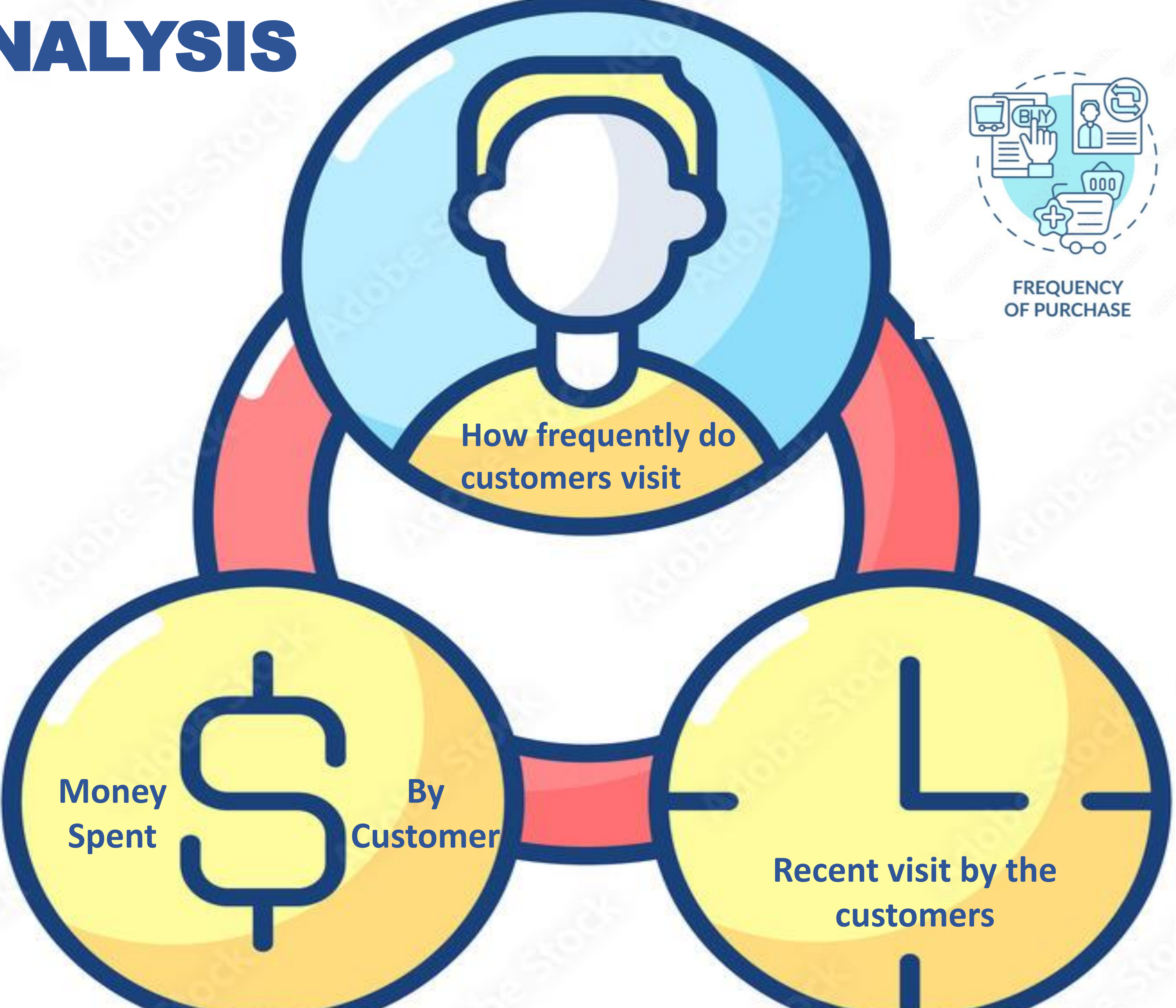
LOG TRANSFORMATION

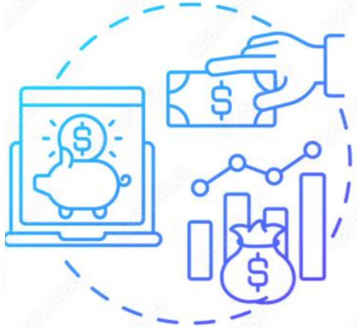


1. After applying log transformation now the distribution plot looks comparatively better than being skewed.

2. We use log transformation when our original continuous data does not follow the bell curve, we can log transform this data to make it as "normal" as possible so that the analysis results from this data become more valid.

RFM ANALYSIS





RFM MODELLING

Customer Name	Recency	Frequency	Monetary
Anthony	326	15	7183
Rahul	2	182	4310
Syed	75	31	1765

RFM TABLE

CONCLUSIONS:

Anthony

Anthony visited 326 days (approx. 1 year) ago and visited 15 times and spent around 7183 Sterlings

Lost Potential Customer

Rahul

Rahul visited 2 days ago and visited 182 times and spent around 4310 Sterlings

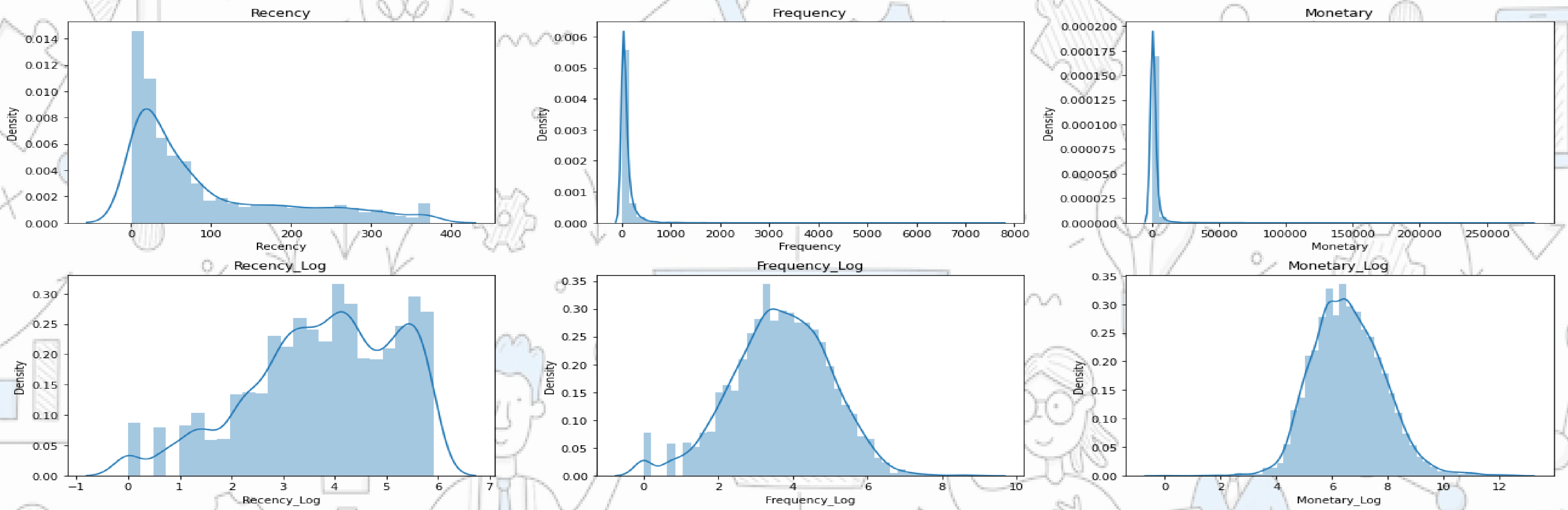
Recently visited Potential Customer

Syed

Syed visited 75 days ago (2.5 months)and visited 31 times and spent around 1765 Sterlings

About to Lose Average Customer

RFM MODELLING

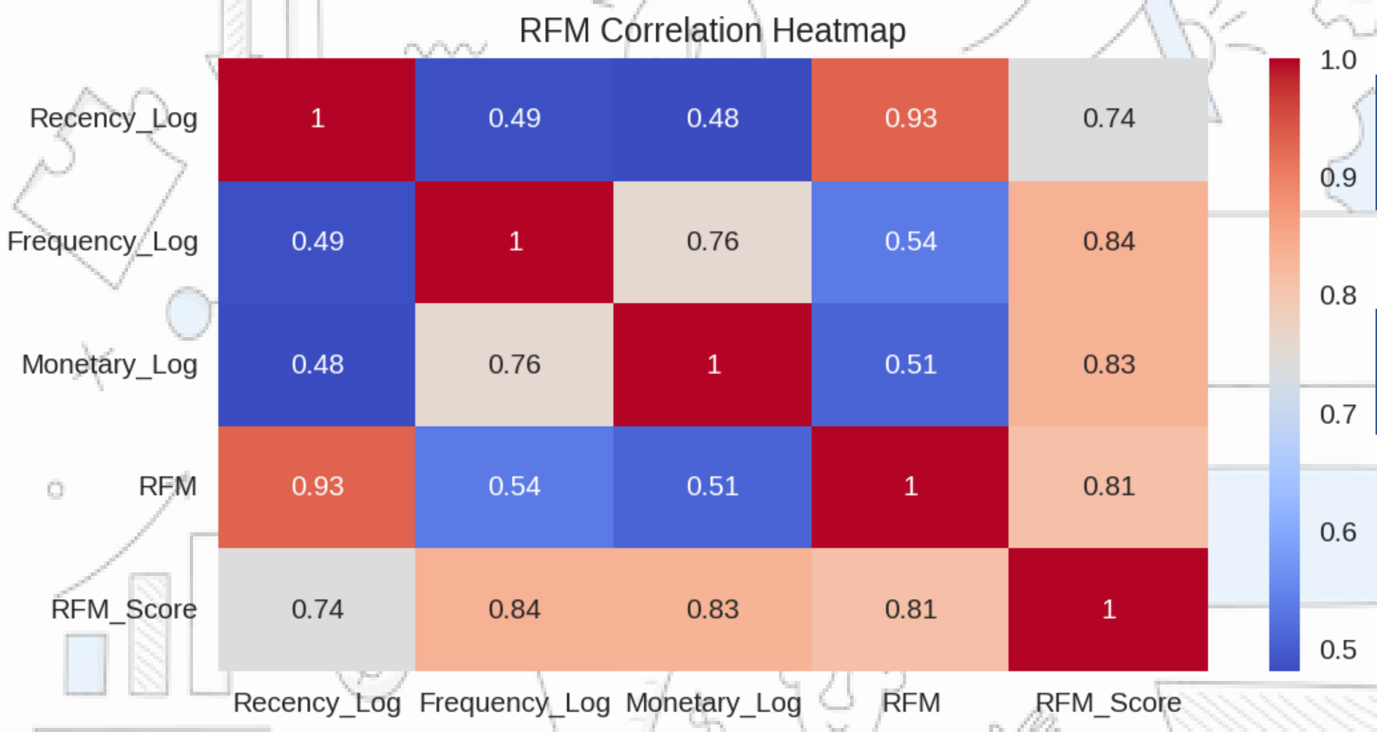


1. Earlier the distributions of Recency, Frequency and Monetary columns were positively skewed but after applying log transformation, the distributions appear to be symmetrical and normally distributed.

2. It will be more suitable to use the transformed features for better visualization of clusters.

RFM CORRELATION HEATMAP

AI



1. We can see that Recency is highly correlated with the RFM value.

2. Frequency and Monetary are moderately correlated with the RFM.

Scaling for CLUSTERING Analysis

1. Log Transformation of Features like Recency Frequency and Monetary

2. Standard Scaler on X variables, (0) mean and (1) as standard deviation

Followed by

Modelling

Clustering Analysis

Pipeline

AI

EXTRACTING DATA → **DATA CLEANING** → **DATA VISUALIZATION** → **RFM ANALYSIS**

Online Retail

Observation:541908
(shape=8x541908)

Checking Missing data

1. 25 % of items
   (i.e 135080)
2. CustomerID – 1454

Checking duplicates

5268 data points were Duplicated

401604 DATA POINT LEFT

RECENCY: Must be **LESS**

FREQUENCY: Must be **MORE**

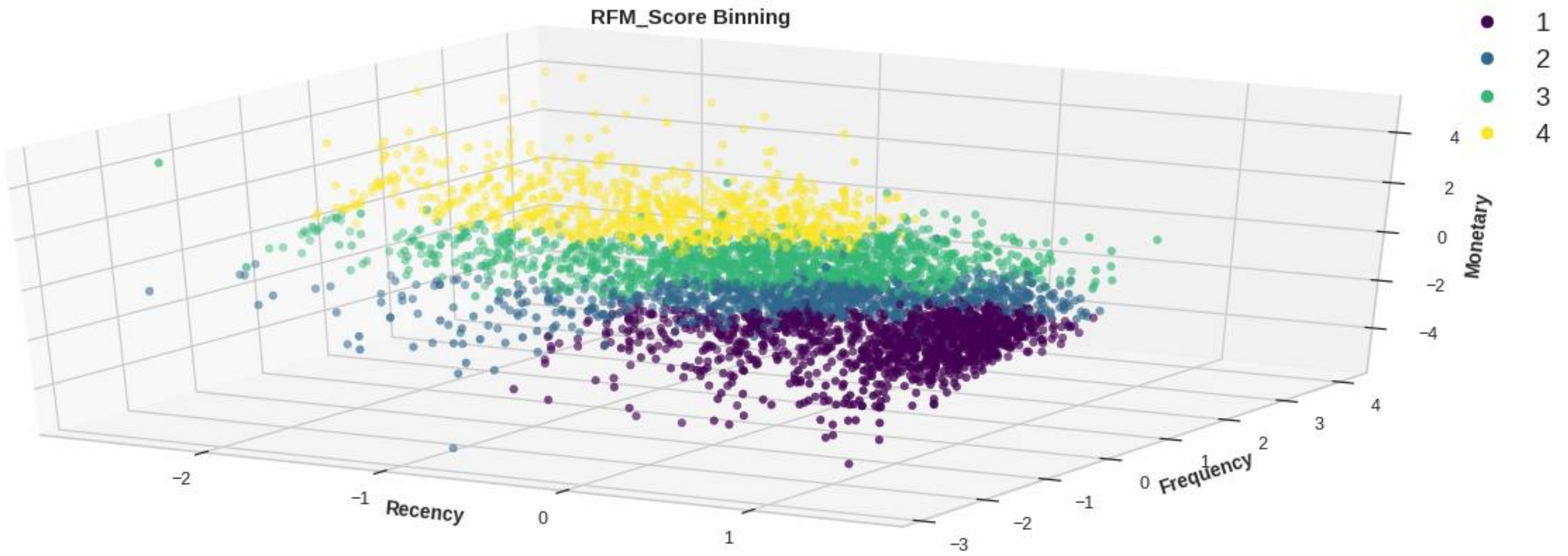
MONETARY: Must be **MORE**

Condition: For Best Customers

MODELLING → **CUSTOMER SEGMENTATION** → **CONCLUSION**

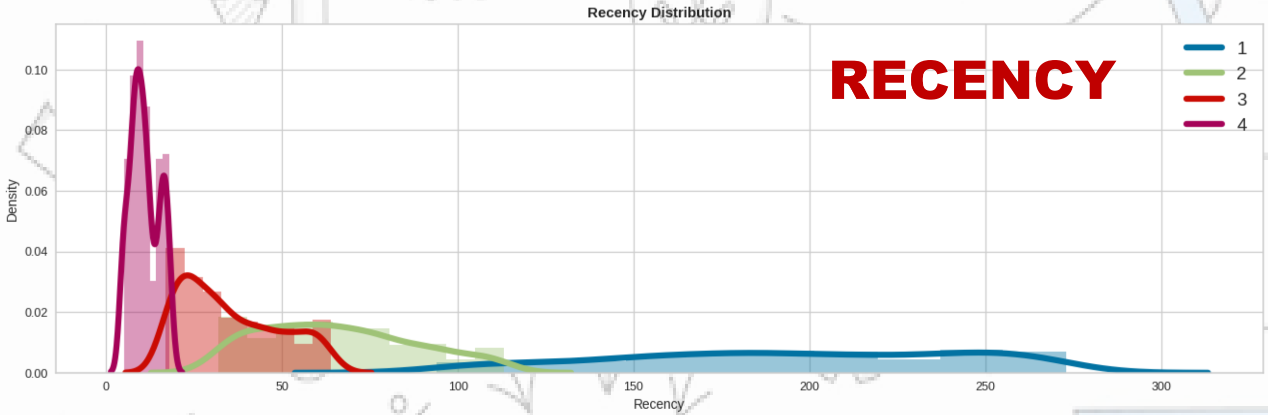
- **Binning (RFM SCORE)**
- **Binning (RFM combination)**
- **K-Means**
- **Hierarchical**
- **DBSCAN Clustering**

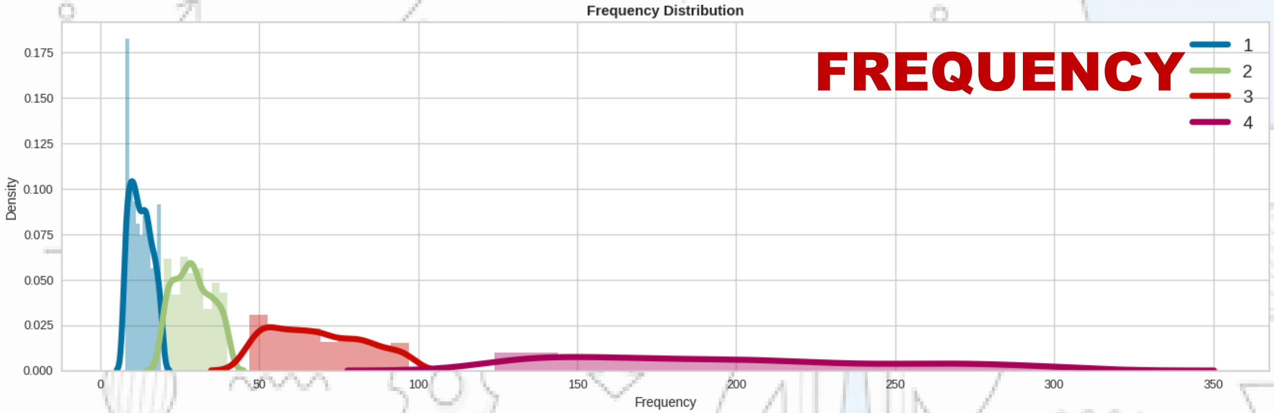
BINNING RFM SCORES

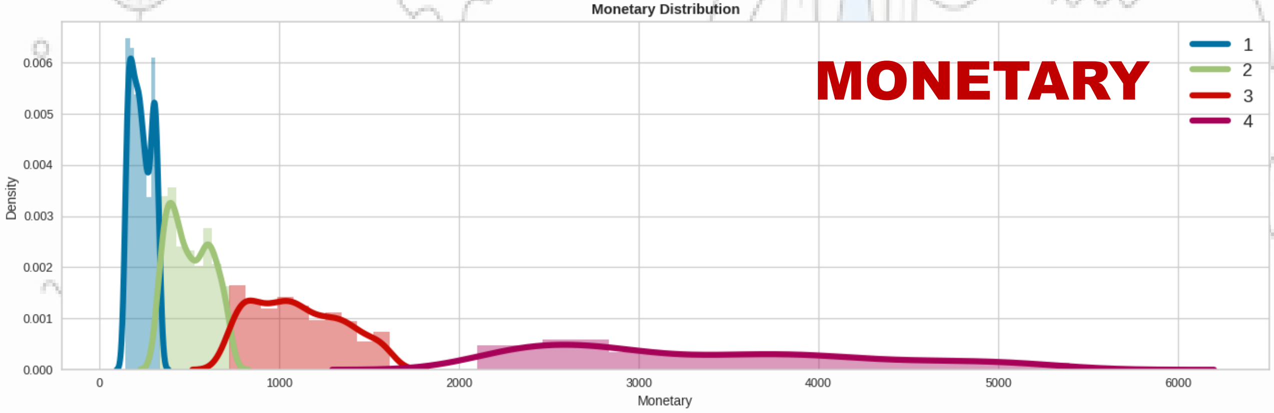


Binning	Recency_mean	Recency_median	Frequency_mean	Frequency_median	Monetary_mean	Monetary_median	Count_
1	192.165501	196.000000	15.062160	12.000000	266.505704	225.900000	1287
2	87.606949	64.000000	32.930510	29.000000	788.401130	488.200000	921
3	47.848532	31.000000	81.241886	67.000000	1597.725141	1076.100000	1294
4	13.761051	10.000000	284.218638	190.000000	6870.541553	3158.130000	837

BINNING RFM SCORES







Binning	Last_visited	Purchase_frequency	Money_spent
1	93 to 274 days ago	Bought 7 to 20 times	Spent around 142 to 335 Sterling
2	31 to 114 days ago	Bought 19 to 41 times	Spent around 327 to 725 Sterling
3	16 to 65 days ago	Bought 46 to 98 times	Spent around 717 to 1613 Sterling
4	4 to 19 days ago	Bought 123 to 305 times	Spent around 2093 to 5398 Sterling

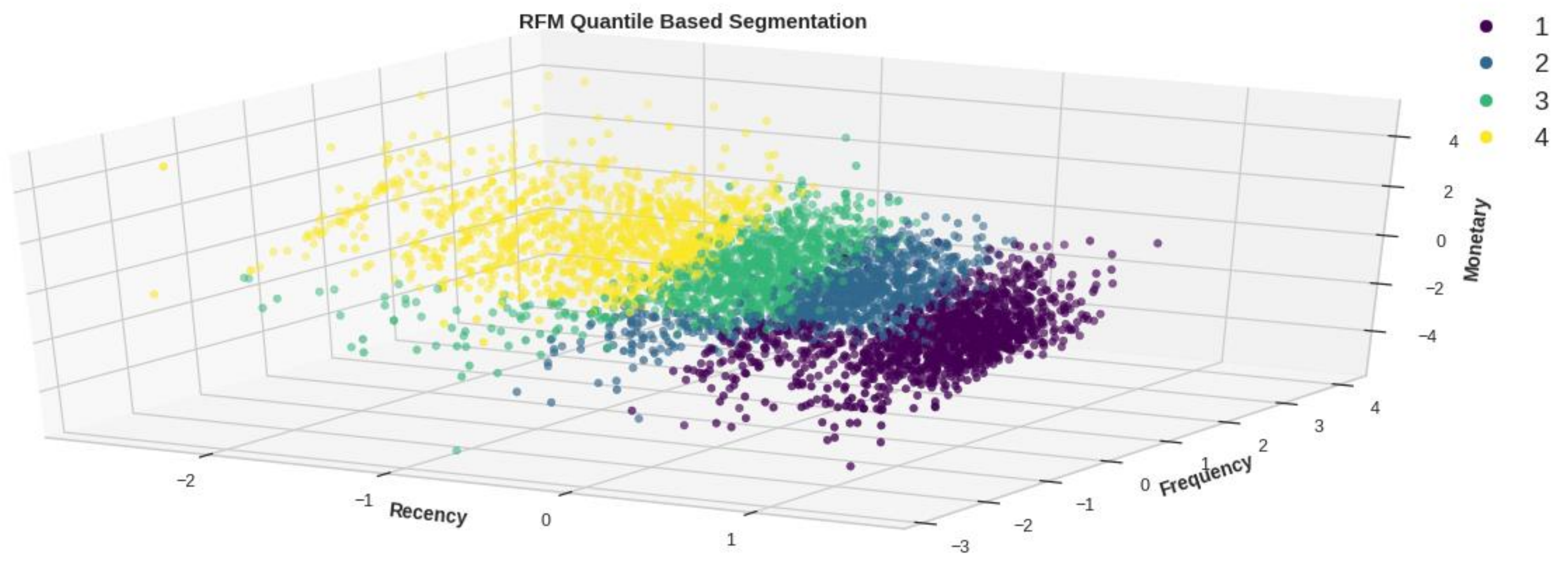
GROUP 1 → LOST POOR CUSTOMERS

GROUP 2 → AVERAGE CUSTOMERS

GROUP 3 → GOOD CUSTOMERS

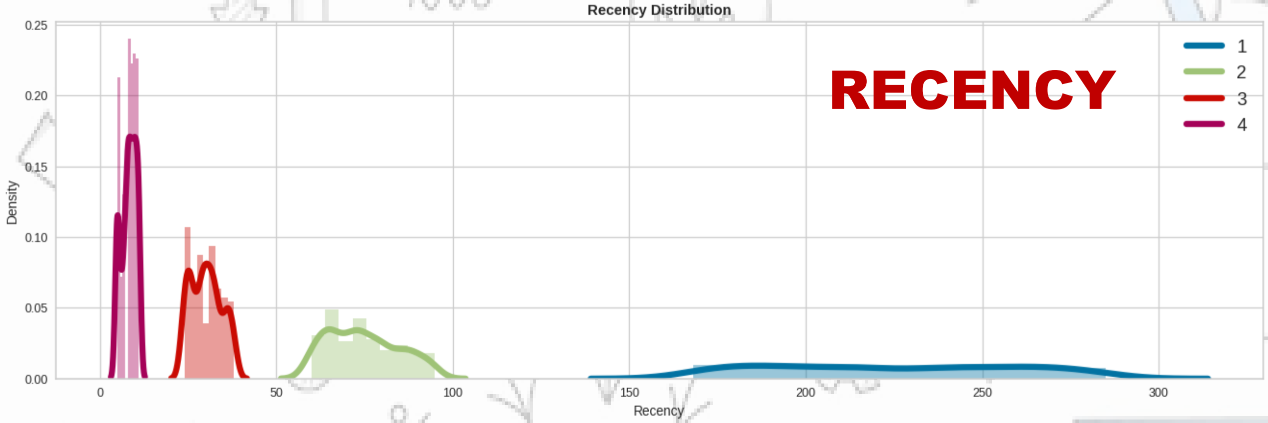
GROUP 4 → BEST CUSTOMERS

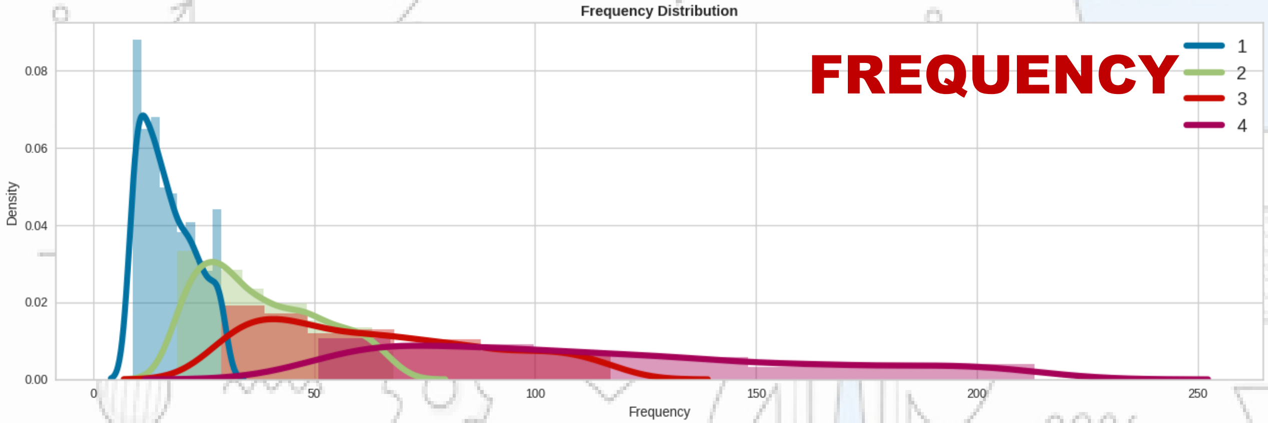
QUANTILE CUT

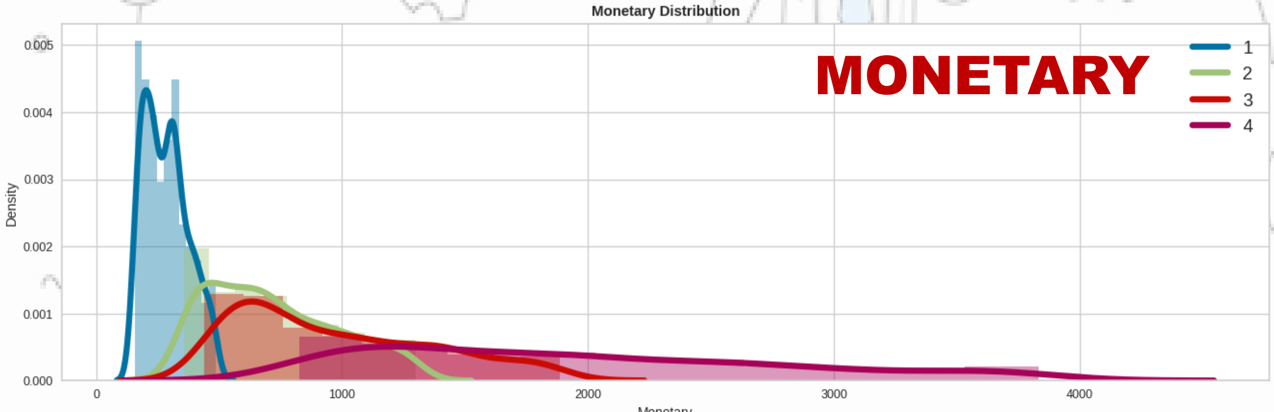


QuantileCut	Recency_mean	Recency_median	Frequency_mean	Frequency_median	Monetary_mean	Monetary_median	Count_
1	224.110055	220.000000	26.190024	15.000000	582.373025	280.550000	1263
2	77.805941	73.000000	54.198020	36.000000	1078.258853	675.645000	1010
3	30.647175	30.000000	94.935580	61.000000	1831.494709	881.290000	1009
4	8.400189	8.000000	197.846736	106.000000	4933.446698	1814.120000	1057

QUANTILE CUT







QuantileCut	Last_visited	Purchase_frequency	Money_spent
1	166 to 286 days ago	Bought 8 to 30 times	Spent around 156 to 486 Sterling
2	59 to 96 days ago	Bought 18 to 69 times	Spent around 355 to 1301 Sterling
3	23 to 39 days ago	Bought 28 to 118 times	Spent around 439 to 1887 Sterling
4	4 to 12 days ago	Bought 50 to 214 times	Spent around 822 to 3849 Sterling

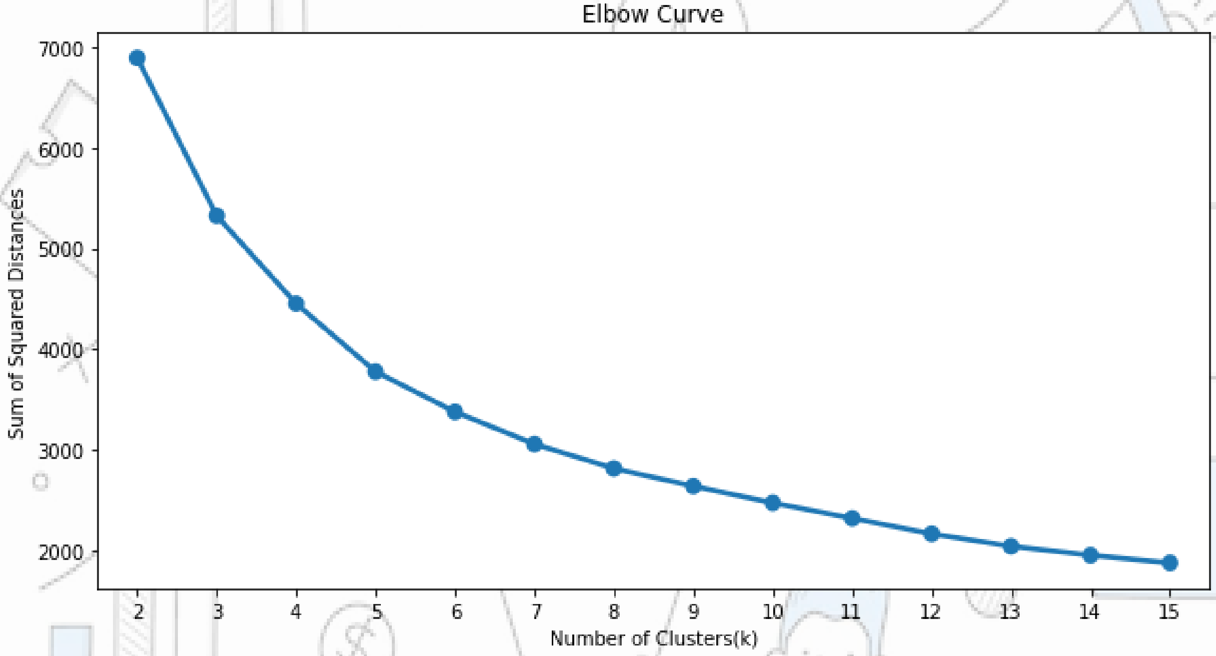
GROUP 1 → LOST POOR CUSTOMERS

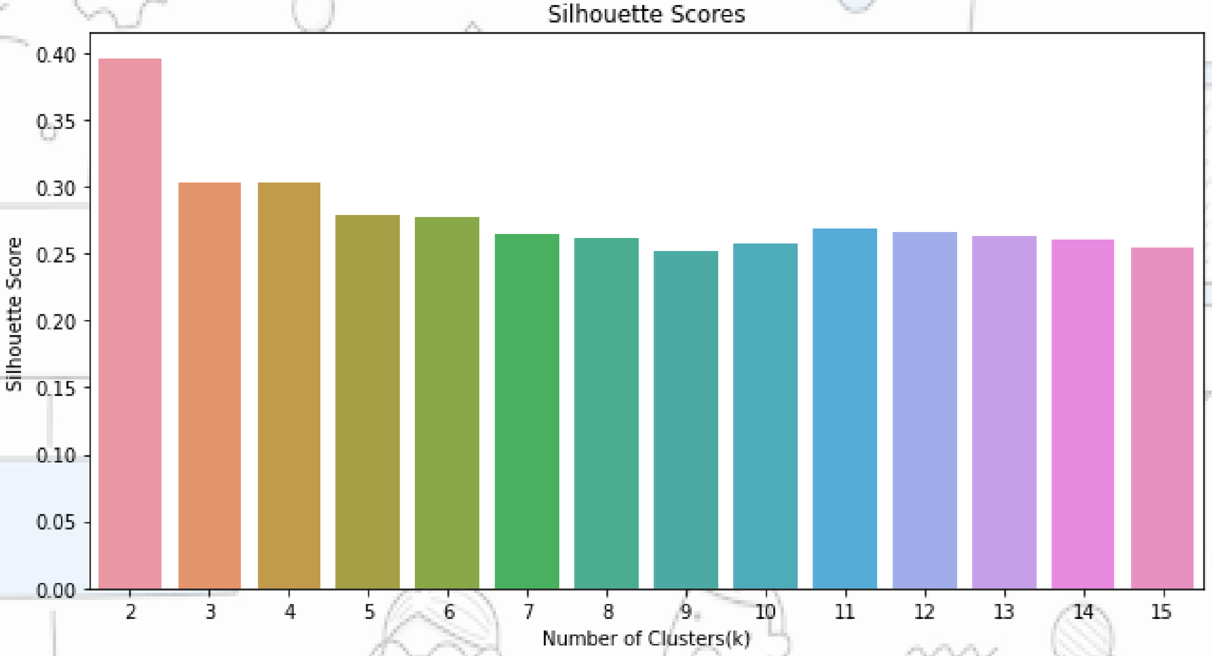
GROUP 2 → LOSING LOYAL CUSTOMERS

GROUP 3 → GOOD CUSTOMERS

GROUP 4 → BEST CUSTOMERS

K-MEANS CLUSTERING



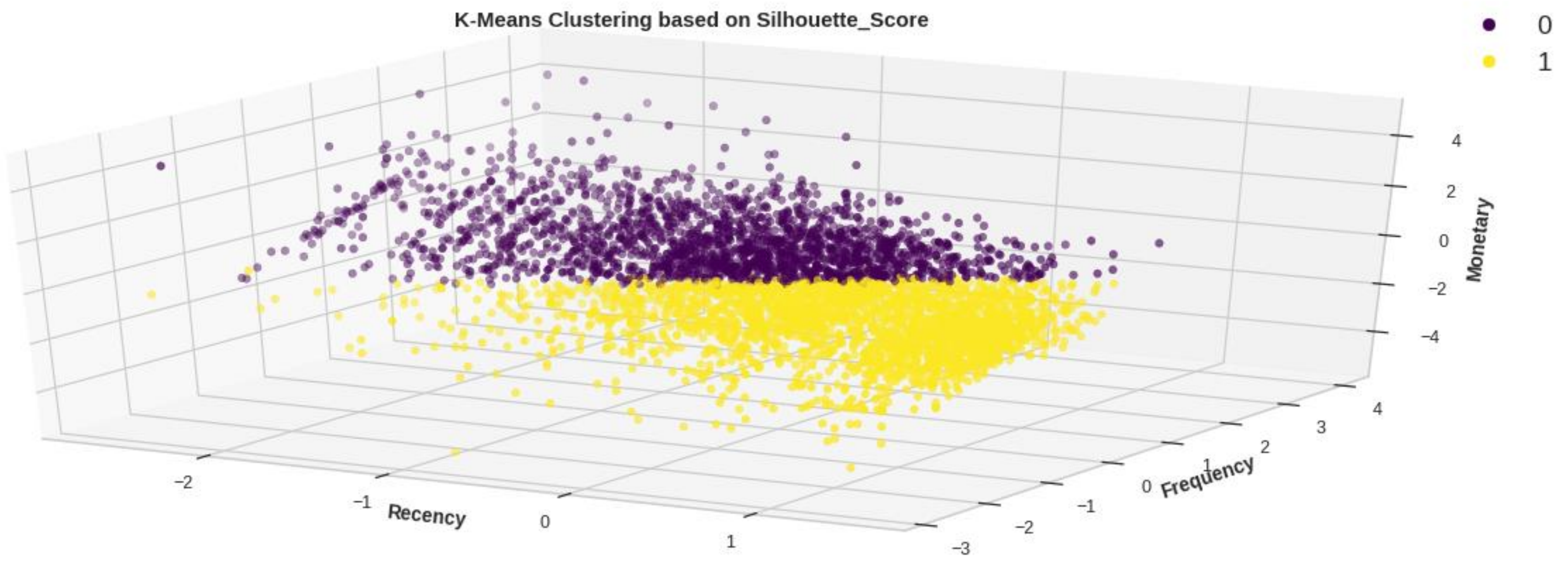


1. From the Elbow curve 5 appears to be at the elbow and hence can be considered as the number of clusters. n_clusters=4 or 6 can also be considered.

2. If we go by the maximum Silhouette Score as the criteria for selecting an optimal number of clusters, then n_clusters=2 can be chosen.

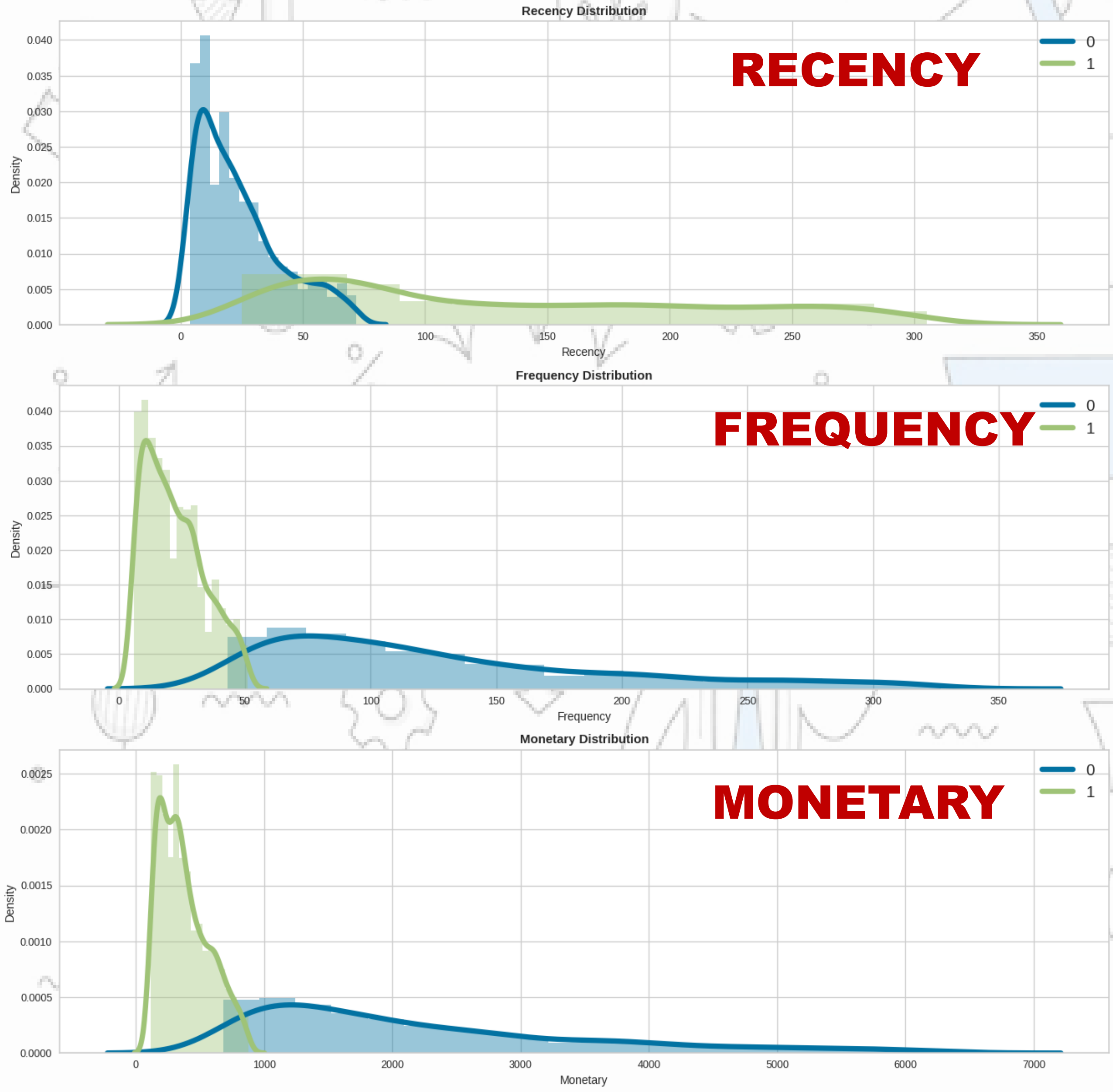
3. If we look at both of the graphs at the same time to decide the optimal number of clusters, So 4 appears to be a good choice, having a decent Silhouette score as well as near the elbow of the elbow curve.

K-MEANS | 2CLUSTER



K-Means|2Cluster	Recency_mean	Recency_median	Frequency_mean	Frequency_median	Monetary_mean	Monetary_median	Count_
0	31.074883	18.000000	173.084763	108.000000	4029.985352	1823.520000	1923
1	141.423841	109.000000	24.788907	20.000000	470.839430	331.210000	2416

K-MEANS | 2CLUSTER

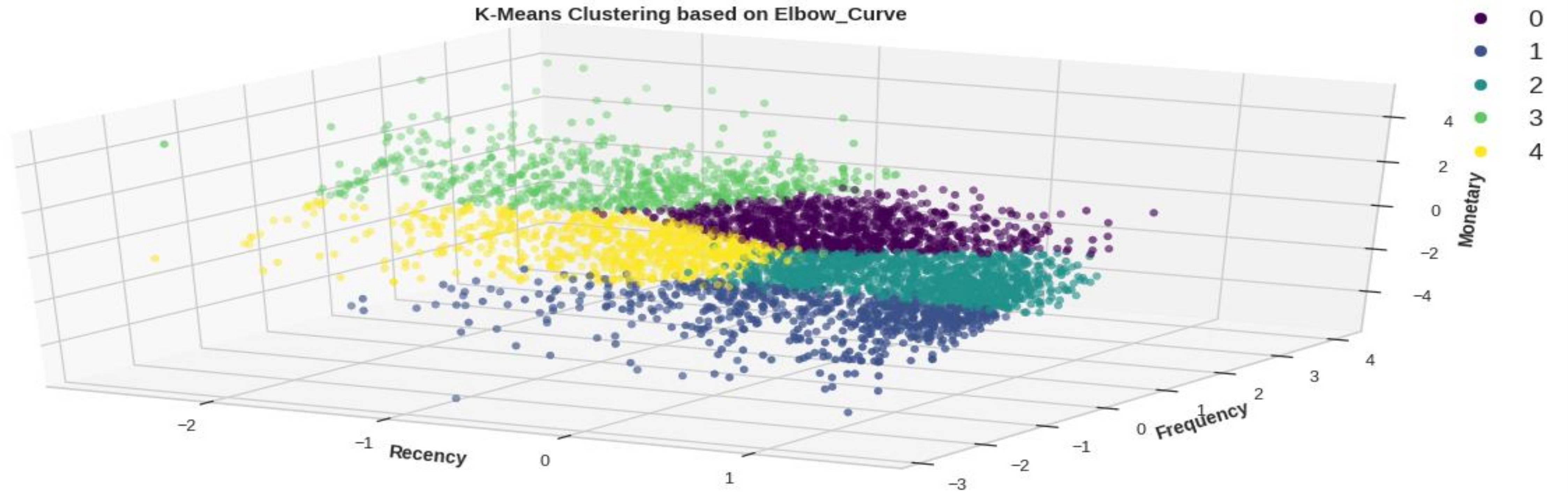


K-Means|2Cluster	Last_visited	Purchase_frequency	Money_spent
0	8 to 38 days ago	Bought 67 to 192 times	Spent around 1068 to 3350 Sterling
1	51 to 227 days ago	Bought 10 to 33 times	Spent around 189 to 571 Sterling

GROUP 0 → BEST CUSTOMERS

GROUP 1 → LOST POOR CUSTOMERS

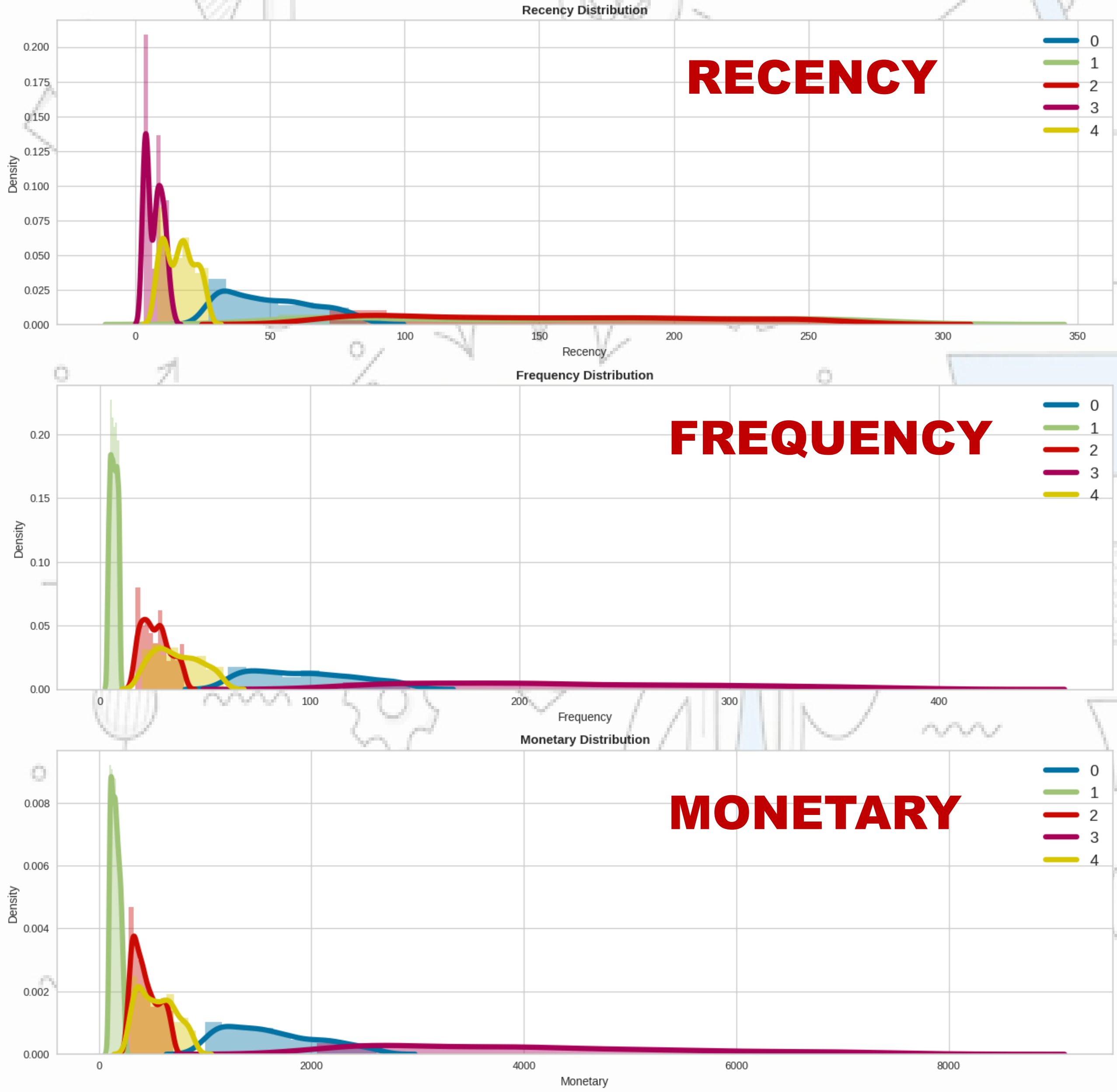
K-MEANS | 5CLUSTER



K-Means|5Cluster	Recency_mean	Recency_median	Frequency_mean	Frequency_median	Monetary_mean	Monetary_median	Count_
0	63.086481	47.000000	110.100398	95.500000	2070.036472	1549.570000	1006
1	168.216332	165.000000	6.982808	7.000000	199.447765	152.600000	698
2	167.344426	151.000000	30.317804	26.000000	515.163404	415.040000	1202
3	9.059091	7.000000	316.063636	213.000000	8411.127045	3808.520000	660
4	17.373868	17.000000	41.465718	35.000000	640.321347	529.410000	773

K-MEANS | 5CLUSTER

AI



K-Means|5Cluster	Last_visited	Purchase_frequency	Money_spent
0	29 to 76 days ago	Bought 64 to 136 times	Spent around 1080 to 2328 Sterling
1	61 to 264 days ago	Bought 4 to 10 times	Spent around 104 to 215 Sterling
2	78 to 246 days ago	Bought 18 to 38 times	Spent around 302 to 636 Sterling
3	3 to 12 days ago	Bought 129 to 341 times	Spent around 2304 to 6486 Sterling
4	8 to 25 days ago	Bought 21 to 54 times	Spent around 328 to 815 Sterling

GROUP 0 — LOSING LOYAL CUSTOMERS

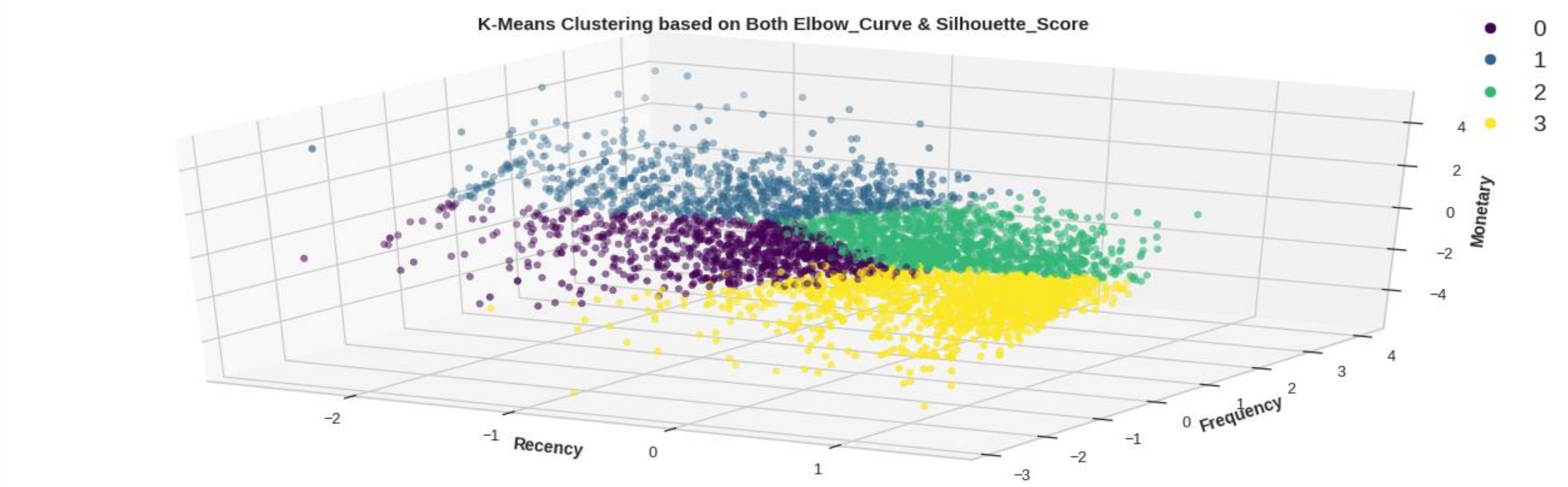
GROUP 1 — LOST POOR CUSTOMERS

GROUP 2 — AVERAGE CUSTOMERS

GROUP 3 — BEST CUSTOMERS

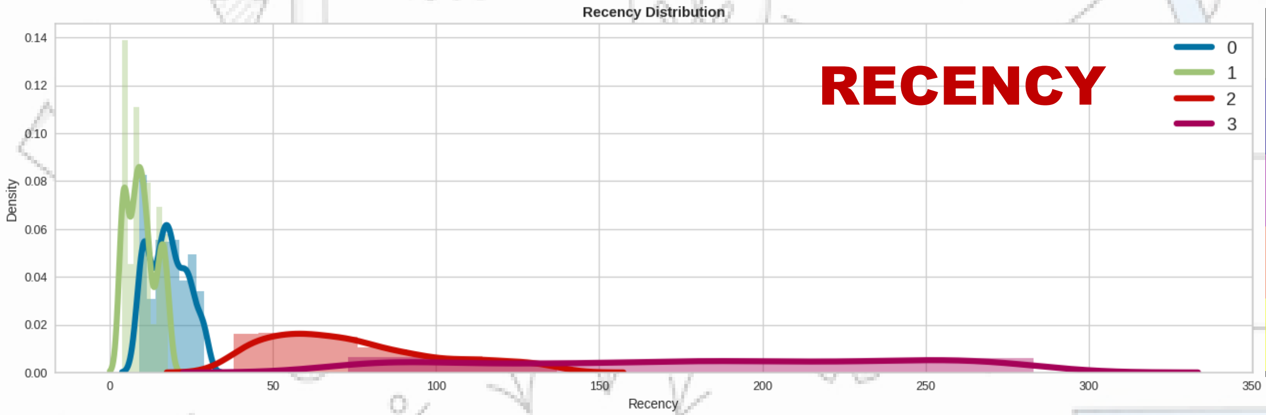
GROUP 4 — RECENTLY VISITED AVERAGE CUSTOMERS

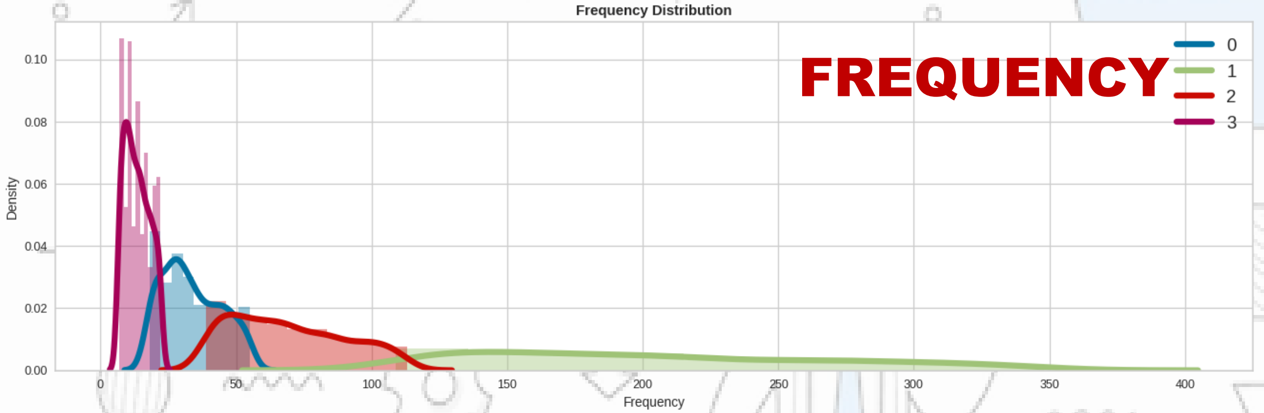
K-MEANS | 4CLUSTER

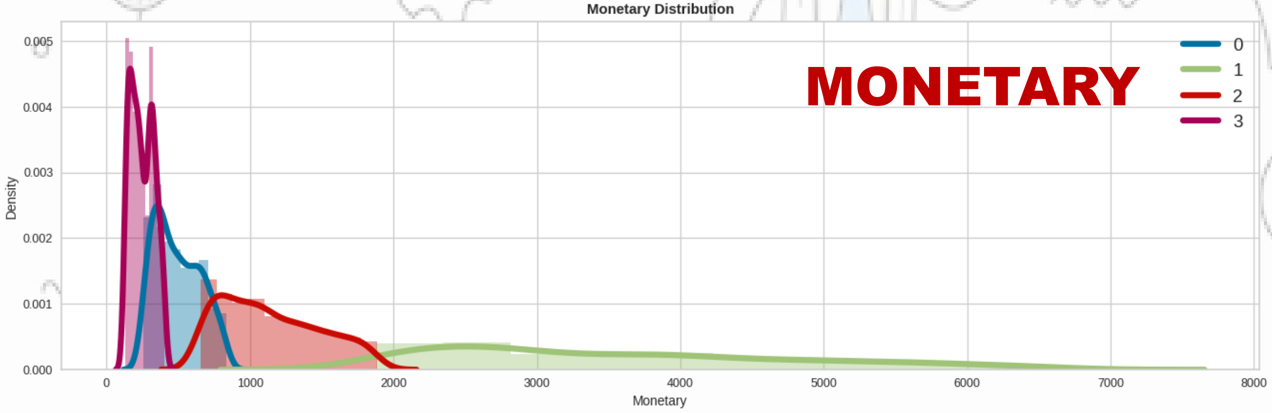


K-Means|4Cluster	Recency_mean	Recency_median	Frequency_mean	Frequency_median	Monetary_mean	Monetary_median	Count_
0	19.645509	17.000000	38.350898	32.000000	589.801401	470.760000	835
1	12.136364	9.000000	283.193780	192.500000	7205.348792	3316.310000	836
2	93.539413	71.000000	80.159969	66.000000	1518.087591	1083.840000	1294
3	184.750364	185.000000	14.724891	12.000000	295.959819	240.275000	1374

K-MEANS | 4CLUSTER







K-Means|4Cluster	Last_visited	Purchase_frequency	Money_spent
0	9 to 28 days ago	Bought 20 to 51 times	Spent around 291 to 742 Sterling
1	4 to 17 days ago	Bought 120 to 308 times	Spent around 2068 to 5601 Sterling
2	43 to 119 days ago	Bought 42 to 103 times	Spent around 708 to 1706 Sterling
3	82 to 268 days ago	Bought 7 to 21 times	Spent around 144 to 368 Sterling

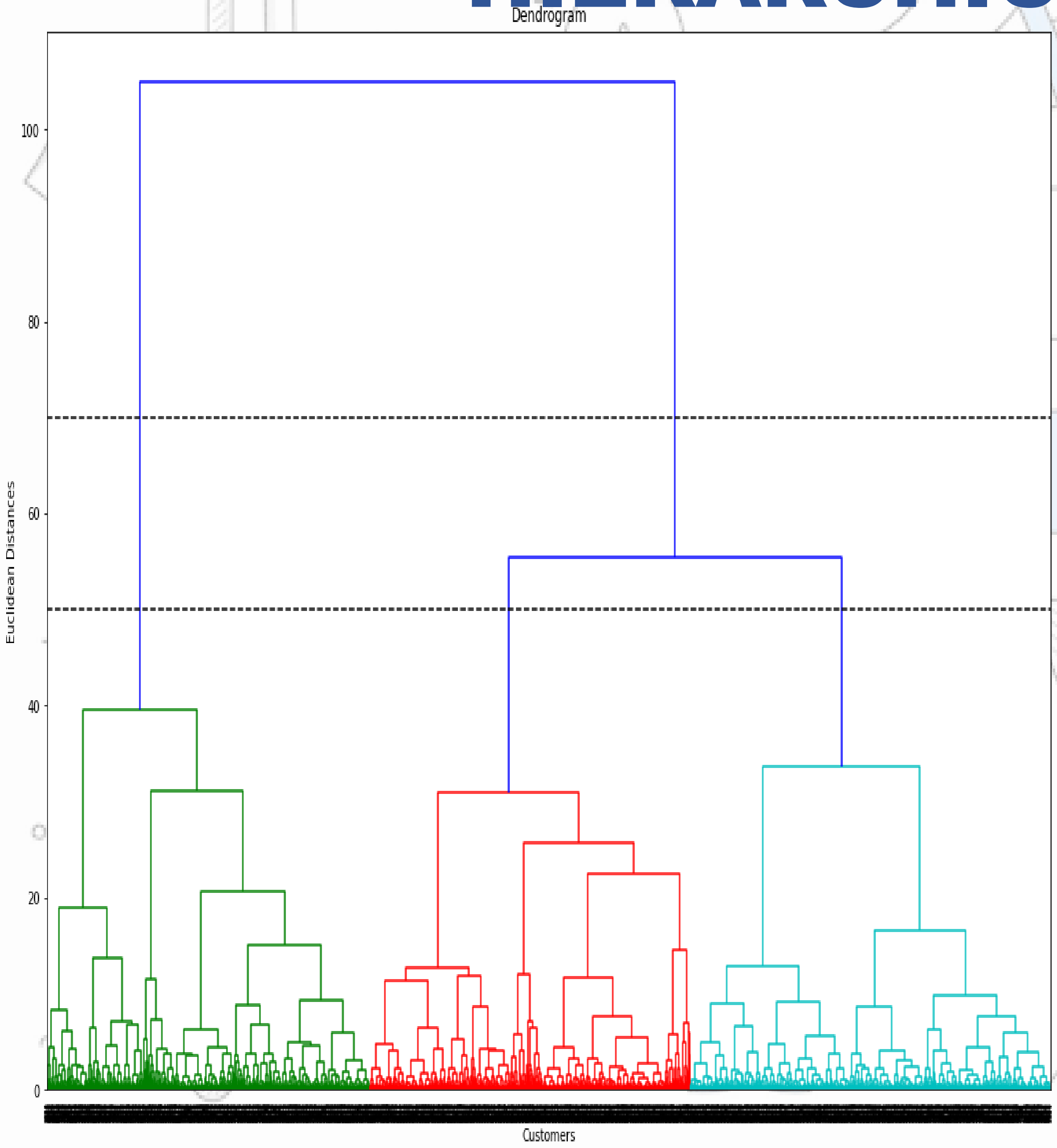
GROUP 0 → RECENTLY VISITED AVERAGE CUSTOMERS

GROUP 1 → BEST CUSTOMERS

GROUP 2 → LOSING LOYAL CUSTOMERS

GROUP 3 → LOST POOR CUSTOMERS

HIERARCHICAL CLUSTERING



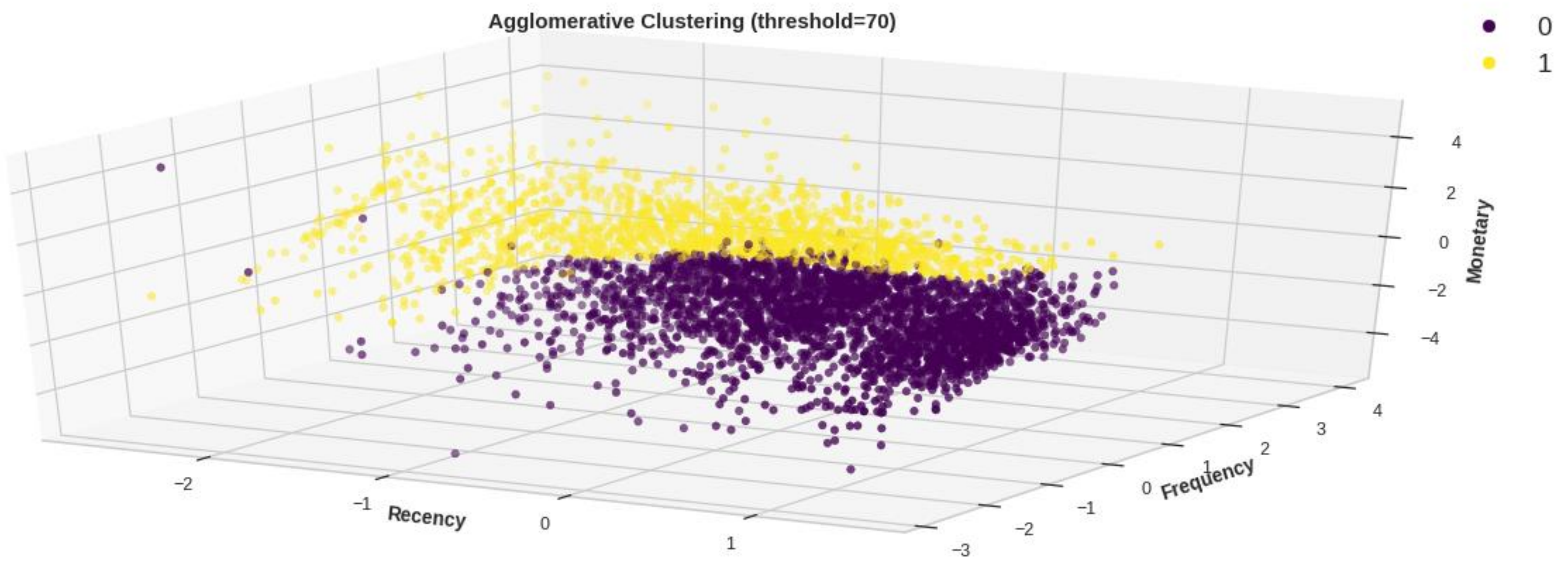
In the K-means clustering there is a challenge to predetermine the number of clusters, and it always tries to create the clusters of the same size. To solve these two challenges, we can opt for the hierarchical clustering algorithm because, in this algorithm, we don't need to have knowledge about the predefined number of clusters. Hierarchical clustering is based on two techniques:

a. Agglomerative: Agglomerative is a bottom-up approach, in which the algorithm starts with taking all data points as single clusters and merging them until one cluster is left.

b. Divisive: Divisive algorithm is the reverse of the agglomerative algorithm as it is a top-down approach.

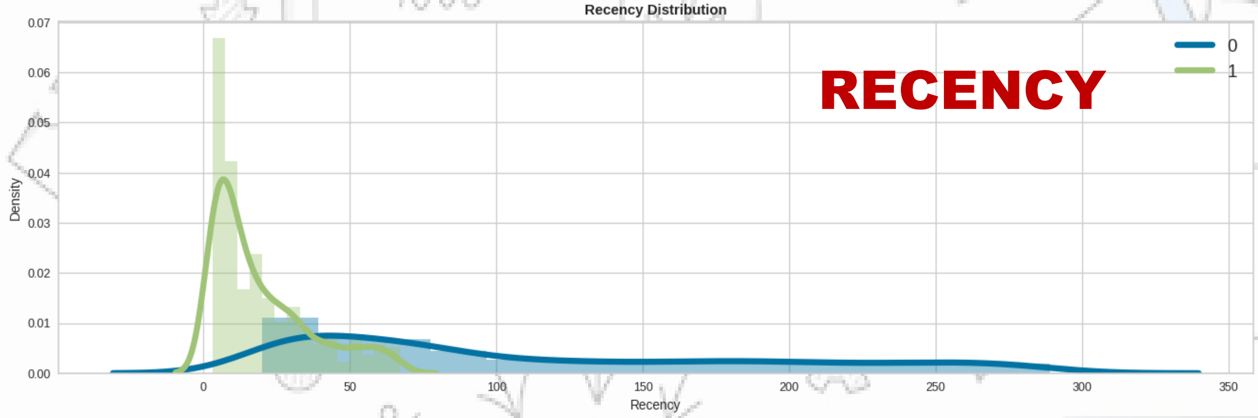
We have defined the optimal number of clusters based on dendrogram as shown here

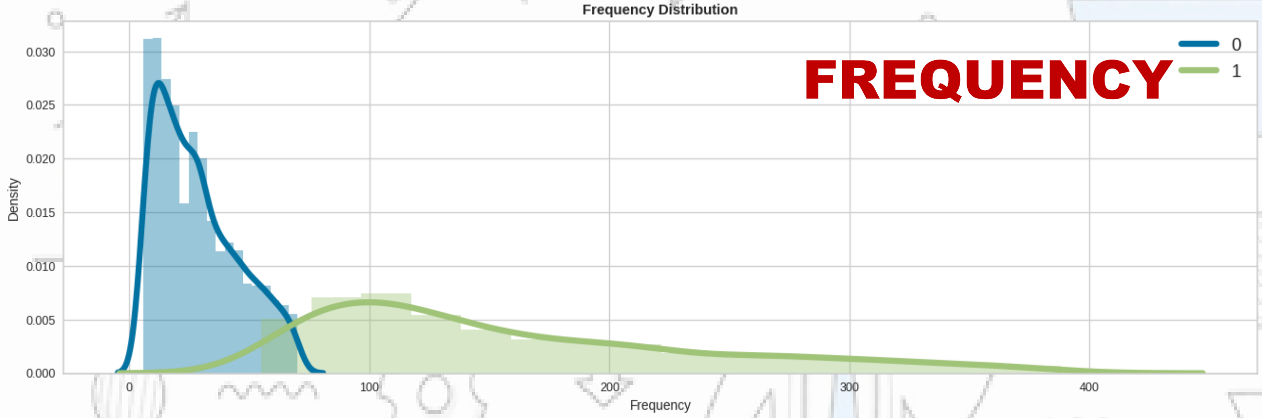
HIERARCHICAL | 2CLUSTER

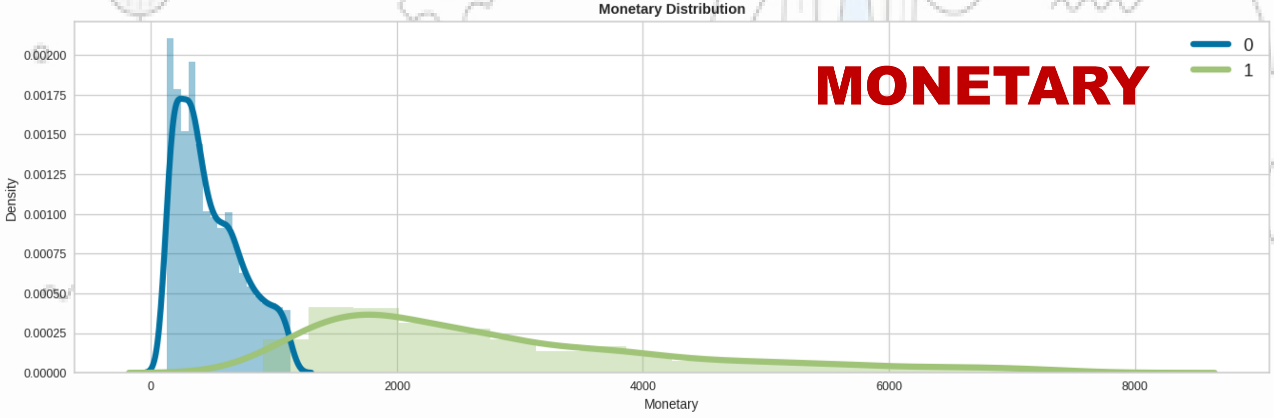


hierarchical|2Cluster	Recency_mean	Recency_median	Frequency_mean	Frequency_median	Monetary_mean	Monetary_median	Count_
0	123.608696	80.000000	33.610394	25.000000	684.108391	409.685000	2944
1	26.905376	12.000000	210.597133	135.000000	4927.021356	2404.170000	1395

HIERARCHICAL | 2CLUSTER





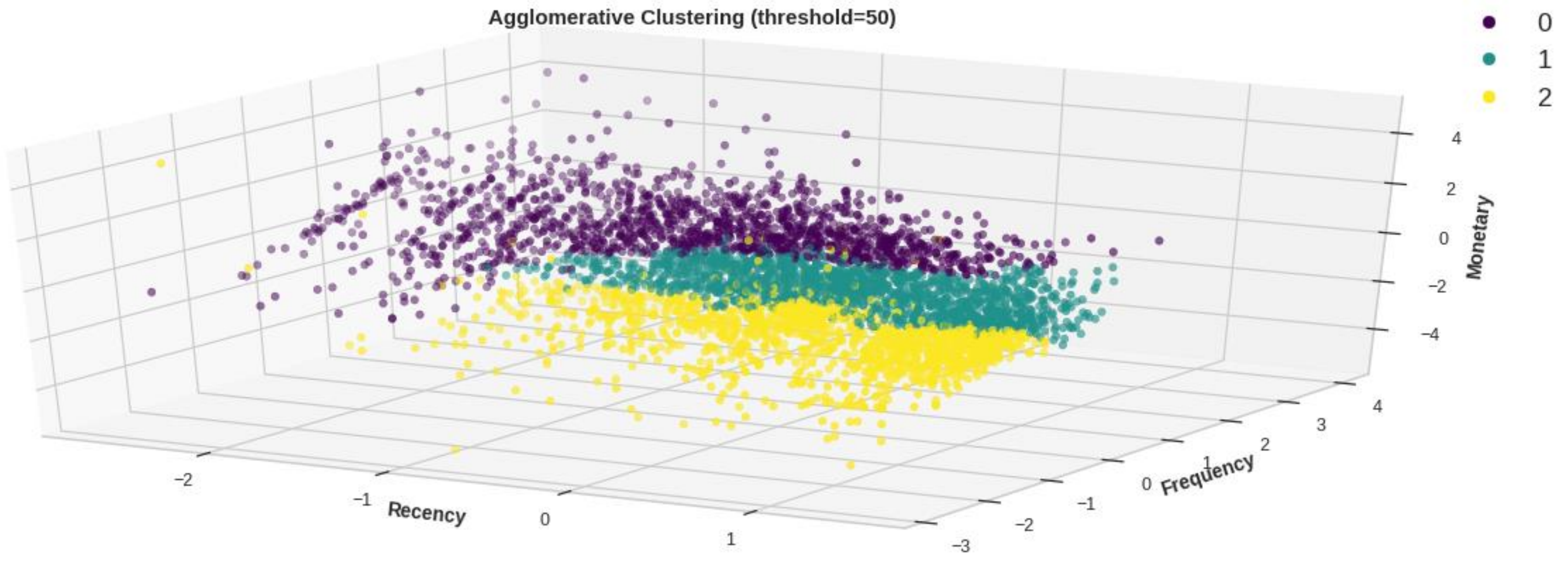


hierarchical|2Cluster	Last_visited	Purchase_frequency	Money_spent
0	36 to 200 days ago	Bought 12 to 46 times	Spent around 219 to 739 Sterling
1	4 to 33 days ago	Bought 87 to 233 times	Spent around 1546 to 4020 Sterling

GROUP 0 → AVERAGE CUSTOMERS

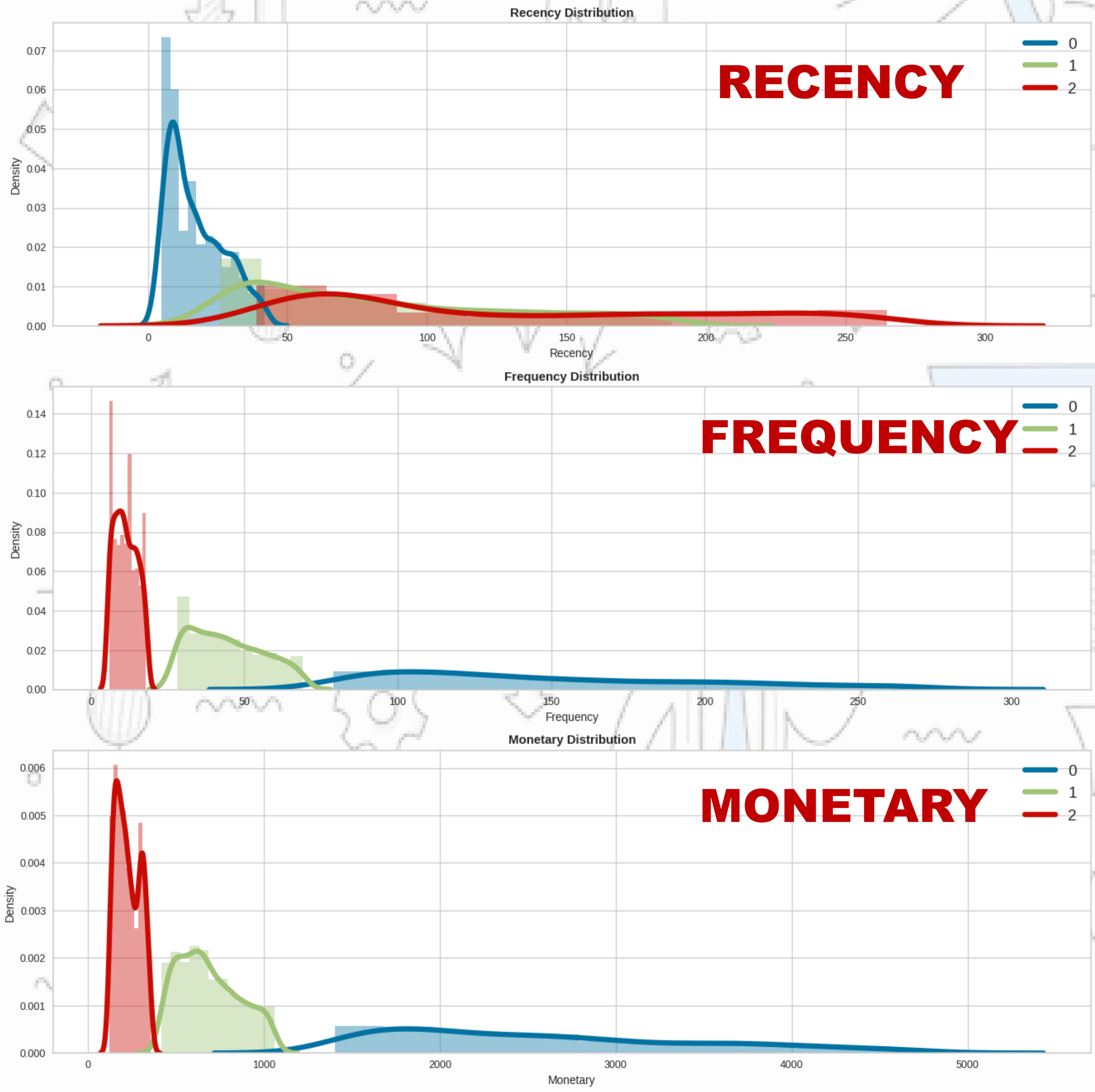
GROUP 1 → BEST CUSTOMERS

HIERARCHICAL | 3CLUSTER



hierarchical|3Cluster	Recency_mean	Recency_median	Frequency_mean	Frequency_median	Monetary_mean	Monetary_median	Count_
0	26.905376	12.000000	210.597133	135.000000	4927.021356	2404.170000	1395
1	105.246312	71.000000	51.658114	43.000000	756.610450	657.300000	1559
2	144.277978	99.000000	13.295307	11.000000	602.497770	215.480000	1385

HIERARCHICAL | 3CLUSTER



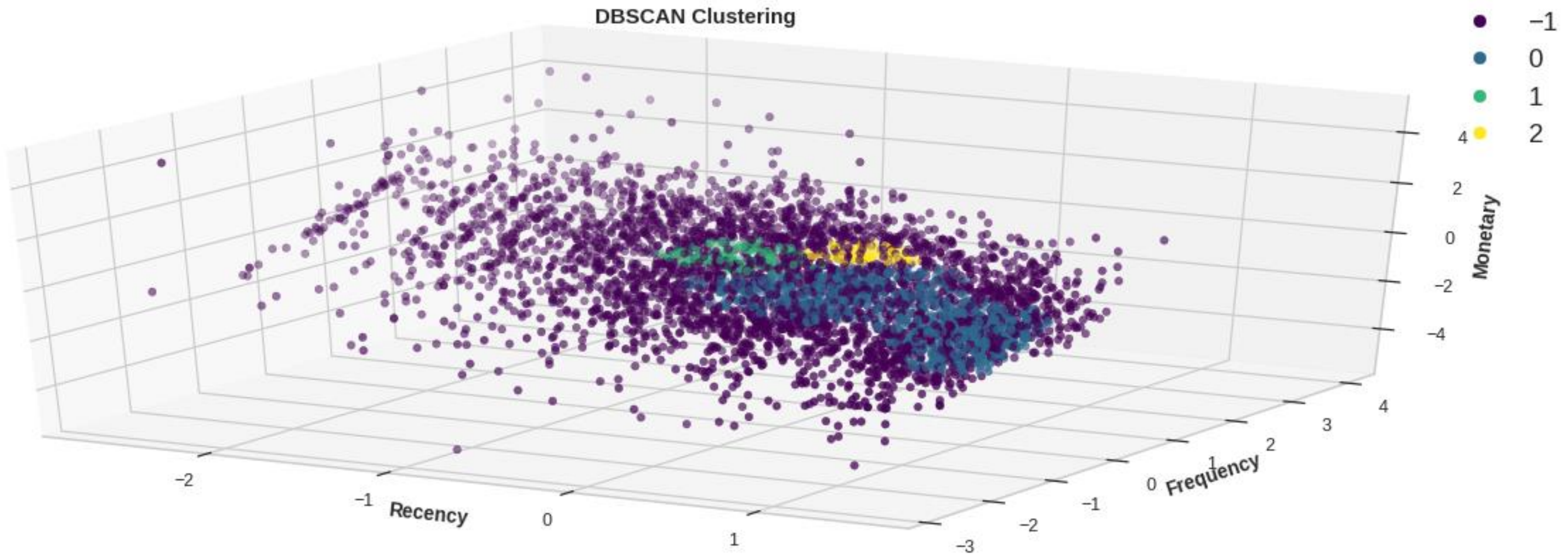
hierarchical|3Cluster	Last_visited	Purchase_frequency	Money_spent
0	4 to 33 days ago	Bought 87 to 233 times	Spent around 1546 to 4020 Sterling
1	30 to 163 days ago	Bought 29 to 63 times	Spent around 463 to 977 Sterling
2	49 to 243 days ago	Bought 6 to 18 times	Spent around 139 to 327 Sterling

GROUP 0 → BEST CUSTOMERS

GROUP 1 → LOSING LOYAL CUSTOMERS

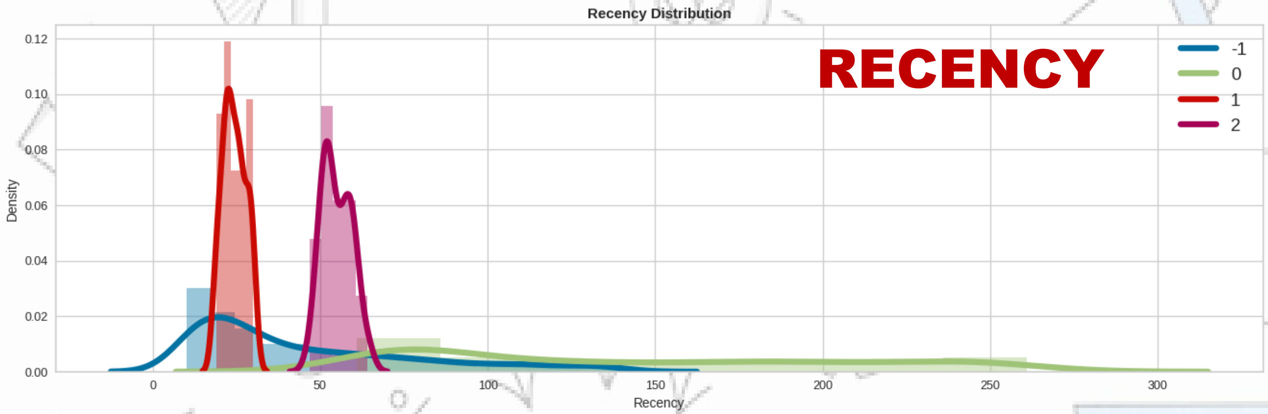
GROUP 2 → LOST POOR CUSTOMERS

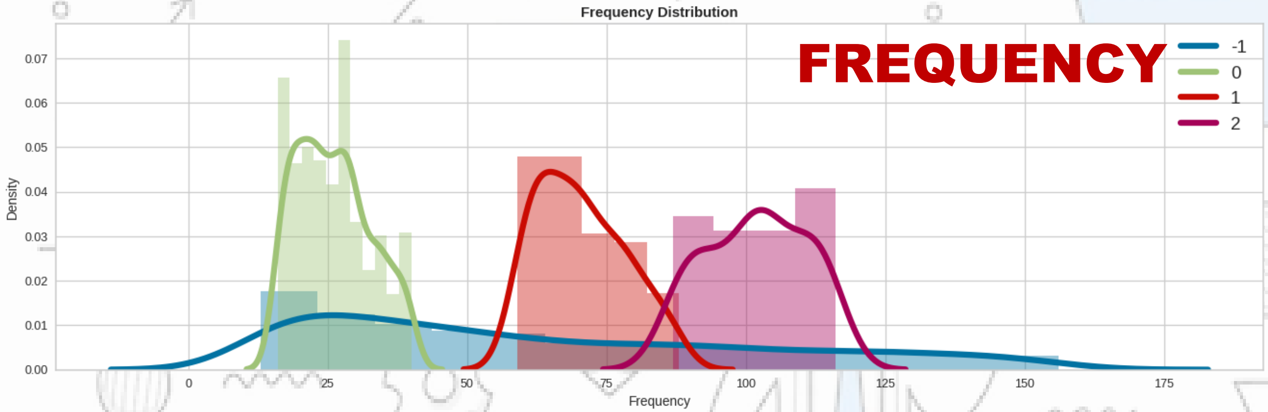
DBSCAN

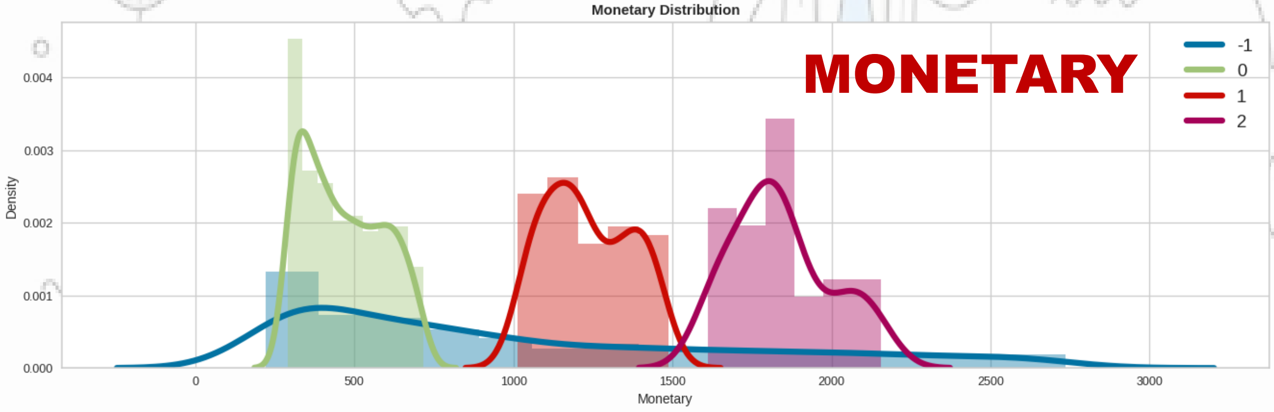


DBSCAN	Recency_mean	Recency_median	Frequency_mean	Frequency_median	Monetary_mean	Monetary_median	Count_
-1	76.209745	32.000000	111.290416	52.000000	2591.443756	797.960000	3099
0	155.415430	124.000000	28.556874	25.000000	514.588776	451.440000	1011
1	25.253247	24.500000	73.376623	69.500000	1264.077597	1212.910000	154
2	56.653333	54.000000	102.293333	102.000000	1885.446533	1824.230000	75

DBSCAN







DBSCAN	Last_visited	Purchase_frequency	Money_spent
-1	11 to 107 days ago	Bought 15 to 130 times	Spent around 278 to 2245 Sterling
0	66 to 245 days ago	Bought 17 to 37 times	Spent around 309 to 658 Sterling
1	19 to 30 days ago	Bought 60 to 84 times	Spent around 1052 to 1425 Sterling
2	50 to 62 days ago	Bought 89 to 114 times	Spent around 1637 to 2094 Sterling

GROUP -1 → AVERAGE CUSTOMERS

GROUP 0 → LOST POOR CUSTOMERS

GROUP 1 → GOOD CUSTOMERS

GROUP 2 → LOSING LOYAL CUSTOMERS

SUMMARY

Clusterer	Binning	Quantile Cut	K-Means	K-Means	K-Means	Agglomerative	Agglomerative	DBSCAN
Criterion	RFM Score Binning	RFM Quantile Cut	Elbow Curve	Silhouette Score	Elbow Curve & Silhouette Score	Dendogram (y=70)	Dendogram (y=50)	eps=0.2, min_samples=25
Segments	4	4	5	2	4	2	3	4

- We started with a simple binning and quantile based simple segmentation model first then moved to more complex models because simple implementation helps having a first glance at the data and know where/how to exploit it better.
- Then we moved to k-means clustering and visualized the results with different number of clusters. As we know there is no assurance that k-means will lead to the global best solution. We moved forward and tried Hierarchical Clustering and DBSCAN clusterer as well.
- We created several useful clusters of customers on the basis of different metrics and methods to cateorize the customers on the basis of their behavioral attributes to define their valuability, loyalty, profitability etc. for the business. Though significantly separated clusters are not visible in the plots, but the clusters obtained is fairly valid and useful as per the algorithms and the statistics extracted from the data.
- Segments depends on how the business plans to use the results, and the level of granularity they want to see in the clusters. Keeping these points in view we clustered the major segments based on our understanding as per different criteria as shown in the summary dataframe.

FINAL CONCLUSION

CUSTOMER SEGMENTS OBTAINED FROM CLUSTERING ANALYSIS

	LOST POOR CUSTOMERS❌	AVERAGE CUSTOMERS🥉	RECENTLY VISITED AVERAGE CUSTOMERS🤍	GOOD CUSTOMERS🥈	BEST CUSTOMERS❤️	LOSING LOYAL CUSTOMERS❌
Binning	Yes	Yes	No	Yes	Yes	No
QuantileCut	Yes	No	No	Yes	Yes	Yes
K-Means|2Cluster	Yes	No	No	No	Yes	No
K-Means|4Cluster	Yes	No	Yes	No	Yes	Yes
K-Means|5Cluster	Yes	Yes	Yes	No	Yes	Yes
hierarchical|2Cluster	No	Yes	No	No	Yes	No
hierarchical|3Cluster	Yes	No	No	No	Yes	Yes
DBSCAN	Yes	Yes	No	Yes	No	Yes