Capstone 3 Project

Customer Segmentation for An Online Retail

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1. Introduction

The transnational data has been collected from 2009-12-01 to 2011-12-09 for a UK-based and registered non-store online retail. The 1044848 records of customer ID, price, quantity, invoice date, description, and country are included in the data set. The manager is interested in targeting customers for developing business development strategies. This project will use various features, e.g., Recency, Frequency, and Monetary Value (RFM), for customer segmentation and explore the difference among customer groups.

1.1 Problem statement

How many groups we can segment the customers by using the given features?

1.2 Scope of solution space

- This project will focus on the price, quantity, and invoice date to explore measures for improving the RFM values
- The categories of merchandise will be a good supplement for optimizing the RFM values.

1.3 Constraints

- The data is mainly from the UK. The scarce data from other countries may bring noise into the analysis.

1.4 Project plan

This project is implemented by following the procedure below.

a. Problem Identification
b. Data Wrangling
    - Check data integrity
    - Clean data: missing values, duplicates, etc.
c. Exploratory Data Analysis
    - Summarize important features
    - Statistical property analysis
    - Visualize data
    - Identify trends and patterns
d. Pre-Processing and Training Data Development
    - Finalize the dataset by removing dispensable features
    - Splitting the dataset into testing and training subsets

- Train the model

e. Modeling
   - Retrain the model with a whole set of data
   - Predictions and result analysis

f. Documentation
   A project report, a slide deck, and Jupyter notebooks will be generated and shared in a GitHub repo.

   https://github.com/z-fan-git/Customer-Segmentation.git

1.5 Data Source

A transnational data set that contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail. The company mainly sells unique all-occasion gifts. Many customers of the company are wholesalers. The data can be found on Kaggle and UCI Machine Learning Repository.

There are 8 features listed below.

- Invoice No: 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: Invice Date and time. Numeric, the day and time when each transaction was generated.
- UnitPrice: 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.

2. Data wrangling

The objectives of this section are to explore:

- Identify any issues that will require data cleaning
- Analyze features in the dataset

2.1 Data Integrity

The dataset summary listed in Table 2.1 shows features, non-null values, and data types.

Table 2.1 Dataset summary

Column	Non-Null	Count	Type
Customer ID	809561	non-null	float64
Invoice	1044848	non-null	object
InvoiceDate	1044848	non-null	object
Price	1044848	non-null	float64
Quantity	1044848	non-null	int64
StockCode	1044848	non-null	object
Description	1040573	non-null	object
Country	1044848	non-null	object

We can find that:

- This dataset contains 1,044,848 records and 8 features.
- There are missing values in `Customer ID` and `Description`.
- 3 numerical features: Customer ID, Price, and Quantity
- 5 categorical features.

Missing data:

There are 235287 missing values for Customer ID and 4275 missing values for Description. The missing data in customer ID contribute nothing to the objective of this project, i.e., customer segmentation. Therefore, all these missing values are dropped. As a result, there are 809491 rows left in the dataset.

Duplicates:

There are also 11676 duplicated rows as shown in Table 2.2. Dropping all the duplicates yields a dataset with 797815 rows.

Table 2.2 Sample of duplicated records

	Customer ID	Invoice	InvoiceDate	Price	Quantity	StockCode	Description	Country
255587	12346	C514024	2010-06-30 11:22:00	12.94	-1	M	manual	United Kingdom
255589	12346	C514024	2010-06-30 11:22:00	12.94	-1	M	manual	United Kingdom
485600	12356	534804	2010-11-24 12:24:00	1.95	1	22629	spaceboy lunch box	Portugal
485615	12356	534804	2010-11-24 12:24:00	1.95	1	22629	spaceboy lunch box	Portugal

2.2 Feature Analysis

Categorical features

- The stock code and description are the information for goods. We will ignore these two columns for now.
- The distribution of customers worldwide is shown in Figure 2.1. Most of the customers (91%) were from the United Kingdom. There were 1.8% of customers from Germany and 1.6% of customers from France.

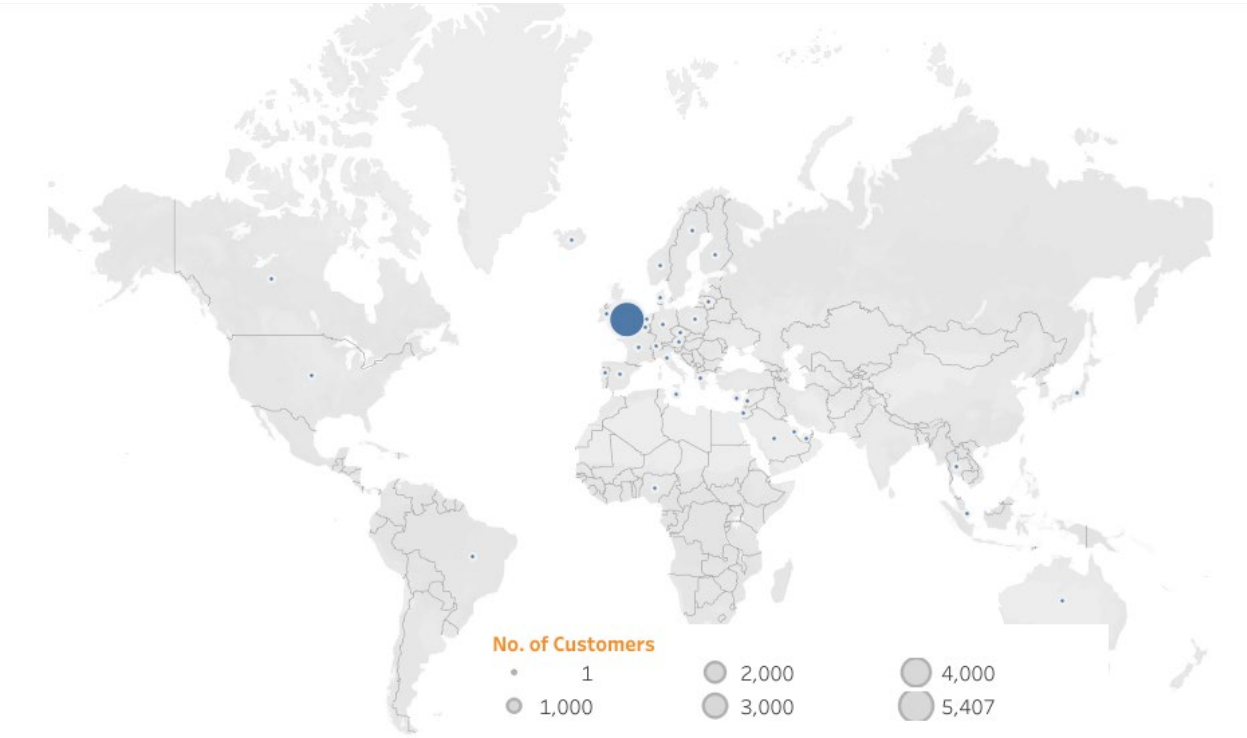


Figure 2.1 Customer distribution in countries

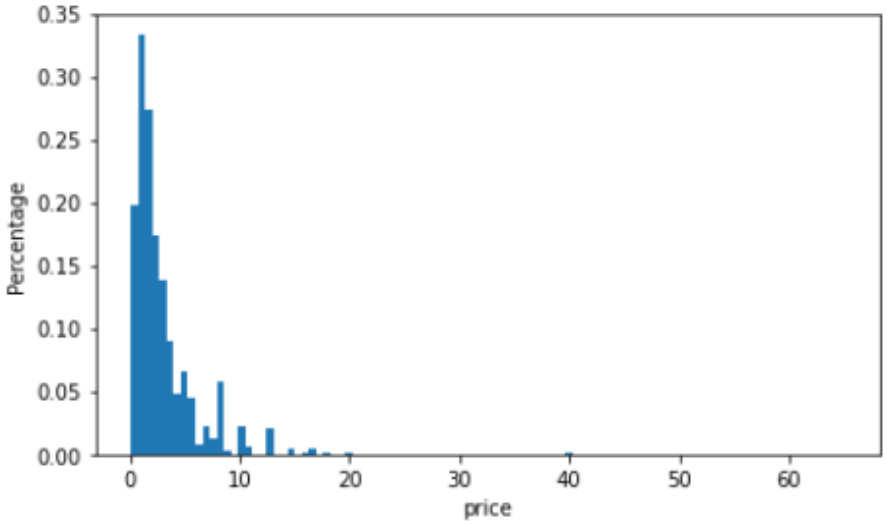
Numerical features

The statistics of numerical features is listed in Table 2.3. Both the price and quantity distribution are skewed. By removing the 0.1% and 99.9 percentile as the threshold, we removed the outliers and showed the distribution of price and quantity in Figure 2.2.

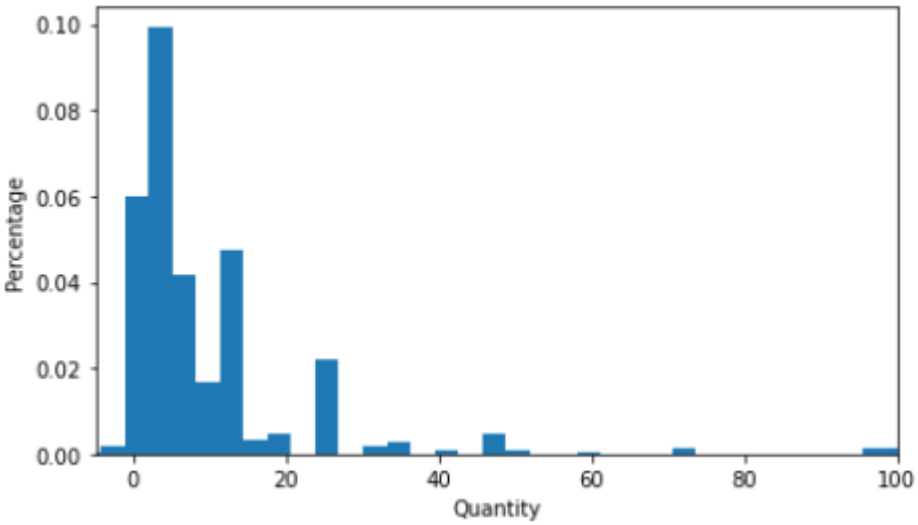
- The distribution is extremely skewed.
- It suggests a transformation in modeling.

Table 2.2 Statistics of numerical features

	Price	Quantity
count	1.044848e+06	1.044848e+06
mean	4.590546e+00	9.993649e+00
std	1.217042e+02	1.742185e+02
min	-5.359436e+04	-8.099500e+04
0.1%	0.000000e+00	-1.141530e+02
25%	1.250000e+00	1.000000e+00
50%	2.100000e+00	3.000000e+00
75%	4.130000e+00	1.000000e+01
99.9%	2.145879e+02	5.000000e+02
max	3.897000e+04	8.099500e+04



(a)



(b)

Figure 2.1 Price (a) and quantity (b) distribution

3. Exploratory Data Analysis

The objective of EDA is to explore the characteristics of features and the use of features to derive valuable insights like RFM value.

3.1 Price vs quantity

There is no clear correlation between price and quantity as shown in Figure 3.1.

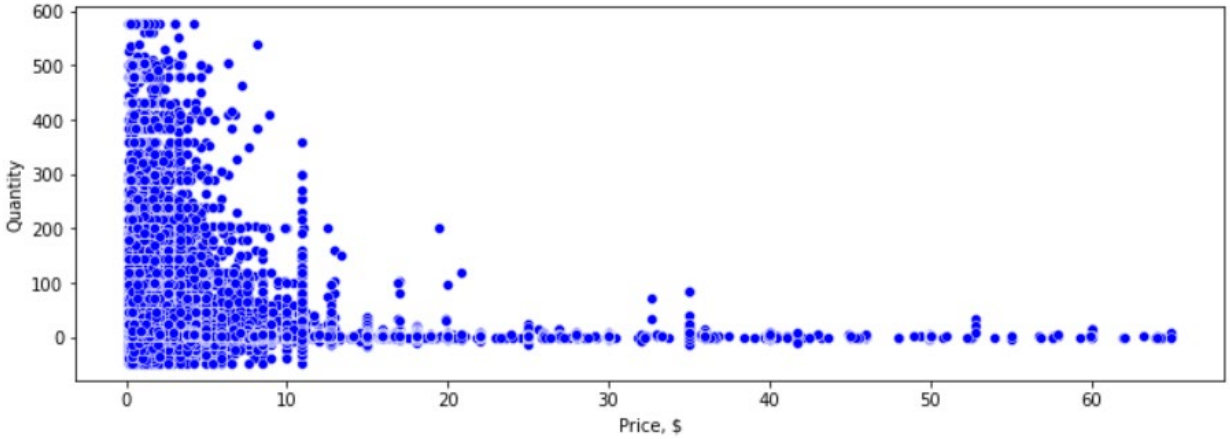


Figure 3.1 Price vs quantity

3.2 Revenue Analysis

The revenue is calculated by using the equation below.

*Revenue = Active Customer Count * Order Count * Average Revenue per Order*

As there is no cost reported, the revenue can also be treated as the lifetime value for each customer as indicated by the equation below. Note that the time window is determined by the business. It can be 1 month, 3 months, 6 months, 1 year, etc.

Lifetime Value =(Total Gross Revenue - Total Cost) within a time window

Based on the invoice date, we can estimate:

- Monthly revenue (Figure 3.2). A strong seasonality exhibits in the monthly revenue, which shows two peaks around November. In addition, the monthly revenue is quite stable in the first half year and progressively increases after August.
- Monthly revenue growth rate (Figure 3.3). The growth rate varies significantly in quarters. The trend is in line with the monthly revenue.
- Monthly revenue per customer (Figure 3.4). The customers spend more money in September - November and much less in April - June.

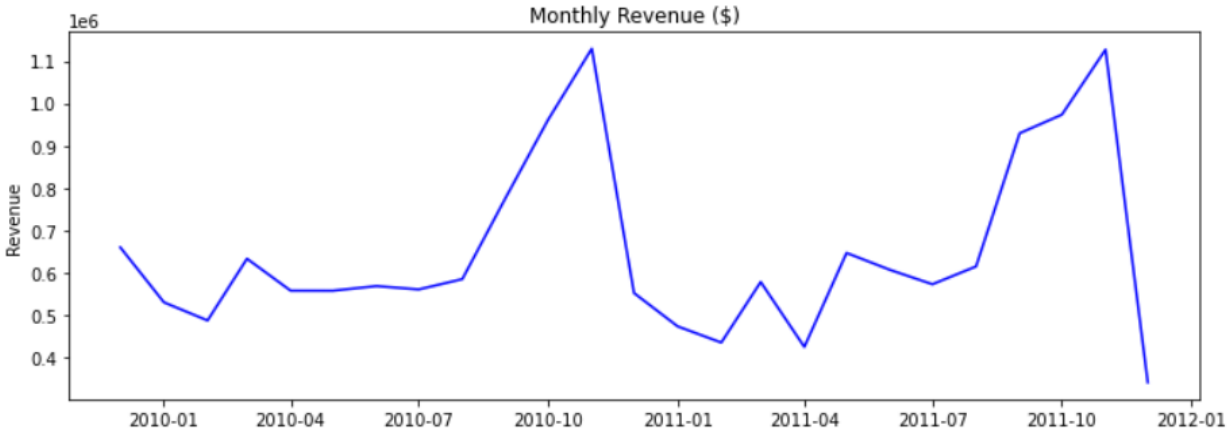


Figure 3.2 Monthly revenue variation

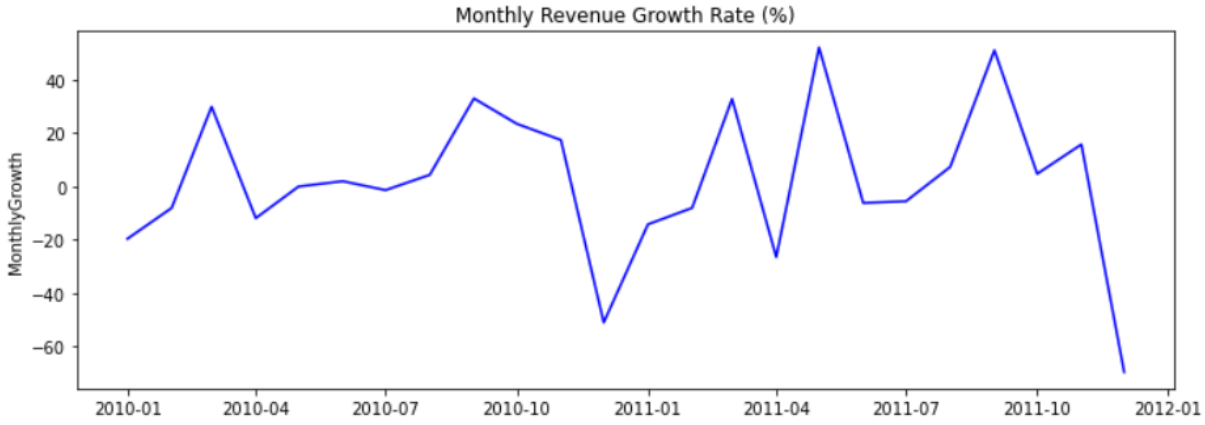


Figure 3.3 Monthly revenue growth rate variation

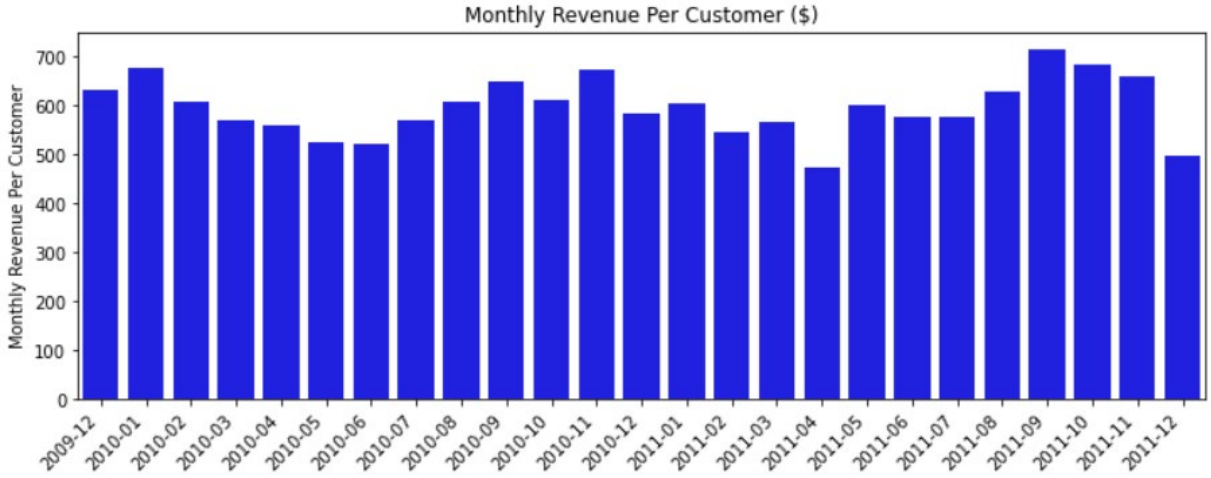


Figure 3.4 Monthly revenue per customer variation

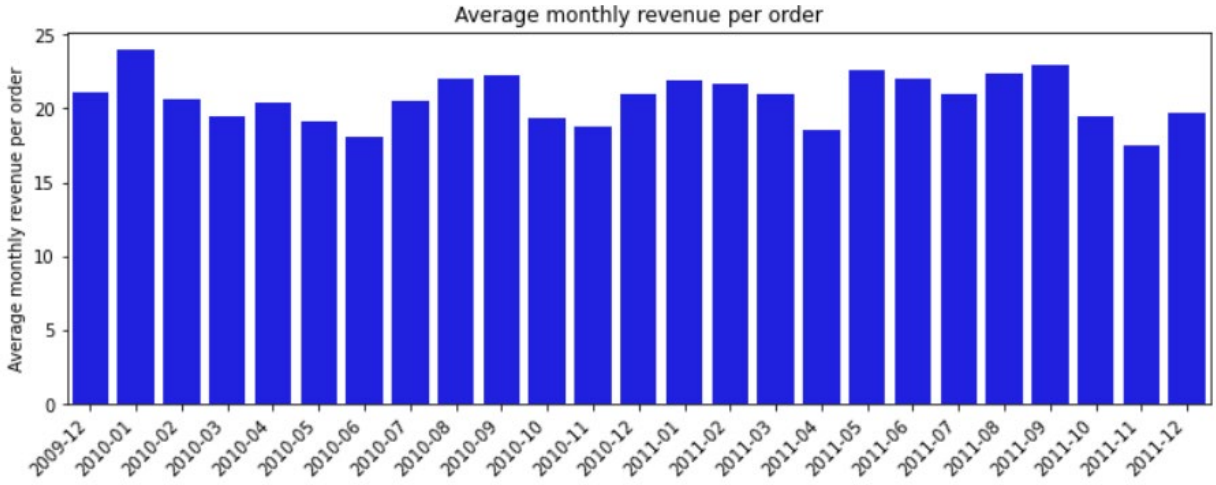


Figure 3.5 Monthly revenue per order variation

- Monthly revenue per order (Figure 3.5). The trend is slightly different. The revenue per order doesn't increase significantly in October and November, which implies customers buy more goods instead of buying more expensive ones.

3.3 Customer Analysis

In this section, the new and existing customers are identified by using the invoice date. Figure 3.6 shows that existing customers contribute way more than new customers.

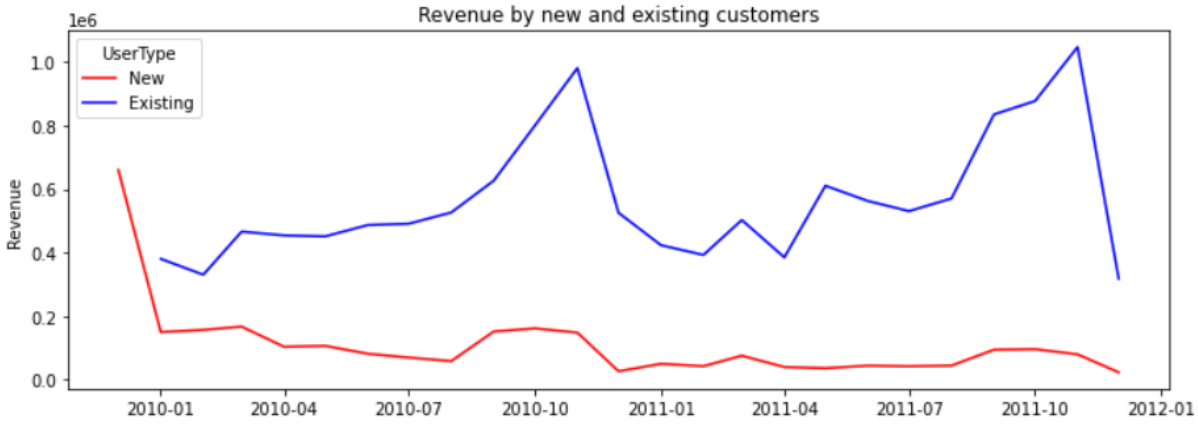


Figure 3.6 Revenue by customers

The ratio of new and existing customers each month is a good indicator of the growth of a business. Figure 3.7 shows that more new customers are coming to the store in February – March and September – November each year. We can convert this ratio into the retention rate shown in Figure 3.8. The retention rate is 0.4 on average and it also

shows seasonality to a certain extent. The retention rate is higher in October-November, which is in line with the revenue analysis.

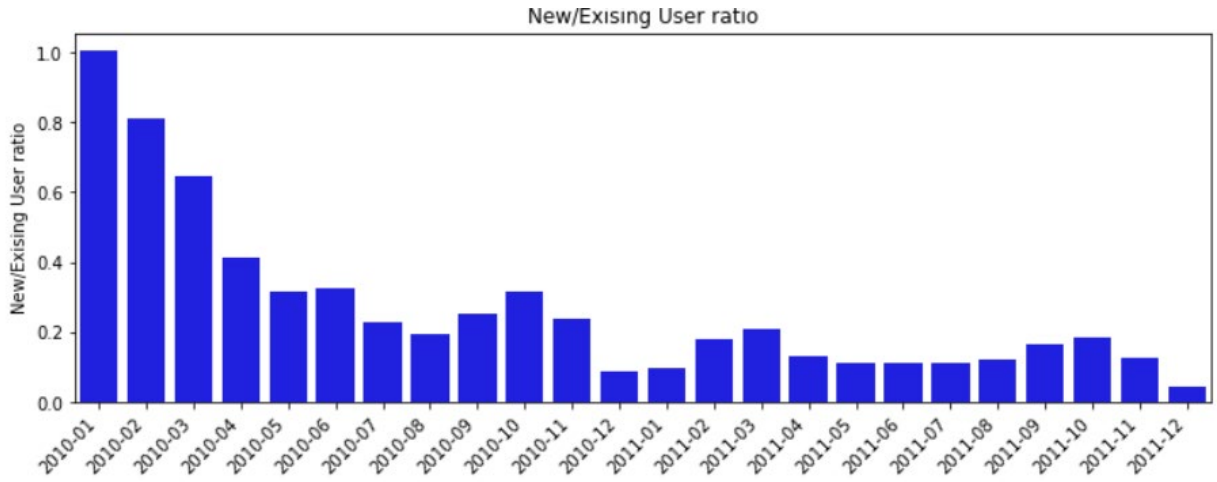


Figure 3.7 New – existing customer ratio

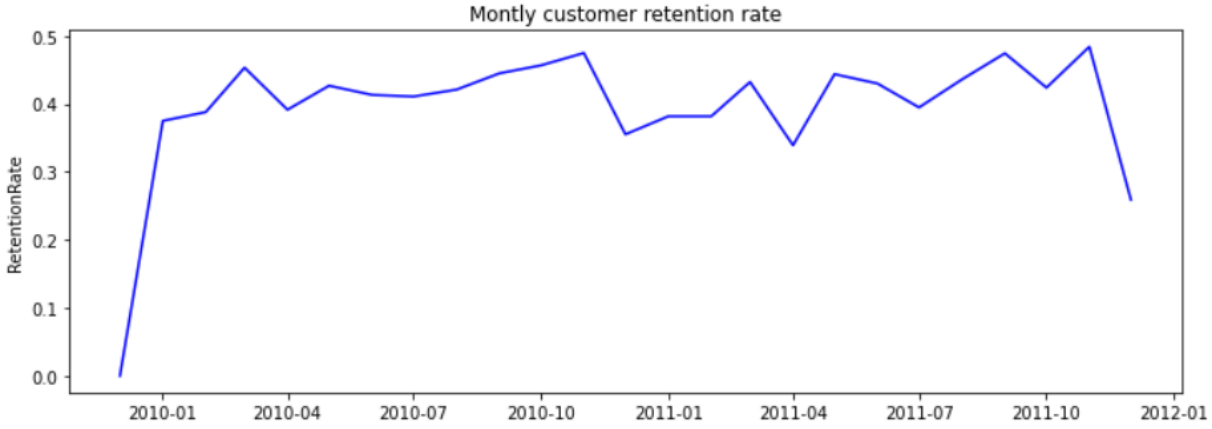


Figure 3.8 Retention rate

4. Clustering

The objectives of this step are

- Pre-process the features as necessary
- Segment customers based on various features.

4.1 Recency-Frequency-Monetary (RFM) value

Recency-Frequency-Monetary (RFM) value is a commonly used feature for customer segmentation.

4.1.1 Recency calculation and clustering

To calculate recency, we need to find out the most recent purchase date of each customer and see how many days they are inactive. Figure 4.1 shows the recency in days for all customs. After having the number of inactive days for each customer, we apply the K-means clustering algorithm to assign customers a recency cluster/score as shown in Table 4.1. A high score means the customer is more active while a low score means the customer is less active.

Table 4.1 Recency scores/clusters

RecencyCluster	count	mean	std	min	25%	50%	75%	max
0	673.0	621.983655	65.012623	516.0	568.0	618.0	674.00	738.0
1	1133.0	409.353045	49.093665	310.0	378.0	407.0	441.00	515.0
2	968.0	209.136364	52.880052	123.0	164.0	205.0	254.25	309.0
3	3165.0	35.881201	31.345800	0.0	9.0	27.0	57.00	122.0

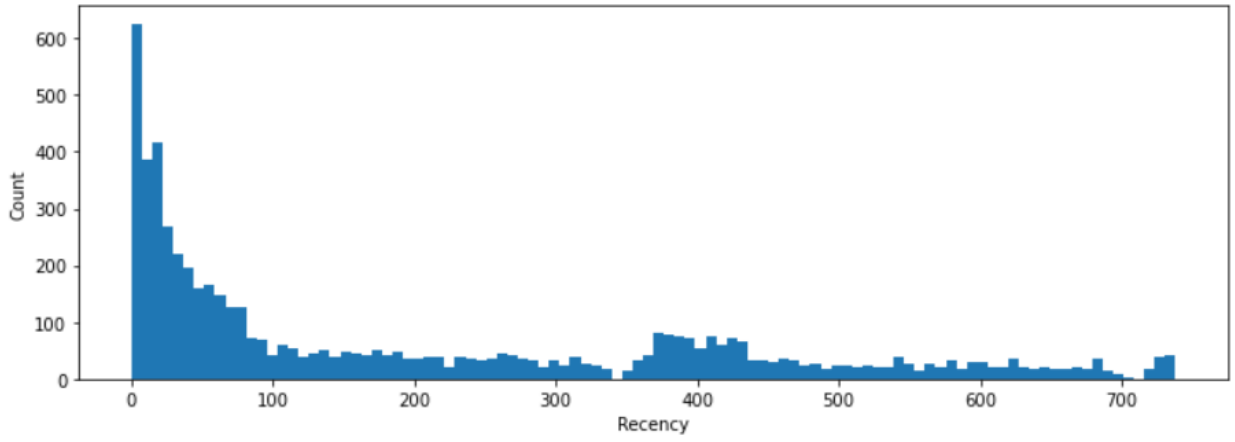


Figure 4.1 Recency distribution

4.1.2 Frequency calculation and clustering

To create frequency clusters, we need to find the total number of orders for each customer. Figure 4.2 shows the frequency in the number of orders for all customs. Then, we apply the KMeans clustering algorithm to assign customers a frequency cluster/score as shown in Table 4.2. A high score means the customer placed more orders while a low score means the customer placed fewer orders.

Table 4.2 Frequency scores/clusters

FrequencyCluster	count	mean	std	min	25%	50%	75%	max
0	5515.0	79.655485	85.588707	1.0	19.00	46.0	110.00	385.0
1	408.0	689.620098	306.629750	387.0	465.75	589.0	821.25	2077.0
2	14.0	3790.714286	1445.820844	2352.0	2728.00	3244.0	4463.75	6660.0
3	2.0	12040.000000	845.699710	11442.0	11741.00	12040.0	12339.00	12638.0

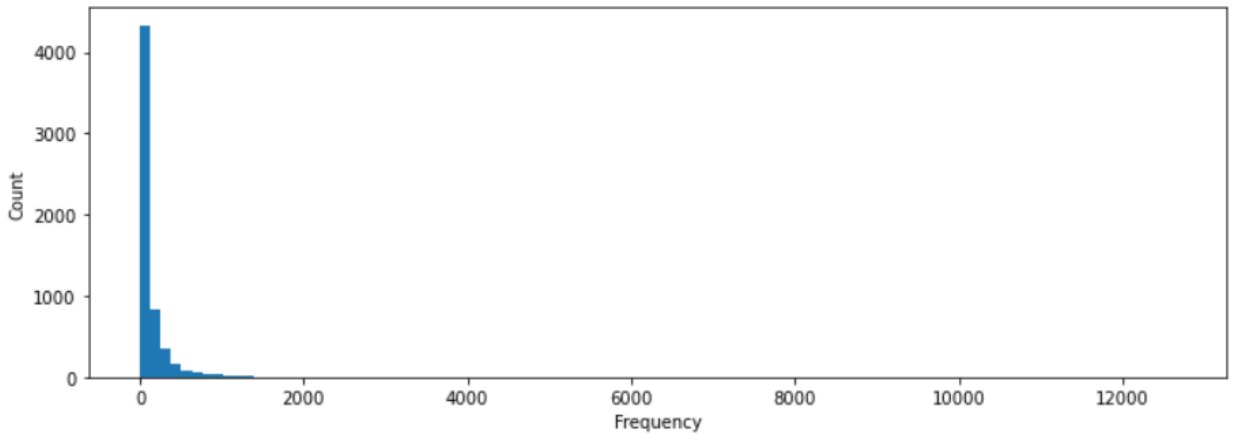


Figure 4.2 Frequency distribution

4.1.3 Monetary calculation and clustering

To create monetary clusters, we need to use the revenue. Figure 4.3 shows the monetary revenue for all customs. Then, we apply KMeans clustering algorithm to assign customers a monetary cluster/score as shown in Table 4.3. A high score means the customers have more monetary value while a low score means have a less monetary value.

Table 4.3 Revenue scores/clusters

RevenueCluster	count	mean	std	min	25%	50%	75%	max
0	5858.0	1821.652251	2830.594995	-25111.09	317.0125	800.135	2052.270	21535.90
1	71.0	41740.448493	22088.363188	21893.53	25539.2050	33480.820	52250.470	111739.36
2	8.0	195182.235000	62923.301710	124961.98	142827.5300	179256.230	239982.390	296063.44
3	2.0	546861.340000	33261.270611	523342.07	535101.7050	546861.340	558620.975	570380.61

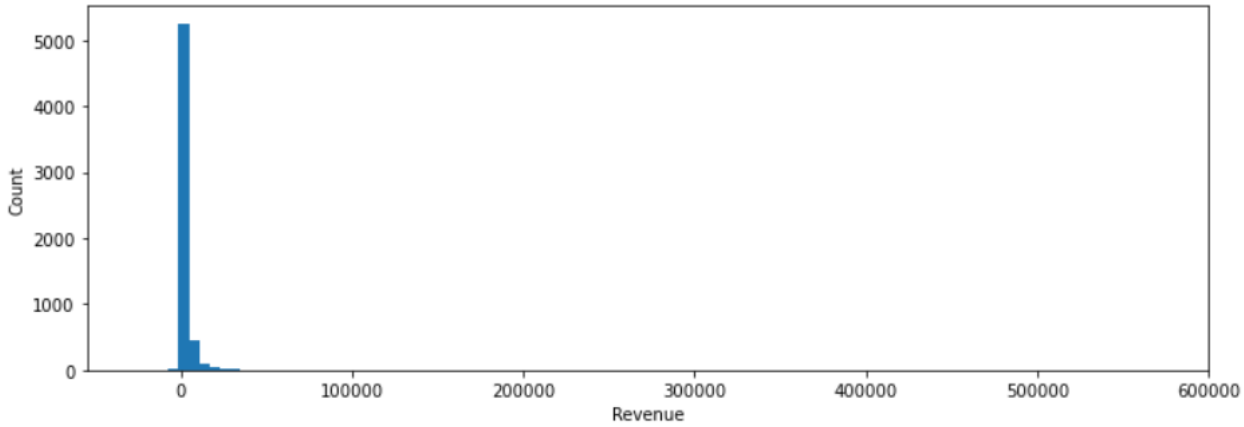


Figure 4.3 Frequency distribution

4.1.4 RFM calculation and clustering

RMF values are calculated by adding up recency, frequency, and monetary scores, which have been shown in Table 4.4.

Table 4.4 RFM values

RFM value	Recency	Frequency	Revenue
0	621.494815	23.662222	275.126803
1	408.922872	49.085106	748.954301
2	209.935857	64.652997	1168.003012
3	39.865217	114.338768	2105.548216
4	20.097765	633.480447	9776.187405
5	14.553191	974.808511	32971.483468
6	4.384615	2747.000000	103344.460769
7	2.400000	5155.000000	231052.704000
8	0.500000	7663.500000	394549.990000

The scoring above clearly shows us that customers with a score of 8 are our best customers whereas 0 is the worst. We can name these scores:

- 0 to 2: Low Value: good candidates for improving retention
- 3 to 4: Mid Value: good candidates for improving retention and increasing frequency
- 5+: High Value: good candidates for increasing frequency

The clustering of customers can be visualized in Figures 4.4 and 4.5. In general, the RFM value segment the customers into three categories satisfactorily. But we can still see some customers have been mistakenly grouped.

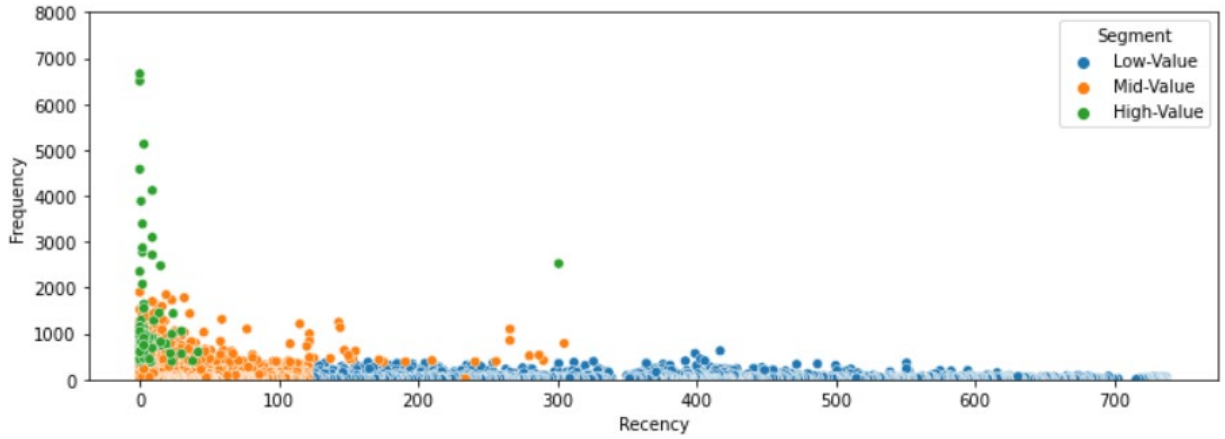


Figure 4.4 Customer Segmentation (Frequency vs. Recency)

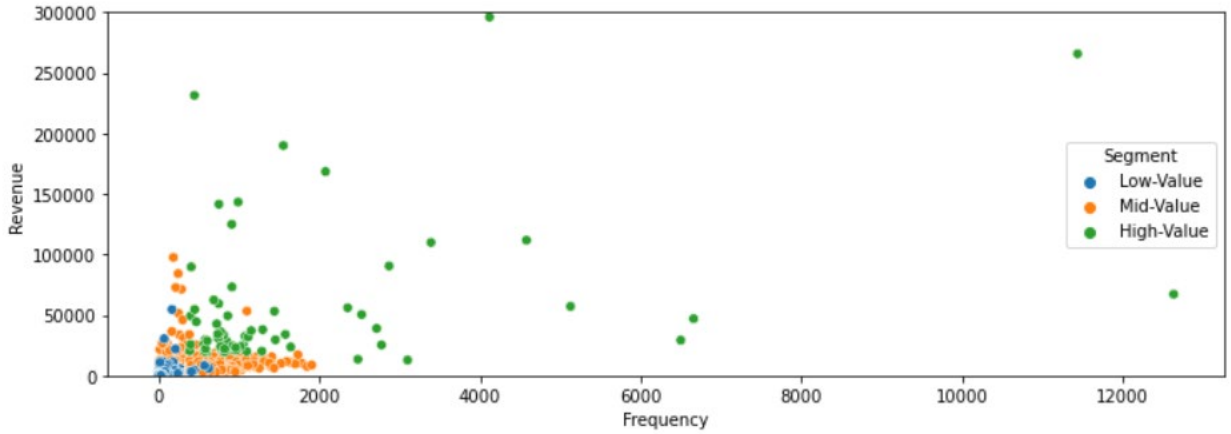


Figure 4.5 Customer Segmentation (Revenue vs. Frequency)

4.2 RFM + Price + Quantity

4.1.1 Data scaling

In this section, we will use the recency score, frequency score, and monetary score, together with price and quantity to build the customer clusters. Recency-Frequency-Monetary (RFM) value is a commonly used feature for customer segmentation. Table 4.5 shows the data for clustering. As demonstrated in previous sections, all the features are skewed. Therefore, scaling is applied to improve the quality of data. KMeans cluster relies on the distance calculation, which is sensitive to values of features. Therefore, it is necessary to process the multiple-feature data for clustering. Figure 4.6 illustrates the distribution of each feature after the following transformation.

- logarithmic transformation is applied to price and frequency
- cubic root transformation is applied to quantity and revenue
- We leave the recency unchanged.

Table 4.5 Statistics of data for clustering

	Price	Quantity	Recency	Frequency	Revenue
count	5939.000000	5939.000000	5939.000000	5939.000000	5939.000000
mean	19.835088	18.512167	201.784812	134.334905	2742.884541
std	405.031023	83.275333	211.727459	348.092835	13679.955199
min	0.151333	-16.000000	0.000000	1.000000	-25111.090000
25%	2.323423	5.155944	24.000000	20.000000	321.365000
50%	3.010753	9.075472	95.000000	52.000000	823.530000
75%	3.962383	13.409903	380.000000	140.000000	2143.280000
max	25111.090000	3255.074627	738.000000	12638.000000	570380.610000

4.1.2 Silhouette analysis

The silhouette analysis indicates that 2 clusters yield the best result and 3 clusters may also be a good option if we know more information about the customers.

Table 4.5 Statistics of data for clustering

Clusters	Silhouette score
2	0.485
3	0.392
4	0.350
5	0.374

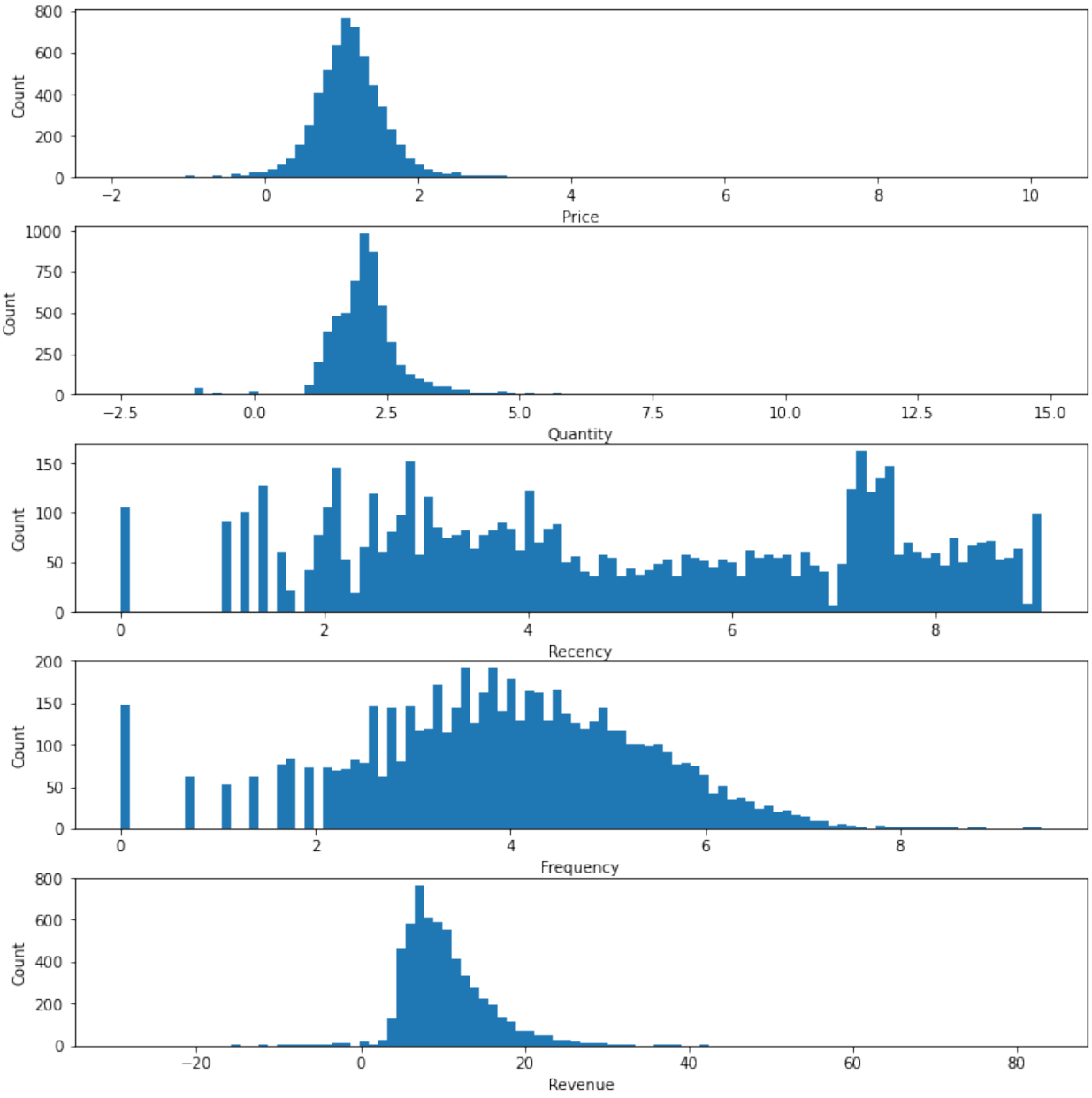


Figure 4.6 Distribution of features after transformation

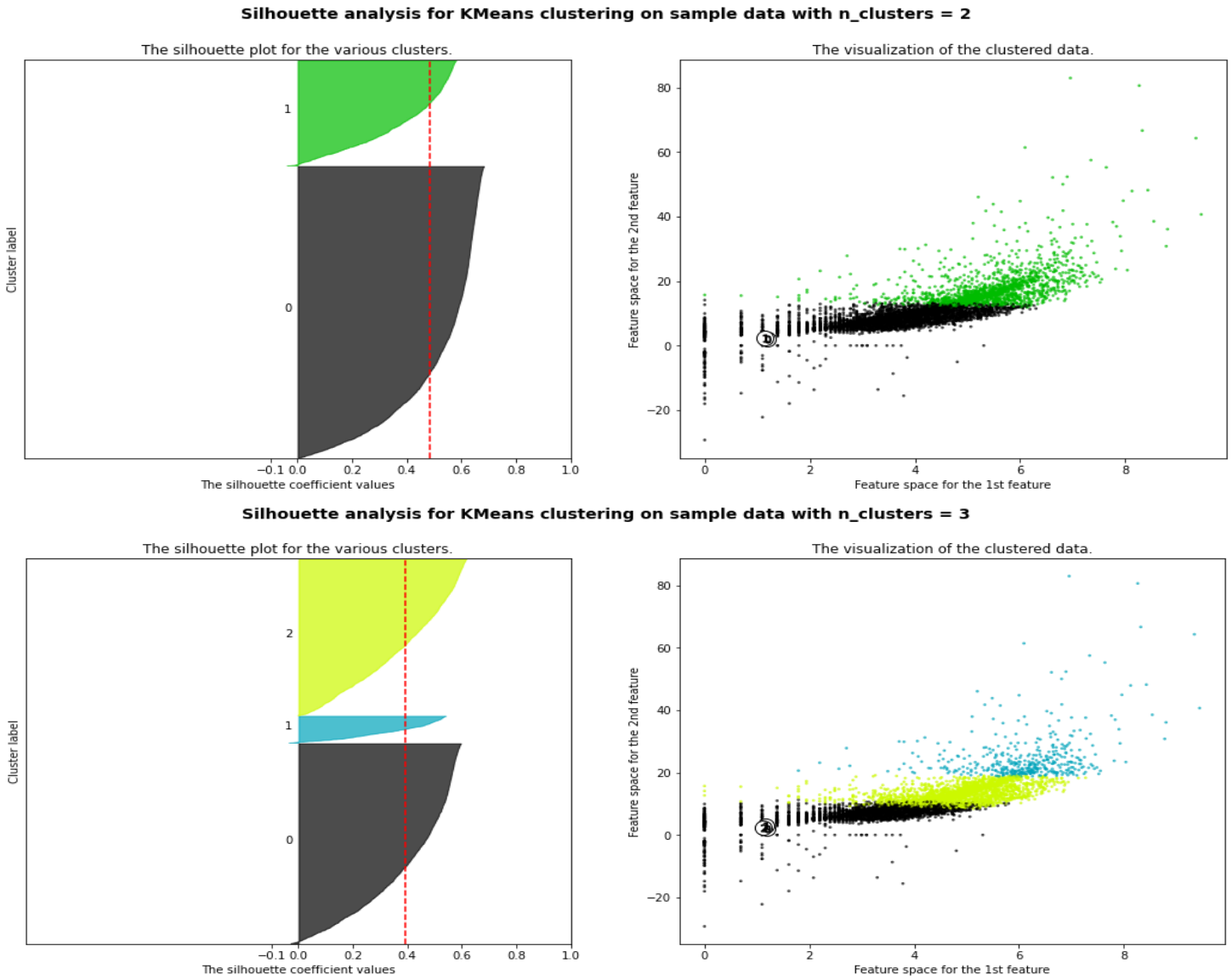


Figure 4.7 Silhouette analysis (clusters = 2 or 3)

Figure 4.7 shows more details for the 2 and 3 clusters silhouette analysis. It can be seen 2 clusters segment customers pretty well and the size of the clusters is reasonable. Figure 4.8 shows two clusters on the revenue and frequency plot. Cluster 0 represents customers with high frequency and high revenue while Cluster 1 represents customers with relatively low frequency and low revenue. But there are still overlaps between the two clusters.

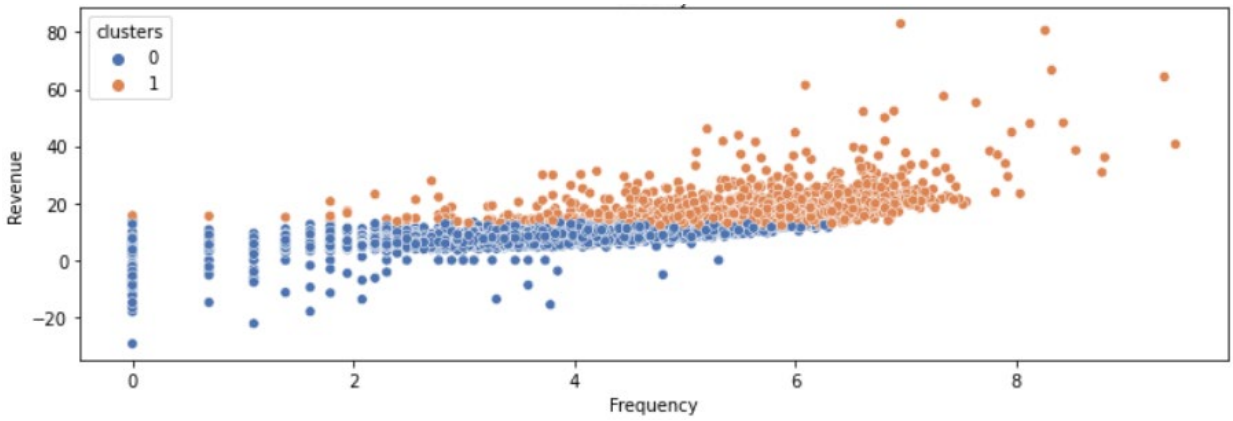


Figure 4.8 Two cluster customer segmentation

For three clusters, there is one relatively small size of the cluster as shown in Figure 4.7. Meanwhile, Figure 4.9 demonstrates three clusters on revenue and frequency plots. The small size cluster represents the highest frequency and revenue; therefore, it may be a good choice to make it an individual segment.

5. Conclusions

The customers of an online store have been segmented based on the numerical features of the dataset by using KMeans clustering. Two clusters work quite well with a silhouette score of 0.485. However, three clusters may also be a good option due to a more specific subset can be defined. The following observations are summarized from this project.

- All missing and duplicated records are dropped;
- EDA is conducted on all available features.
- The revenue analysis and customer analysis reveal the seasonality associated with sales and customer retention rates.
- Only numerical features are used in the modeling process.
- The Elbow method and silhouette analysis are used to determine the best clusters of KMeans algorithm.
- Two or three clusters of customers are recommended. With various business plans or more information about customers, corresponding strategies may be developed for either two or three clusters.

6. Recommendations & Future Work

To build a more robust clustering model for stakeholders, the following actions are recommended.

- Using natural language processing tools to interpret the stock code and description features, which may reveal customers' preference for goods and further split subsets for customer segmentation.
- Collecting and importing more data into the modeling. For example, the cost of goods can be used to estimate profit. High revenue doesn't mean high profit. It is critical for a business to identify which goods have the highest profit and which group of customers contribute the highest profits.