رواد مصر الرقمية

DEPI GRADUATION PROJECT

BIKES STORE

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OUT LINE

Introduction

- Brief Overview of Problem
- About Data set
- Meta data
- ERD digram

Data Exploration

- Data cleaning
- Data Pre-procesing

Data visualization

- Data Analytics Dashboard

RFM analysis & segmentation

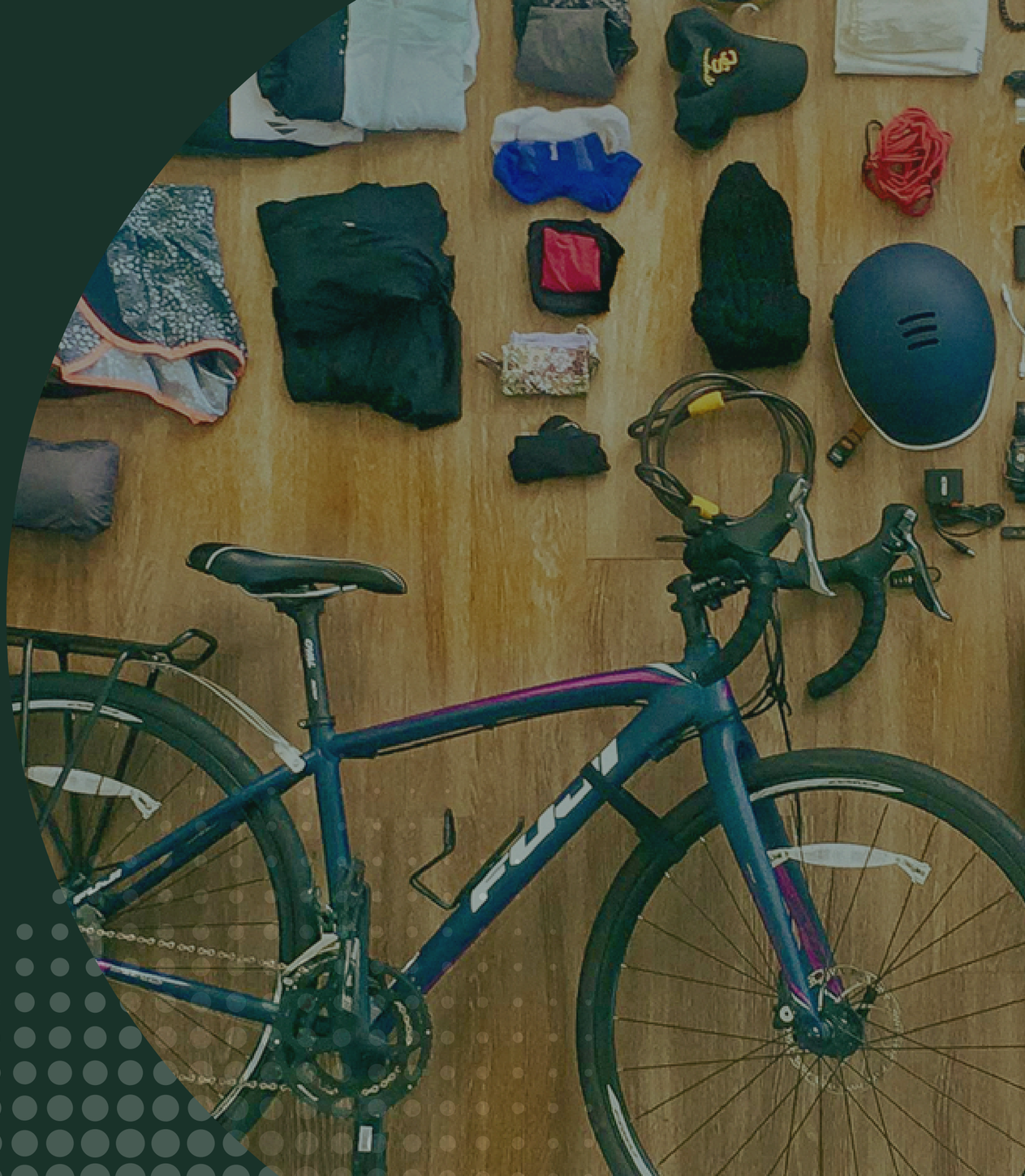
RFM (Recency, Frequency, Monetary) analysis is a marketing technique that evaluates customer purchasing behavior by analyzing the recency of purchases, frequency of purchases, and total monetary spend.

Machine learning models

Make some prediction models that can classify and predict the customer's behaviour

INTRODUCTION

Bike Shop



STEPS

- Data collection and preprocessing
- RFM analysis
- customer segmentation
- Data visualization
- insights and recommendations

TOOLS

Power Bi

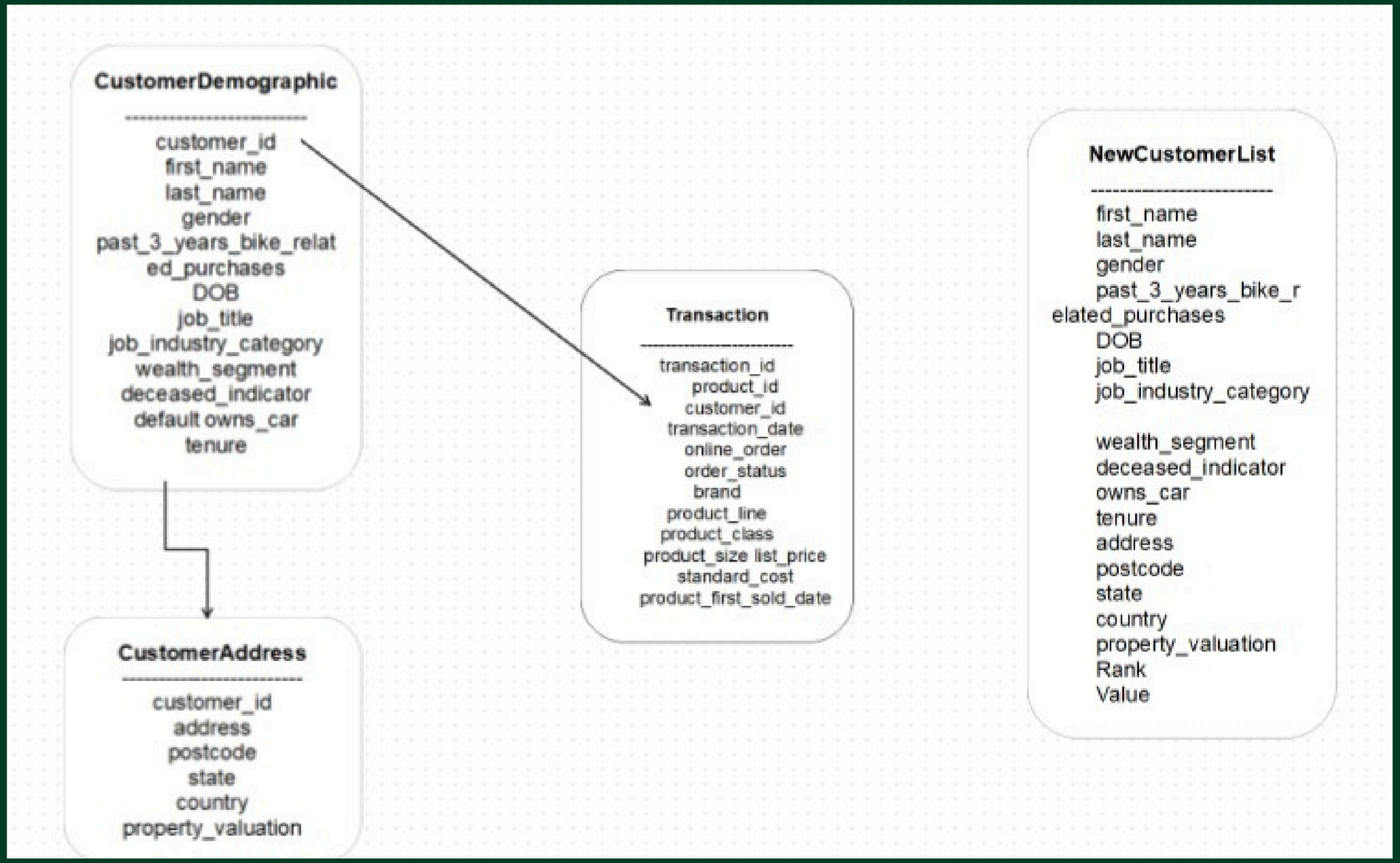
python

Power BI

GOALS

The project aims to segment customers based on purchasing behavior to identify high-value groups for targeted marketing and retention strategies, while also identifying at-risk customers to improve retention efforts.

ERD DIAGRAM


CustomerDemographic
customer_id
first_name
last_name
gender
past_3_years_bike_relat
ed_purchases
DOB
job_title
job_industry_category
wealth_segment
deceased_indicator
default owns_car
tenure
Transaction
transaction_id
product_id
customer_id
transaction_date
online_order
order_status
brand
product_line
product_class
product_size list_price
standard_cost
product_first_sold_date
NewCustomerList
first_name
last_name
gender
past_3_years_bike_r
elated_purchases
DOB
job_title
job_industry_category
wealth_segment
deceased_indicator
owns_car
tenure
address
postcode
state
country
property_valuation
Rank
Value
CustomerAddress
customer_id
address
postcode
state
country
property_valuation

ABOUT THE DATASET

- THE DATASET CAPTURES KEY INFORMATION ON BIKE STORE TRANSACTIONS IN AUSTRALIA FOR 2017, ORGANIZED INTO FOUR MAIN SECTIONS:

Customer Demographic:

New Customer List

Customer Address

Transactions

Tables

Customer Demographic

This includes important details about the customers, such as their age, gender, and occupation, allowing for an in-depth understanding of the customer base.

Customer Address

Provides geographical data including customer addresses, states, and postal codes, which helps in regional analysis and understanding the spread of customers.

New Customer List

Shows all the new customers acquired during 2017, providing insight into customer acquisition and growth.

Transactions

This section records transaction details, including transaction IDs, dates, product information, and the total purchase amount, which is essential for analyzing customer purchasing behavior and the store's performance

DATA QUALITY ASSESSMENT AND DATA CLEANING

DATA PREPARATION

The first step towards generating useful insights from the data was the data preparation, quality assessment and data cleaning step. After the cleaning process exploratory data analysis on the dataset and identification customer purchasing behaviors to generate insights can be performed.

In the data cleaning step the data quality of the following datasets were first assessed. After a data quality assessment the following data quality issues was observed and the necessary process to mitigate the issue was followed :

CUSTOMER DEMOGRAPHICS :

- 1 Irrelevent column was present and such columns were dropped from the dataset.
- There were 5 columns where Missing values were present. For such columns based on the volume of the missing values either the records were dropped or appropriate values were imputed at places of missing values
- For the gender column there was no standardization of data. Based on the values available the column data was standardized to remove data inconsistency.
- The Date of Birth column was transformed to create a new feature column 'Age' and 'Age Group' to check for discrepancy of age distribution. An outlier was observed and the record was removed.
- Checked whether there are duplicate records present in the dataset. In this dataset there were no duplicate records.

NEWCUSTOMER LIST.XLSX :

- 5 Irrelevent column was present and such columns were dropped from the dataset.
- There were 4 columns where Missing values were present. For such columns based on the volume of the missing values either the records were dropped or appropriate values were imputed at places of missing values
- The Date of Birth column was transformed to create a new feature column 'Age' and 'Age Group' to check for discrepancy of age distribution.
- There was no data inconsistency.
- Checked whether there are duplicate records present in the dataset. In this dataset there were no duplicate records.

TRANSACTION_DATA.XLSX :

- The product_first_sold_date column is not in datetime format. The data type of this column was changed from int64 to datetime format.
- There were 7 columns where Missing values were present. For such columns based on the volume of the missing values either the records were dropped or appropriate values were imputed at places of missing values
- A new feature column 'Profit' was created which is basically the difference between list price and standard price.
- There was no data inconsistency.
- Checked whether there are duplicate records present in the dataset. In this dataset there were no duplicate records.

CUSTOMER ADDRESS.XLSX :

- For the states column there was no standardization of data. Based on the values available the column data was standardized to remove data inconsistency.

- There were certain customer IDs from the Customer Demographics table which were getting dropped in the Address table.

META DATA:

Table Name	Column_Name	Description	Data_Type	Values
Transaction	transaction_id	Unique identifier for each transaction.	Numerical	Serial number
	product_id	Unique identifier for each product.	Numerical	Serial number
	customer_id	Unique identifier for each customer.	Numerical	Serial number
	transaction_date	Date when the transaction occurred.	DateTime	Date
	online_order	Whether the order was placed online	Categorical	True/False
	order_status	Status of the order	Categorical	Approved / Cancelled
	brand	Product brand.	Categorical	Brand's name
	product_line	Category of the product.	Categorical	Mountain , Road , Standard ,Touring
	product_class	Classification of the product.	Categorical	High , Medium , Low
	product_size	Size of the product.	Categorical	Large , Medium, Small
	list_price	Selling price, including any services or additional fees (shipping, quantities.....)	Numerical	selling price value
	standard_cost	Cost requried from the vendor on the Product	Numerical	Cost price value
	product_first_sold_date	First date the product was sold (as a serial date).	DateTime	serial date
CustomerDemographic	customer_id	Unique identifier for each customer.	Numerical	Serial number
	first name	Customer's first name.	Categorical	Name value
	last name	Customer's last name.	Categorical	Name value
	gender	Gender of the customer.	Categorical	Male , Female , Unknown
	past_3_years_bike_related_purchases	Number of purchases made in the past 3 years.	Numerical	Number of Purchases
	DOB	date os birth of the customer.	Numerical	Age value
	job_title	Job title of the customer.	Categorical	Accountant , Adminstrative, ……..etc
	job_industry_category	Industry of the job.	Categorical	Financial Services , Health, IT,…….etc
	wealth_segment	Customer's wealth segment.	Categorical	High net worth, Mass, Affluent customer
	deceased_indicator	Whether the customer is deceased.	Categorical	Yes , No
	owns_car	Whether the customer owns a car.	Categorical	Yes , No
	tenure	Number of years the customer has been associated with the company.	Numerical	tenure Value
CustomerAddress	customer_id	Unique identifier for each customer.	Numerical	Serial number
	address	Location Information	Categorical	street name and city
	postcode	Location information.	Categorical	serial number
	state	Location information.	Categorical	New South Wales , Victoria , Queensland
	country	Location information.	Categorical	Australia
	property_valuation	Value of the customer's property.	Numerical	Property value
	first name	Customer's first name.	Categorical	Name value
	last name	Customer's last name.	Categorical	Name value

META DATA:

CustomerAddress	customer_id	Unique identifier for each customer.	Numerical	Serial number
	address	Location Information	Categorical	street name and city
	postcode	Location information.	Categorical	serial number
	state	Location information.	Categorical	New South Wales , Victoria , Queensland
	country	Location information.	Categorical	Australia
	property_valuation	Value of the customer's property.	Numerical	Property value
NewCustomerList	first name	Customer's first name.	Categorical	Name value
	last name	Customer's last name.	Categorical	Name value
	gender	Gender of the customer.	Categorical	Male , Female , Unknown
	past_3_years_bike_related_purchases	Number of purchases made in the past 3 years.	Numerical	Number of Purchases
	DOB	date os birth of the customer.	Numerical	Age value
	job_title	Job title of the customer.	Categorical	Accountant , Adminstrative, ……..etc
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	customer_id	Unique identifier for each customer.	Numerical	Serial number
	address	Location Information	Categorical	street name and city
	postcode	Location information.	Categorical	serial number
	state	Location information.	Categorical	New South Wales , Victoria , Queensland
	country	Location information.	Categorical	Australia
	property_valuation	Value of the customer's property.	Numerical	Property value
	rank	the rank of customer segment	Numerical	values from 1 to 11

DATA VISUALIZATION

Bike Shop

DASHBOARD

- Thl'll be showing you a dashboard that focuses on transaction and customer analysis. The goal is to help us better understand customer behavior, including how often they make purchases, how much they spend, and how we can group them based on their activity.

- Through this dashboard, we'll look at things like how often customers buy, how much they spend, and how we can group them based on their behaviors. These insights can help us improve customer satisfaction, increase sales, and find areas for growth.

Vlew Dashboard

Country

Australia

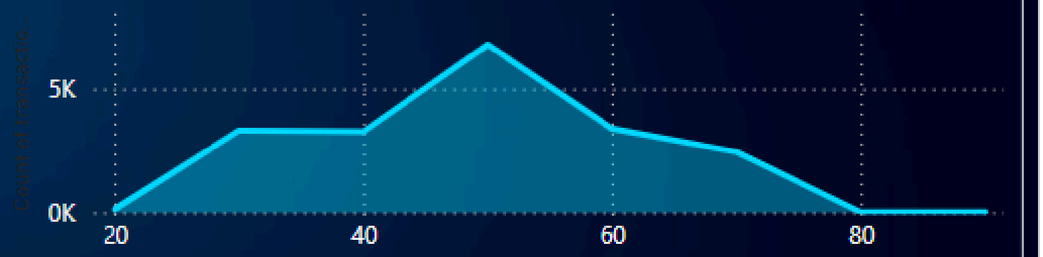
Customer

3.999K

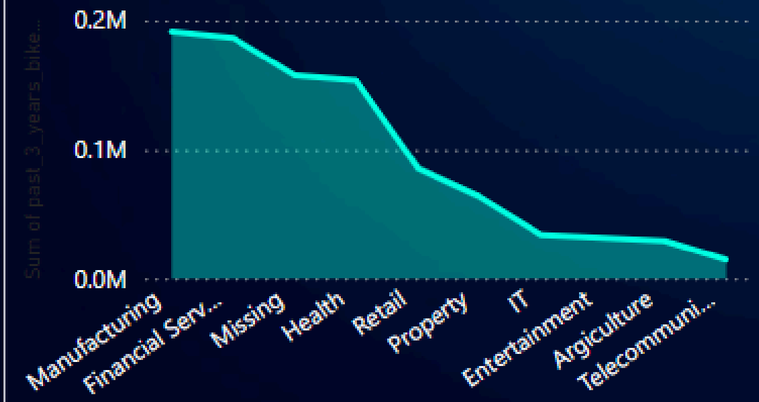
Status

3

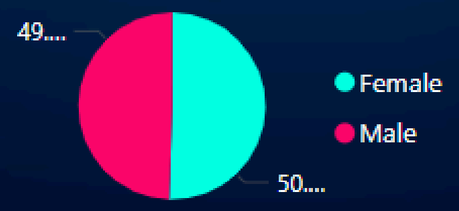
Customer by Age



Profit By Customer job category



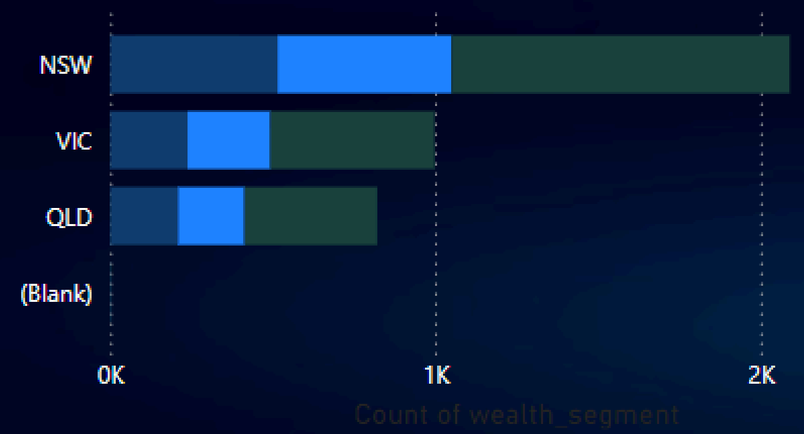
Numer bike purches accreoss gender



Customer by Title

Wealth segment across state

wealth_segment Affluent Customer High Net Worth Mass Customer



customer by frequency

2880/2880 displayed

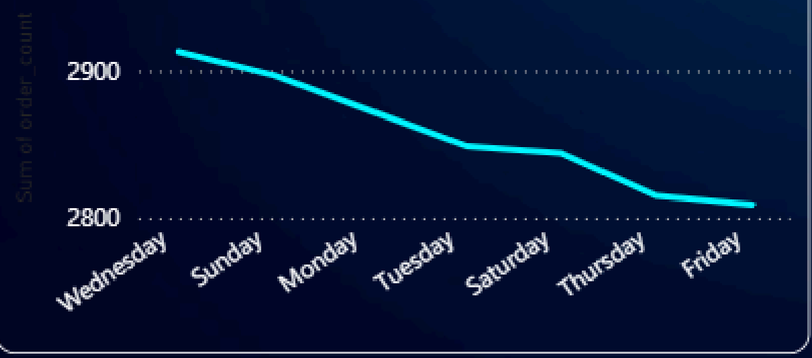
Revenue
21.42M

Total Profit
10.66M

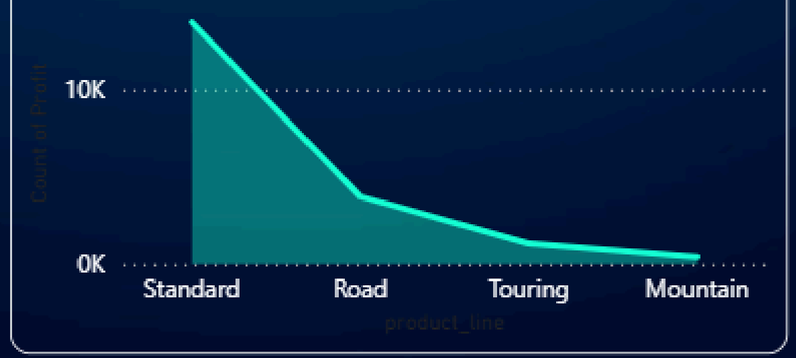
Total Transactions
19.35...

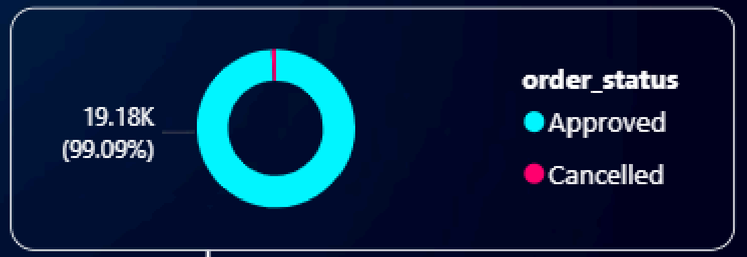
Averag Daily Transaction
54.90

Total Transactions By day of week

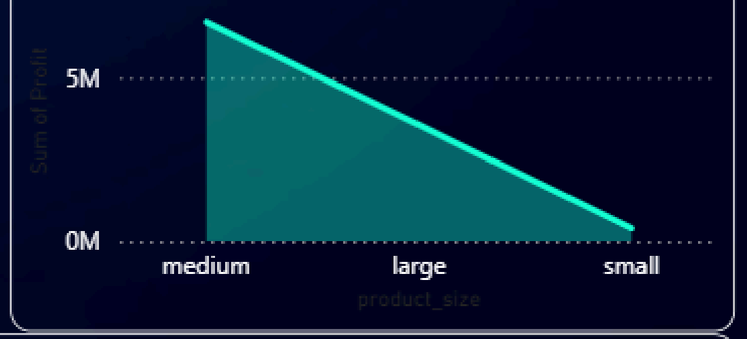


Profit by Product Line





Profit By product Size

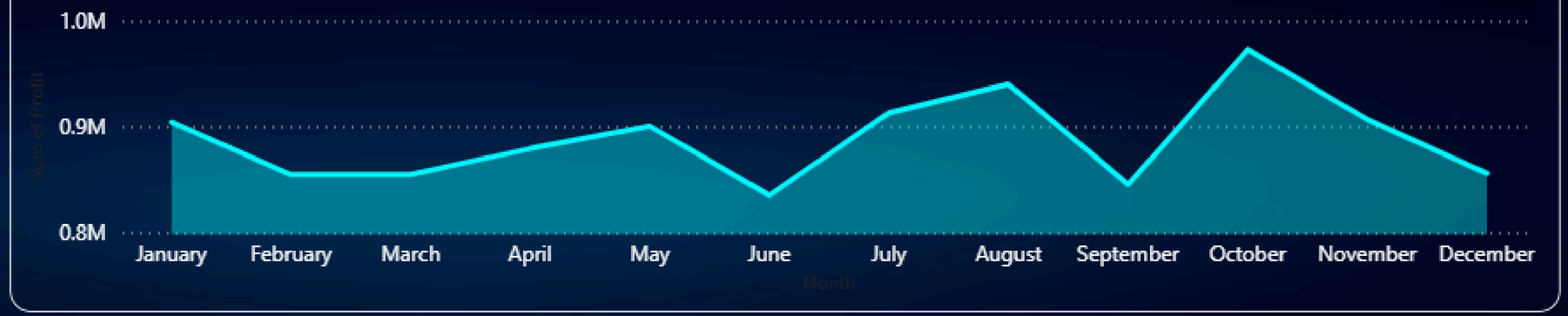


Profit by brand

Transaction Date

1/1/2017 — 12/30/2017

Profit Over time



RFM ANALYSIS & SEGMENTATION

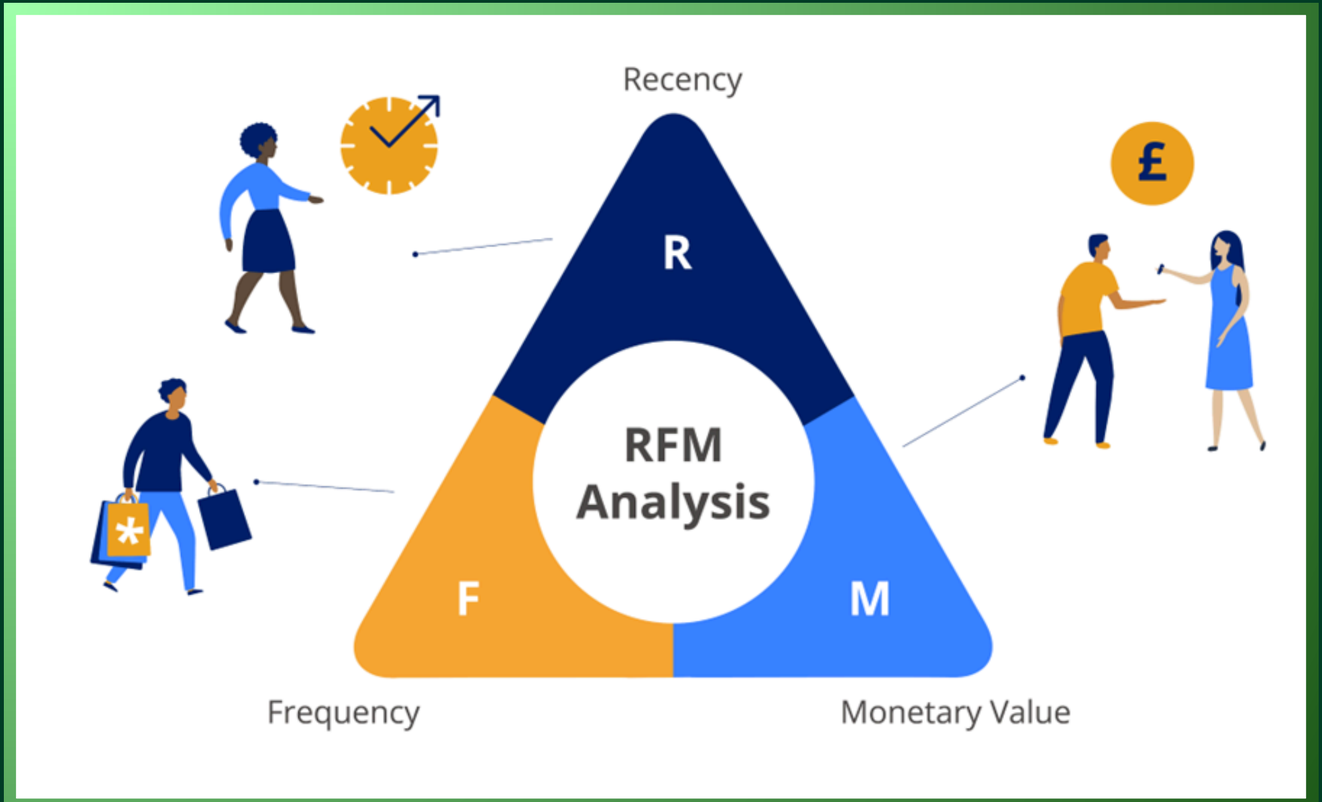
Bike Shop

RFM ANALYSIS

- Resency :
  Number of days since last purchase

- Frequency :
  Total number of purchases

- Monetary :
  the total money customer spent



BASIC CALCULATIONS :

- Creating a new table for measuring R,F and M.
- Computing R as the difference between that day and last transaction for same customer
- Computing F : How much the same Customer_id appears for different transactions?
- Computing M : Sum of list price for same customer_id.

GIVING A DEGREE FOR EACH RFM FROM 0 TO 4

```
# Dividing the recency, frequency and monetary into 4 quartiles (min, 25%, 50%, 75% and max).
# These values will help us to calculate RFM score for a customer and classify based on their RFM score.

rfm_table['r_quartile'] = pd.qcut(rfm_table['recency'], 4, ['4','3','2','1'])
rfm_table['f_quartile'] = pd.qcut(rfm_table['frequency'], 4, ['1','2','3','4'])
rfm_table['m_quartile'] = pd.qcut(rfm_table['monetary'], 4, ['1','2','3','4'])
```

THE NEW DATA SET :

customer_id	recency	frequency	monetary	r_quartile	f_quartile	m_quartile
1	7	11	3018.09	4	4	3
2	128	3	2226.26	1	1	2
3	102	8	3362.81	1	4	3
4	195	2	220.57	1	1	1
5	16	6	2394.94	4	2	2
6	64	5	3946.55	2	2	3
7	253	3	220.11	1	1	1
8	22	10	7066.94	3	4	4
9	78	6	2353.11	2	2	2
10	43	5	3358.28	3	2	3

DEFINING THE RFM SCORE

- We can define the rfm score as a column that contains the merge of r_quartile, f_quartile and m_quartile.

- Giving a title for each rfm_score as :
  - Bronze
  - Silver
  - Gold
  - Platinum

THE NEW VERSION OF DATA SET :

customer_id	recency	frequency	monetary	r_quartile	f_quartile	m_quartile	rfm_score	customer_title
1	7	11	3018.09	4	4	3	443	Platinum
2	128	3	2226.26	1	1	2	112	Bronze
3	102	8	3362.81	1	4	3	143	Bronze
4	195	2	220.57	1	1	1	111	Bronze
5	16	6	2394.94	4	2	2	422	Platinum
6	64	5	3946.55	2	2	3	223	Silver
7	253	3	220.11	1	1	1	111	Bronze
8	22	10	7066.94	3	4	4	344	Gold
9	78	6	2353.11	2	2	2	222	Silver
10	43	5	3358.28	3	2	3	323	Gold
11	46	6	3638.84	2	2	3	223	Silver

CUSTOMER SEGMENTATION

MERGING BOTH RFM TABLE WITH TRANSACTION AND CUSTOMER TABLES

- •The RFM_Table dataframe is merged with the Transactions and Customer Demographics datasets, to gain better insights of Customer Segements along with transactions. The dataframes are joined based on customer_ids from both the datasets

```
cust_trans_rfm = pd.merge(merged_trans_cust, rfm_table, left_on='customer_id', right_on='customer_id', how='inner')
```

THE NEW DATA SET :

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19354 entries, 0 to 19353
Data columns (total 34 columns):
transaction_id                          19354 non-null int64
product_id                              19354 non-null int64
customer_id                             19354 non-null int64
transaction_date                        19354 non-null datetime64[ns]
online_order                            19354 non-null float64
order_status                            19354 non-null object
brand                                   19354 non-null object
product_line                            19354 non-null object
product_class                           19354 non-null object
product_size                            19354 non-null object
list_price                              19354 non-null float64
standard_cost                           19354 non-null float64
product_first_sold_date                 19354 non-null float64
Profit                                  19354 non-null float64
first_name                              19354 non-null object
last_name                               19354 non-null object
gender                                  19354 non-null object
past_3_years_bike_related_purchases     19354 non-null int64
DOB                                     19354 non-null object
job_title                               19354 non-null object
job_industry_category                   19354 non-null object
wealth_segment                          19354 non-null object
deceased_indicator                      19354 non-null object
owns_car                                19354 non-null object
tenure                                  19354 non-null float64
Age                                     19354 non-null int64
recency                                 19354 non-null int64
frequency                               19354 non-null int64
monetary                                19354 non-null float64
r_quartile                              19354 non-null category
f_quartile                              19354 non-null category
m_quartile                              19354 non-null category
rfm_score                               19354 non-null int32
customer_title                          19354 non-null category
dtypes: category(4), datetime64[ns](1), float64(7), int32(1), int64(7), object(1
```

BASED ON RFM_SCORE WE COULD GIVE A DETAILED DESCRIPTION FOR EACH CUSTOMER

```python
# Function as a lookup to appropiate customer titles based on RFM score.

def cust_score_title_lkup(cols):

    rfm_score = cols[0]

    if rfm_score >= 444:
        return 'Platinum Customer'
    elif rfm_score >=433 and rfm_score < 444:
        return 'Very Loyal'
    elif rfm_score >=421 and rfm_score < 433:
        return 'Becoming Loyal'
    elif rfm_score >=344 and rfm_score < 421:
        return 'Recent Customer'
    elif rfm_score >=323 and rfm_score < 344:
        return 'Potential Customer'
    elif rfm_score >=311 and rfm_score < 323:
        return 'Late Bloomer'
    elif rfm_score >=224 and rfm_score < 311:
        return 'Loosing Customer'
    elif rfm_score >=212 and rfm_score < 224:
        return 'High Risk Customer'
    elif rfm_score >=124 and rfm_score < 212:
        return 'Almost Lost Customer'
    elif rfm_score >=112 and rfm_score < 124:
        return 'Evasive Customer'
    else :
        return 'Lost Customer'
```

MERGING BOTH RFM TABLE WITH TRANSACTION AND CUSTOMER TABLES

- •The RFM_Table dataframe is merged with the Transactions and Customer Demographics datasets, to gain better insights of Customer Segements along with transactions. The dataframes are joined based on customer_ids from both the datasets

```
cust_trans_rfm = pd.merge(merged_trans_cust, rfm_table, left_on='customer_id', right_on='customer_id', how='inner')
```

SOME VISUALIZATIONS

Detailed_Customer_title	Explanation
Very Loyal	High Frequency and Monetary Value, slightly low between 433 and 443
Recent	High Recency, moderate Frequency and Monetar between 344 and 420
Potential	Moderate Recency, Frequency, and Monetary Val 323 and 343
Platinum	High Recency, Frequency, and Monetary Value 4
Lost	Very Low Recency, Frequency, and Monetary Valu
Losing	Low Recency, moderate Frequency and Monetar between 224 and 310
High Risk	Low Recency and Frequency, moderate Monetar between 212 and 223
Evasive	Very Low Recency and Frequency, low Monetary 112 and 123
Becoming Loyal	Moderate to High Frequency and Monetary Valu Recency between 421 and 432
Almost Lost	1.Low Recency, Frequency, and Monetary Value b and 211
Late Bloomers	Moderate to Low Recency, moderate Frequency Value between 311 and 322

Average Recency

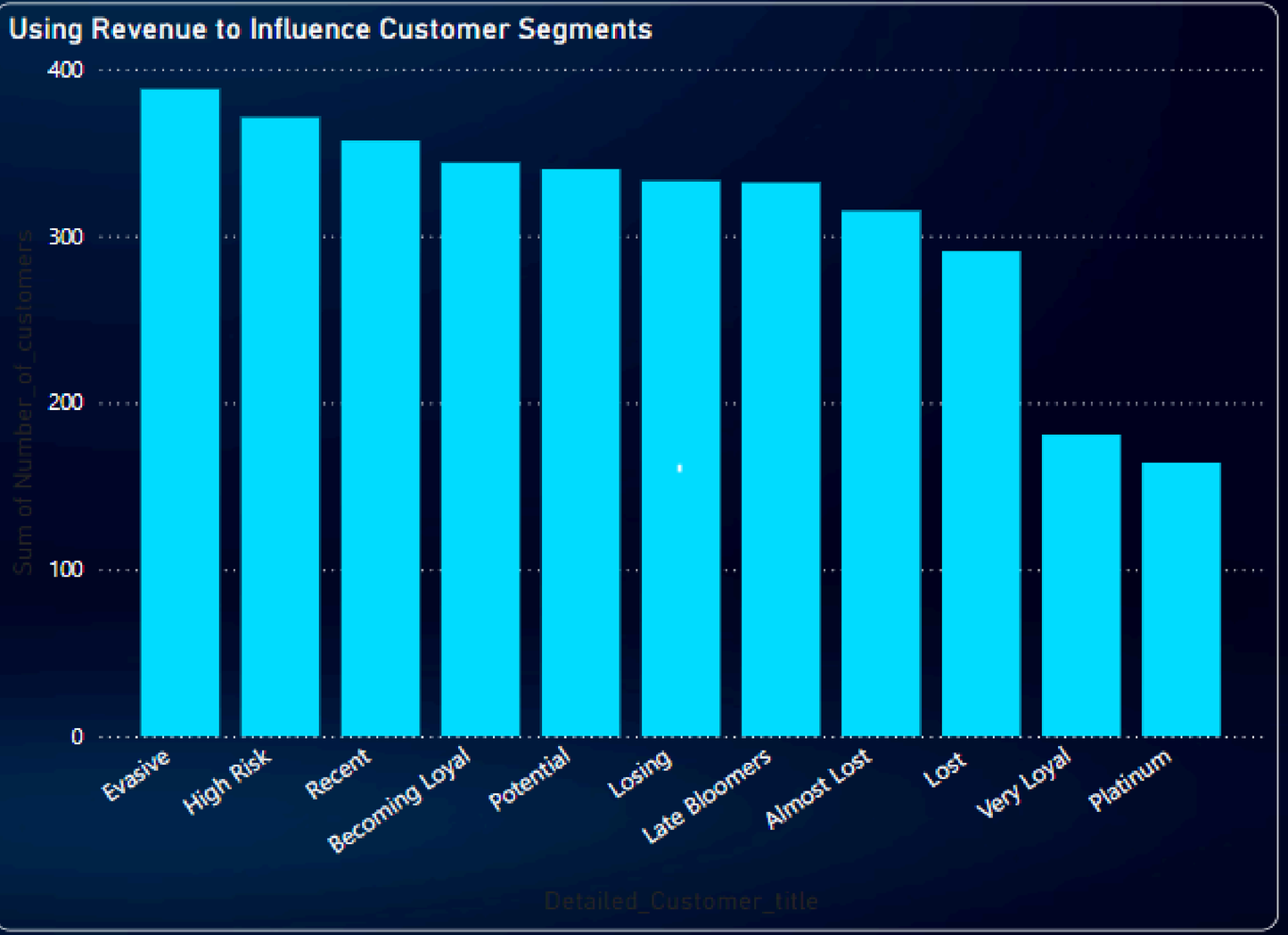
61.80

Average Frequency

5.72

Average Monetary

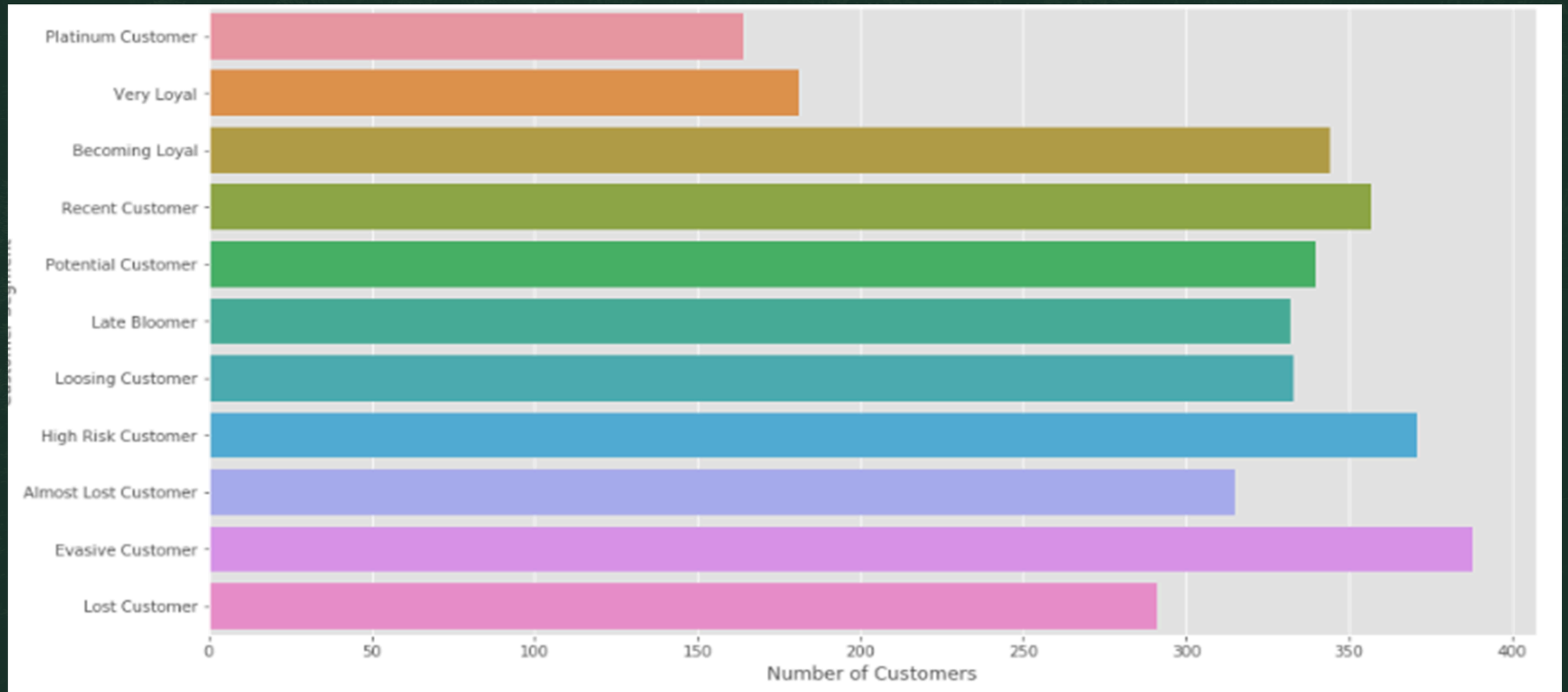
3.488K



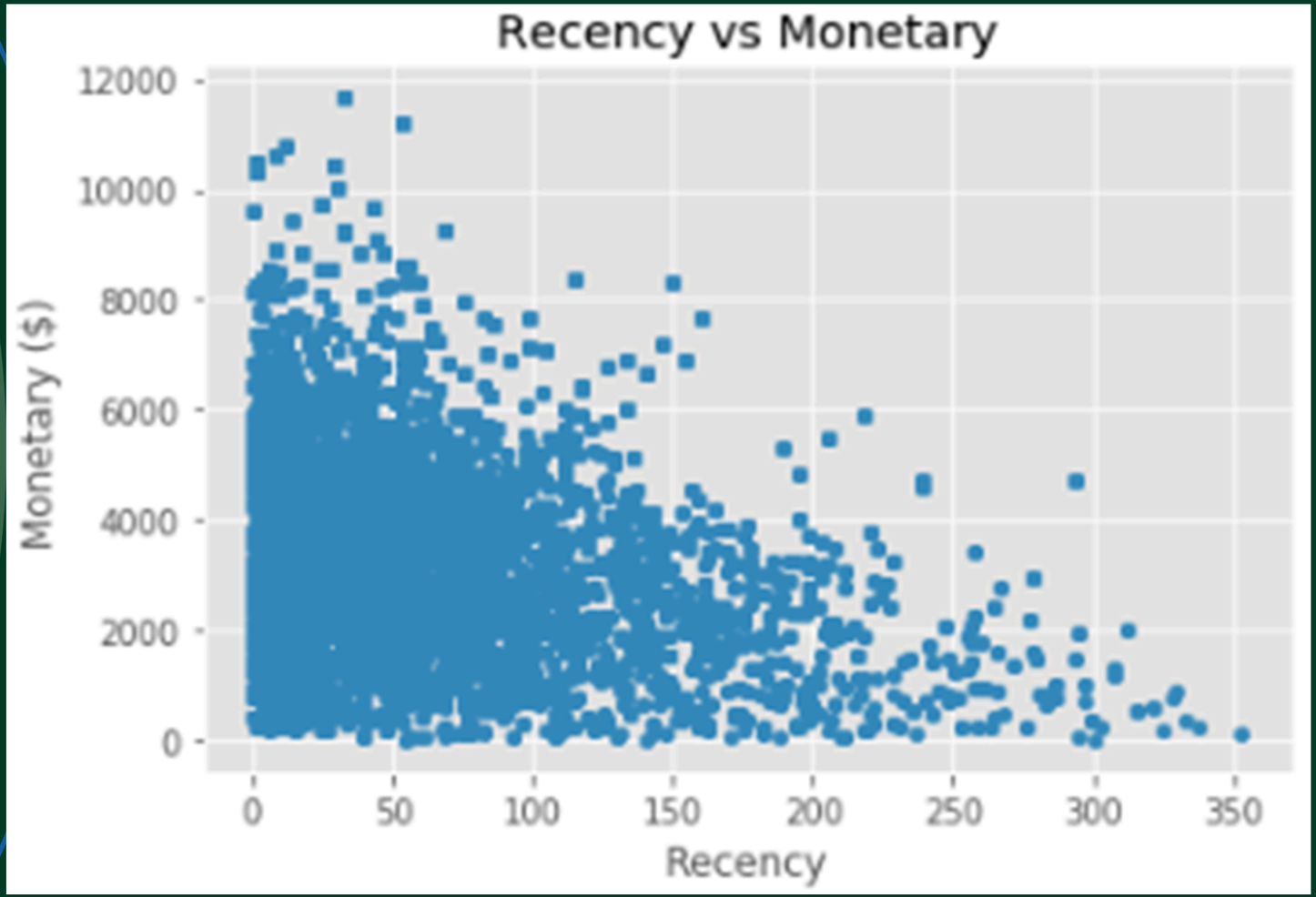
Distribution of customer segmentations

detail_cust_title	rank	Number of Customers
Platinum Customer	1	164
Very Loyal	2	181
Becoming Loyal	3	344
Recent Customer	4	357
Potential Customer	5	340
Late Bloomer	6	332
Loosing Customer	7	333
High Risk Customer	8	371
Almost Lost Customer	9	315
Evasive Customer	10	388
Lost Customer	11	291

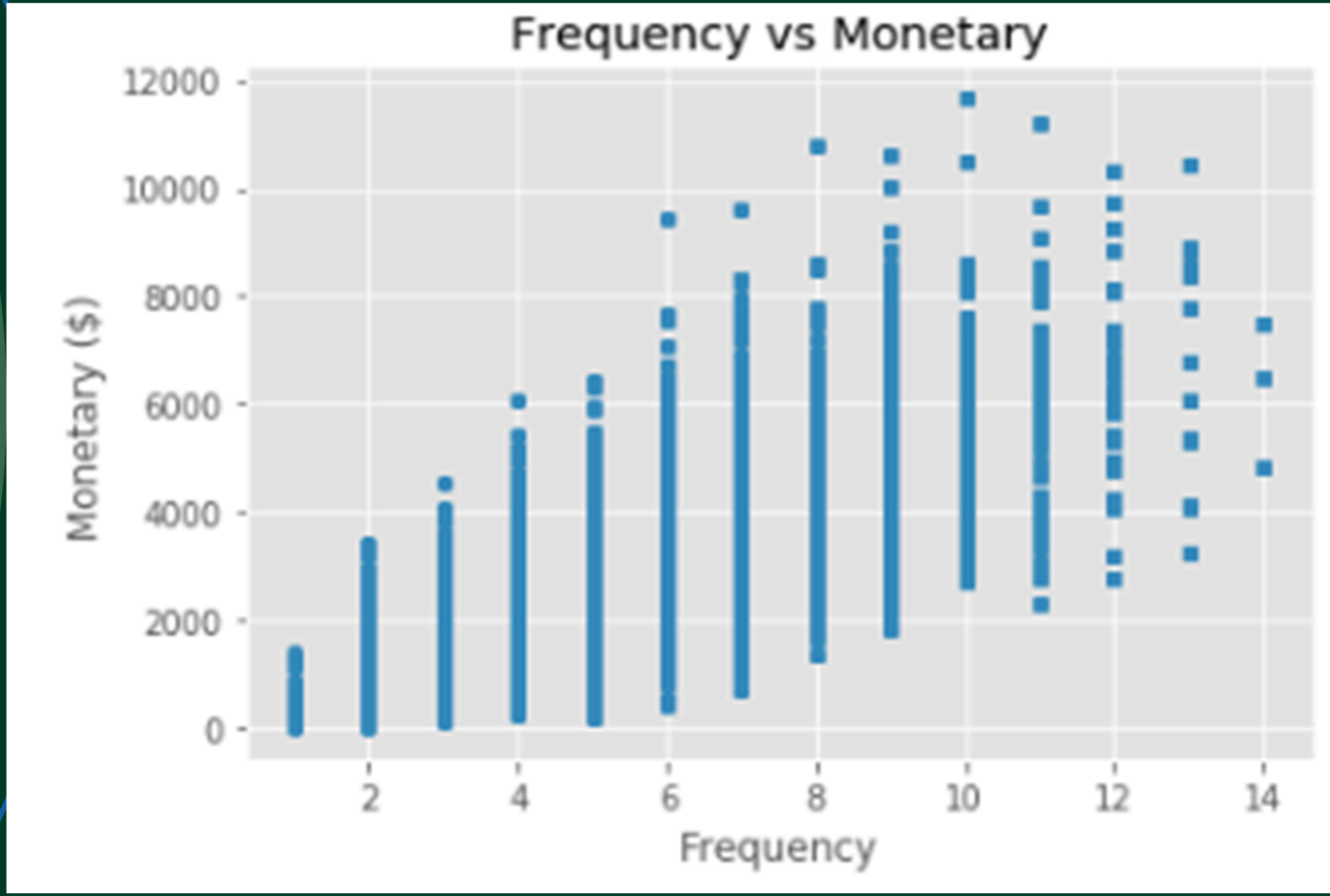
Number of Customers vs Customer segments



Recency vs Monetary



Frequency vs Monetary



SEGMENTATION INSIGHTS AND MARKETING STRATEGIES

1. Platinum Customers (Rank 1)

- **Characteristics:** Highest loyalty, frequent purchases, high spending.
- Marketing Strategy:

  Personalized Services. Rewards Programs. Early Access.

2.Very Loyal Customers (Rank 2)

- **Characteristics**: Consistent purchases, high spending.
- Marketing Strategy:

  Exclusive Offers Engagement Campaigns Loyalty Programs

SEGMENTATION INSIGHTS AND MARKETING STRATEGIES

3.Becoming Loyal Customers (Rank 3)

- **Characteristics:** •Increasing loyalty, moderate to high spending.
- Marketing Strategy:

Incentives for Frequency | Educational Content | Personalized Communication

4. Recent Customers (Rank 4)

- **Characteristics**: Recent purchases, potential for loyalty.
- Marketing Strategy:

Welcome Campaigns | Follow-Up | Customer Onboarding

SEGMENTATION INSIGHTS AND MARKETING STRATEGIES

5. Potential Customers (Rank 5)

- **Characteristics:** Moderate engagement, potential for higher spending.
- Marketing Strategy:

  Trial Offers Educational Content Nurturing Campaigns

2.Very Loyal Customers (Rank 2)

- **Characteristics**: •: Recently increased engagement, moderate spending.
- Marketing Strategy:

  Time-Sensitive Deals Highlight Benefits Personalized Offers

SEGMENTATION INSIGHTS AND MARKETING STRATEGIES

7. Losing Customers (Rank 7)

- **Characteristics:** Declining engagement, risk of churn.
- Marketing Strategy:

  Re-Engagement Campaigns Personal Outreach Incentives for return

2.Very Loyal Customers (Rank 2)

- **Characteristics**: •Significant risk of churn, low recent engagement.
- Marketing Strategy:

  Immediate action Custom offers retention strategies

SEGMENTATION INSIGHTS AND MARKETING STRATEGIES

7. Losing Customers (Rank 9)

- **Characteristics:** •Very low engagement, high risk of being lost..
- Marketing Strategy:

Win-Back Campaigns

Reflect Past Purchases

2.Very Loyal Customers (Rank 10)

- **Characteristics**: Erratic purchase patterns, low spending..
- Marketing Strategy:

Unpredictable Promotions

Highlight Value

SEGMENTATION INSIGHTS AND MARKETING STRATEGIES

11. Losing Customers (Rank 9)

- **Characteristics:** No recent purchases, very low engagement
- Marketing Strategy:

in-Back Campaigns

feedback request

Re-Engagement Offers

PREDICTIONS

Implementing ML models

OBJECTIVES

Customer Segmentation:

- **Group customers based on their purchasing behavior, spending patterns, and other relevant criteria. This helps businesses understand customer diversity and cater to specific needs.**

- Marketing Strategy: Develop targeted marketing campaigns for each customer segment. High-value customers can be targeted with loyalty programs and exclusive offers, while low-value customers might receive general promotions to encourage increased spending.

OBJECTIVES

Product Characteristics and Sales:

- **predict a product's likelihood of being sold online based on its features like product class and brand.**

- understanding which products are more likely to sell online, businesses can create more targeted online advertising campaigns

BENEFITS OF CUSTOMER SEGMENTATION

- Identify which customers generate the highest profit, allowing businesses to optimize their product or service offerings. It helps to align business strategies with customer profitability to ensure the company achieves sustainable growth.

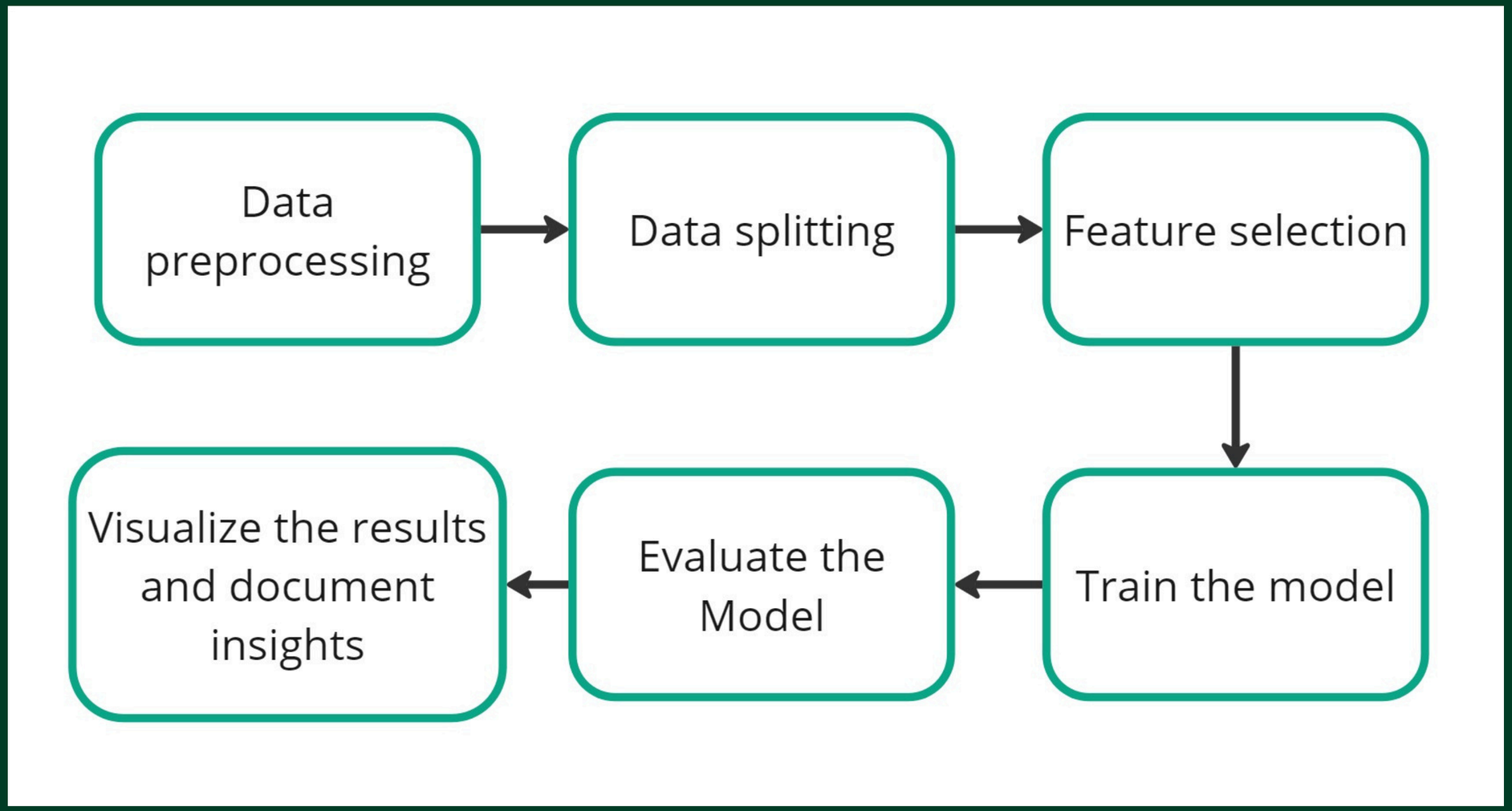
- Classification provides a foundation for more informed decision-making. Insights from this segmentation help the business decide where to invest, which products to develop, and how to grow the customer base strategically.

BENEFITS OF PRODUCT CHARACTERISTICS AND SALES

- **Products that are more likely to be sold online can be prioritized in online distribution centers, ensuring efficient inventory turnover and lower holding costs.**

- **The model can be used to make personalized product recommendations to online customers, increasing the likelihood of purchases and improving customer satisfaction.**

HOW TO BUILD A MODEL



CUSTOMER SEGMENTATION MODEL BUILDING

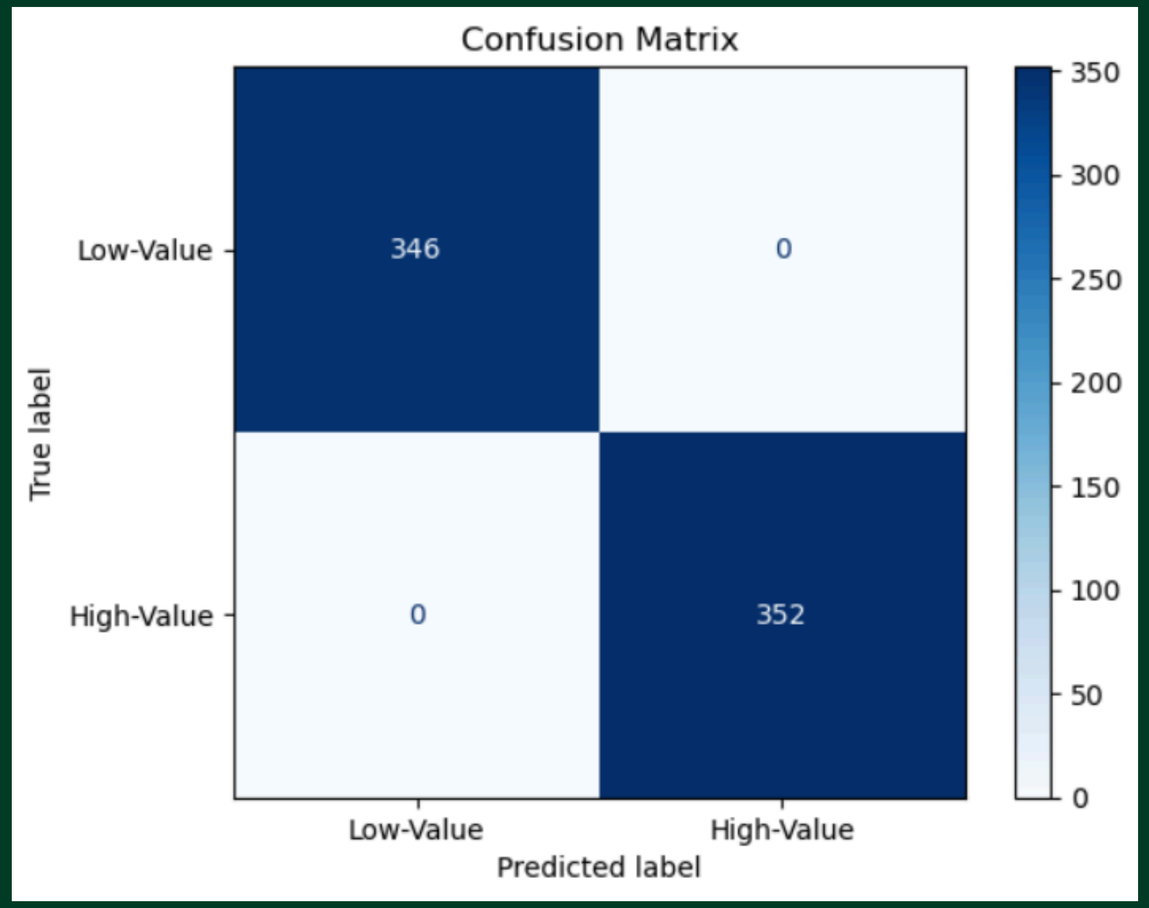
- Define threshold (Median) for high-value and low-value customers
- Select the needed features (Recency, Frequency, Monetary)
- Split the data into training and testing sets (80% training, 20% testing)
- Initialize and train the Random Forest Classifier
- Predict the target variable on the test set

```python
# Define threshold (Median) for high-value and low-value customers
threshold = rfm_df['Monetary'].median()
rfm_df['high_value'] = (rfm_df['Monetary'] > threshold).astype(int)

# Features and target
X = rfm_df[['Recency', 'Frequency', 'Monetary']]
y = rfm_df['high_value']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the Random Forest Classifier
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_scaled, y_train)

# Predict the target variable on the test set
y_pred = rf_model.predict(X_test_scaled)
```

CUSTOMER SEGMENTATION MODEL BUILDING

- Evaluate the model using accuracy
- Visualize the output using confusion matrix

```
Accuracy: 100.00%

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       346
           1       1.00      1.00      1.00       352

    accuracy                           1.00       698
   macro avg       1.00      1.00      1.00       698
weighted avg       1.00      1.00      1.00       698


Confusion Matrix:
 [[346   0]
 [  0 352]]
```



PRODUCT CHARACTRESTIC AND SALES MODEL BUILDING

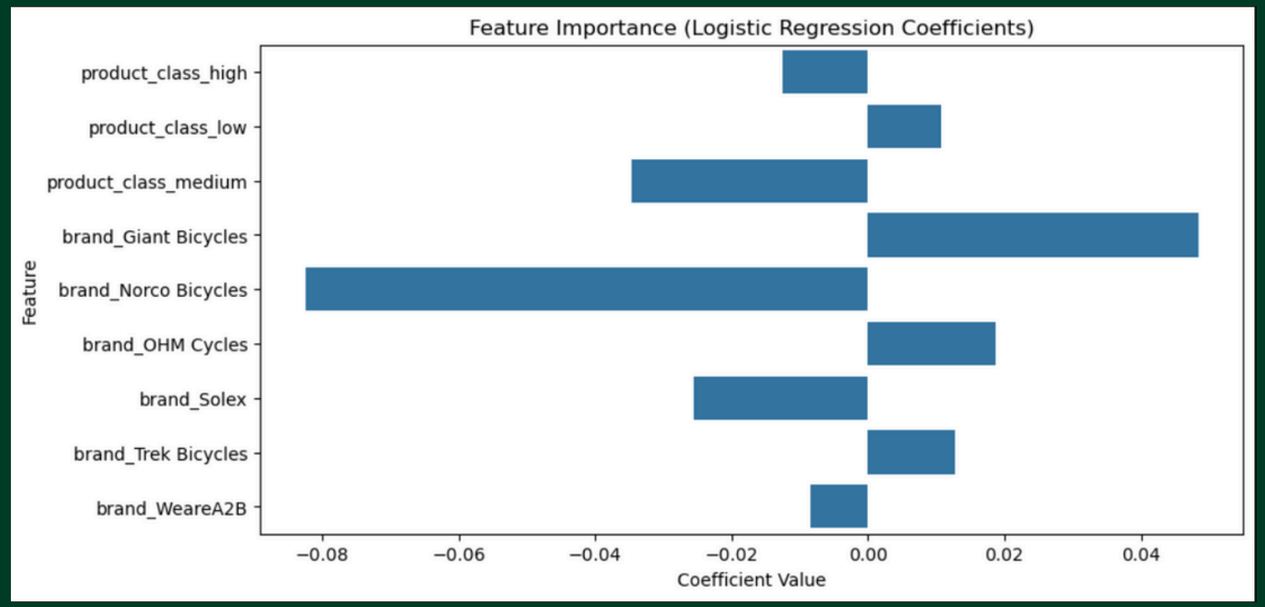
- Merge datasets on relevant keys (Product id , Customer id)
- Select the needed features (product class, brand , product line , list price , product size)
- Split the data into training and testing sets (80% training, 20% testing)
- Train the Logistic Regression model
- Make predictions

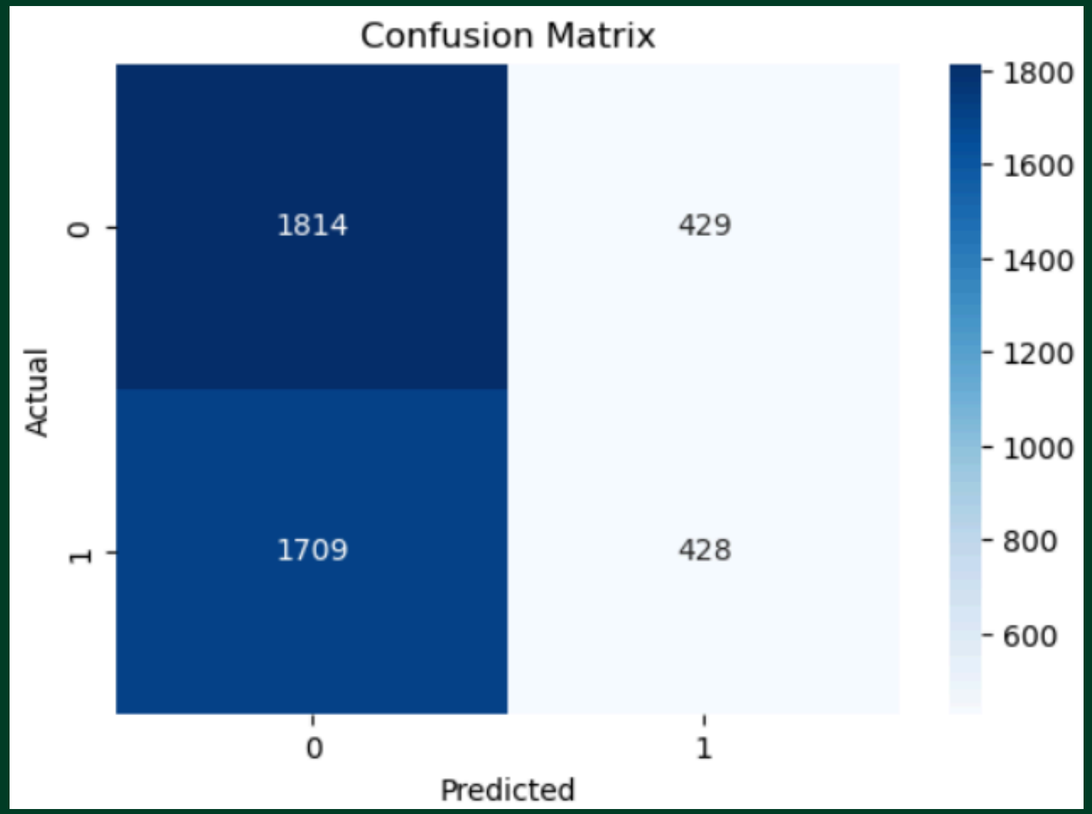
```
X = df[['product_class', 'brand' , 'product_line' , 'list_price' , 'product_size']]
y = df['online_order']
```

```
# One-hot encode the categorical features
encoder = OneHotEncoder()
X_encoded = encoder.fit_transform(X).toarray()

# Step 3: Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.2, random_state=42)

# Step 4: Train the Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Step 5: Make predictions
y_pred = model.predict(X_test)
y_pred_proba = model.predict_proba(X_test)[:, 1]
```

PRODUCT CHARACTRESTIC AND SALES MODEL BUILDING

- Evaluate the model using accuracy
- Visualize the output using confusion matrix & Feature Importance graphs






```
Accuracy: 0.51
Classification Report:
              precision    recall  f1-score   support

           0       0.51      0.81      0.63      2243
           1       0.50      0.20      0.29      2137

    accuracy                           0.51      4380
   macro avg       0.51      0.50      0.46      4380
weighted avg       0.51      0.51      0.46      4380
```

HOW TO IMPROVE THE ACCURACY OF THE MODEL

- **Regularization**: Regularization helps to prevent overfitting by penalizing large coefficients:

- **L1 Regularization (Lasso)**: Can be useful to reduce the number of features by enforcing some coefficients to zero.

- **L2 Regularization (Ridge)**: Helps by shrinking coefficients and reducing model complexity.

- **Preprocessing Pipeline**: helps streamline and automate a sequence of data processing and modeling steps. It ensures that each step is performed consistently and allows for easy replication, parameter tuning, and deployment.

- **Use K-Fold Cross-Validation** to ensure that the model is generalizing well.

THANK YOU

DO YOU HAVE ANY QUESTIONS?