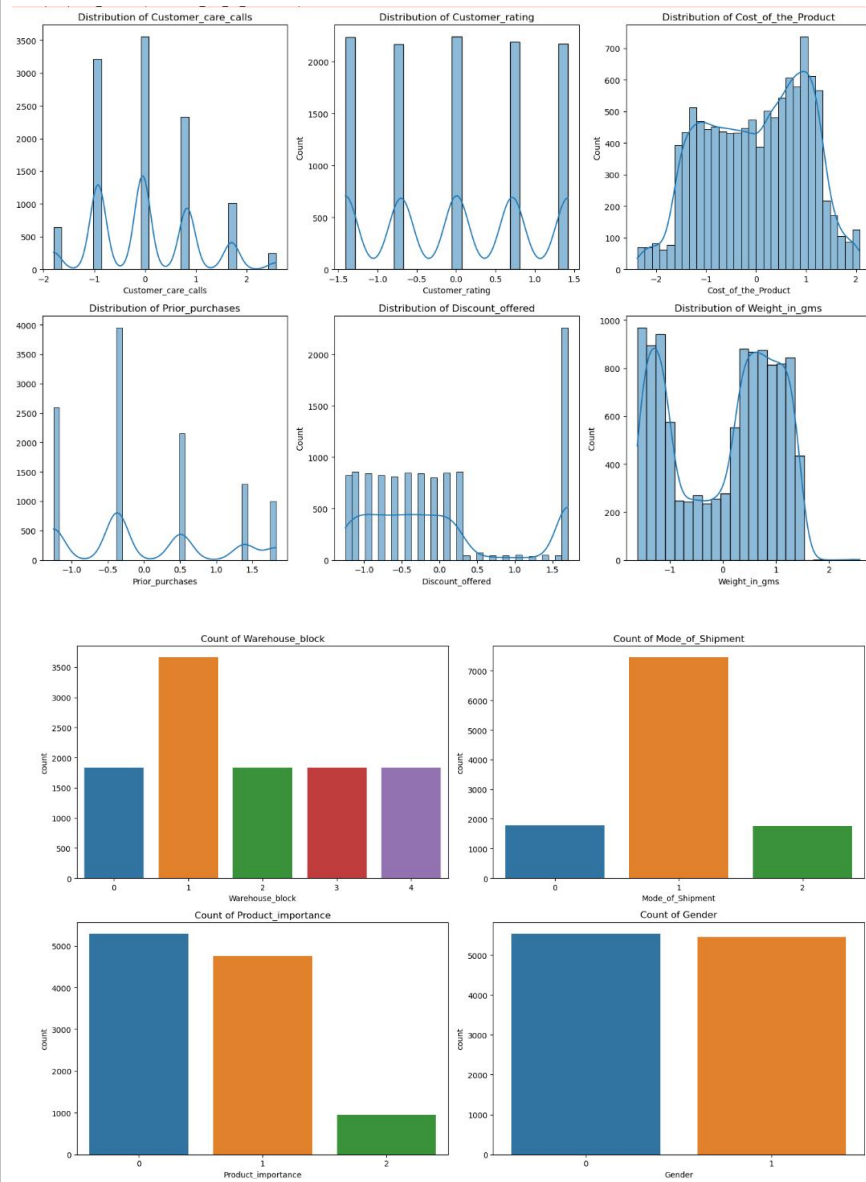


Date	15 June 2024
Team ID	SWTID1720196555
Project Title	Ecommerce Shipping Prediction Using Machine Learning
Maximum Marks	6 Marks

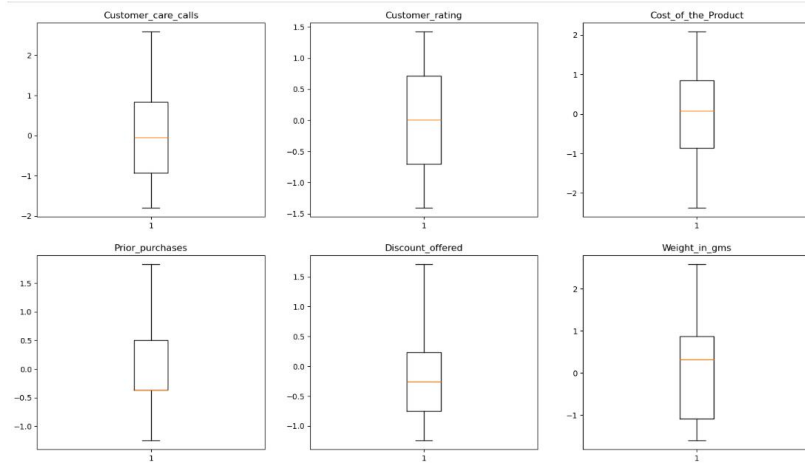
Identifies data sources, assesses quality issues like missing values and duplicates, and implements resolution plans to ensure accurate and reliable analysis.

Section	Description																																																																																																				
Data Overview	<table><tr><th></th><th>ID</th><th>Warehouse_block</th><th>Mode_of_Shipment</th><th>Customer_care_calls</th><th>Customer_rating</th><th>Cost_of_the_Product</th><th>Prior_purchases</th><th>Product_importance</th><th>Gender</th></tr><tr><td>count</td><td>10999.000000</td><td>10999.000000</td><td>10999.000000</td><td>1.0999000e+04</td><td>1.0999000e+04</td><td>1.0999000e+04</td><td>1.0999000e+04</td><td>10999.000000</td><td>10999.000000</td></tr><tr><td>mean</td><td>5500.00000</td><td>1.833167</td><td>0.998454</td><td>2.325624e-16</td><td>-5.975562e-17</td><td>-1.343694e-16</td><td>-7.235275e-17</td><td>0.604600</td><td>0.495861</td></tr><tr><td>std</td><td>3175.28214</td><td>1.343823</td><td>0.567099</td><td>1.000045e+00</td><td>1.000045e+00</td><td>1.000045e+00</td><td>1.000045e+00</td><td>0.641464</td><td>0.500000</td></tr><tr><td>min</td><td>1.00000</td><td>0.000000</td><td>0.000000</td><td>-1.799887e+00</td><td>-1.408199e+00</td><td>-2.376077e+00</td><td>-1.250497e+00</td><td>0.000000</td><td>0.000000</td></tr><tr><td>25%</td><td>2750.50000</td><td>1.000000</td><td>1.000000</td><td>-9.237994e-01</td><td>-7.007551e-01</td><td>-8.571765e-01</td><td>-3.708746e-01</td><td>0.000000</td><td>0.000000</td></tr><tr><td>50%</td><td>5500.00000</td><td>1.000000</td><td>1.000000</td><td>-4.771132e-02</td><td>6.689172e-03</td><td>7.913188e-02</td><td>-3.708746e-01</td><td>1.000000</td><td>0.000000</td></tr><tr><td>75%</td><td>8249.50000</td><td>3.000000</td><td>1.000000</td><td>8.283768e-01</td><td>7.141334e-01</td><td>8.489855e-01</td><td>5.087480e-01</td><td>1.000000</td><td>1.000000</td></tr><tr><td>max</td><td>10999.00000</td><td>4.000000</td><td>2.000000</td><td>2.580553e+00</td><td>1.421578e+00</td><td>2.076590e+00</td><td>1.828182e+00</td><td>2.000000</td><td>1.000000</td></tr><tr><td colspan="10"><div></div></td></tr></table>		ID	Warehouse_block	Mode_of_Shipment	Customer_care_calls	Customer_rating	Cost_of_the_Product	Prior_purchases	Product_importance	Gender	count	10999.000000	10999.000000	10999.000000	1.0999000e+04	1.0999000e+04	1.0999000e+04	1.0999000e+04	10999.000000	10999.000000	mean	5500.00000	1.833167	0.998454	2.325624e-16	-5.975562e-17	-1.343694e-16	-7.235275e-17	0.604600	0.495861	std	3175.28214	1.343823	0.567099	1.000045e+00	1.000045e+00	1.000045e+00	1.000045e+00	0.641464	0.500000	min	1.00000	0.000000	0.000000	-1.799887e+00	-1.408199e+00	-2.376077e+00	-1.250497e+00	0.000000	0.000000	25%	2750.50000	1.000000	1.000000	-9.237994e-01	-7.007551e-01	-8.571765e-01	-3.708746e-01	0.000000	0.000000	50%	5500.00000	1.000000	1.000000	-4.771132e-02	6.689172e-03	7.913188e-02	-3.708746e-01	1.000000	0.000000	75%	8249.50000	3.000000	1.000000	8.283768e-01	7.141334e-01	8.489855e-01	5.087480e-01	1.000000	1.000000	max	10999.00000	4.000000	2.000000	2.580553e+00	1.421578e+00	2.076590e+00	1.828182e+00	2.000000	1.000000	<div></div>									
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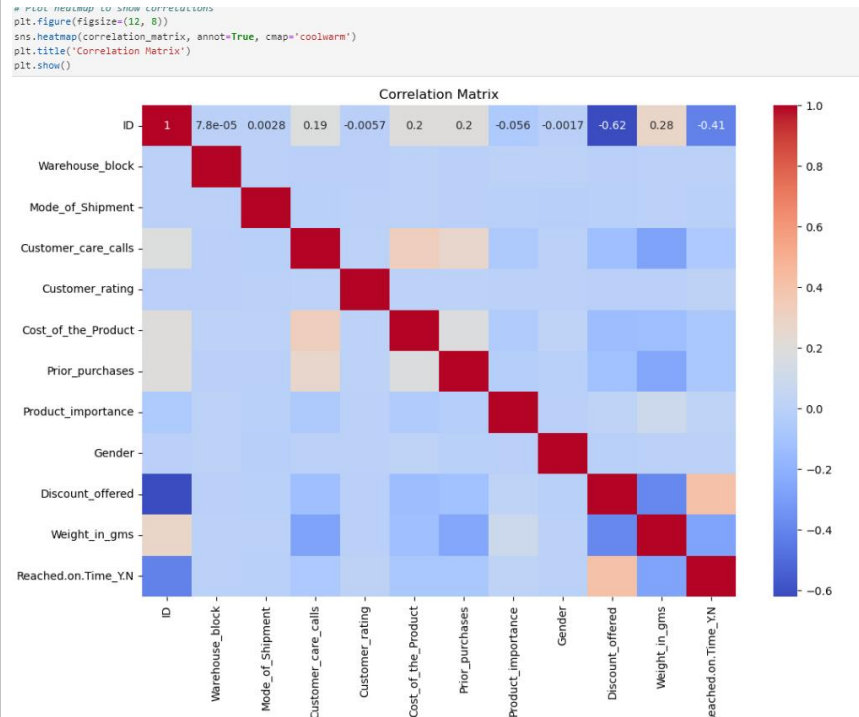
## Univariate Analysis



## Bivariate Analysis



## Multivariate Analysis



## Outliers and Anomalies

```
import matplotlib.pyplot as plt

c = 0

plt.figure(figsize=(18, 10))

for i in data.drop(columns=[
    'Warehouse_block', 'Mode_of_Shipment', 'Product_importance', 'Gender', 'Reached.on.Time_Y.N', 'ID'
]).columns:

    if str(data[i].dtype) == 'object':
        continue

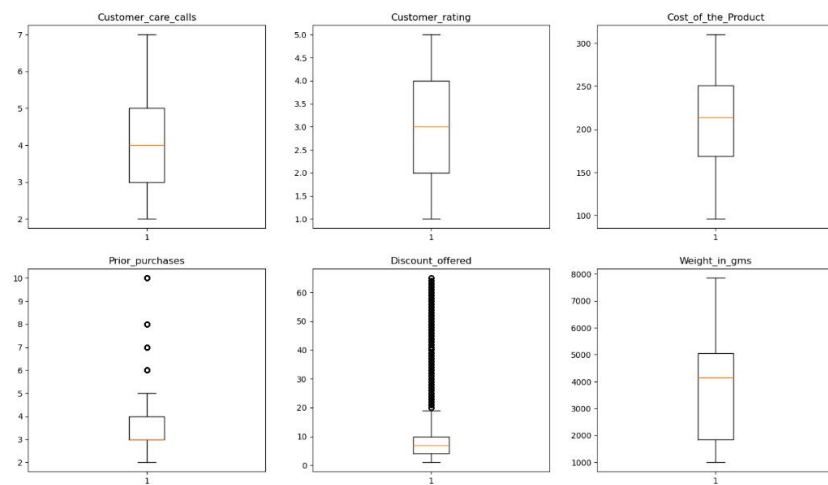
    plt.subplot(2, 3, c + 1)

    plt.boxplot(data[i])

    plt.title(i)

    c += 1

plt.show()
```



## Data Preprocessing Code Screenshots

### Loading Data

Code to load the dataset into the preferred environment (e.g., Python, R).

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

data = pd.read_csv('Train.csv')
```

## Handling Missing Data

```
[5]: data.isnull().any()
```

```
[5]: ID                False
Warehouse_block       False
Mode_of_Shipment       False
Customer_care_calls    False
Customer_rating        False
Cost_of_the_Product     False
Prior_purchases        False
Product_importance     False
Gender                 False
Discount_offered       False
Weight_in_gms          False
Reached.on.Time_Y.N    False
dtype: bool
```

```
[6]: data.isnull().sum()
```

```
[6]: ID                0
Warehouse_block       0
Mode_of_Shipment       0
Customer_care_calls    0
Customer_rating        0
Cost_of_the_Product     0
Prior_purchases        0
Product_importance     0
Gender                 0
Discount_offered       0
Weight_in_gms          0
Reached.on.Time_Y.N    0
dtype: int64
```

## Data Transformation

```
unique_values = {
    'Warehouse_block': data['Warehouse_block'].unique(),
    'Mode_of_Shipment': data['Mode_of_Shipment'].unique(),
    'Product_importance': data['Product_importance'].unique(),
    'Gender': data['Gender'].unique()
}
```

```
unique_values
```

```
{'Warehouse_block': array(['D', 'F', 'A', 'B', 'C'], dtype=object),
 'Mode_of_Shipment': array(['Flight', 'Ship', 'Road'], dtype=object),
 'Product_importance': array(['low', 'medium', 'high'], dtype=object),
 'Gender': array(['F', 'M'], dtype=object)}
```

	<pre> label_map={} for i in data.columns:     if str(data[i].dtype) == 'object':         temp={}         cats=data[i].unique()         for index in range(len(cats)):             temp[cats[index]]=index         label_map[i]=temp         #Labeling         data[i]=data[i].map(temp) label_map </pre> <p> {'Warehouse_block': {'D': 0, 'F': 1, 'A': 2, 'B': 3, 'C': 4},  'Mode_of_Shipment': {'Flight': 0, 'Ship': 1, 'Road': 2},  'Product_importance': {'low': 0, 'medium': 1, 'high': 2},  'Gender': {'F': 0, 'M': 1}} </p>
Feature Engineering	Attached the codes in final submissions
Save Processed Data	-