ML Data Cleaning and Feature Selection

In this assignment, we will use a dataset for predictive learning and check the quality of the data and determine which features are important.

Answer the following questions:

- What are the data types? (Only numeric and categorical)
- Are there missing values?
- What are the likely distributions of the numeric variables?
- Which independent variables are useful to predict a target (dependent variable)? (Use at least three methods)
- Which independent variables have missing data? How much?
- Do the training and test sets have the same data?
- In the predictor variables independent of all the other predictor variables?
- Which predictor variables are the most important?
- Do the ranges of the predictor variables make sense?
- What are the distributions of the predictor variables?
- Remove outliers and keep outliers (does if have an effect of the final predictive model)?
- Remove 1%, 5%, and 10% of your data randomly and impute the values back using at least 3 imputation methods. How well did the methods recover the missing values? That is remove some data, check the % error on residuals for numeric data and check for bias and variance of the error.

For categorical data, calculate the accuracy and a confusion matrix.

Abstract

Context

An international e-commerce company based wants to discover key insights from their customer database. They want to use some of the most advanced machine learning techniques to study their customers. The company sells electronic products.

Link to the Data Set: kaggle-dataset

Content

The dataset used for model building contained 10999 observations of 12 variables. The data contains the following information:

ID: ID Number of Customers.

Warehouse block: The Company have big Warehouse which is divided in to block such as A,B,C,D,E.

Mode of shipment:The Company Ships the products in multiple way such as Ship, Flight and Road.

Customer care calls: The number of calls made from enquiry for enquiry of the shipment.

Customer rating: The company has rated from every customer. 1 is the lowest (Worst), 5 is the highest (Best).

Cost of the product: Cost of the Product in US Dollars.

Prior purchases: The Number of Prior Purchase.

Product importance: The company has categorized the product in the various parameter such as low, medium, high.

Gender: Male and Female.

Discount offered: Discount offered on that specific product.

Weight in gms: It is the weight in grams.

Reached on time: It is the target variable, where 1 Indicates that the product has NOT reached on time and 0 indicates it has reached on time.

Summary: The dataset is consistent, with no missing values or outliers. In this model, we calculated the significance of predictor variables and used a logistic regression model to predict the target variable "Reached on time" and we try to answer each question below.

```
#install eli5 dependency for permutation sequence
!pip install eli5

Collecting eli5
  Downloading eli5-0.13.0.tar.gz (216 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0.0/216.2 kB ? eta -:--:--
━━━━━━━ ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 41.0/216.2 kB 1.2 MB/s eta
0:00:01 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ ━━━━━━━━━━━ 153.6/216.2 kB 2.1
MB/s eta 0:00:01 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 216.2/216.2
kB 2.4 MB/s eta 0:00:00
etadata (setup.py) ... ent already satisfied: attrs>17.1.0 in
/usr/local/lib/python3.10/dist-packages (from eli5) (23.2.0)
Requirement already satisfied: jinja2>=3.0.0 in
/usr/local/lib/python3.10/dist-packages (from eli5) (3.1.3)
Requirement already satisfied: numpy>=1.9.0 in
```

```
/usr/local/lib/python3.10/dist-packages (from eli5) (1.23.5)
Requirement already satisfied: scipy in
/usr/local/lib/python3.10/dist-packages (from eli5) (1.11.4)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-
packages (from eli5) (1.16.0)
Requirement already satisfied: scikit-learn>=0.20 in
/usr/local/lib/python3.10/dist-packages (from eli5) (1.2.2)
Requirement already satisfied: graphviz in
/usr/local/lib/python3.10/dist-packages (from eli5) (0.20.1)
Requirement already satisfied: tabulate>=0.7.7 in
/usr/local/lib/python3.10/dist-packages (from eli5) (0.9.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2>=3.0.0->eli5)
(2.1.5)
Requirement already satisfied: joblib>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20-
>eli5) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20-
>eli5) (3.2.0)
Building wheels for collected packages: eli5
  Building wheel for eli5 (setup.py) ... e=eli5-0.13.0-py2.py3-none-
any.whl size=107717
sha256=e323647e25f64a9dd837730a94080feb343ce6b0c608a11acc66a2f30bf1842
e
  Stored in directory:
/root/.cache/pip/wheels/b8/58/ef/2cf4c306898c2338d51540e0922c8e0d6028e
07007085c0004
Successfully built eli5
Installing collected packages: eli5
Successfully installed eli5-0.13.0

# importing required libraries for performing data analysis
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import pandas.testing as tm
from scipy import stats
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

plt.rcParams['figure.figsize'] = (8, 5)

# Reading the data from the file
data = pd.read_csv('/content/Train.csv')
data
```

```
          ID Warehouse_block Mode_of_Shipment  Customer_care_calls  \
0          1               D           Flight                    4   
1          2               F           Flight                    4   
2          3               A           Flight                    2   
3          4               B           Flight                    3   
4          5               C           Flight                    2   
...      ...             ...              ...                  ...   
10994  10995               A             Ship                    4   
10995  10996               B             Ship                    4   
10996  10997               C             Ship                    5   
10997  10998               F             Ship                    5   
10998  10999               D             Ship                    2   

       Customer_rating  Cost_of_the_Product  Prior_purchases  \
0                    2                  177                3   
1                    5                  216                2   
2                    2                  183                4   
3                    3                  176                4   
4                    2                  184                3   
...                ...                  ...              ...   
10994                1                  252                5   
10995                1                  232                5   
10996                4                  242                5   
10997                2                  223                6   
10998                5                  155                5   

      Product_importance Gender  Discount_offered  Weight_in_gms  \
0                    low      F                44           1233   
1                    low      M                59           3088   
2                    low      M                48           3374   
3                 medium      M                10           1177   
4                 medium      F                46           2484   
...                  ...    ...               ...            ...   
10994             medium      F                 1           1538   
10995             medium      F                 6           1247   
10996                low      F                 4           1155   
10997             medium      M                 2           1210   
10998                low      F                 6           1639   

       Reached.on.Time_Y.N  
0                        1  
1                        1  
2                        1  
3                        1  
4                        1  
...                    ...  
10994                    1  
10995                    0  
10996                    0  
10997                    0  
```

```
10998                    0

[10999 rows x 12 columns]
```

What are the data types? (Only numeric and categorical)

```
numerical_columns = []
categorical_columns = []
for col in data.columns:
  if data[col].dtype == 'int64':
    numerical_columns.append(col)
  if data[col].dtype == 'object':
    categorical_columns.append(col)

print("Numerical Columns: ", numerical_columns)
print("Categorical Columns: ", categorical_columns)
print("There are", len(numerical_columns), "numerical_Columns")
print("There are", len(categorical_columns), "categorical_columns")

Numerical Columns:  ['ID', 'Customer_care_calls', 'Customer_rating',
'Cost_of_the_Product', 'Prior_purchases', 'Discount_offered',
'Weight_in_gms', 'Reached.on.Time_Y.N']
Categorical Columns:  ['Warehouse_block', 'Mode_of_Shipment',
'Product_importance', 'Gender']
There are 8 numerical_Columns
There are 4 categorical_columns
```

Q2: Are there missing values?

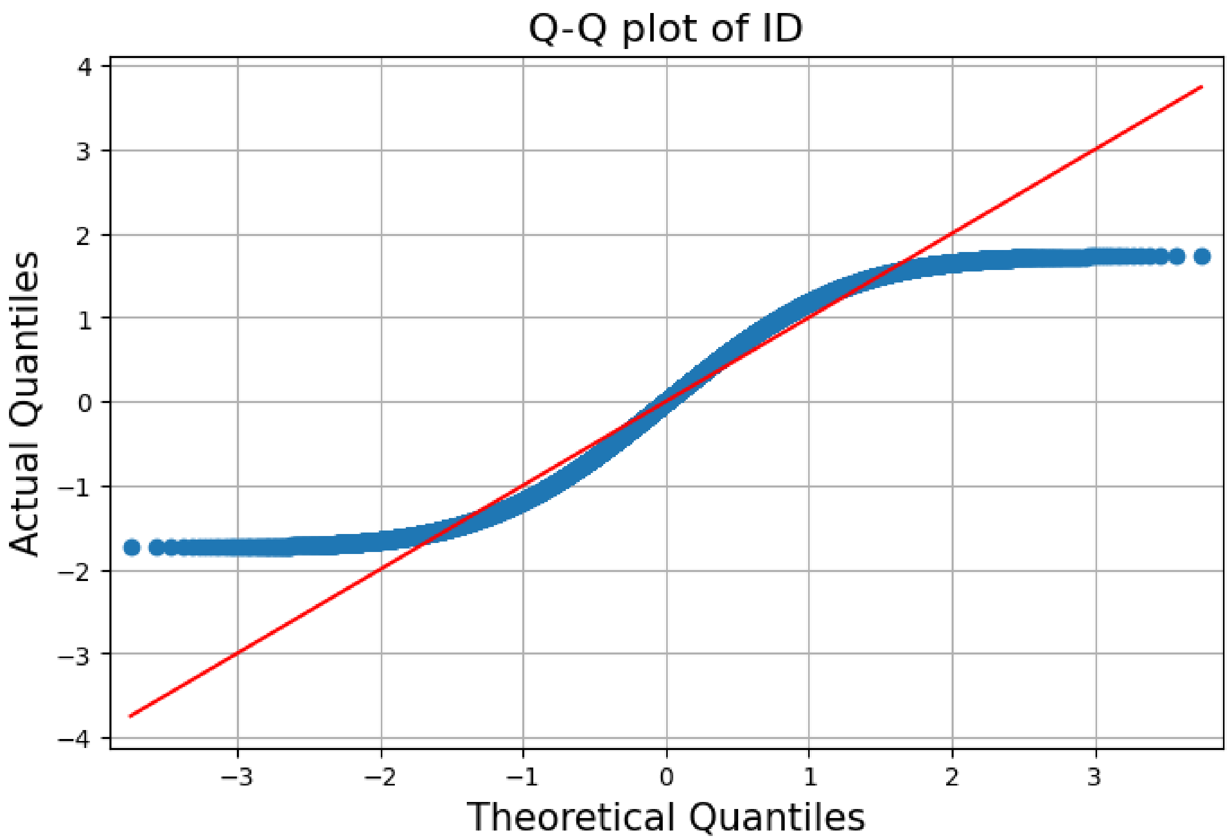
```
data.isnull().sum()

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
```

Q3: What are the likely distributions of the numeric variables?

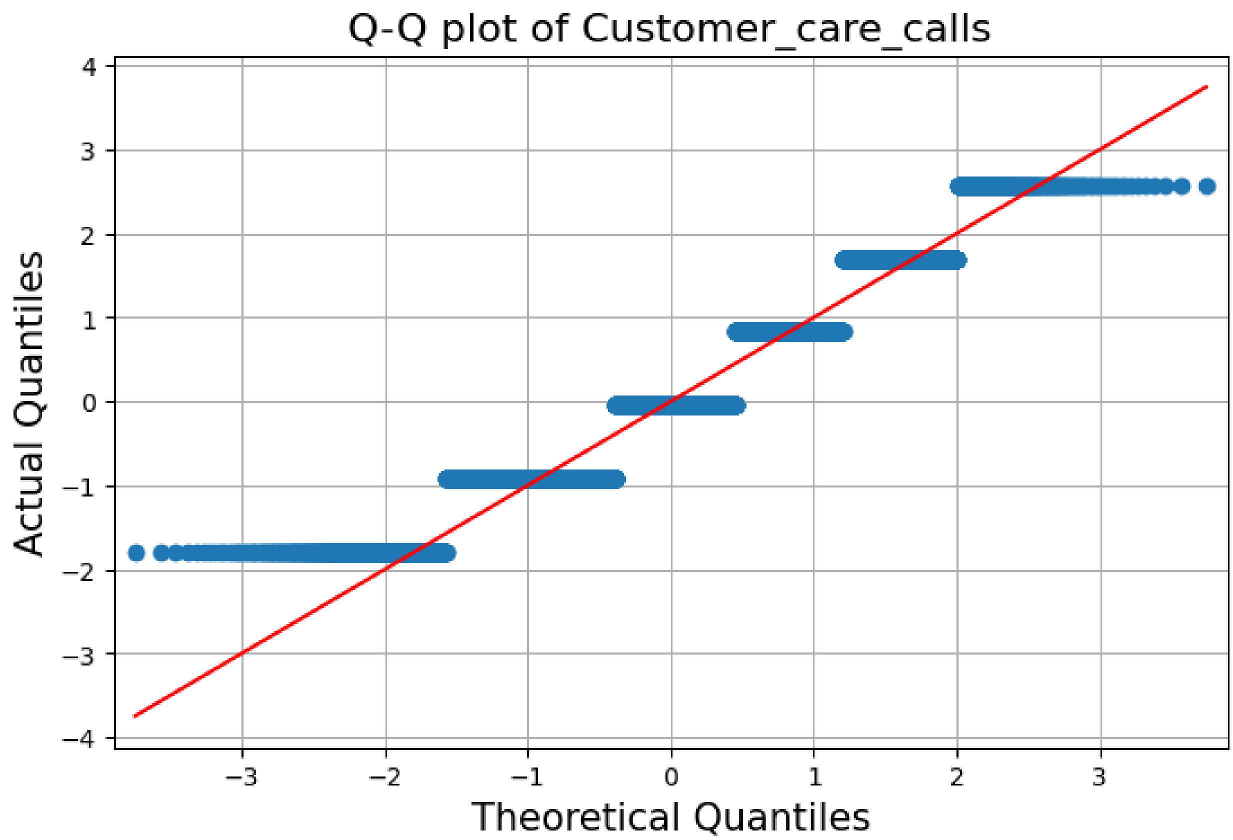
Q-Q Plot, Normality Tests and sns plots on numerical data to plot the distributions of numeric variables

```
# Q-Q plot to check how well the numerical column or variable aligns
with normal distribution.
from statsmodels.graphics.gofplots import qqplot

for col in numerical_columns:
  plt.figure(figsize=(3,4))
  fig = qqplot(data[col], line="s", fit="True")
  plt.xlabel("Theoretical Quantiles", fontsize=15)
  plt.ylabel("Actual Quantiles", fontsize=15)
  plt.title("Q-Q plot of {}". format(col), fontsize=16)
  plt.grid(True)
  plt.show()
```

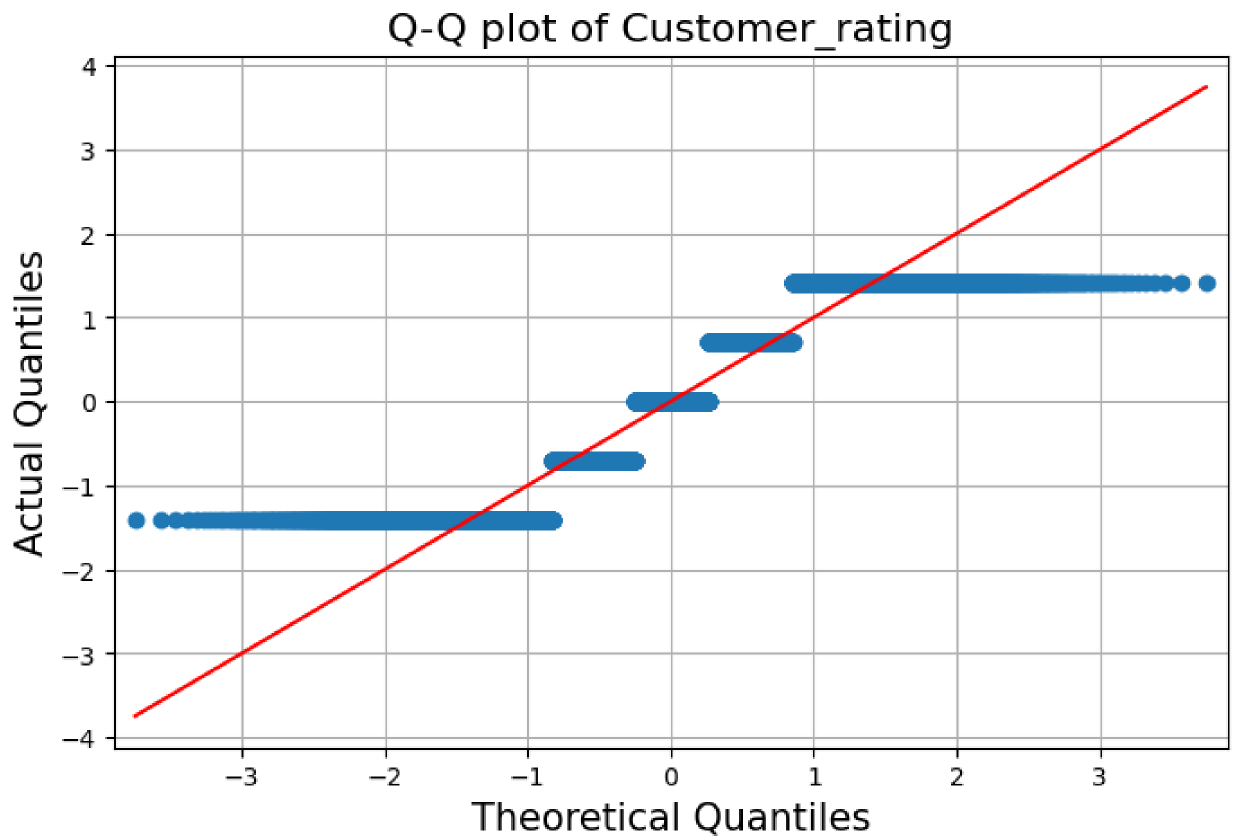
```
<Figure size 300x400 with 0 Axes>
```



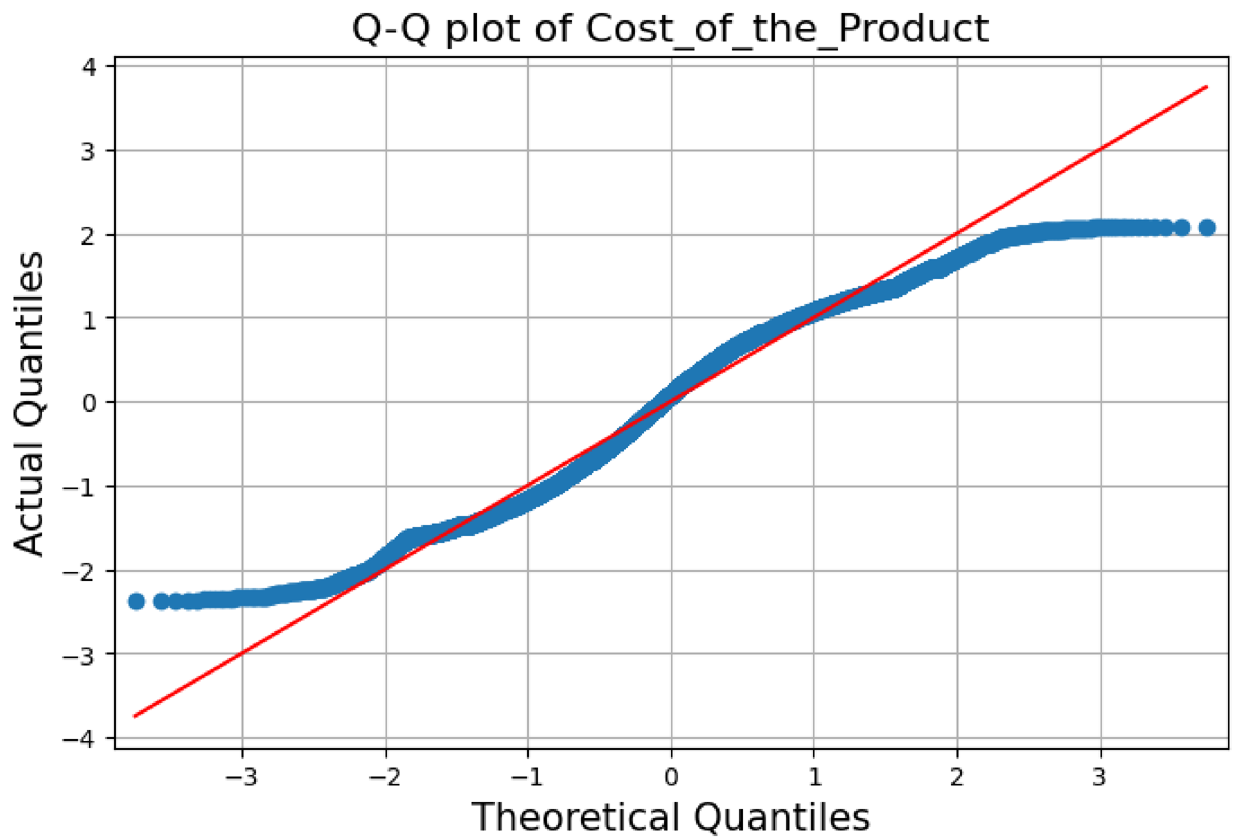

```
<Figure size 300x400 with 0 Axes>
```



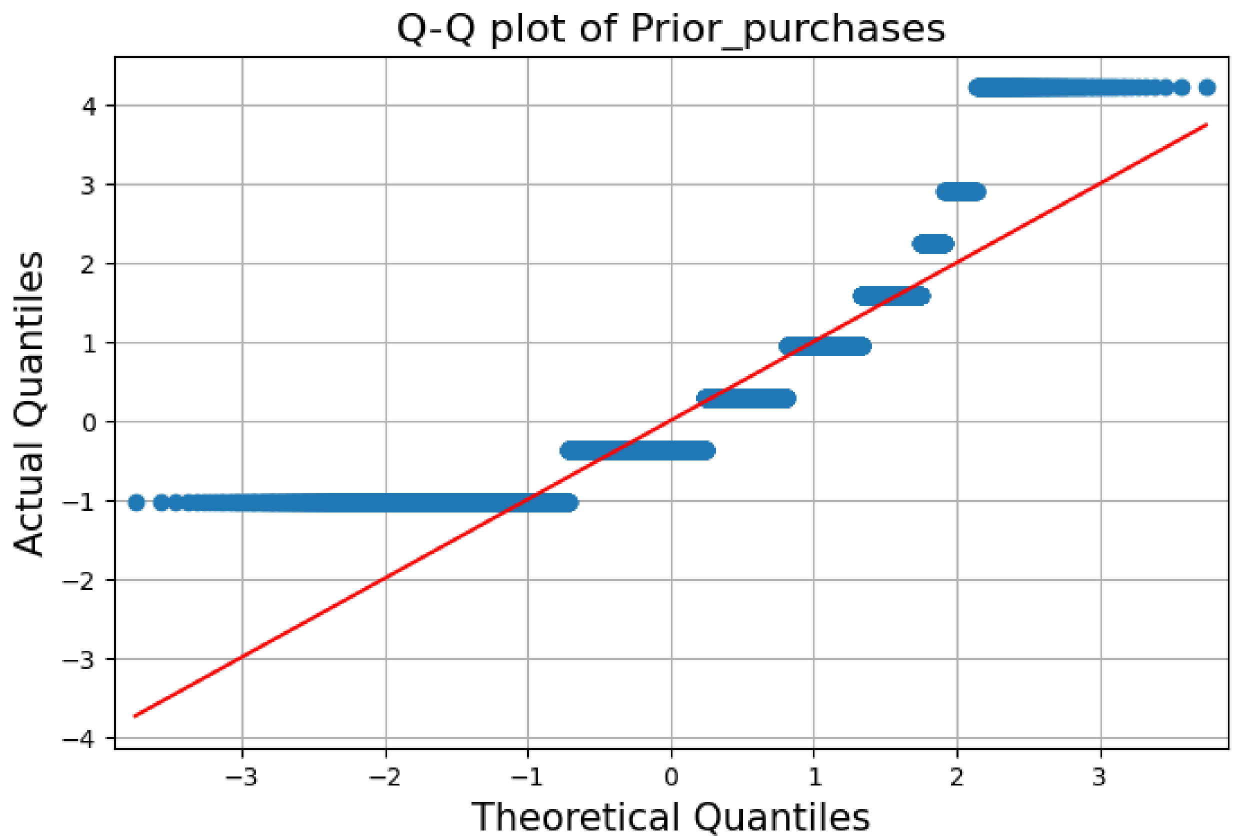

```
<Figure size 300x400 with 0 Axes>
```



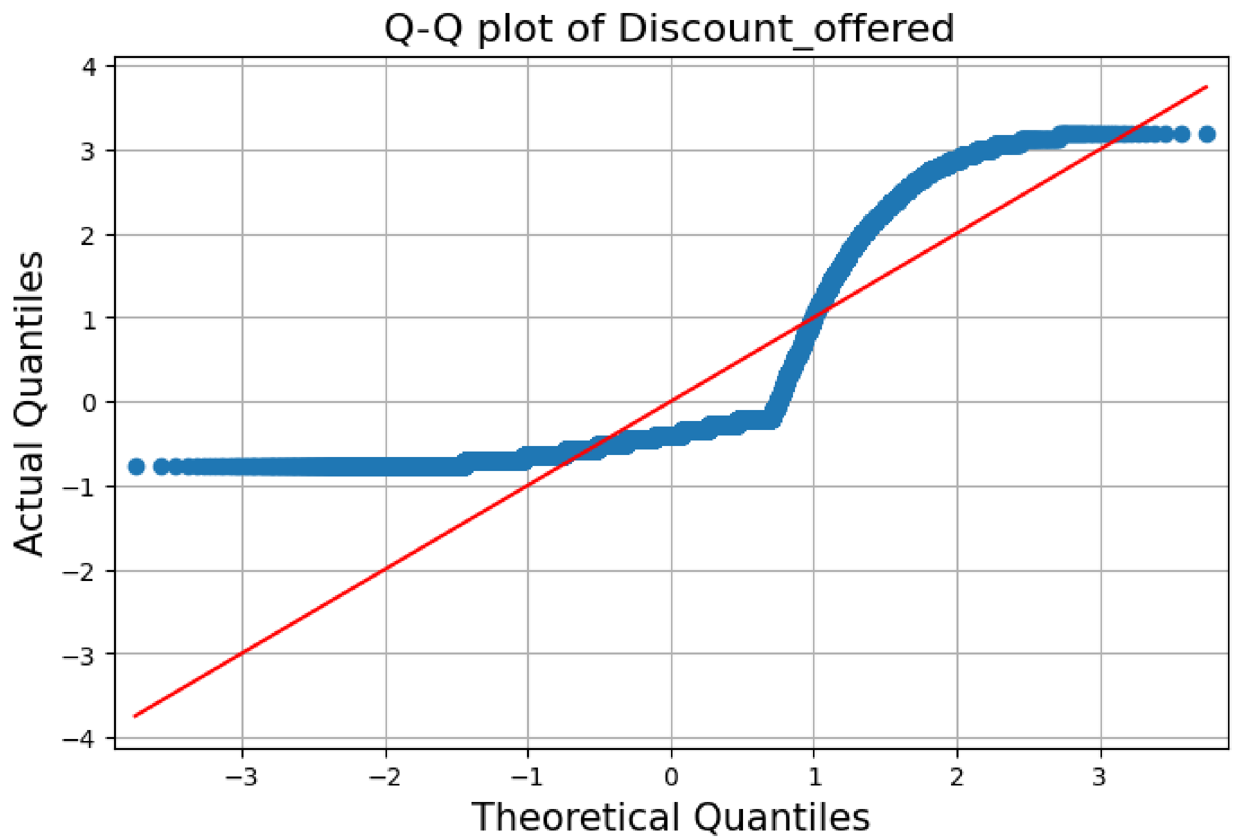

```
<Figure size 300x400 with 0 Axes>
```



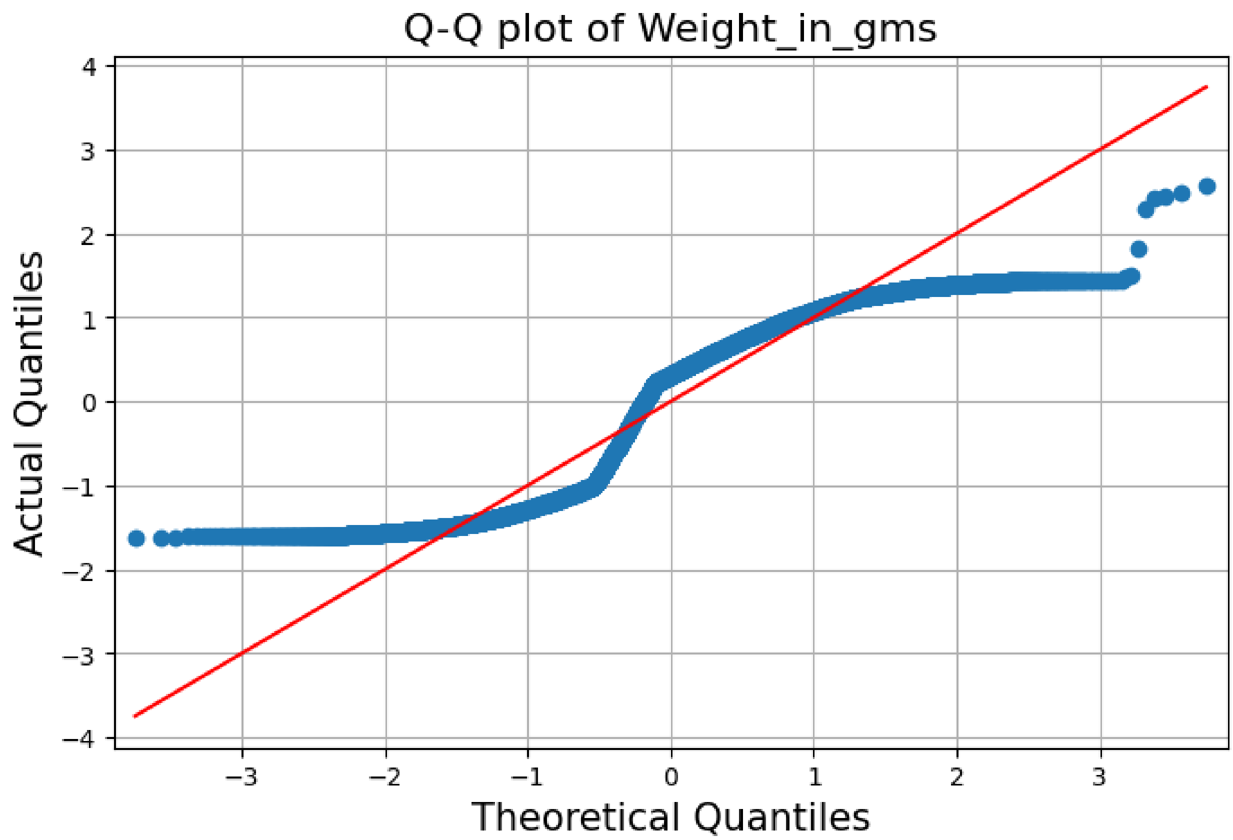

```
<Figure size 300x400 with 0 Axes>
```



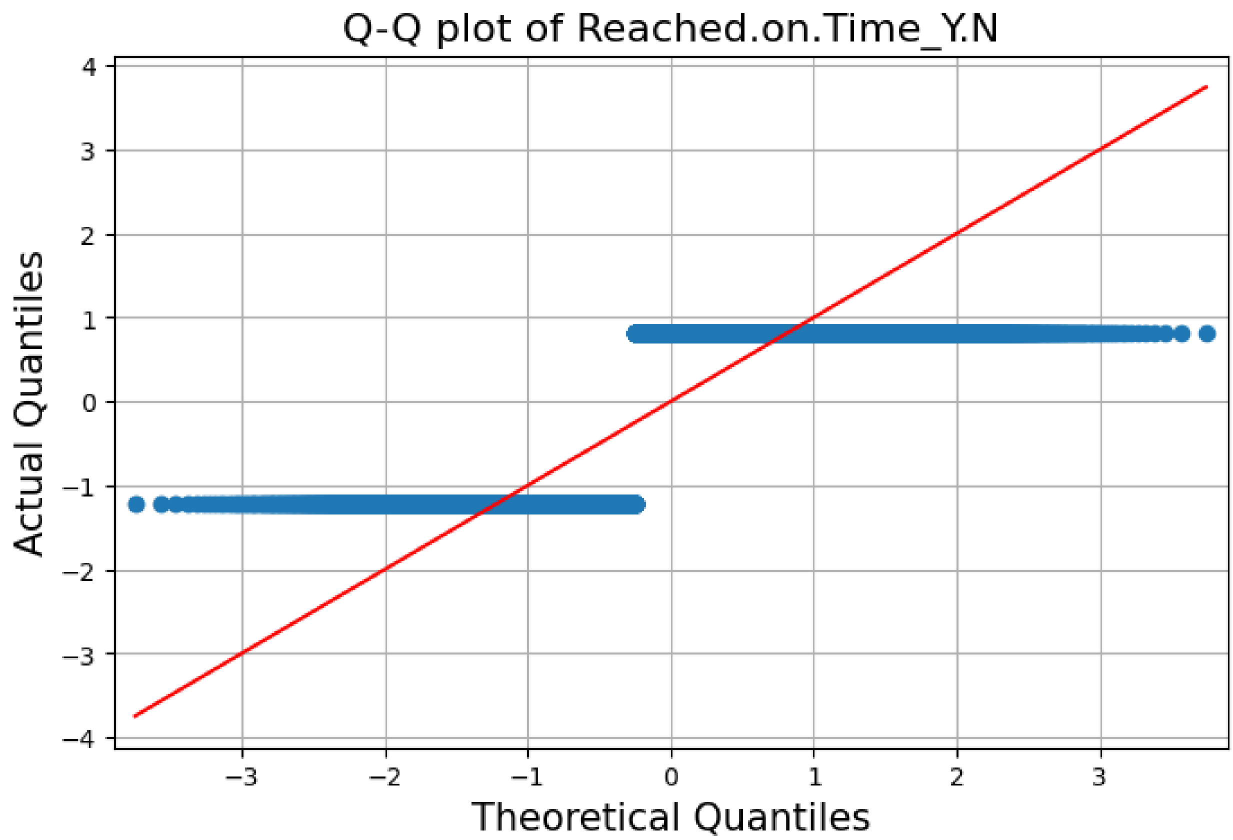

```
<Figure size 300x400 with 0 Axes>
```




```
<Figure size 300x400 with 0 Axes>
```



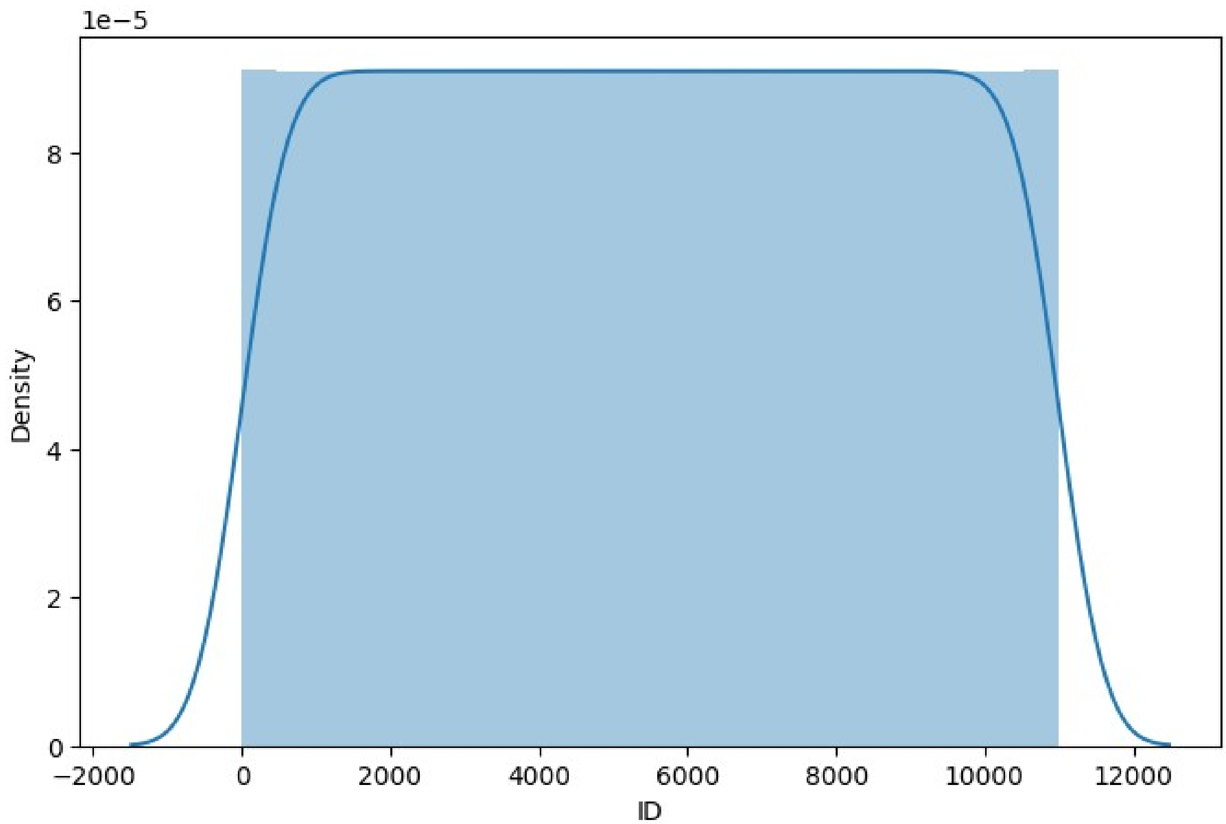

```
<Figure size 300x400 with 0 Axes>
```



SNS plots for statistical visualization

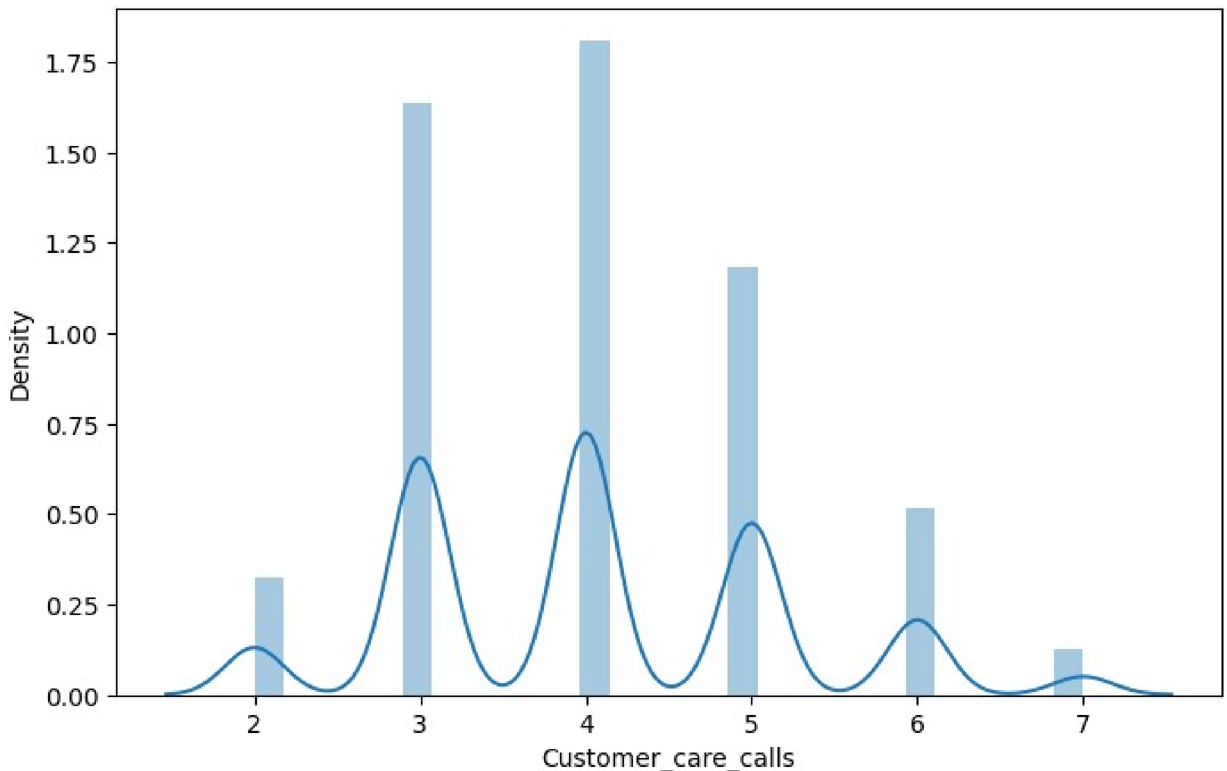
```
sns.distplot(data['ID'])
```

```
<Axes: xlabel='ID', ylabel='Density'>
```



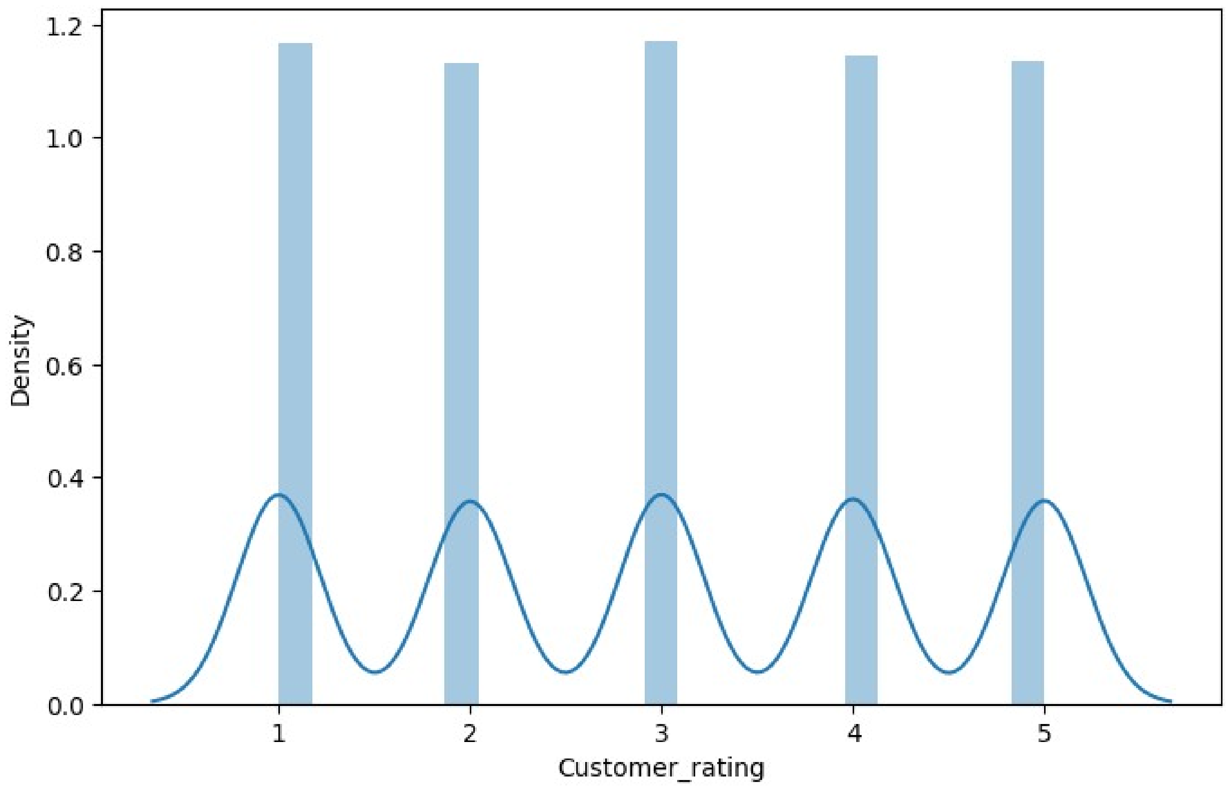

```
sns.distplot(data['Customer_care_calls'])
```

```
<Axes: xlabel='Customer_care_calls', ylabel='Density'>
```



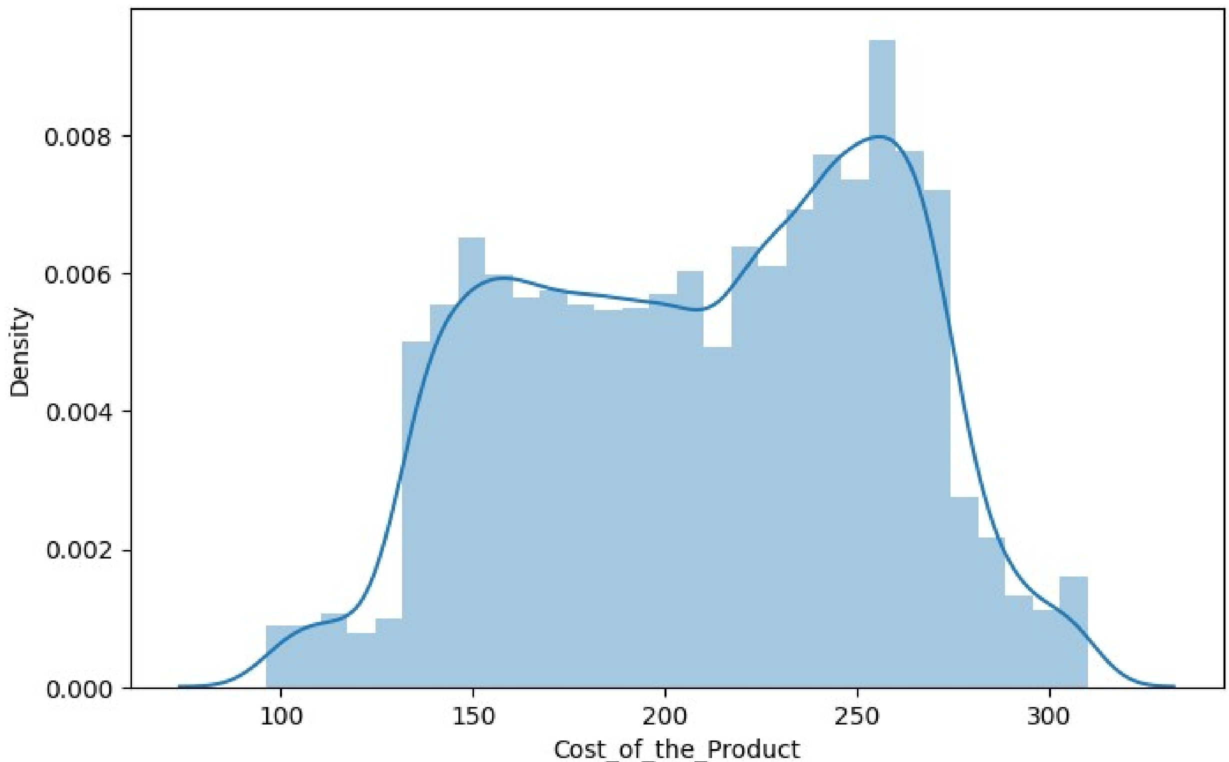

```
sns.distplot(data['Customer_rating'])
```

```
<Axes: xlabel='Customer_rating', ylabel='Density'>
```



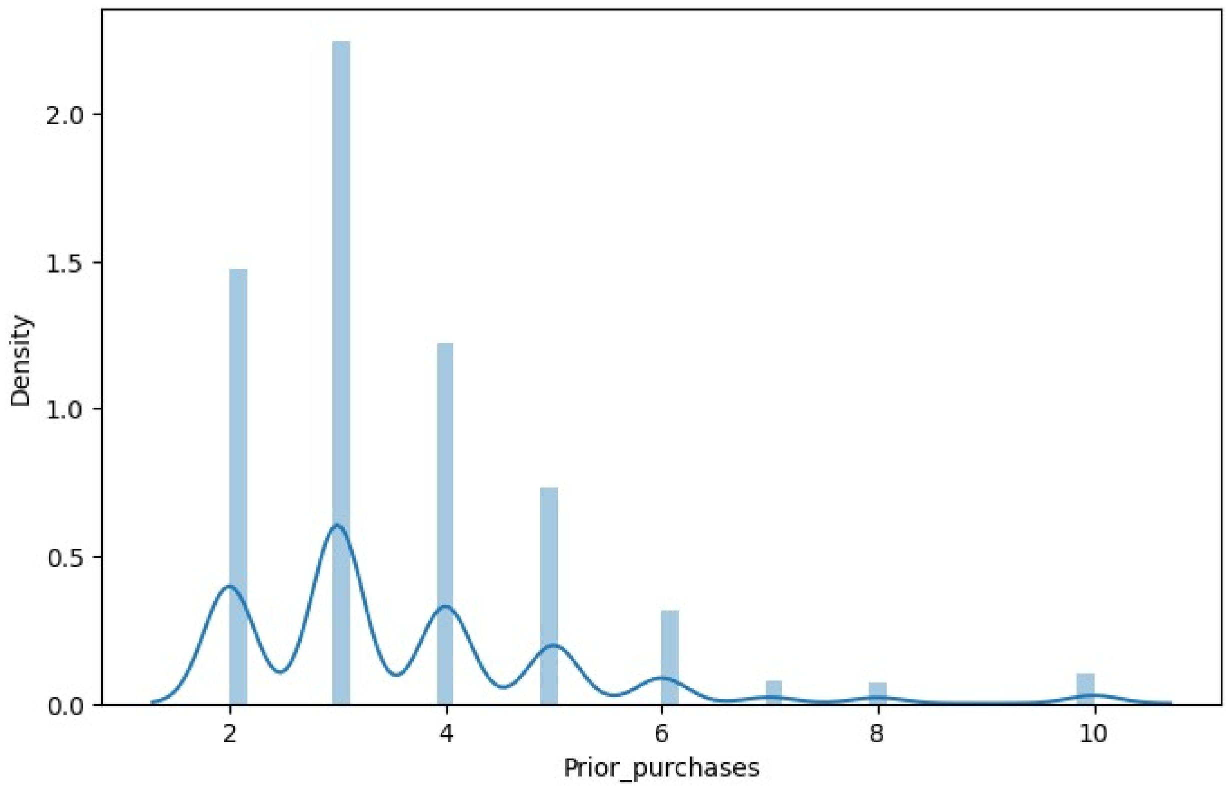

```
sns.distplot(data['Cost_of_the_Product'])
```

```
<Axes: xlabel='Cost_of_the_Product', ylabel='Density'>
```



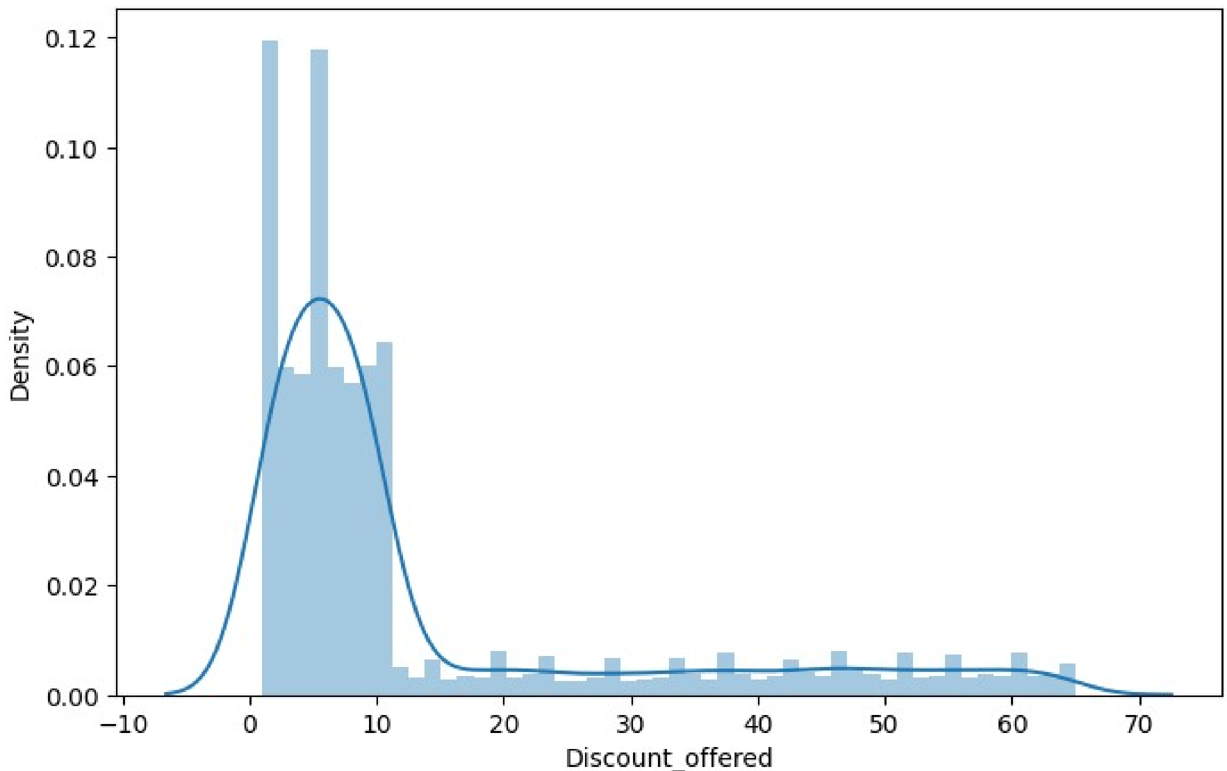

```
sns.distplot(data['Prior_purchases'])
```

```
<Axes: xlabel='Prior_purchases', ylabel='Density'>
```



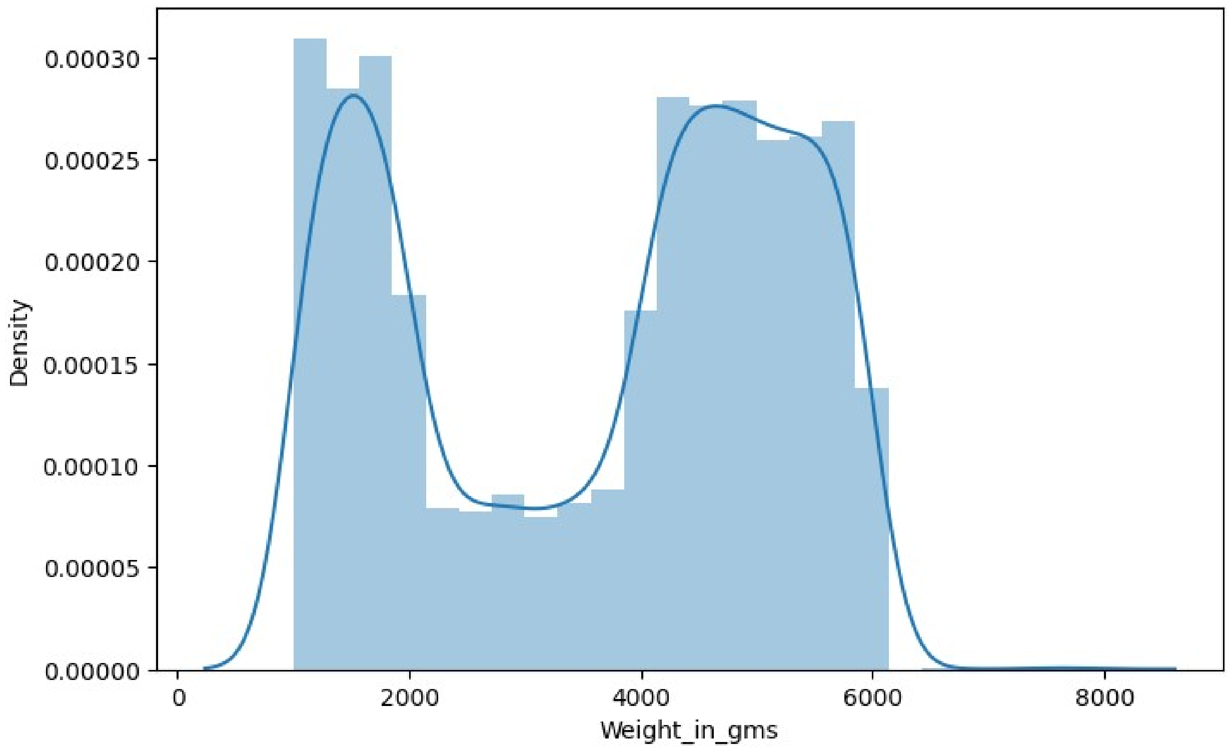

```
sns.distplot(data['Discount_offered'])
```

```
<Axes: xlabel='Discount_offered', ylabel='Density'>
```



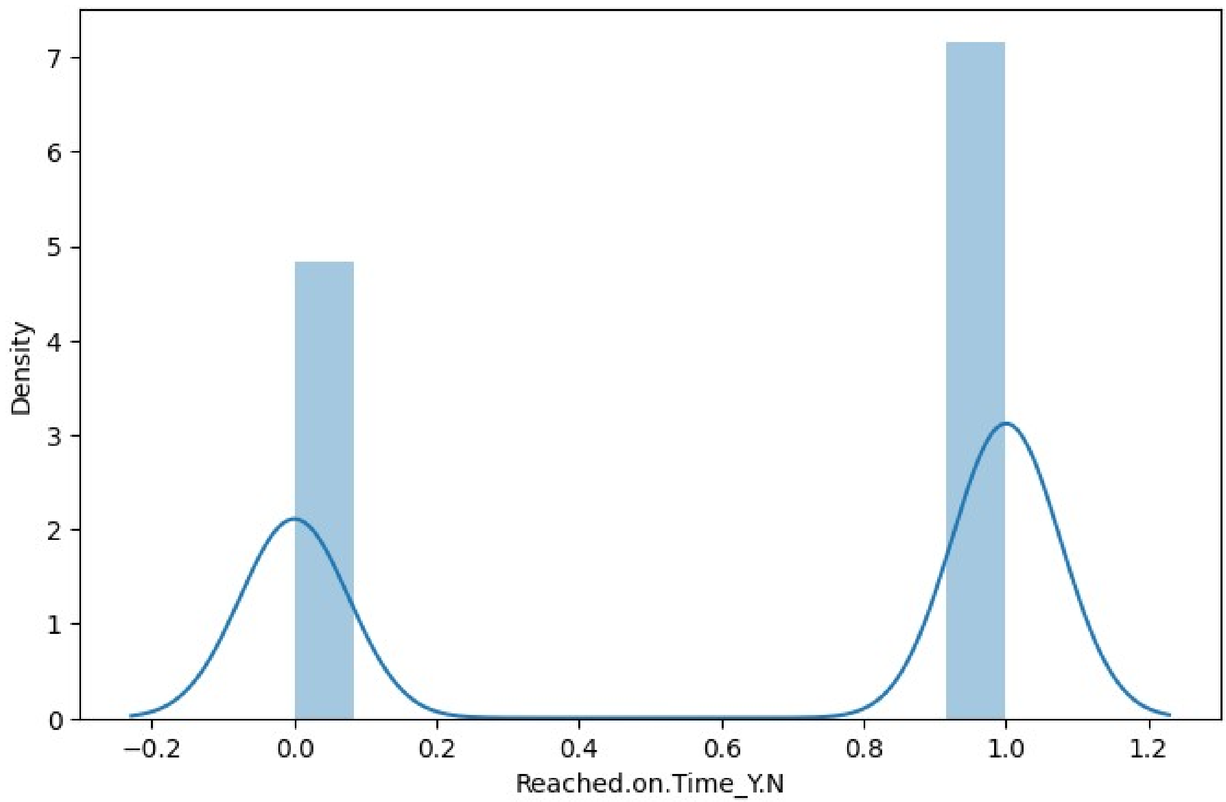

```
sns.distplot(data['Weight_in_gms'])
```

```
<Axes: xlabel='Weight_in_gms', ylabel='Density'>
```




```
sns.distplot(data['Reached.on.Time_Y.N'])
```

```
<Axes: xlabel='Reached.on.Time_Y.N', ylabel='Density'>
```




```
#Anderson-darling tests for normality to verify normality from Q-Q
plots
for col in numerical_columns:
  print("Anderson-Darling test for {}".format(col))
  print(stats.anderson(data[col], dist='norm'))

Anderson-Darling test for ID
AndersonResult(statistic=122.26710413957699,
critical_values=array([0.576, 0.656, 0.787, 0.918, 1.092]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=5500.0, scale=3175.282139695096)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
Anderson-Darling test for Customer_care_calls
AndersonResult(statistic=392.3605288329545,
critical_values=array([0.576, 0.656, 0.787, 0.918, 1.092]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=4.054459496317847, scale=1.141489647105304)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
Anderson-Darling test for Customer_rating
AndersonResult(statistic=393.2367465937041,
critical_values=array([0.576, 0.656, 0.787, 0.918, 1.092]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=2.9905445949631786, scale=1.4136031713232975)
```

```
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
Anderson-Darling test for Cost_of_the_Product
AndersonResult(statistic=104.94426119000309,
critical_values=array([0.576, 0.656, 0.787, 0.918, 1.092]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=210.19683607600692, scale=48.06327175153258)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
Anderson-Darling test for Prior_purchases
AndersonResult(statistic=543.4978789820234,
critical_values=array([0.576, 0.656, 0.787, 0.918, 1.092]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=3.5675970542776616, scale=1.5228600423832288)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
Anderson-Darling test for Discount_offered
AndersonResult(statistic=1417.2200070604358,
critical_values=array([0.576, 0.656, 0.787, 0.918, 1.092]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=13.37321574688608, scale=16.205527080640096)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
Anderson-Darling test for Weight_in_gms
AndersonResult(statistic=411.0426908915688,
critical_values=array([0.576, 0.656, 0.787, 0.918, 1.092]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=3634.016728793527, scale=1635.3772514018872)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
Anderson-Darling test for Reached.on.Time_Y.N
AndersonResult(statistic=2074.633641649887,
critical_values=array([0.576, 0.656, 0.787, 0.918, 1.092]),
significance_level=array([15. , 10. ,  5. ,  2.5,  1. ]), fit_result=
params: FitParams(loc=0.5966906082371125, scale=0.4905841493710292)
 success: True
 message: '`anderson` successfully fit the distribution to the data.')
```

Q3 answer:

Based on the Anderson-Darling test, we see that the statistic is exceeding the critical_values for each column hence it rejects null hypothesis of normal distributions.

The QQ plot and sns plots indicate the 'Cost_of_product' roughly follows normal distribution.

The QQ plot and sns plots indicate ID, 'Weight_in_gms' and 'Reached.on.Time_Y.N' follows uniform distribution.

The QQ plot and sns plots indicate the 'Discount_offered' column roughly follows pastero distribution.

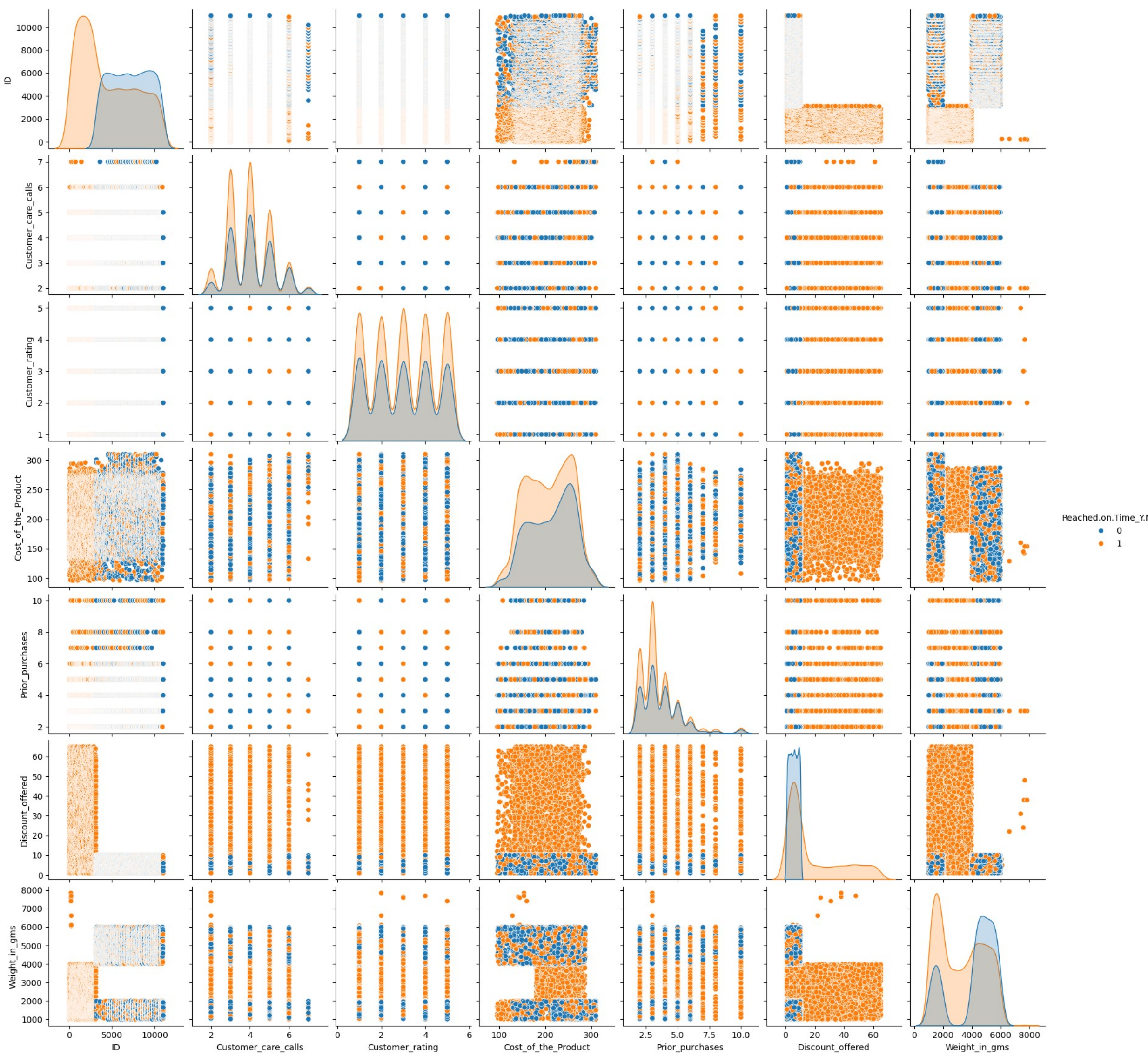
The distribution of 'Customer_care_calls', 'Customer_rating', 'Prior_purchases' indicate no definite distribution pattern.

Q4: Which independent variables are useful to predict a target (dependent variable)? (Use at least three methods)

The three methods used here to filter independent variables for better model are correlation matrix(pairplot), Logit Regression Results from statsmodel, Permutation Importance.

```
sns.pairplot(data, hue="Reached.on.Time_Y.N")
```

```
<seaborn.axisgrid.PairGrid at 0x7d25e296c790>
```



Based on the pairplot analysis, it is evident that plots like "discount_offered vs cost_of_product" and "cost_of_product vs weight_in_grams" provide sufficient evidence to categorize whether the product reached on time. There appears to be a linear relationship in these plots.

As a result, we intend to enhance our predictive model by incorporating dummy variables into the categorical_columns, thus introducing additional predictors.

```
# dropping ID column as it is just unique value representing data.
data = data.drop("ID", 1)

#adding dummy data to categorical_columns to include additional
predictor varibles
data = pd.get_dummies(data)
data
```

```
       Customer_care_calls  Customer_rating  Cost_of_the_Product  \
0                        4                2                  177
1                        4                5                  216
2                        2                2                  183
3                        3                3                  176
4                        2                2                  184
...                    ...              ...                  ...
10994                    4                1                  252
10995                    4                1                  232
10996                    5                4                  242
10997                    5                2                  223
10998                    2                5                  155

       Prior_purchases  Discount_offered  Weight_in_gms
Reached.on.Time_Y.N  \
0                    3                44           1233
1
1                    2                59           3088
1
2                    4                48           3374
1
3                    4                10           1177
1
4                    3                46           2484
1
...                ...               ...            ...
...
10994                5                 1           1538
1
10995                5                 6           1247
0
10996                5                 4           1155
0
10997                6                 2           1210
0
10998                5                 6           1639
0

       Warehouse_block_A  Warehouse_block_B  Warehouse_block_C  \
```

```
0                        0                   0                   0
1                        0                   0                   0
2                        1                   0                   0
3                        0                   1                   0
4                        0                   0                   1
...                    ...                 ...                 ...
10994                    1                   0                   0
10995                    0                   1                   0
10996                    0                   0                   1
10997                    0                   0                   0
10998                    0                   0                   0

       Warehouse_block_D  Warehouse_block_F
Mode_of_Shipment_Flight  \
0                        1                   0                         1

1                        0                   1                         1

2                        0                   0                         1

3                        0                   0                         1

4                        0                   0                         1

...                    ...                 ...                       ...

10994                    0                   0                         0

10995                    0                   0                         0

10996                    0                   0                         0

10997                    0                   1                         0

10998                    1                   0                         0


       Mode_of_Shipment_Road  Mode_of_Shipment_Ship
Product_importance_high  \
0                            0                        0
0
1                            0                        0
0
2                            0                        0
0
3                            0                        0
0
4                            0                        0
0
...                        ...                      ...
```

```
...
10994                          0                         1
0
10995                          0                         1
0
10996                          0                         1
0
10997                          0                         1
0
10998                          0                         1
0

       Product_importance_low  Product_importance_medium  Gender_F
Gender_M
0                           1                          0         1
0
1                           1                          0         0
1
2                           1                          0         0
1
3                           0                          1         0
1
4                           0                          1         1
0
...                       ...                        ...       ...
...
10994                       0                          1         1
0
10995                       0                          1         1
0
10996                       1                          0         1
0
10997                       0                          1         0
1
10998                       1                          0         1
0

[10999 rows x 20 columns]
```

```
import statsmodels.api as sm

model = sm.Logit(
    data["Reached.on.Time_Y.N"],
    data[
        [
            "Customer_care_calls",
            "Customer_rating",
            "Cost_of_the_Product",
            "Prior_purchases",
            "Discount_offered",
```

```
            "Weight_in_gms",
            "Mode_of_Shipment_Flight",
            "Mode_of_Shipment_Road",
            "Mode_of_Shipment_Ship",
            "Warehouse_block_A",
            "Warehouse_block_B",
            "Warehouse_block_C",
            "Warehouse_block_D",
            "Warehouse_block_F",
            "Product_importance_high",
            "Product_importance_low",
            "Product_importance_medium",
            "Gender_F",
            "Gender_M",
        ]
    ],
).fit()

model.summary()

Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.545802
         Iterations: 35

<class 'statsmodels.iolib.summary.Summary'>
"""
                            Logit Regression Results

======================================================================
=========
Dep. Variable:     Reached.on.Time_Y.N   No. Observations:
10999
Model:                           Logit   Df Residuals:
10983
Method:                            MLE   Df Model:
15
Date:                 Mon, 29 Jan 2024   Pseudo R-squ.:
0.1906
Time:                         17:56:06   Log-Likelihood:
-6003.3
converged:                       False   LL-Null:
-7417.0
Covariance Type:             nonrobust   LLR p-value:
0.000
======================================================================
=======================
                                coef    std err          z      P>|z|
[0.025      0.975]
----------------------------------------------------------------------
-----------------------
```

```
Customer_care_calls                -0.1071      0.022     -4.979      0.000
-0.149      -0.065
Customer_rating                     0.0248      0.015      1.605      0.108
-0.005       0.055
Cost_of_the_Product                -0.0020      0.001     -3.955      0.000
-0.003      -0.001
Prior_purchases                    -0.0771      0.015     -5.082      0.000
-0.107      -0.047
Discount_offered                    0.1118      0.004     25.087      0.000
0.103       0.121
Weight_in_gms                      -0.0002   1.61e-05    -14.875      0.000
-0.000      -0.000
Mode_of_Shipment_Flight             0.3731        nan        nan        nan
nan         nan
Mode_of_Shipment_Road               0.3385        nan        nan        nan
nan         nan
Mode_of_Shipment_Ship               0.3529        nan        nan        nan
nan         nan
Warehouse_block_A                   0.1647   2.63e+06   6.27e-08      1.000
-5.15e+06    5.15e+06
Warehouse_block_B                   0.2445   2.63e+06    9.3e-08      1.000
-5.15e+06    5.15e+06
Warehouse_block_C                   0.2189   2.64e+06    8.3e-08      1.000
-5.17e+06    5.17e+06
Warehouse_block_D                   0.2257   2.63e+06   8.57e-08      1.000
-5.16e+06    5.16e+06
Warehouse_block_F                   0.2106   2.61e+06   8.06e-08      1.000
-5.12e+06    5.12e+06
Product_importance_high             0.5800   1.87e+06   3.11e-07      1.000
-3.66e+06    3.66e+06
Product_importance_low              0.2373   1.87e+06   1.27e-07      1.000
-3.66e+06    3.66e+06
Product_importance_medium           0.2471   1.95e+06   1.27e-07      1.000
-3.81e+06    3.81e+06
Gender_F                            0.5067    1.1e+06    4.6e-07      1.000
-2.16e+06    2.16e+06
Gender_M                            0.5577    1.1e+06   5.06e-07      1.000
-2.16e+06    2.16e+06
======================================================================
=======================
"""
```

The model results may become confused due to the presence of multiple dummy variables for the same category, such as both 'Gender_M' and 'Gender_F'. Therefore, we can exclude one variable from our predictors and perform analysis again.

```
import statsmodels.api as sm

model = sm.Logit(
```

```
    data["Reached.on.Time_Y.N"],
    data[
        [
            "Customer_care_calls",
            "Customer_rating",
            "Cost_of_the_Product",
            "Prior_purchases",
            "Discount_offered",
            "Weight_in_gms",
            "Warehouse_block_A",
            "Warehouse_block_B",
            "Warehouse_block_C",
            "Warehouse_block_D",
            "Mode_of_Shipment_Flight",
            "Mode_of_Shipment_Road",
            "Product_importance_high",
            "Product_importance_low",
            "Gender_F",
        ]
    ],
).fit()

model.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.548155
         Iterations 8

<class 'statsmodels.iolib.summary.Summary'>
"""
                            Logit Regression Results

======================================================================
=========
Dep. Variable:     Reached.on.Time_Y.N   No. Observations:
10999
Model:                           Logit   Df Residuals:
10984
Method:                            MLE   Df Model:
14
Date:                 Mon, 29 Jan 2024   Pseudo R-squ.:
0.1871
Time:                         17:42:11   Log-Likelihood:
-6029.2
converged:                        True   LL-Null:
-7417.0
Covariance Type:             nonrobust   LLR p-value:
0.000
======================================================================
=====================
```

```
                              coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------------
Customer_care_calls        -0.0406      0.019     -2.100      0.036
-0.078      -0.003
Customer_rating             0.0512      0.015      3.416      0.001
0.022       0.081
Cost_of_the_Product        -0.0001      0.000     -0.239      0.811
-0.001       0.001
Prior_purchases            -0.0428      0.014     -3.001      0.003
-0.071      -0.015
Discount_offered            0.1217      0.004     27.925      0.000
0.113       0.130
Weight_in_gms              -0.0002   1.15e-05    -13.957      0.000
-0.000      -0.000
Warehouse_block_A           0.0172      0.065      0.267      0.789
-0.109       0.144
Warehouse_block_B           0.0887      0.065      1.367      0.172
-0.038       0.216
Warehouse_block_C           0.0637      0.065      0.981      0.326
-0.063       0.191
Warehouse_block_D           0.0740      0.065      1.145      0.252
-0.053       0.201
Mode_of_Shipment_Flight     0.0470      0.060      0.785      0.433
-0.070       0.165
Mode_of_Shipment_Road       0.0085      0.060      0.141      0.888
-0.110       0.127
Product_importance_high     0.3543      0.083      4.244      0.000
0.191       0.518
Product_importance_low      0.0391      0.045      0.867      0.386
-0.049       0.128
Gender_F                   -0.0110      0.043     -0.256      0.798
-0.096       0.074
======================================================================================
"""
```

It can be concluded from the Logistic Regression results that the p-values of predictors, including 'Customer_care_calls', 'Customer_rating', 'Prior_purchases', 'Discount_offered', 'Weight_in_gms', and 'Product_importance_high', are < 0.05. Therefore, these predictors are considered more significant. We will include only these variables in our training and testing data when performing logistic regression.

```
data_significant = data[['Customer_care_calls', 'Customer_rating',
'Prior_purchases', 'Discount_offered', 'Weight_in_gms',
'Product_importance_high']]
data_significant
```

```
       Customer_care_calls  Customer_rating  Prior_purchases  \
0                        4                2                3
1                        4                5                2
2                        2                2                4
3                        3                3                4
4                        2                2                3
...                    ...              ...              ...
10994                    4                1                5
10995                    4                1                5
10996                    5                4                5
10997                    5                2                6
10998                    2                5                5

       Discount_offered  Weight_in_gms  Product_importance_high
0                    44           1233                        0
1                    59           3088                        0
2                    48           3374                        0
3                    10           1177                        0
4                    46           2484                        0
...                 ...            ...                      ...
10994                 1           1538                        0
10995                 6           1247                        0
10996                 4           1155                        0
10997                 2           1210                        0
10998                 6           1639                        0

[10999 rows x 6 columns]
```

The predictors cost_of_product, all the warehouse blocks, modes_of_shipment, low product importance and gender are insignificat hence we can exclude them

Q5: Which independent variables have missing data? How much?

There is no missing data in independent variables.

Q7: In the predictor variables independent of all the other predictor variables?

```
data.corr()

                         Customer_care_calls  Customer_rating  \
Customer_care_calls                 1.000000         0.012209
Customer_rating                     0.012209         1.000000
Cost_of_the_Product                 0.323182         0.009270
Prior_purchases                     0.180771         0.013179
Discount_offered                   -0.130750        -0.003124
Weight_in_gms                      -0.276615        -0.001897
Reached.on.Time_Y.N                -0.067126         0.013119
Warehouse_block_A                  -0.006375        -0.010471
Warehouse_block_B                  -0.013428        -0.003222
Warehouse_block_C                   0.004099         0.001093
```

```
Warehouse_block_D                  -0.000401        0.008687
Warehouse_block_F                   0.012732        0.003092
Mode_of_Shipment_Flight             0.019093       -0.002481
Mode_of_Shipment_Road               0.003292        0.001516
Mode_of_Shipment_Ship              -0.017629        0.000765
Product_importance_high            -0.048995        0.000679
Product_importance_low              0.047111       -0.004752
Product_importance_medium          -0.019761        0.004408
Gender_F                           -0.002545       -0.002775
Gender_M                            0.002545        0.002775

                           Cost_of_the_Product  Prior_purchases  \
Customer_care_calls                 0.323182        0.180771
Customer_rating                     0.009270        0.013179
Cost_of_the_Product                 1.000000        0.123676
Prior_purchases                     0.123676        1.000000
Discount_offered                   -0.138312       -0.082769
Weight_in_gms                      -0.132604       -0.168213
Reached.on.Time_Y.N                -0.073587       -0.055515
Warehouse_block_A                  -0.013299        0.002979
Warehouse_block_B                   0.018260        0.002178
Warehouse_block_C                   0.009255       -0.003750
Warehouse_block_D                   0.006618        0.010095
Warehouse_block_F                  -0.016472       -0.009095
Mode_of_Shipment_Flight            -0.008130       -0.000263
Mode_of_Shipment_Road               0.002531        0.003913
Mode_of_Shipment_Ship               0.004419       -0.002864
Product_importance_high            -0.040421        0.018066
Product_importance_low              0.037361       -0.024921
Product_importance_medium          -0.014785        0.014902
Gender_F                           -0.019759        0.009395
Gender_M                            0.019759       -0.009395

                           Discount_offered  Weight_in_gms  \
Customer_care_calls               -0.130750      -0.276615
Customer_rating                   -0.003124      -0.001897
Cost_of_the_Product               -0.138312      -0.132604
Prior_purchases                   -0.082769      -0.168213
Discount_offered                   1.000000      -0.376067
Weight_in_gms                     -0.376067       1.000000
Reached.on.Time_Y.N                0.397108      -0.268793
Warehouse_block_A                 -0.004157      -0.005078
Warehouse_block_B                 -0.005135       0.000461
Warehouse_block_C                  0.000736       0.002000
Warehouse_block_D                 -0.007714      -0.001414
Warehouse_block_F                  0.012864       0.003187
Mode_of_Shipment_Flight           -0.005750      -0.001245
Mode_of_Shipment_Road             -0.007787       0.004146
Mode_of_Shipment_Ship              0.010643      -0.002273
```

Product_importance_high	0.024514	0.069775
Product_importance_low	-0.019638	-0.080468
Product_importance_medium	0.005920	0.041634
Gender_F	0.011777	-0.003573
Gender_M	-0.011777	0.003573

	Reached.on.Time_Y.N	Warehouse_block_A \
Customer_care_calls	-0.067126	-0.006375
Customer_rating	0.013119	-0.010471
Cost_of_the_Product	-0.073587	-0.013299
Prior_purchases	-0.055515	0.002979
Discount_offered	0.397108	-0.004157
Weight_in_gms	-0.268793	-0.005078
Reached.on.Time_Y.N	1.000000	-0.009317
Warehouse_block_A	-0.009317	1.000000
Warehouse_block_B	0.005106	-0.199978
Warehouse_block_C	0.000132	-0.199978
Warehouse_block_D	0.000830	-0.200044
Warehouse_block_F	0.002568	-0.316189
Mode_of_Shipment_Flight	0.004371	0.000570
Mode_of_Shipment_Road	-0.007671	0.000461
Mode_of_Shipment_Ship	0.002577	-0.000811
Product_importance_high	0.033242	0.006098
Product_importance_low	-0.007667	0.012815
Product_importance_medium	-0.011099	-0.016380
Gender_F	-0.004689	0.001911
Gender_M	0.004689	-0.001911

	Warehouse_block_B	Warehouse_block_C \
Customer_care_calls	-0.013428	0.004099
Customer_rating	-0.003222	0.001093
Cost_of_the_Product	0.018260	0.009255
Prior_purchases	0.002178	-0.003750
Discount_offered	-0.005135	0.000736
Weight_in_gms	0.000461	0.002000
Reached.on.Time_Y.N	0.005106	0.000132
Warehouse_block_A	-0.199978	-0.199978
Warehouse_block_B	1.000000	-0.199978
Warehouse_block_C	-0.199978	1.000000
Warehouse_block_D	-0.200044	-0.200044
Warehouse_block_F	-0.316189	-0.316189
Mode_of_Shipment_Flight	-0.000093	-0.000755
Mode_of_Shipment_Road	0.000461	0.000461
Mode_of_Shipment_Ship	-0.000289	0.000233
Product_importance_high	-0.010419	0.008706
Product_importance_low	-0.013551	-0.004274
Product_importance_medium	0.019570	-0.000621
Gender_F	-0.007847	-0.001504
Gender_M	0.007847	0.001504

```
                            Warehouse_block_D  Warehouse_block_F  \
Customer_care_calls                 -0.000401           0.012732
Customer_rating                      0.008687           0.003092
Cost_of_the_Product                  0.006618          -0.016472
Prior_purchases                      0.010095          -0.009095
Discount_offered                    -0.007714           0.012864
Weight_in_gms                       -0.001414           0.003187
Reached.on.Time_Y.N                  0.000830           0.002568
Warehouse_block_A                   -0.200044          -0.316189
Warehouse_block_B                   -0.200044          -0.316189
Warehouse_block_C                   -0.200044          -0.316189
Warehouse_block_D                    1.000000          -0.316292
Warehouse_block_F                   -0.316292           1.000000
Mode_of_Shipment_Flight              0.000463          -0.000146
Mode_of_Shipment_Road               -0.000976          -0.000323
Mode_of_Shipment_Ship                0.000401           0.000369
Product_importance_high              0.006891          -0.008914
Product_importance_low              -0.000115           0.004051
Product_importance_medium           -0.003788           0.000965
Gender_F                             0.004104           0.002637
Gender_M                            -0.004104          -0.002637

                            Mode_of_Shipment_Flight
Mode_of_Shipment_Road  \
Customer_care_calls                        0.019093
0.003292
Customer_rating                           -0.002481
0.001516
Cost_of_the_Product                       -0.008130
0.002531
Prior_purchases                           -0.000263
0.003913
Discount_offered                          -0.005750               -
0.007787
Weight_in_gms                             -0.001245
0.004146
Reached.on.Time_Y.N                        0.004371               -
0.007671
Warehouse_block_A                          0.000570
0.000461
Warehouse_block_B                         -0.000093
0.000461
Warehouse_block_C                         -0.000755
0.000461
Warehouse_block_D                          0.000463               -
0.000976
Warehouse_block_F                         -0.000146               -
0.000323
Mode_of_Shipment_Flight                    1.000000               -
```

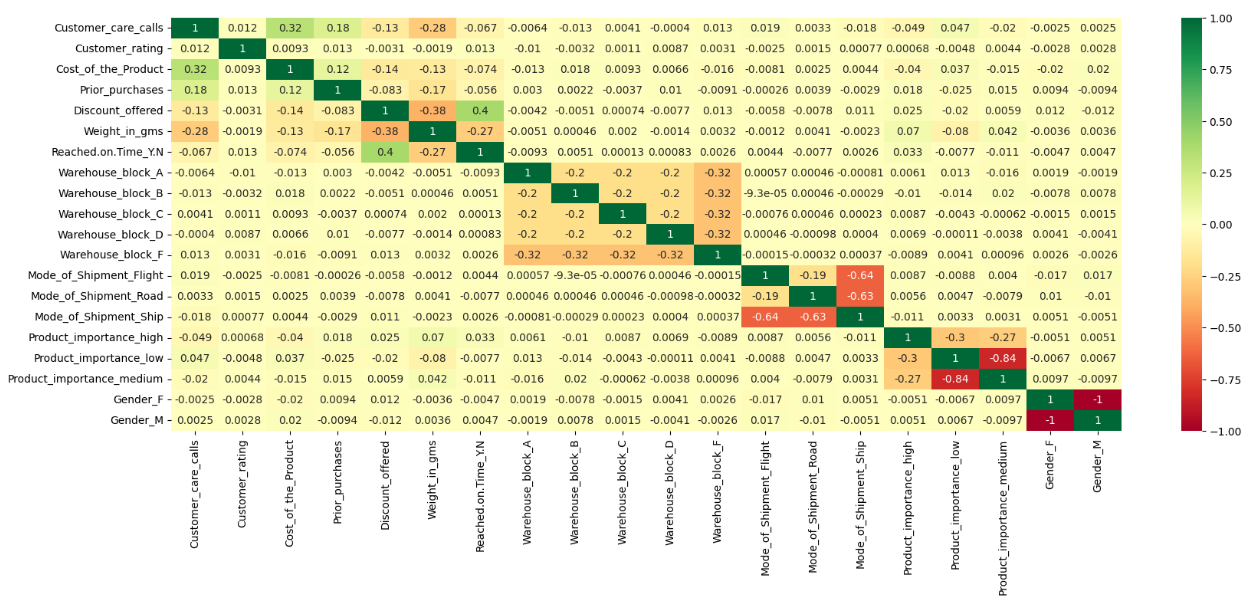
```
0.191591
Mode_of_Shipment_Road                          -0.191591
1.000000
Mode_of_Shipment_Ship                          -0.637590              -
0.633948
Product_importance_high                         0.008662
0.005572
Product_importance_low                         -0.008792
0.004667
Product_importance_medium                       0.003961              -
0.007864
Gender_F                                       -0.016725
0.010277
Gender_M                                        0.016725              -
0.010277

                           Mode_of_Shipment_Ship
Product_importance_high  \
Customer_care_calls                           -0.017629               -
0.048995
Customer_rating                                0.000765
0.000679
Cost_of_the_Product                            0.004419               -
0.040421
Prior_purchases                               -0.002864
0.018066
Discount_offered                               0.010643
0.024514
Weight_in_gms                                 -0.002273
0.069775
Reached.on.Time_Y.N                            0.002577
0.033242
Warehouse_block_A                             -0.000811
0.006098
Warehouse_block_B                             -0.000289               -
0.010419
Warehouse_block_C                              0.000233
0.008706
Warehouse_block_D                              0.000401
0.006891
Warehouse_block_F                              0.000369               -
0.008914
Mode_of_Shipment_Flight                       -0.637590
0.008662
Mode_of_Shipment_Road                         -0.633948
0.005572
Mode_of_Shipment_Ship                          1.000000               -
0.011199
Product_importance_high                       -0.011199
```

```
1.000000
Product_importance_low                      0.003265                -
0.296006
Product_importance_medium                   0.003052                -
0.267956
Gender_F                                    0.005112                -
0.005133
Gender_M                                   -0.005112
0.005133

                           Product_importance_low
Product_importance_medium  \
Customer_care_calls                      0.047111                   -
0.019761
Customer_rating                         -0.004752
0.004408
Cost_of_the_Product                      0.037361                   -
0.014785
Prior_purchases                         -0.024921
0.014902
Discount_offered                        -0.019638
0.005920
Weight_in_gms                           -0.080468
0.041634
Reached.on.Time_Y.N                     -0.007667                   -
0.011099
Warehouse_block_A                        0.012815                   -
0.016380
Warehouse_block_B                       -0.013551
0.019570
Warehouse_block_C                       -0.004274                   -
0.000621
Warehouse_block_D                       -0.000115                   -
0.003788
Warehouse_block_F                        0.004051
0.000965
Mode_of_Shipment_Flight                 -0.008792
0.003961
Mode_of_Shipment_Road                    0.004667                   -
0.007864
Mode_of_Shipment_Ship                    0.003265
0.003052
Product_importance_high                 -0.296006                   -
0.267956
Product_importance_low                   1.000000                   -
0.840939
Product_importance_medium               -0.840939
1.000000
Gender_F                                -0.006701
```

```
0.009666
Gender_M                                                   0.006701                   -
0.009666

                           Gender_F  Gender_M
Customer_care_calls       -0.002545  0.002545
Customer_rating           -0.002775  0.002775
Cost_of_the_Product       -0.019759  0.019759
Prior_purchases            0.009395 -0.009395
Discount_offered           0.011777 -0.011777
Weight_in_gms             -0.003573  0.003573
Reached.on.Time_Y.N       -0.004689  0.004689
Warehouse_block_A          0.001911 -0.001911
Warehouse_block_B         -0.007847  0.007847
Warehouse_block_C         -0.001504  0.001504
Warehouse_block_D          0.004104 -0.004104
Warehouse_block_F          0.002637 -0.002637
Mode_of_Shipment_Flight   -0.016725  0.016725
Mode_of_Shipment_Road      0.010277 -0.010277
Mode_of_Shipment_Ship      0.005112 -0.005112
Product_importance_high   -0.005133  0.005133
Product_importance_low    -0.006701  0.006701
Product_importance_medium  0.009666 -0.009666
Gender_F                   1.000000 -1.000000
Gender_M                  -1.000000  1.000000
```

```python
plt.figure(figsize=(20,7))
sns.heatmap(data.corr(), annot=True, cmap="RdYlGn")
```

```
<Axes: >
```



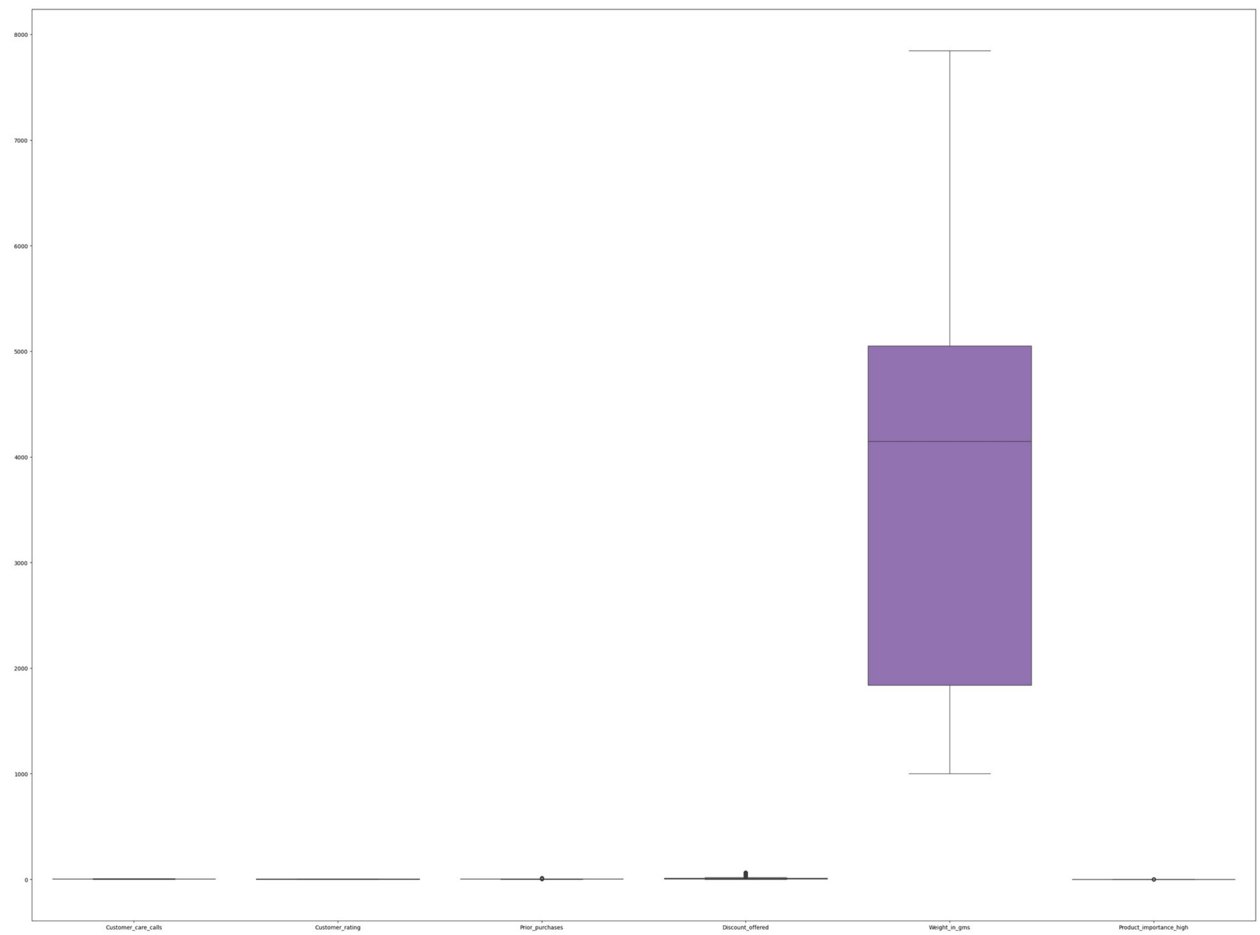
We can observe from the correlation heatmap that there are no higher correlation coefficients between independent variables, indicating no dependency among them.

Q9: Do the ranges of the predictor variables make sense?

Below is the box plot to visualize the distribution and range of the outliers. We can observe there aren't many outliers to significantly impact the accuracy of the model.

```
plt.figure(figsize=(40,30))
sns.boxplot(data_significant)
```

```
<Axes: >
```



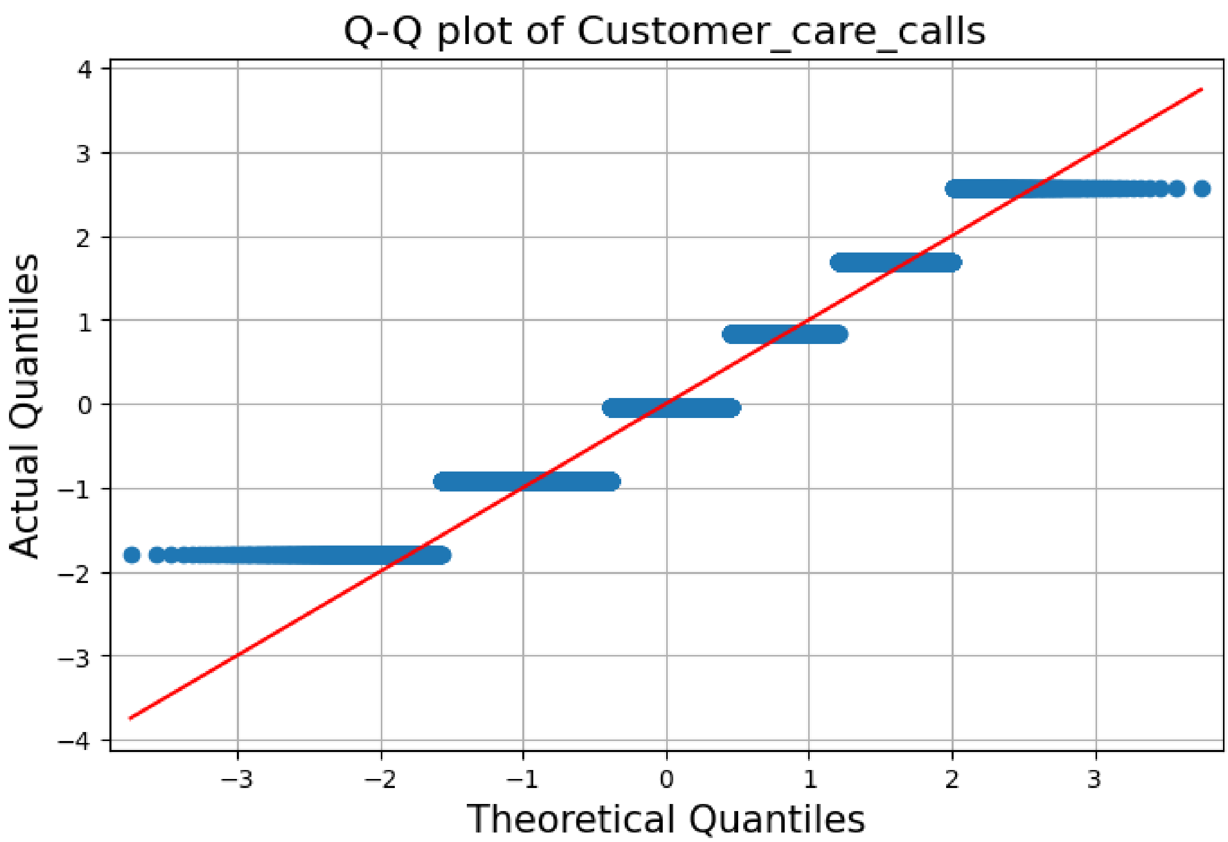
Q10: What are the distributions of the predictor variables?

Q-Q plots and sns plots

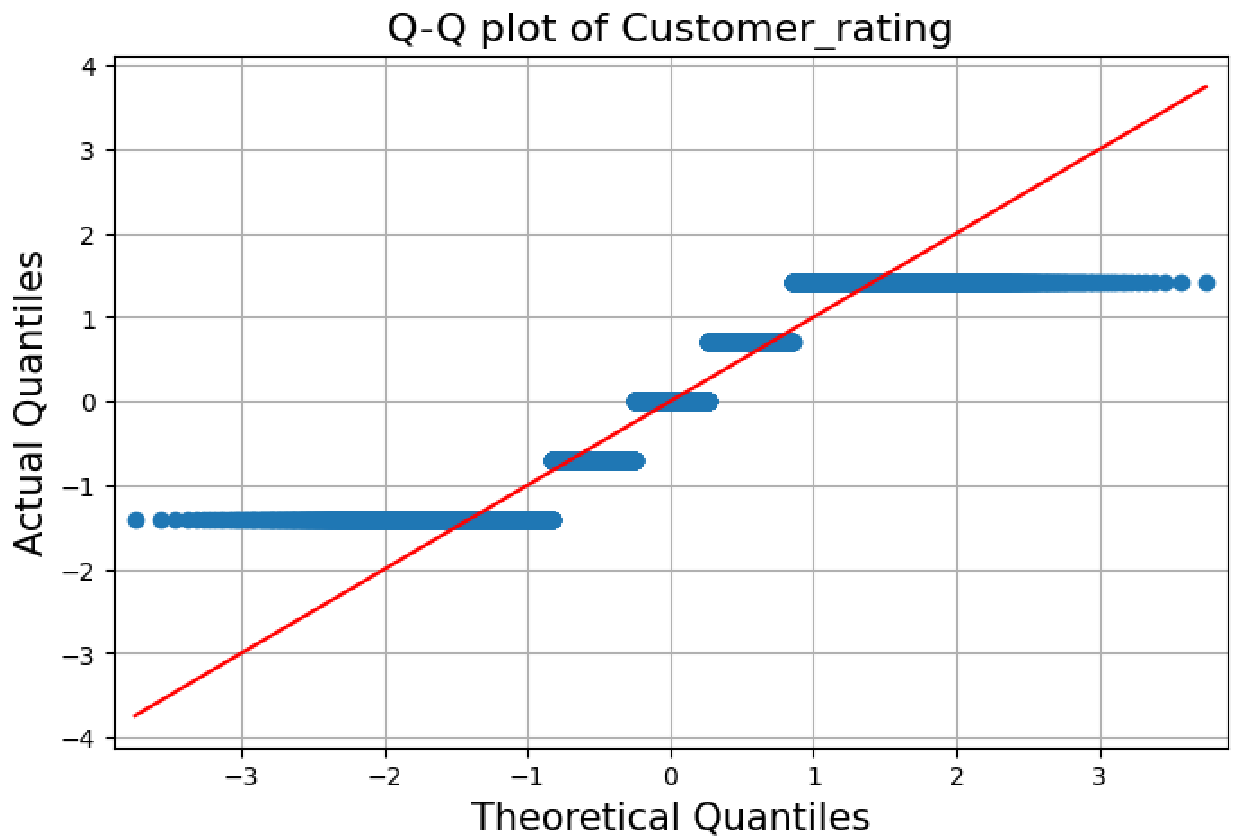
```
for col in data_significant:
  plt.figure(figsize=(3,4))
  fig = qqplot(data[col], line="s", fit="True")
  plt.xlabel("Theoretical Quantiles", fontsize=15)
  plt.ylabel("Actual Quantiles", fontsize=15)
```

```
  plt.title("Q-Q plot of {}". format(col), fontsize=16)
  plt.grid(True)
  plt.show()
```

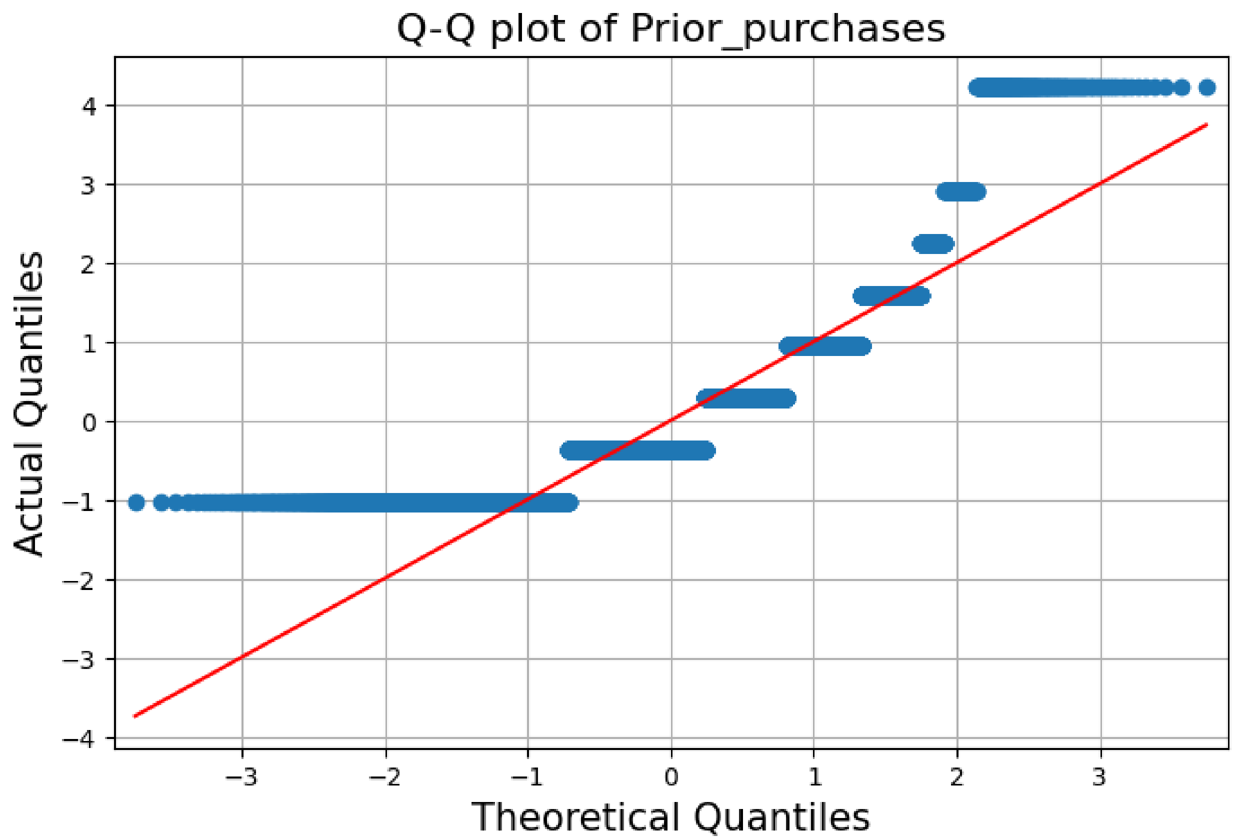
```
<Figure size 300x400 with 0 Axes>
```



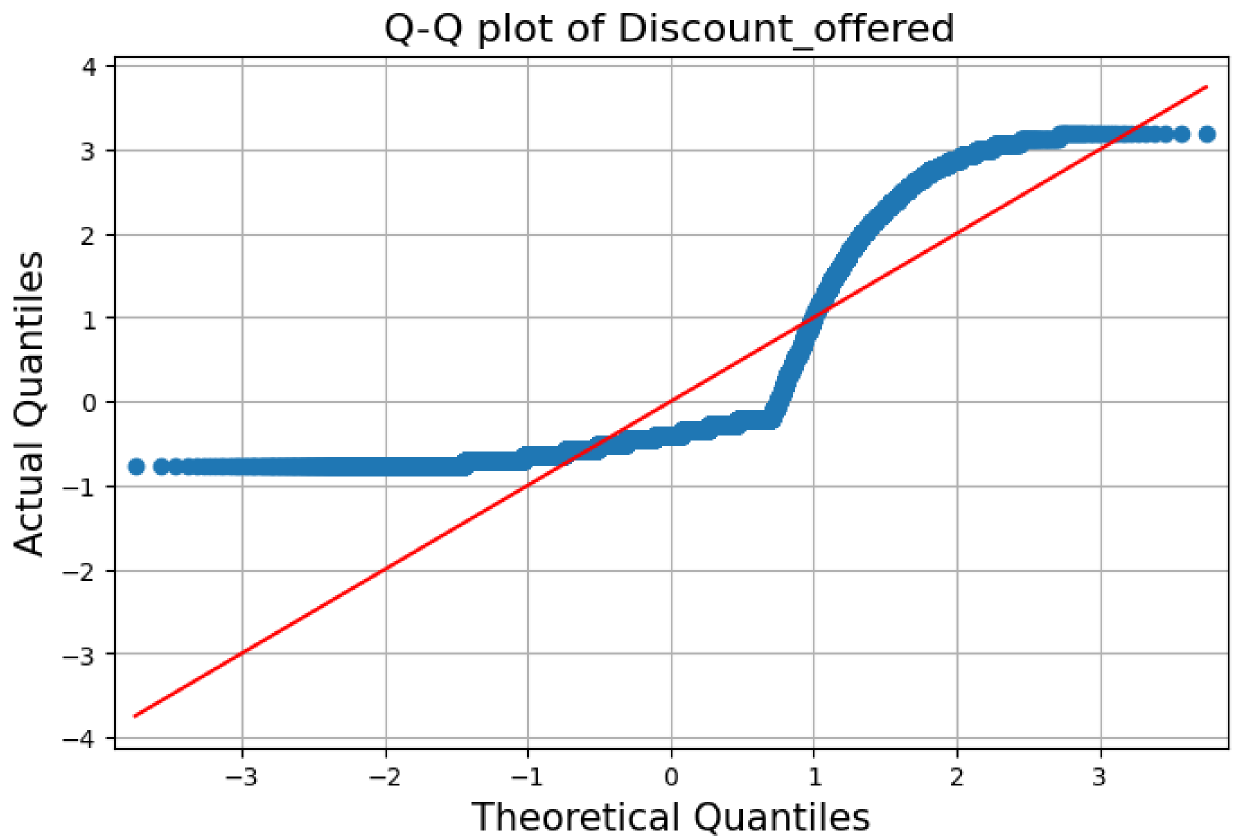

```
<Figure size 300x400 with 0 Axes>
```



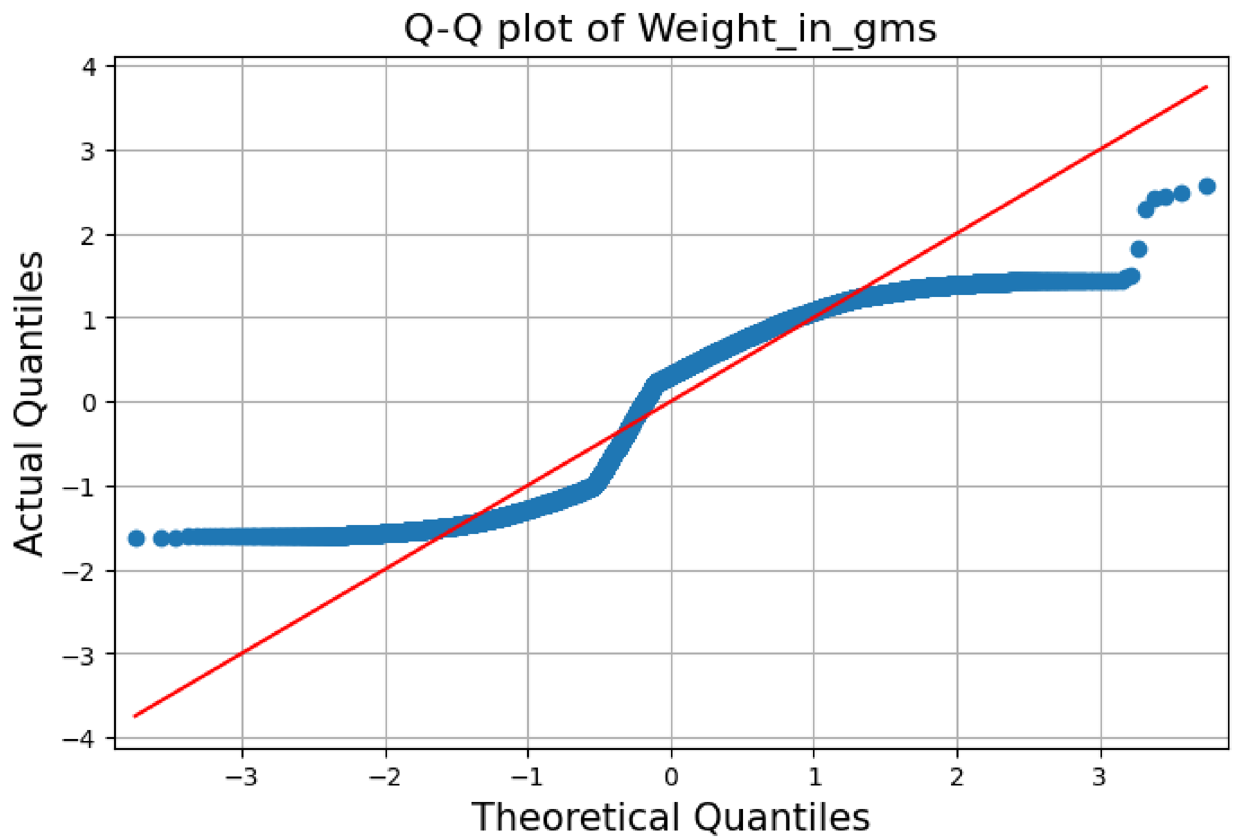

```
<Figure size 300x400 with 0 Axes>
```



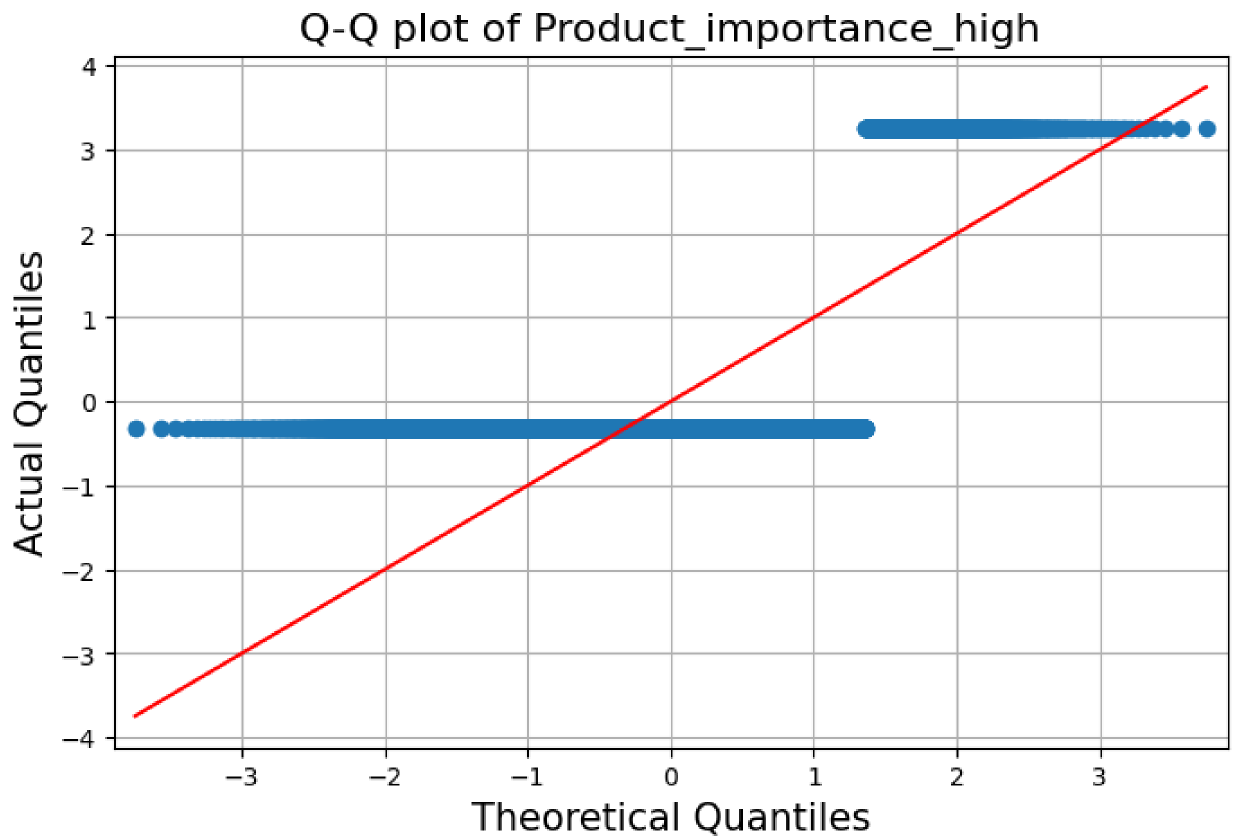

```
<Figure size 300x400 with 0 Axes>
```




```
<Figure size 300x400 with 0 Axes>
```



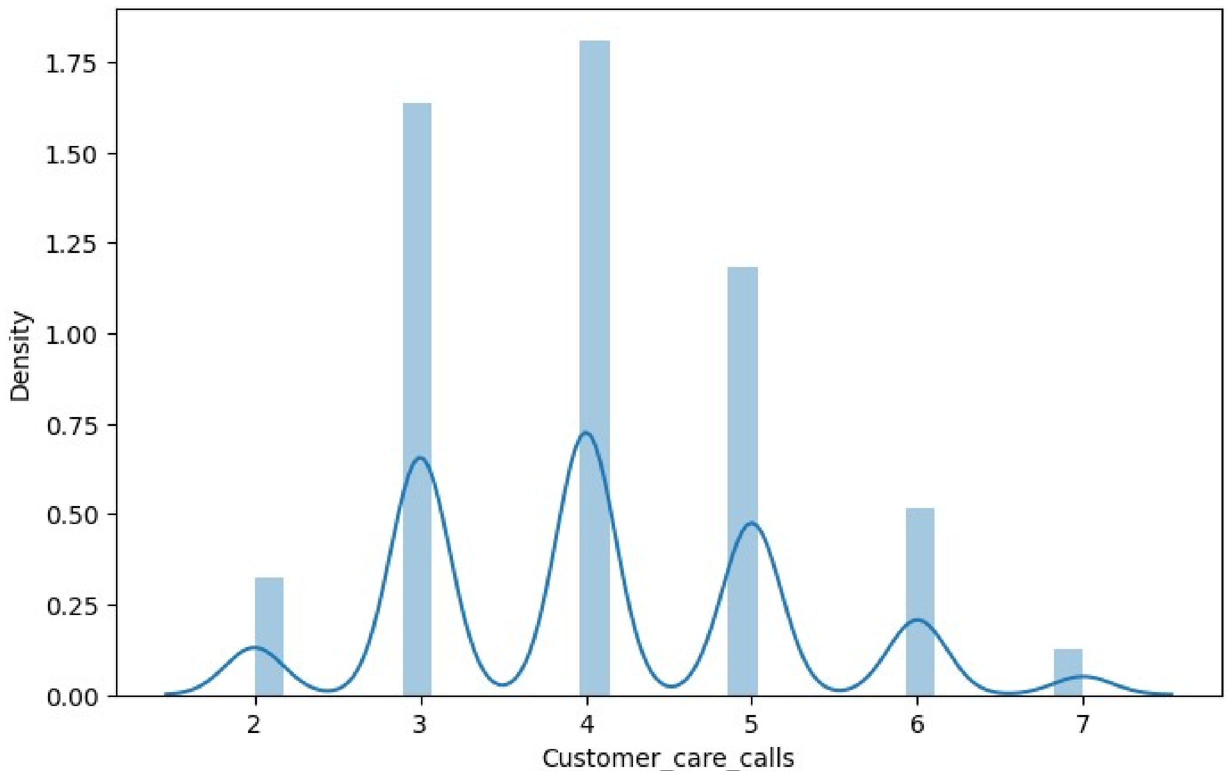

```
<Figure size 300x400 with 0 Axes>
```



The 'Weight in grams' roughly follows normal distribution

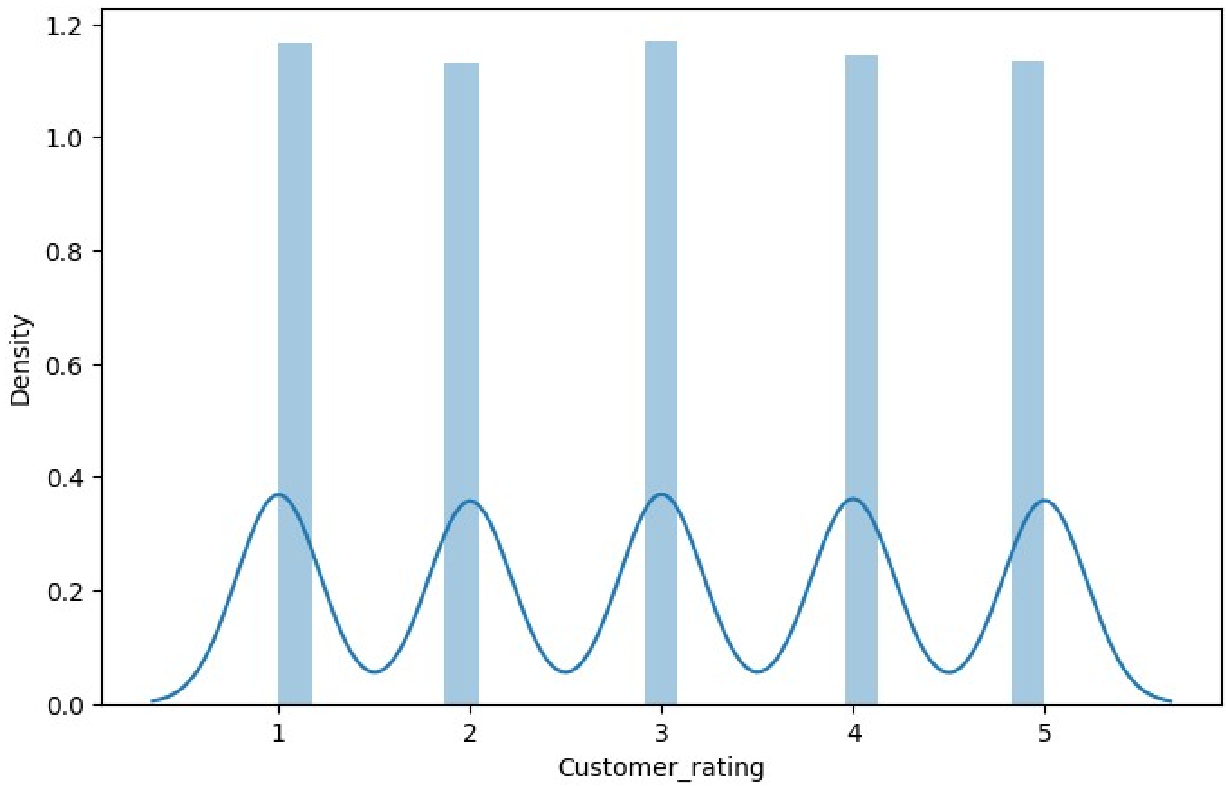
```
sns.distplot(data_significant['Customer_care_calls'])
```

```
<Axes: xlabel='Customer_care_calls', ylabel='Density'>
```



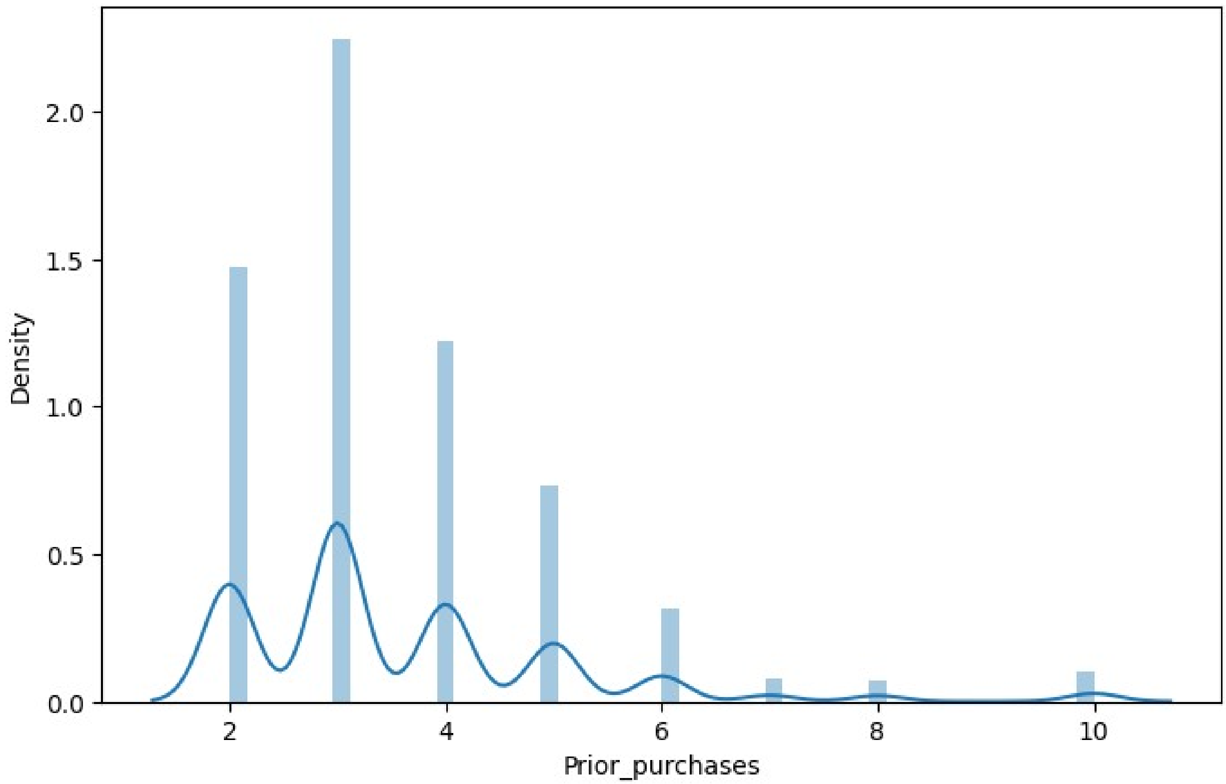

```
sns.distplot(data_significant['Customer_rating'])
```

```
<Axes: xlabel='Customer_rating', ylabel='Density'>
```



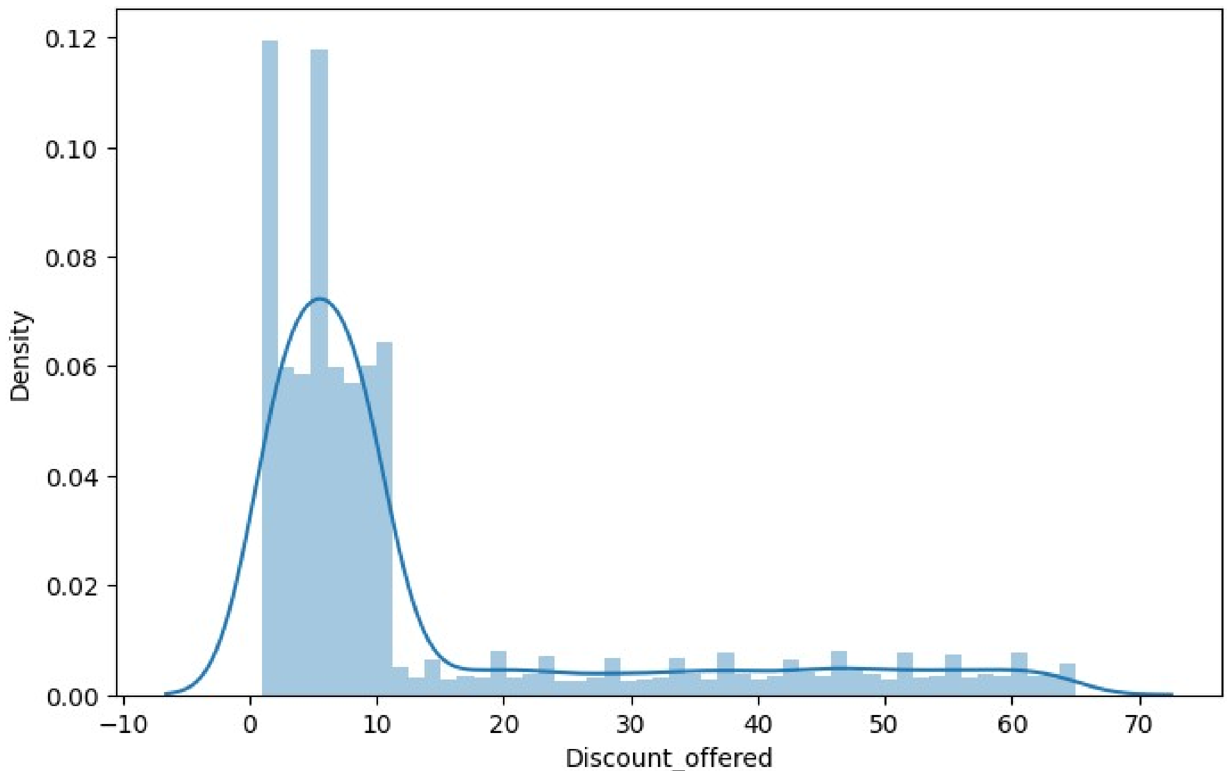

```
sns.distplot(data_significant['Prior_purchases'])
```

```
<Axes: xlabel='Prior_purchases', ylabel='Density'>
```



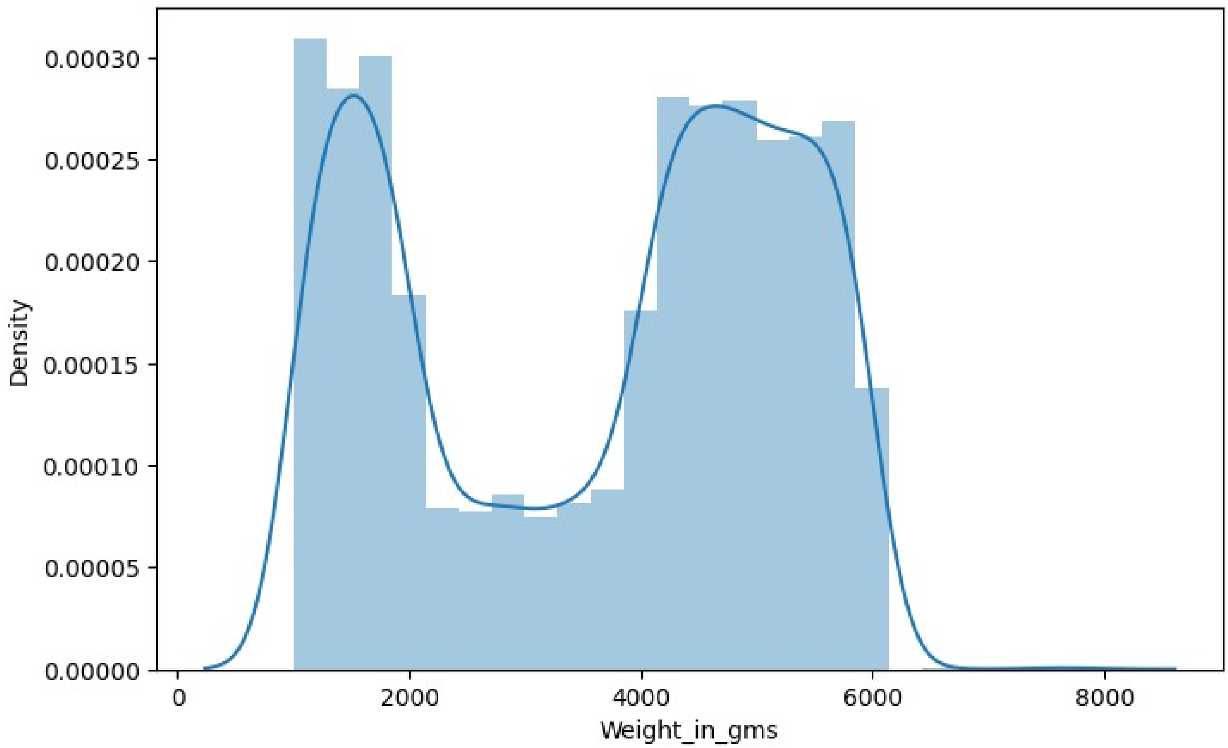

```
sns.distplot(data_significant['Discount_offered'])
```

```
<Axes: xlabel='Discount_offered', ylabel='Density'>
```

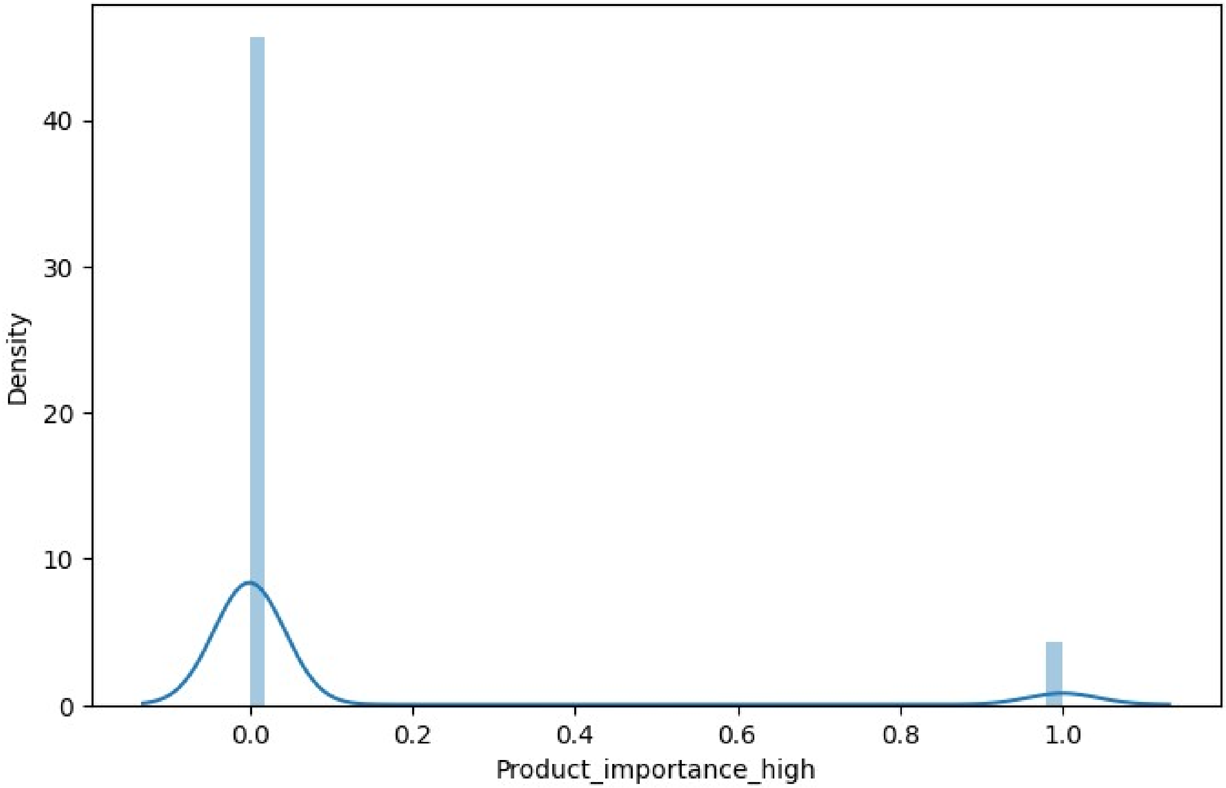



```
sns.distplot(data_significant['Weight_in_gms'])
```

```
<Axes: xlabel='Weight_in_gms', ylabel='Density'>
```




```
sns.distplot(data_significant['Product_importance_high'])

<Axes: xlabel='Product_importance_high', ylabel='Density'>
```




```
import statsmodels.api as sm

model = sm.Logit(
    data["Reached.on.Time_Y.N"],
    data_significant,
).fit()

model.summary()

Optimization terminated successfully.
         Current function value: 0.548349
         Iterations 8

<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results

======================================================================
=========
Dep. Variable:     Reached.on.Time_Y.N   No. Observations:
10999
Model:                           Logit   Df Residuals:
10993
Method:                            MLE   Df Model:
5
```

```
Date:                    Mon, 29 Jan 2024   Pseudo R-squ.:
0.1868
Time:                            18:43:21   Log-Likelihood:
-6031.3
converged:                           True   LL-Null:
-7417.0
Covariance Type:                nonrobust   LLR p-value:
0.000
======================================================================
=====================
                              coef    std err          z      P>|z|
[0.025      0.975]
----------------------------------------------------------------------
---------------------
Customer_care_calls        -0.0367      0.015     -2.497      0.013
-0.065      -0.008
Customer_rating             0.0527      0.015      3.575      0.000
0.024       0.082
Prior_purchases            -0.0413      0.014     -3.012      0.003
-0.068      -0.014
Discount_offered            0.1222      0.004     28.346      0.000
0.114       0.131
Weight_in_gms              -0.0002   1.07e-05    -14.647      0.000
-0.000      -0.000
Product_importance_high     0.3364      0.080      4.196      0.000
0.179       0.494
======================================================================
=====================
"""

# performing logistic regression
from sklearn.model_selection import KFold, cross_val_score,
train_test_split
from sklearn import metrics
import random
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
y = data['Reached.on.Time_Y.N']
X_train, X_test, y_train, y_test = train_test_split(data_significant,
y, test_size=.3, random_state=1)
X_train.head()

       Customer_care_calls  Customer_rating  Prior_purchases  \
4177                     4                5                3
1616                     3                4                3
2775                     4                1                3
10272                    4                4                3
6836                     4                3                3
```

```
       Discount_offered  Weight_in_gms  Product_importance_high
4177                  9           4953                        0
1616                 63           1611                        0
2775                 19           1906                        0
10272                 5           4440                        0
6836                  1           5214                        1
```

```
lr = LogisticRegression(C=1e9)
LRm = lr.fit(X_train, y_train)
LRm.predict_proba(X_test)
```

```
array([[0.68985371, 0.31014629],
       [0.01290386, 0.98709614],
       [0.56361364, 0.43638636],
       ...,
       [0.33349764, 0.66650236],
       [0.61349119, 0.38650881],
       [0.57988324, 0.42011676]])
```

```
y_pred = LRm.predict(X_test)
print(y_pred)
print("Accuracy of the model is:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:")
confusion_matrix(y_test, y_pred)
```

```
[0 1 0 ... 1 0 0]
Accuracy of the model is: 0.6357575757575757
Confusion Matrix:
```

```
array([[ 765,  577],
       [ 625, 1333]])
```

Q11: Remove outliers and keep outliers (does if have an effect of the final predictive model)?

From box plots we can observe that there no significant outliers in the dataset. We add outliers to the independent variables and observe the effect on the model using methods.

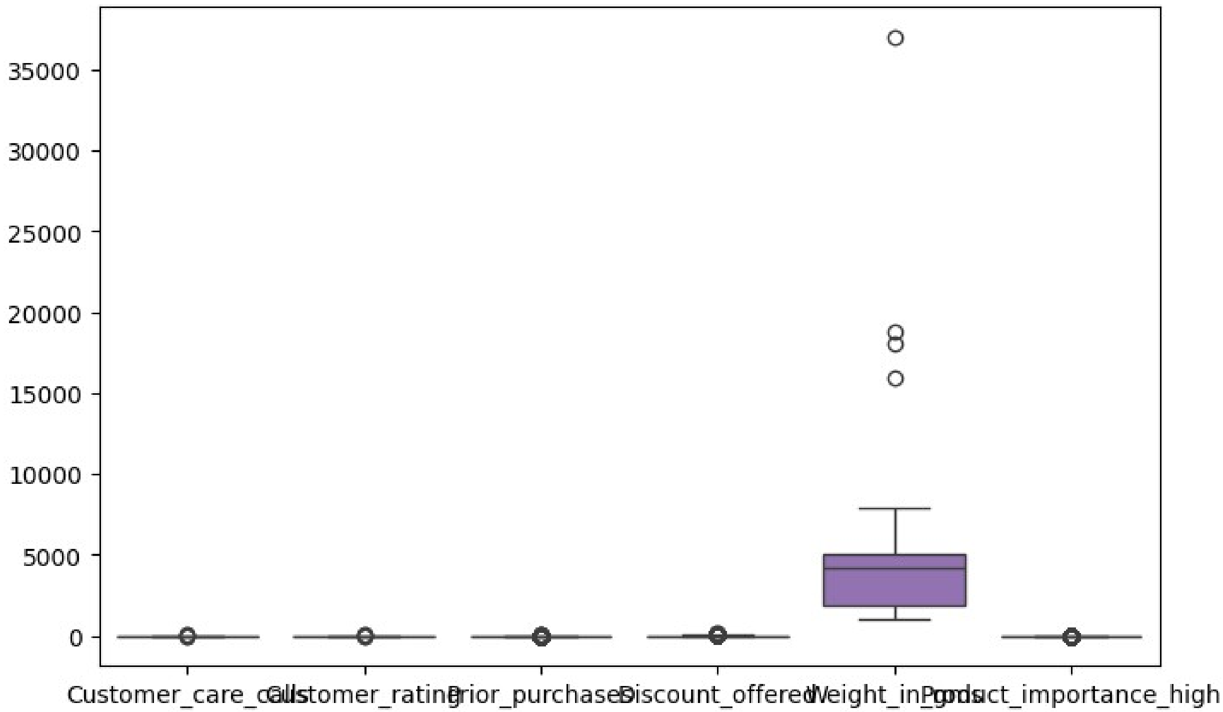
```
data_significant.mean()
```

```
Customer_care_calls           4.054459
Customer_rating               2.990545
Prior_purchases               3.567597
Discount_offered             13.373216
Weight_in_gms              3634.016729
Product_importance_high       0.086190
dtype: float64
```

```
import copy

deep_copy_significant_data = copy.deepcopy(data_significant)
for col in deep_copy_significant_data:
```

```
  colMean = data_significant[col].mean()
  outliers = pd.Series(np.random.uniform(colMean/10, 10*colMean, 
size=5))
  deep_copy_significant_data.loc[100:104, col] += outliers.values

sns.boxplot(deep_copy_significant_data)
```

```
<Axes: >
```




```
# perfroming logistic regression again with new data with outliers.
X_train_new, X_test_new, y_train_new, y_test_new = 
train_test_split(deep_copy_significant_data, y, test_size=.3, 
random_state=1)
X_train_new.head()
```

```
       Customer_care_calls  Customer_rating  Prior_purchases  \
4177                   4.0              5.0              3.0   
1616                   3.0              4.0              3.0   
2775                   4.0              1.0              3.0   
10272                  4.0              4.0              3.0   
6836                   4.0              3.0              3.0   

       Discount_offered  Weight_in_gms  Product_importance_high  
4177                9.0         4953.0                      0.0  
1616               63.0         1611.0                      0.0  
2775               19.0         1906.0                      0.0  
```

```
10272                    5.0         4440.0                      0.0
6836                     1.0         5214.0                      1.0
```

```
lr = LogisticRegression(C=1e9)
LRm_new = lr.fit(X_train_new, y_train_new)
LRm_new.predict_proba(X_test_new)
```

```
array([[0.68359496, 0.31640504],
       [0.01378277, 0.98621723],
       [0.56766316, 0.43233684],
       ...,
       [0.36462765, 0.63537235],
       [0.6124586 , 0.3875414 ],
       [0.59738613, 0.40261387]])
```

```
y_pred_new = LRm_new.predict(X_test_new)
print(y_pred_new)
print("Accuracy of the model is:", accuracy_score(y_test_new,
y_pred_new))
print("Confusion Matrix:")
confusion_matrix(y_test_new, y_pred_new)
```

```
[0 1 0 ... 1 0 0]
Accuracy of the model is: 0.6263636363636363
Confusion Matrix:
```

```
array([[ 755,  587],
       [ 646, 1312]])
```

The Accuracy of the model has decreased by ~1% from 63.5 to 62.6 and confusion matrix indicates the varaiation between true positives, false positives, true negatives, false negatives.

Q12: Remove 1%, 5%, and 10% of your data randomly and impute the values back using at least 3 imputation methods. How well did the methods recover the missing values? That is remove some data, check the % error on residuals for numeric data and check for bias and variance of the error.

```
#Remove 1% of data
#Remove 5% of data
#Remove 10% of data
missing_mask_1 = np.random.choice([1, 0], data.shape, p=[0.01, 0.99])
missing_mask_5 = np.random.choice([1, 0], data.shape, p=[0.05, 0.95])
missing_mask_10 = np.random.choice([1, 0], data.shape, p=[0.10, 0.90])

data_with_missing_1 = np.where(missing_mask_1, np.nan, data)
data_with_missing_5 = np.where(missing_mask_5, np.nan, data)
data_with_missing_10 = np.where(missing_mask_10, np.nan, data)
```

Now we impute the missing data using mean, median and most_frequent element in each column

```
from sklearn.impute import SimpleImputer

imp_mean = SimpleImputer(strategy='mean')
imp_median = SimpleImputer(strategy='median')
imp_frequent = SimpleImputer(strategy='most_frequent')

imputed_data_with_mean =
pd.DataFrame(imp_mean.fit_transform(data_with_missing_1))
imputed_data_with_median =
pd.DataFrame(imp_median.fit_transform(data_with_missing_5))
imputed_data_with_frequent =
pd.DataFrame(imp_frequent.fit_transform(data_with_missing_10))
```

calculating the mean absolute error

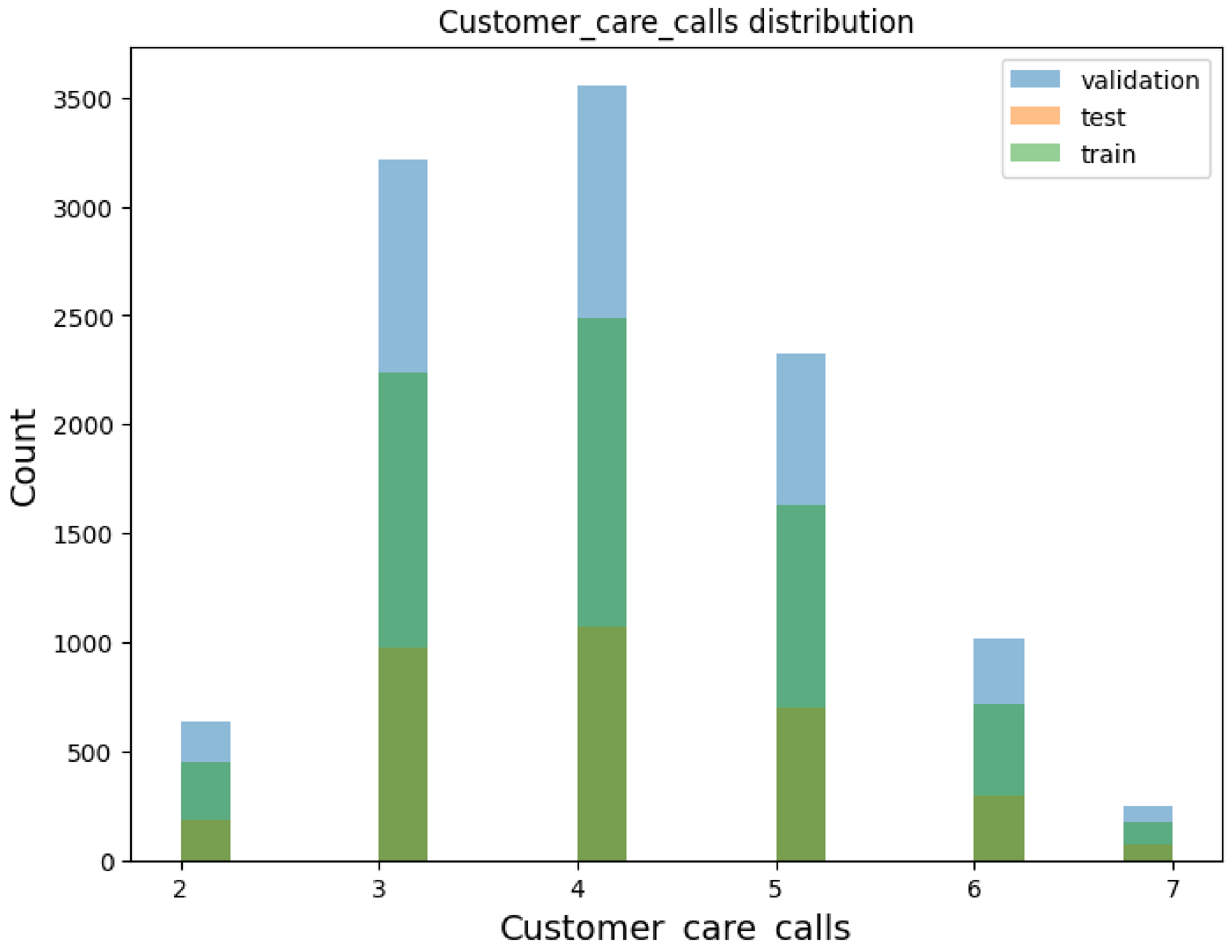
```
from sklearn.metrics import mean_absolute_error

mae_mean = mean_absolute_error(data, imputed_data_with_mean)
print("Mean absolute error when imputed with mean:", mae_mean)
mae_median = mean_absolute_error(data, imputed_data_with_median)
print("Mean absolute error when imputed with median:", mae_median)
mae_frequent = mean_absolute_error(data, imputed_data_with_frequent)
print("Mean absolute error when imputed with most frequent number in a
column:", mae_frequent)
```

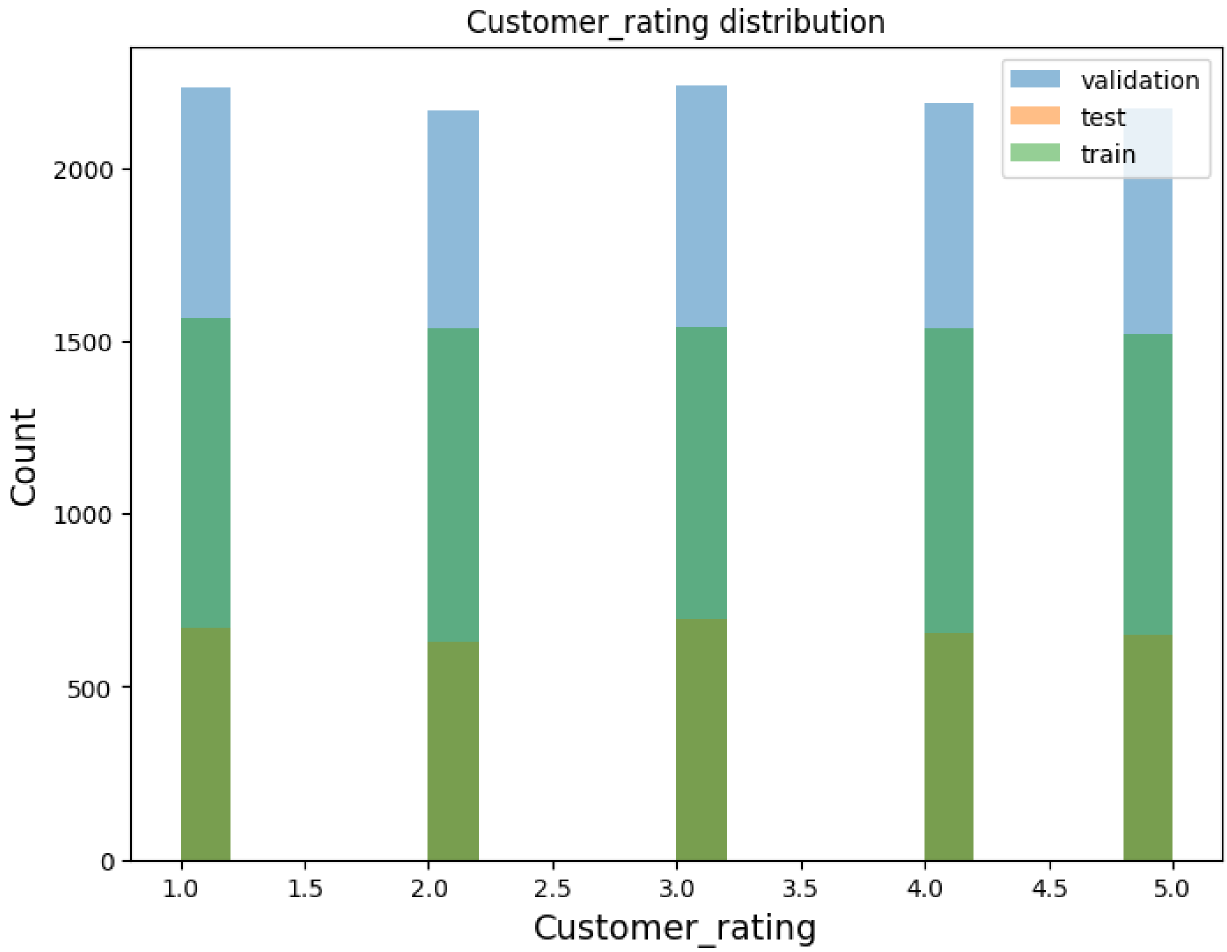
```
Mean absolute error when imputed with mean: 0.7481265274169766
Mean absolute error when imputed with median: 3.6684925902354757
Mean absolute error when imputed with most frequent number in a
column: 8.476602418401672
```

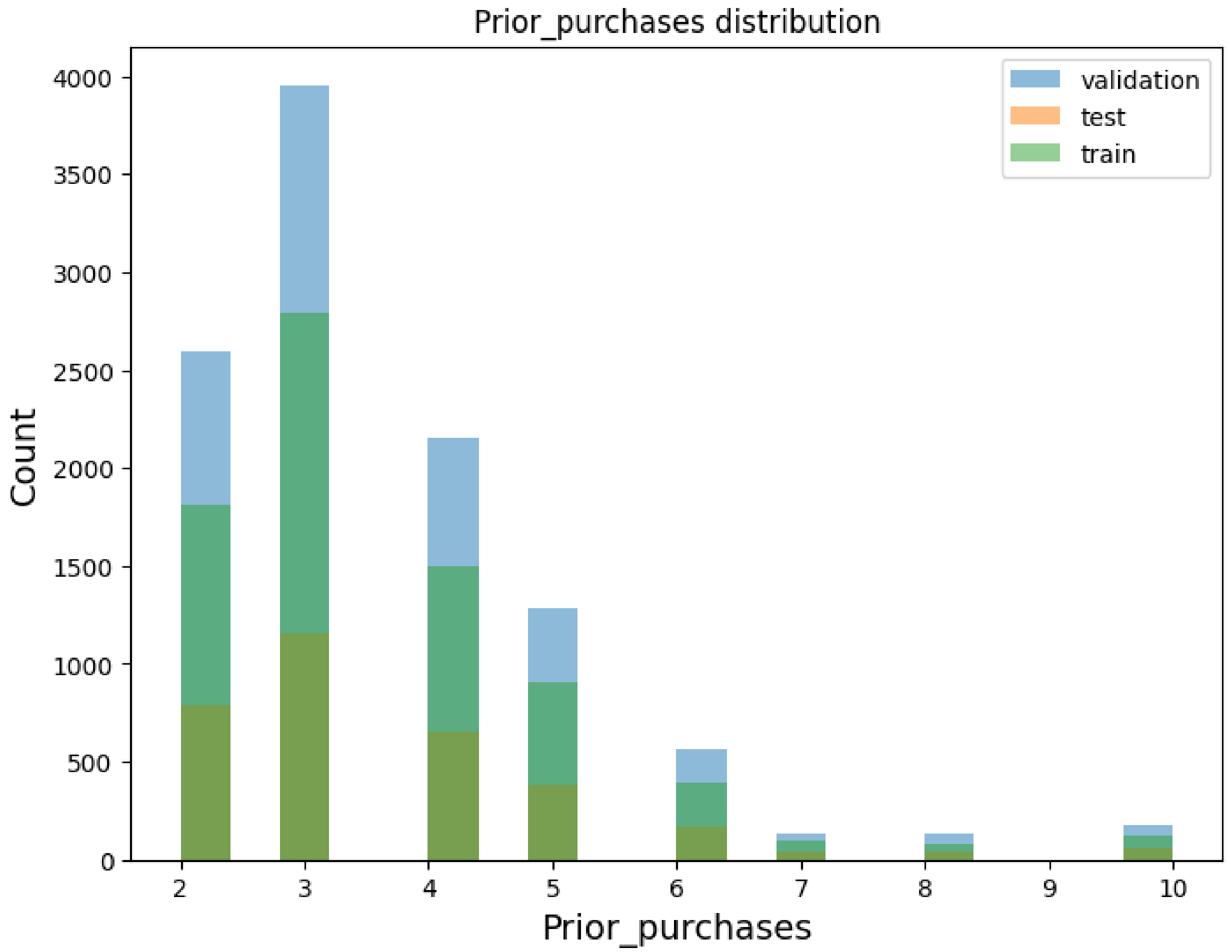
Q6: Do the training and test sets have the same data?

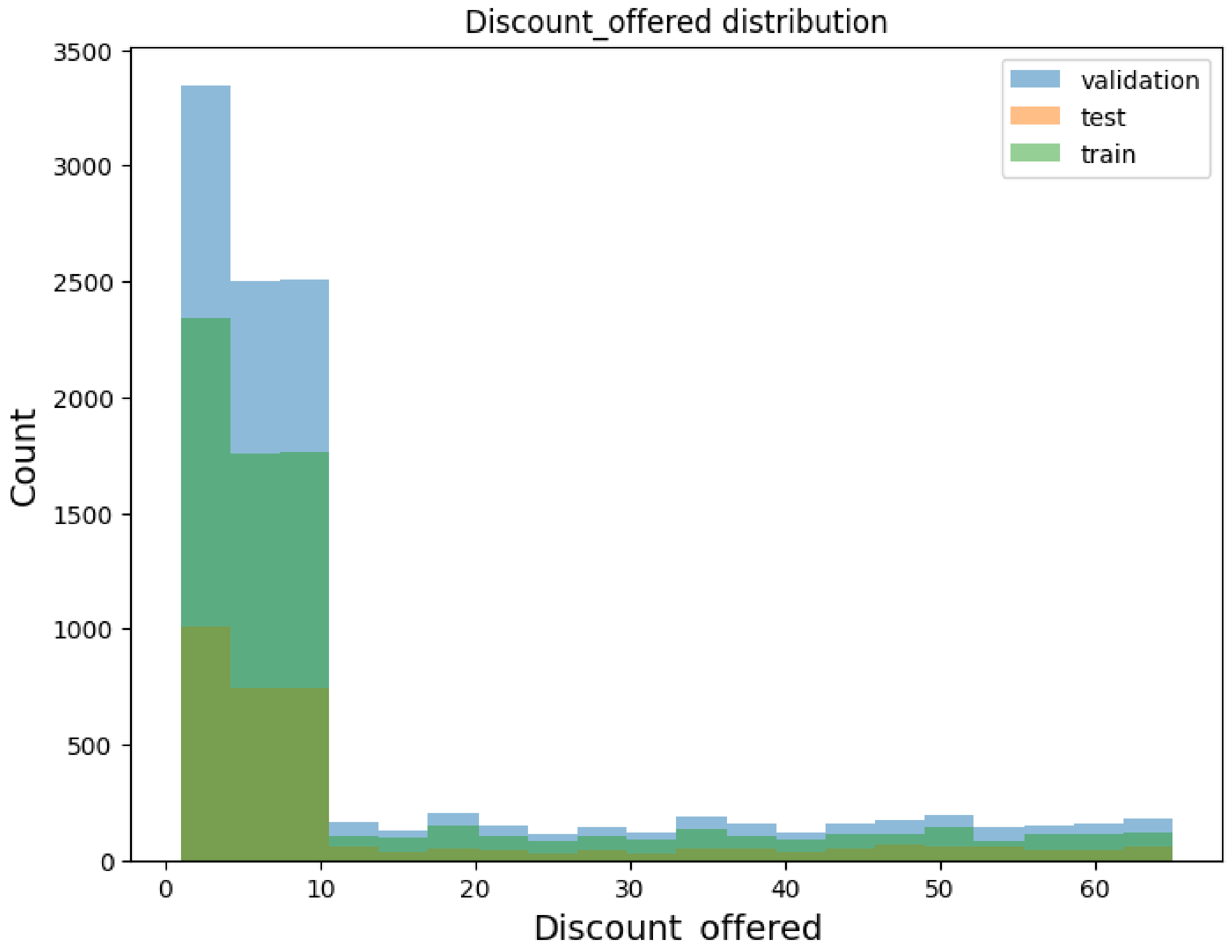
Below are plots showing test and training data. We can conclude they have different data.

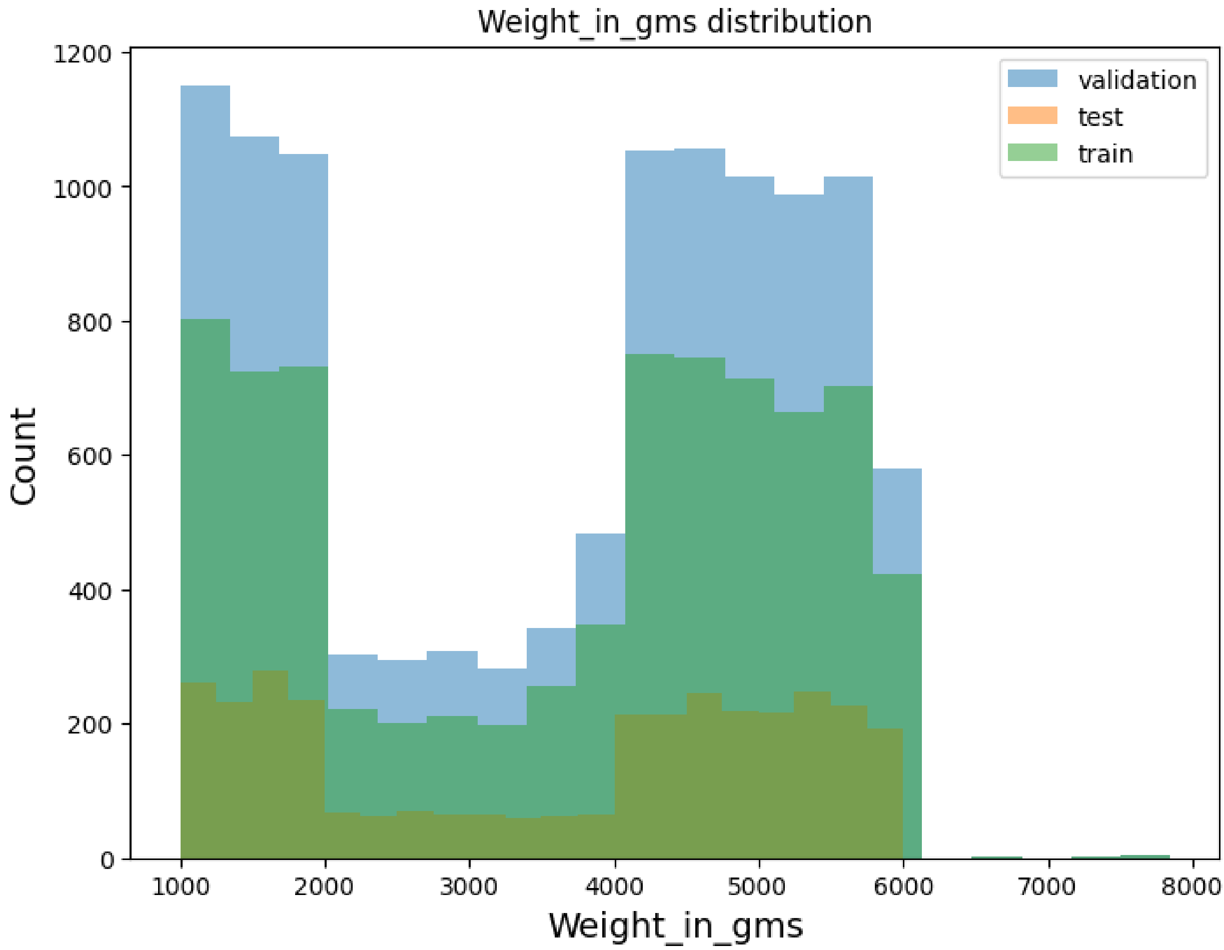
```
for col in data_significant:
  plt.figure(figsize=(8,6))
  plt.hist(data_significant[col], bins=20, alpha=0.5,
label="validation")
  plt.hist(X_test[col], bins=20, alpha=0.5, label="test")
  plt.hist(X_train[col], bins=20, alpha=0.5, label="train")
  plt.xlabel(col, size=14)
  plt.ylabel("Count", size=14)
  plt.legend(loc="upper right")
  plt.title("{} distribution".format(col))
  plt.show()
```


Customer_care_calls distribution
validation
test
train
Count
Customer_care_calls
0
500
1000
1500
2000
2500
3000
3500
2
3
4
5
6
7

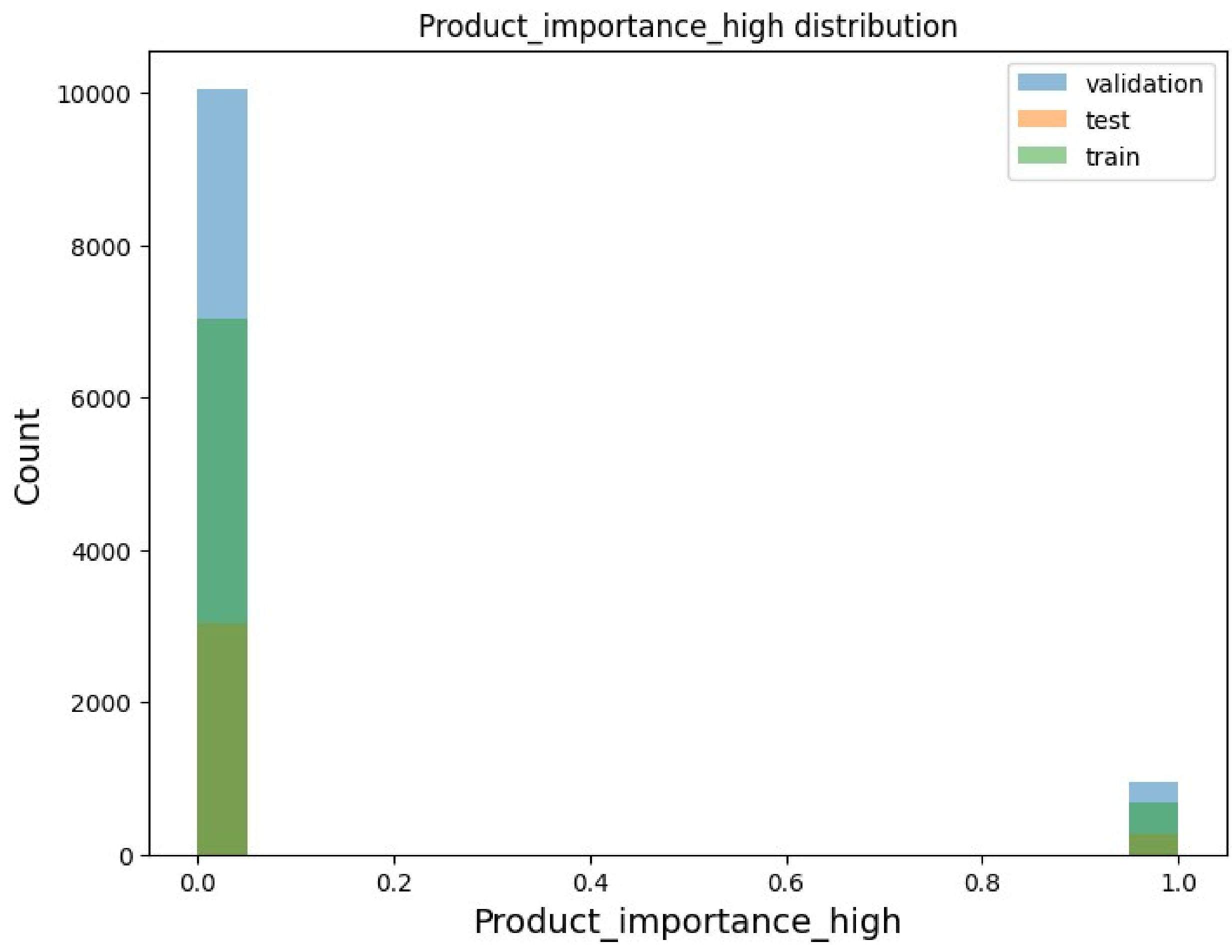

Customer_rating distribution
validation
test
train
2000
1500
1000
500
0
Count
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Customer_rating


Prior_purchases distribution
validation
test
train
Count
Prior_purchases
0
500
1000
1500
2000
2500
3000
3500
4000
2
3
4
5
6
7
8
9
10


Discount_offered distribution
validation
test
train
Count
Discount_offered
0
500
1000
1500
2000
2500
3000
3500
0
10
20
30
40
50
60



Weight_in_gms distribution
validation
test
train
Count
Weight_in_gms
0
200
400
600
800
1000
1200
1000
2000
3000
4000
5000
6000
7000
8000



Q8: Which predictor variables are the most important?

From permutation Importance weights below we can see the most important predictor variables.

```
import eli5
from eli5.sklearn import PermutationImportance

permutate = PermutationImportance(LRm, random_state=1).fit(X_test,
y_test)
eli5.show_weights(permutate, feature_names=X_test.columns.tolist())

<IPython.core.display.HTML object>
```

Conclusion

We have predicted the target variable "Reached On Time" with 64% accuracy using Logistic Regression

Reference

1.Scikit learn official documentation

2.Dataset from kaggle by PRACHI GOPALANI

3.Eli5 official documentation

4.Code Reference from Logistic Regression colab notebook.

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