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1. About Dataset

Brazilian E-Commerce Public Dataset by Olist

Welcome! This is a Brazilian ecommerce public dataset of orders made at Olist Store. The dataset has information of 100k orders from 2016 to 2018 made at multiple marketplaces in Brazil. Its features allows viewing an order from multiple dimensions: from order status, price, payment and freight performance to customer location, product attributes and finally reviews written by customers. We also released a geolocation dataset that relates Brazilian zip codes to lat/lng coordinates.

Data Schema

The data is divided in multiple datasets for better understanding and organization. Please refer to the following data schema when working with it:

2. Importing the necessary libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import scipy.stats as stats
from datetime import datetime as dt

from wordcloud import WordCloud, STOPWORDS

# To visualize the geographical coordinates in the world map
import folium
from folium.plugins import HeatMap

from sklearn.preprocessing import StandardScaler, MinMaxScaler,
PowerTransformer

from sklearn.model_selection import train_test_split

import statsmodels
import statsmodels.api as sm

from sklearn.preprocessing import StandardScaler, MinMaxScaler

from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, cohen_kappa_score,
confusion_matrix, roc_auc_score, roc_curve, accuracy_score,
precision_score, recall_score, f1_score

from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
AdaBoostClassifier,GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
```

```python
from sklearn.model_selection import GridSearchCV
from sklearn import tree

from sklearn.feature_selection import RFE

from warnings import filterwarnings
filterwarnings('ignore')

# To display all the columns in the dataframe
pd.set_option('display.max_columns', None)
```

3. Reading the datasets

```python
#Olist E-Commerce datasets
customers =
pd.read_csv("/kaggle/input/brazilian-ecommerce/olist_customers_dataset
.csv")
geolocation =
pd.read_csv("/kaggle/input/brazilian-ecommerce/olist_geolocation_datas
et.csv")
orderItems =
pd.read_csv("/kaggle/input/brazilian-ecommerce/olist_order_items_datas
et.csv")
payments =
pd.read_csv("/kaggle/input/brazilian-ecommerce/olist_order_payments_da
taset.csv")
orderReviews =
pd.read_csv("/kaggle/input/brazilian-ecommerce/olist_order_reviews_dat
aset.csv")
orders =
pd.read_csv("/kaggle/input/brazilian-ecommerce/olist_orders_dataset.cs
v")
products =
pd.read_csv("/kaggle/input/brazilian-ecommerce/olist_products_dataset.
csv")
sellers =
pd.read_csv("/kaggle/input/brazilian-ecommerce/olist_sellers_dataset.c
sv")
productCategoryTranslation = pd.read_csv("/kaggle/input/brazilian-
ecommerce/product_category_name_translation.csv")
```

Observation:

1. We will not be using the datasets in the marketing funnel. But they can be merged to further the project.

4. Exploratory Data Analysis

4.1. Exploratory Data Analysis On Orders dataframe

```
orders.head(3)
```

```
                           order_id                       customer_id
\
0  e481f51cbdc54678b7cc49136f2d6af7  9ef432eb6251297304e76186b10a928d

1  53cdb2fc8bc7dce0b6741e2150273451  b0830fb4747a6c6d20dea0b8c802d7ef

2  47770eb9100c2d0c44946d9cf07ec65d  41ce2a54c0b03bf3443c3d931a367089


  order_status order_purchase_timestamp    order_approved_at  \
0    delivered      2017-10-02 10:56:33  2017-10-02 11:07:15
1    delivered      2018-07-24 20:41:37  2018-07-26 03:24:27
2    delivered      2018-08-08 08:38:49  2018-08-08 08:55:23

  order_delivered_carrier_date order_delivered_customer_date  \
0          2017-10-04 19:55:00           2017-10-10 21:25:13
1          2018-07-26 14:31:00           2018-08-07 15:27:45
2          2018-08-08 13:50:00           2018-08-17 18:06:29

  order_estimated_delivery_date
0           2017-10-18 00:00:00
1           2018-08-13 00:00:00
2           2018-09-04 00:00:00
```

```
print('Number of Records:',orders.shape[0])
print('Number of Columns:',orders.shape[1])
```

```
Number of Records: 99441
Number of Columns: 8
```

```
orders['order_purchase_timestamp'] =
pd.to_datetime(orders.order_purchase_timestamp)
orders['order_approved_at'] = pd.to_datetime(orders.order_approved_at)
orders['order_delivered_carrier_date'] =
pd.to_datetime(orders.order_delivered_carrier_date)
orders['order_delivered_customer_date'] =
pd.to_datetime(orders.order_delivered_customer_date)
orders['order_estimated_delivery_date'] =
pd.to_datetime(orders.order_estimated_delivery_date)
```

```
orders.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99441 entries, 0 to 99440
Data columns (total 8 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   order_id                       99441 non-null  object
 1   customer_id                    99441 non-null  object
 2   order_status                   99441 non-null  object
 3   order_purchase_timestamp       99441 non-null  datetime64[ns]
 4   order_approved_at              99281 non-null  datetime64[ns]
 5   order_delivered_carrier_date   97658 non-null  datetime64[ns]
 6   order_delivered_customer_date  96476 non-null  datetime64[ns]
 7   order_estimated_delivery_date  99441 non-null  datetime64[ns]
dtypes: datetime64[ns](5), object(3)
memory usage: 6.1+ MB
```

Treating missing values in orders dataframe

```
orders.isna().sum()
```

```
order_id                            0
customer_id                         0
order_status                        0
order_purchase_timestamp            0
order_approved_at                 160
order_delivered_carrier_date     1783
order_delivered_customer_date    2965
order_estimated_delivery_date       0
dtype: int64
```

```
orders.order_id.nunique()
```

```
99441
```

```
orders.dropna()['order_status'].value_counts()
```

```
delivered    96455
canceled         6
Name: order_status, dtype: int64
```

```
orders[orders.isna().any(axis = 1)]['order_status'].value_counts()
```

```
shipped        1107
canceled        619
unavailable     609
invoiced        314
processing      301
delivered        23
created           5
approved          2
Name: order_status, dtype: int64
```

Observations:

1. Since our only target is to find customers who are still within our business, we can consider **only those customers whose orders were delivered to them**.
2. For the records whose delivery date is missing, we could consider that those customer's orders were not delivered or under various stages of the process, for instance, shipped, cancelled, unavailable and so on.
3. So we consider dropping such records where the datetime is missing.
4. Null values are imputed only for the orders which are delivered and has missing values in any of the date time fields.

```
orders['purchased_approved'] = (orders.order_approved_at -
orders.order_purchase_timestamp).dt.seconds
orders['approved_carrier'] = (orders.order_delivered_carrier_date -
orders.order_approved_at).dt.days
orders['carrier_delivered'] = (orders.order_delivered_customer_date -
orders.order_delivered_carrier_date).dt.days
orders['delivered_estimated'] = (orders.order_estimated_delivery_date
- orders.order_delivered_customer_date).dt.days
orders['purchased_delivered'] = (orders.order_delivered_customer_date
- orders.order_purchase_timestamp).dt.days
orders.head()
```

```
                           order_id                       customer_id
\
0  e481f51cbdc54678b7cc49136f2d6af7  9ef432eb6251297304e76186b10a928d

1  53cdb2fc8bc7dce0b6741e2150273451  b0830fb4747a6c6d20dea0b8c802d7ef

2  47770eb9100c2d0c44946d9cf07ec65d  41ce2a54c0b03bf3443c3d931a367089

3  949d5b44dbf5de918fe9c16f97b45f8a  f88197465ea7920adcdbec7375364d82

4  ad21c59c0840e6cb83a9ceb5573f8159  8ab97904e6daea8866dbdbc4fb7aad2c


  order_status order_purchase_timestamp   order_approved_at  \
0    delivered      2017-10-02 10:56:33 2017-10-02 11:07:15
1    delivered      2018-07-24 20:41:37 2018-07-26 03:24:27
2    delivered      2018-08-08 08:38:49 2018-08-08 08:55:23
3    delivered      2017-11-18 19:28:06 2017-11-18 19:45:59
4    delivered      2018-02-13 21:18:39 2018-02-13 22:20:29

  order_delivered_carrier_date order_delivered_customer_date  \
0          2017-10-04 19:55:00           2017-10-10 21:25:13
1          2018-07-26 14:31:00           2018-08-07 15:27:45
2          2018-08-08 13:50:00           2018-08-17 18:06:29
3          2017-11-22 13:39:59           2017-12-02 00:28:42
4          2018-02-14 19:46:34           2018-02-16 18:17:02

  order_estimated_delivery_date  purchased_approved  approved_carrier
```

```
\
0                    2017-10-18                  642.0                 2.0

1                    2018-08-13                24170.0                 0.0

2                    2018-09-04                  994.0                 0.0

3                    2017-12-15                 1073.0                 3.0

4                    2018-02-26                 3710.0                 0.0


   carrier_delivered  delivered_estimated  purchased_delivered
0                6.0                  7.0                  8.0
1               12.0                  5.0                 13.0
2                9.0                 17.0                  9.0
3                9.0                 12.0                 13.0
4                1.0                  9.0                  2.0
```

Observations:

1. New columns are created using the available datetime columns for easy analysis of the available data.
2. `Purchased_approved` represents the **seconds taken for an order to get approved** after the customer purchases it.
3. `approved_carrier` represents the **days taken for the order to go to the delivery carrier** after it being approved.
4. `carrier_delivered` represents the days **taken for the order to be delivered to the customer** from the date it reaches the delivery carrier.
5. `delivered_estimated` represents the **date difference between the estimated delivery date and the actual delivery date**.
6. `purchased_delivered` represents the **days taken for the order to be delivered to the customer** from the date the customer made the purchase.

```
orders.describe(include = np.number)

       purchased_approved  approved_carrier  carrier_delivered  \
count        99281.000000      97644.000000       96475.000000
mean         14198.031496          2.301749           8.878310
std          23663.448160          3.560283           8.746088
min              0.000000       -172.000000         -17.000000
25%            755.000000          0.000000           4.000000
50%           1169.000000          1.000000           7.000000
75%          17166.000000          3.000000          12.000000
max          86399.000000        125.000000         205.000000

       delivered_estimated  purchased_delivered
count         96476.000000         96476.000000
mean             10.876881            12.094086
std              10.183854             9.551746
```

```
min              -189.000000             0.000000
25%                 6.000000             6.000000
50%                11.000000            10.000000
75%                16.000000            15.000000
max               146.000000           209.000000

falsifiedData = orders[orders.approved_carrier < 0].index
orders.drop(index = falsifiedData, inplace = True)

falsifiedData = orders[orders.carrier_delivered < 0].index
orders.drop(index = falsifiedData, inplace = True)

canceledIndex = orders.dropna()[orders.order_status ==
'canceled'].index
orders.drop(index = canceledIndex, inplace = True)
```

Observations:

1. Orders which have **carrier date prior to the date of order getting approved**, and orders which have **delivered date prior to the carrier date** are considered to be **falsified data**, as it could not be logically true.
2. Such records are **dropped**.
3. Also the records which are **cancelled and have no null values are also dropped** as we consider only the records which have a order status of delivered.

```
orders.describe(include = np.number)

       purchased_approved  approved_carrier  carrier_delivered  \
count        97893.000000      96256.000000       95096.000000
mean         13950.420428          2.357224           8.910228
std          23484.689925          3.503335           8.755221
min              0.000000          0.000000           0.000000
25%            752.000000          0.000000           4.000000
50%           1153.000000          1.000000           7.000000
75%          15785.000000          3.000000          12.000000
max          86399.000000        125.000000         205.000000

       delivered_estimated  purchased_delivered
count         95097.000000         95097.000000
mean             10.825568            12.153359
std              10.199320             9.577379
min            -189.000000             0.000000
25%               6.000000             6.000000
50%              11.000000            10.000000
75%              16.000000            15.000000
max             146.000000           209.000000

otherThanDelivered = orders[(orders.isna().any(axis = 1)) &
(orders.order_status != 'delivered')].index
orders.drop(index = otherThanDelivered, inplace = True)
```

```
approvedAtNull = orders[orders.order_approved_at.isna()].index
orders.loc[approvedAtNull, 'order_approved_at'] =
orders.loc[approvedAtNull, 'order_purchase_timestamp'] +
pd.Timedelta(seconds = orders.purchased_approved.median())

deliveredCarrierNull =
orders[orders.order_delivered_carrier_date.isna()].index
orders.loc[deliveredCarrierNull, 'order_delivered_carrier_date'] =
orders.loc[deliveredCarrierNull, 'order_approved_at'] +
pd.Timedelta(days = orders.approved_carrier.median())

deliveredCustomerNull =
orders[orders.order_delivered_customer_date.isna()].index
orders.loc[deliveredCustomerNull, 'order_delivered_customer_date'] =
orders.loc[deliveredCustomerNull, 'order_delivered_carrier_date'] +
pd.Timedelta(days = orders.carrier_delivered.median())
```

Observations:

1. The **null values are dropped** which **do not have the order status as delivered**.
2. The null values in the `order_approved_at` field is imputed by adding the **median number of seconds it took for an order to get approved** after it is purchased, with the `order_purchase_timestamp`.
3. The null values in the `order_delivered_carrier_date` field is imputed by adding the **median number of days it took for an order to reach the carrier** after it is approved, with the `order_approved_at` timestamp.
4. The null values in the `order_delivered_customer_date` field is imputed by adding the **median number of days it took for an order to get delivered to the customer** after it reaches the carrier, with the `order_delivered_carrier_date` timestamp.

```
orders['purchased_approved'] = (orders.order_approved_at -
orders.order_purchase_timestamp).dt.seconds
orders['approved_carrier'] = (orders.order_delivered_carrier_date -
orders.order_approved_at).dt.days
orders['carrier_delivered'] = (orders.order_delivered_customer_date -
orders.order_delivered_carrier_date).dt.days
orders['delivered_estimated'] = (orders.order_estimated_delivery_date
- orders.order_delivered_customer_date).dt.days
orders['purchased_delivered'] = (orders.order_delivered_customer_date
- orders.order_purchase_timestamp).dt.days
orders.head()
```

```
                           order_id                       customer_id  
\
0  e481f51cbdc54678b7cc49136f2d6af7  9ef432eb6251297304e76186b10a928d

1  53cdb2fc8bc7dce0b6741e2150273451  b0830fb4747a6c6d20dea0b8c802d7ef

2  47770eb9100c2d0c44946d9cf07ec65d  41ce2a54c0b03bf3443c3d931a367089
```

```
3  949d5b44dbf5de918fe9c16f97b45f8a  f88197465ea7920adcdbec7375364d82

4  ad21c59c0840e6cb83a9ceb5573f8159  8ab97904e6daea8866dbdbc4fb7aad2c


  order_status order_purchase_timestamp   order_approved_at  \
0    delivered      2017-10-02 10:56:33 2017-10-02 11:07:15
1    delivered      2018-07-24 20:41:37 2018-07-26 03:24:27
2    delivered      2018-08-08 08:38:49 2018-08-08 08:55:23
3    delivered      2017-11-18 19:28:06 2017-11-18 19:45:59
4    delivered      2018-02-13 21:18:39 2018-02-13 22:20:29

  order_delivered_carrier_date order_delivered_customer_date  \
0          2017-10-04 19:55:00           2017-10-10 21:25:13
1          2018-07-26 14:31:00           2018-08-07 15:27:45
2          2018-08-08 13:50:00           2018-08-17 18:06:29
3          2017-11-22 13:39:59           2017-12-02 00:28:42
4          2018-02-14 19:46:34           2018-02-16 18:17:02

  order_estimated_delivery_date  purchased_approved  approved_carrier
\
0                    2017-10-18                 642                 2

1                    2018-08-13               24170                 0

2                    2018-09-04                 994                 0

3                    2017-12-15                1073                 3

4                    2018-02-26                3710                 0


   carrier_delivered  delivered_estimated  purchased_delivered
0                  6                    7                    8
1                 12                    5                   13
2                  9                   17                    9
3                  9                   12                   13
4                  1                    9                    2
```

```
orders.describe(exclude = np.number)
```

```
                                order_id
customer_id  \
count                              95105
95105
unique                             95105
95105
top     e481f51cbdc54678b7cc49136f2d6af7
9ef432eb6251297304e76186b10a928d
freq                                   1
1
```

```
first                                    NaN
NaN
last                                     NaN
NaN

       order_status order_purchase_timestamp    order_approved_at  \
count         95105                    95105                95105
unique            1                    94591                87320
top       delivered      2018-06-01 13:39:44  2018-02-27 04:31:10
freq          95105                        3                    9
first           NaN      2016-09-15 12:16:38  2016-09-15 12:16:38
last            NaN      2018-08-29 15:00:37  2018-08-29 15:10:26

       order_delivered_carrier_date order_delivered_customer_date  \
count                         95105                         95105
unique                        79235                         94311
top             2018-05-09 15:48:00           2018-02-14 21:09:19
freq                             47                             3
first           2016-10-08 10:34:01           2016-10-11 13:46:32
last            2018-09-11 19:48:28           2018-10-17 13:22:46

       order_estimated_delivery_date
count                          95105
unique                           445
top              2017-12-20 00:00:00
freq                             506
first            2016-10-04 00:00:00
last             2018-10-25 00:00:00
```

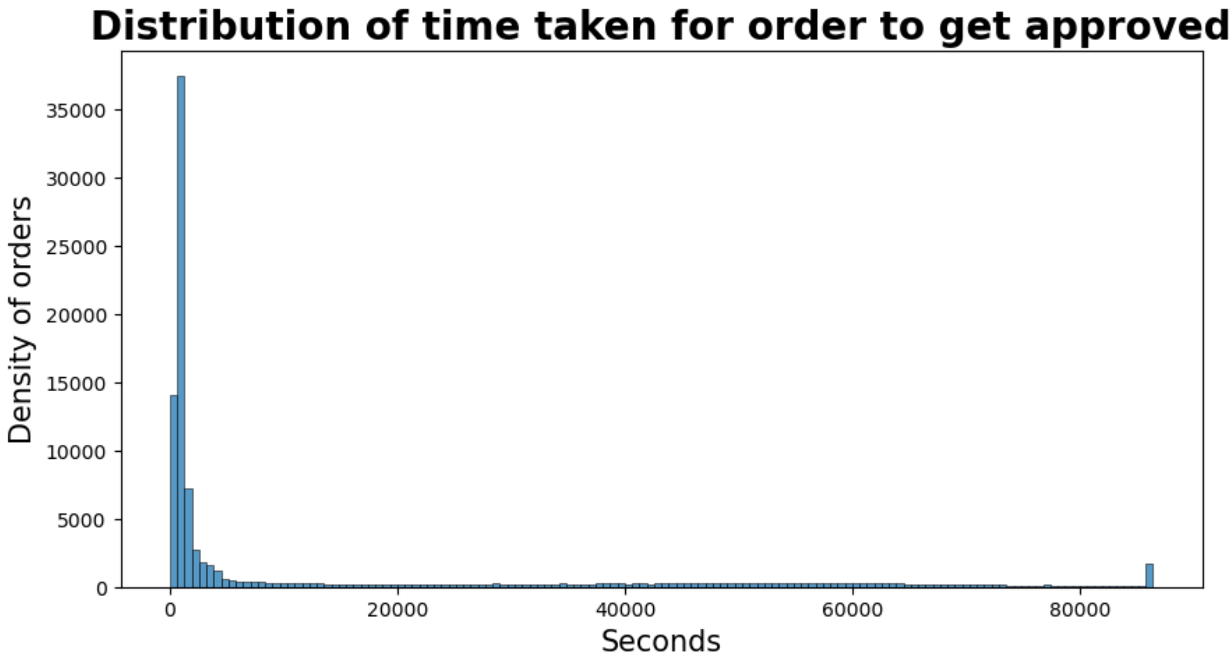
Observations:

1. From the summary statistics, we could infer that the it took an average(median is considered as it is highly right skewed) of **1153 seconds** or **over half an hour hours** for the **order to get approved after the customer purchased it**.
2. It took on an **average of 12 days** for the **order to get delivered to the customer from the date of purchase**.
3. Since we considered orders which are only **delivered**, the `order_status` feature has only **one class**, i.e., **delivered**.
4. The **first order was placed on 15/09/2016** and the **last order was placed on 29/08/2018**, from the available dataset.
5. On an average it took **11 days** for an **order to get delivered to the customer before the estimated date of delivery**. There are **many orders which were delivered late** than the estimated date of delivery.

Distribution of purchased approved

```
plt.figure(figsize=(10, 5))
sns.histplot(x='purchased_approved', data=orders)
plt.title('Distribution of time taken for order to get
```

```
approved',fontweight='bold',fontsize=20)
plt.xlabel('Seconds',fontsize=15)
plt.ylabel('Density of orders',fontsize=15)
plt.show()
```

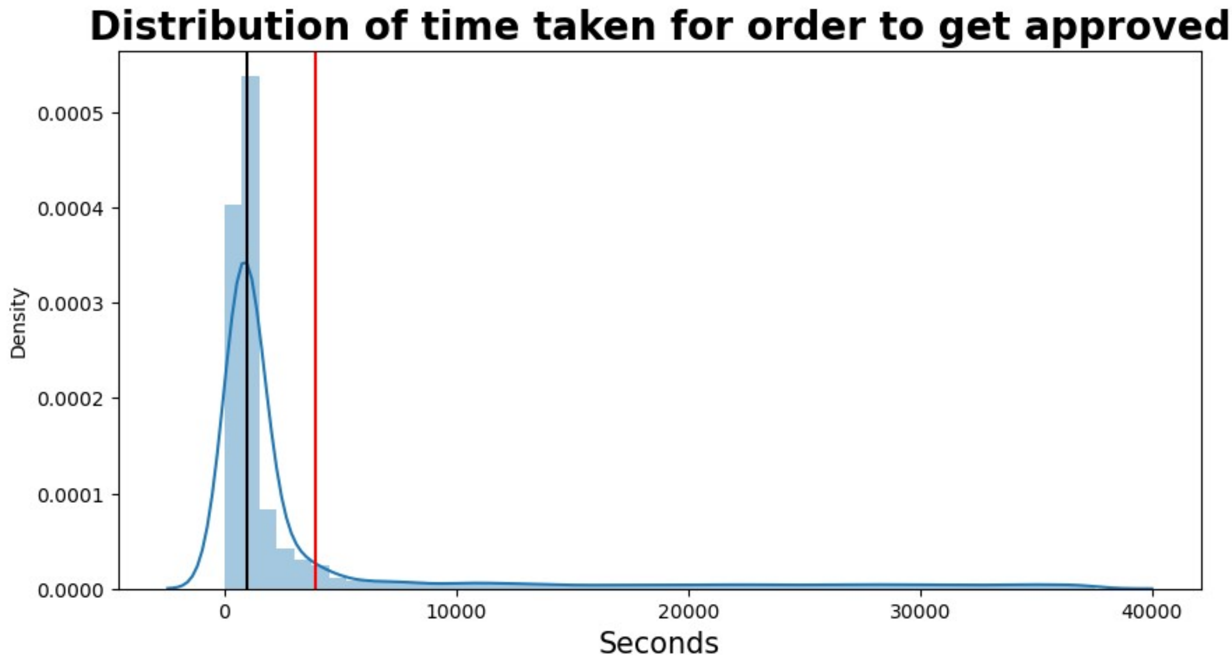



```
Q1 = np.quantile(orders.purchased_approved, 0.25)
Q3 = np.quantile(orders.purchased_approved, 0.75)
IQR = Q3 - Q1
purchasedApprovedDist = orders[~((orders.purchased_approved < Q1 - 1.5
* IQR) | (orders.purchased_approved > Q3 + 1.5 * IQR))]
purchasedApprovedDist.head()
```

```
                           order_id                       customer_id
\
0  e481f51cbdc54678b7cc49136f2d6af7  9ef432eb6251297304e76186b10a928d

1  53cdb2fc8bc7dce0b6741e2150273451  b0830fb4747a6c6d20dea0b8c802d7ef

2  47770eb9100c2d0c44946d9cf07ec65d  41ce2a54c0b03bf3443c3d931a367089

3  949d5b44dbf5de918fe9c16f97b45f8a  f88197465ea7920adcdbec7375364d82

4  ad21c59c0840e6cb83a9ceb5573f8159  8ab97904e6daea8866dbdbc4fb7aad2c


  order_status order_purchase_timestamp   order_approved_at  \
0    delivered      2017-10-02 10:56:33 2017-10-02 11:07:15
1    delivered      2018-07-24 20:41:37 2018-07-26 03:24:27
2    delivered      2018-08-08 08:38:49 2018-08-08 08:55:23
```

```
3    delivered      2017-11-18 19:28:06 2017-11-18 19:45:59
4    delivered      2018-02-13 21:18:39 2018-02-13 22:20:29

  order_delivered_carrier_date order_delivered_customer_date  \
0          2017-10-04 19:55:00           2017-10-10 21:25:13
1          2018-07-26 14:31:00           2018-08-07 15:27:45
2          2018-08-08 13:50:00           2018-08-17 18:06:29
3          2017-11-22 13:39:59           2017-12-02 00:28:42
4          2018-02-14 19:46:34           2018-02-16 18:17:02

  order_estimated_delivery_date  purchased_approved  approved_carrier
\
0                    2017-10-18                 642                 2

1                    2018-08-13               24170                 0

2                    2018-09-04                 994                 0

3                    2017-12-15                1073                 3

4                    2018-02-26                3710                 0


   carrier_delivered  delivered_estimated  purchased_delivered
0                  6                    7                    8
1                 12                    5                   13
2                  9                   17                    9
3                  9                   12                   13
4                  1                    9                    2
```

```
plt.figure(figsize=(10, 5))
sns.distplot(purchasedApprovedDist.purchased_approved)
plt.axvline(purchasedApprovedDist.purchased_approved.mean(), c =
'red')
plt.axvline(purchasedApprovedDist.purchased_approved.median(), c =
'black')
plt.xlabel('Seconds',color='black',fontsize=15)
plt.title('Distribution of time taken for order to get
approved',color='black',fontsize=20,fontweight='bold')
plt.show()
```



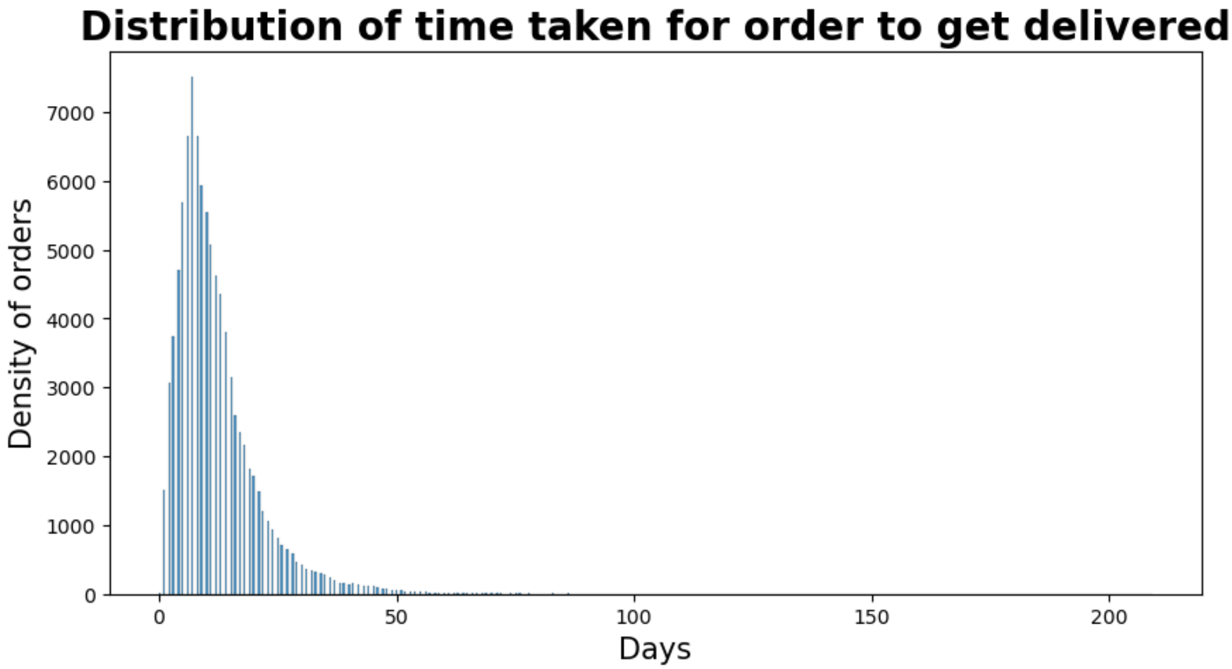

```
purchasedApprovedDist.purchased_approved.describe()

count    78335.000000
mean      3944.854867
std       7741.478369
min          0.000000
25%        707.000000
50%        955.000000
75%       1940.000000
max      37563.000000
Name: purchased_approved, dtype: float64
```

Observations:

1. The approval time of orders within the interquartile range are spread mostly **between 0 and 5000 seconds**, which could be seen in the distribution plot.
2. The **average time taken for approval of the orders is 3844.85 seconds**.

Distribution of `purchased_delivered`

```
plt.figure(figsize=(10, 5))
sns.histplot(x='purchased_delivered', data=orders)
plt.title('Distribution of time taken for order to get
delivered',fontweight='bold',fontsize=20)
plt.xlabel('Days',fontsize=15)
plt.ylabel('Density of orders',fontsize=15)
plt.show()
```

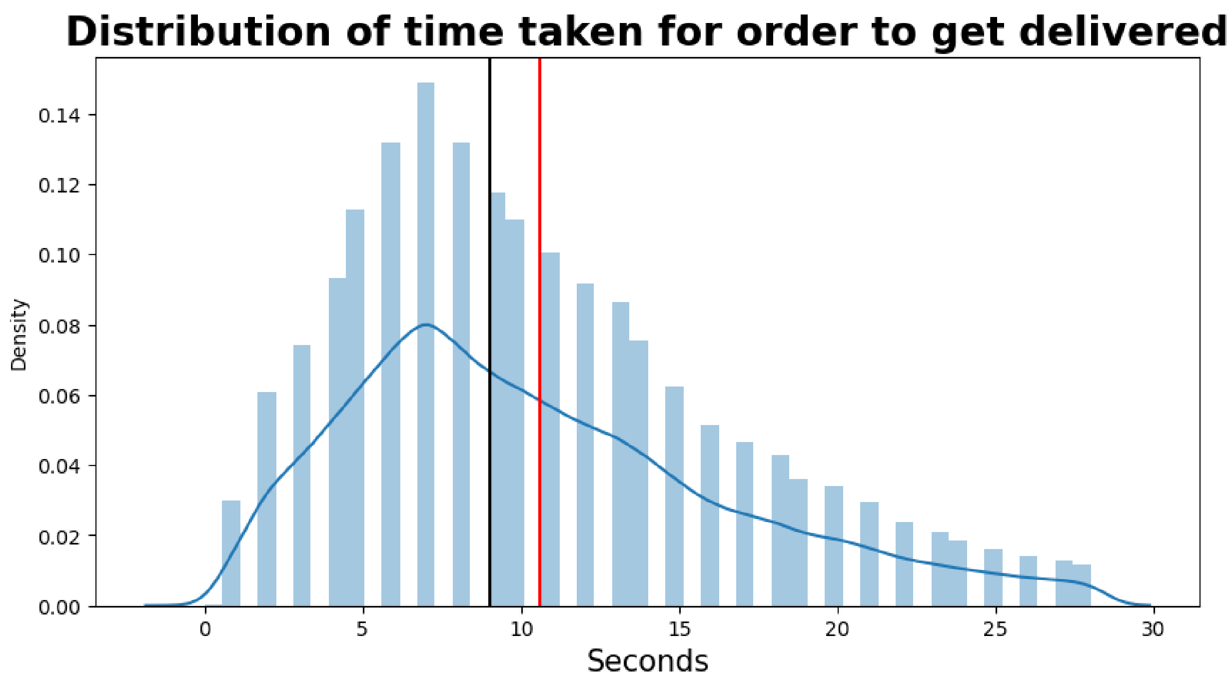



```
Q1 = np.quantile(orders.purchased_delivered, 0.25)
Q3 = np.quantile(orders.purchased_delivered, 0.75)
IQR = Q3 - Q1
purchasedDeliveredDist = orders[~((orders.purchased_delivered < Q1 -
1.5 * IQR) | (orders.purchased_delivered > Q3 + 1.5 * IQR))]
purchasedDeliveredDist.head()
```

```
                           order_id                       customer_id  \
0  e481f51cbdc54678b7cc49136f2d6af7  9ef432eb6251297304e76186b10a928d

1  53cdb2fc8bc7dce0b6741e2150273451  b0830fb4747a6c6d20dea0b8c802d7ef

2  47770eb9100c2d0c44946d9cf07ec65d  41ce2a54c0b03bf3443c3d931a367089

3  949d5b44dbf5de918fe9c16f97b45f8a  f88197465ea7920adcdbec7375364d82

4  ad21c59c0840e6cb83a9ceb5573f8159  8ab97904e6daea8866dbdbc4fb7aad2c


  order_status order_purchase_timestamp   order_approved_at  \
0    delivered      2017-10-02 10:56:33 2017-10-02 11:07:15
1    delivered      2018-07-24 20:41:37 2018-07-26 03:24:27
2    delivered      2018-08-08 08:38:49 2018-08-08 08:55:23
3    delivered      2017-11-18 19:28:06 2017-11-18 19:45:59
4    delivered      2018-02-13 21:18:39 2018-02-13 22:20:29

  order_delivered_carrier_date order_delivered_customer_date  \
0          2017-10-04 19:55:00           2017-10-10 21:25:13
```

```
1          2018-07-26 14:31:00          2018-08-07 15:27:45
2          2018-08-08 13:50:00          2018-08-17 18:06:29
3          2017-11-22 13:39:59          2017-12-02 00:28:42
4          2018-02-14 19:46:34          2018-02-16 18:17:02

  order_estimated_delivery_date  purchased_approved  approved_carrier
\
0                    2017-10-18                 642                 2

1                    2018-08-13               24170                 0

2                    2018-09-04                 994                 0

3                    2017-12-15                1073                 3

4                    2018-02-26                3710                 0


   carrier_delivered  delivered_estimated  purchased_delivered
0                  6                    7                    8
1                 12                    5                   13
2                  9                   17                    9
3                  9                   12                   13
4                  1                    9                    2
```

```
plt.figure(figsize=(10, 5))
sns.distplot(purchasedDeliveredDist.purchased_delivered)
plt.axvline(purchasedDeliveredDist.purchased_delivered.mean(), c =
'red')
plt.axvline(purchasedDeliveredDist.purchased_delivered.median(), c =
'black')
plt.xlabel('Seconds',color='black',fontsize=15)
plt.title('Distribution of time taken for order to get
delivered',color='black',fontsize=20,fontweight='bold')
plt.show()
```




```
purchasedDeliveredDist.purchased_delivered.describe()

count    90096.000000
mean        10.602968
std          6.064321
min          0.000000
25%          6.000000
50%          9.000000
75%         14.000000
max         28.000000
Name: purchased_delivered, dtype: float64
```

Observations:

1. The delivery days of orders within the interquartile range are spread mostly **between 0 and 28 days**, which could be seen in the distribution plot.
2. The **average days taken for delivery** of the orders is **11 days**.

4.2. Exploratory Data Analysis on Customers Dataframe

```
customers.head(3)

                        customer_id                customer_unique_id  \
0  06b8999e2fba1a1fbc88172c00ba8bc7  861eff4711a542e4b93843c6dd7febb0

1  18955e83d337fd6b2def6b18a428ac77  290c77bc529b7ac935b93aa66c333dc3
```

```
2  4e7b3e00288586ebd08712fdd0374a03  060e732b5b29e8181a18229c7b0b2b5e


   customer_zip_code_prefix          customer_city customer_state
0                     14409                 franca             SP
1                      9790  sao bernardo do campo             SP
2                      1151              sao paulo             SP
```

```
print('Number of records:',customers.shape[0])
print('Number of columns:',customers.shape[1])
```

```
Number of records: 99441
Number of columns: 5
```

```
customers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99441 entries, 0 to 99440
Data columns (total 5 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   customer_id               99441 non-null  object
 1   customer_unique_id        99441 non-null  object
 2   customer_zip_code_prefix  99441 non-null  int64 
 3   customer_city             99441 non-null  object
 4   customer_state            99441 non-null  object
dtypes: int64(1), object(4)
memory usage: 3.8+ MB
```

```
customers.isnull().sum()
```

```
customer_id                 0
customer_unique_id          0
customer_zip_code_prefix    0
customer_city               0
customer_state              0
dtype: int64
```

observations:

1. There are 4 categorical variables: `customer_id`, `customer_unique_id`, `customer_city`, `customer_state`.
2. There is one Numeric variable: `customer_zip_code_prefix`, which should be converted to object datatype.
3. There is **no presence of Null values** in the Customer dataset.

```
customers['customer_zip_code_prefix'] = 
customers['customer_zip_code_prefix'].astype(object)

customers.describe(include='object')
```

```
                              customer_id
customer_unique_id  \
count                               99441
99441
unique                              99441
96096
top     06b8999e2fba1a1fbc88172c00ba8bc7
8d50f5eadf50201ccdcedfb9e2ac8455
freq                                    1
17

        customer_zip_code_prefix customer_city customer_state
count                      99441         99441          99441
unique                     14994          4119             27
top                        22790     sao paulo             SP
freq                         142         15540          41746
```

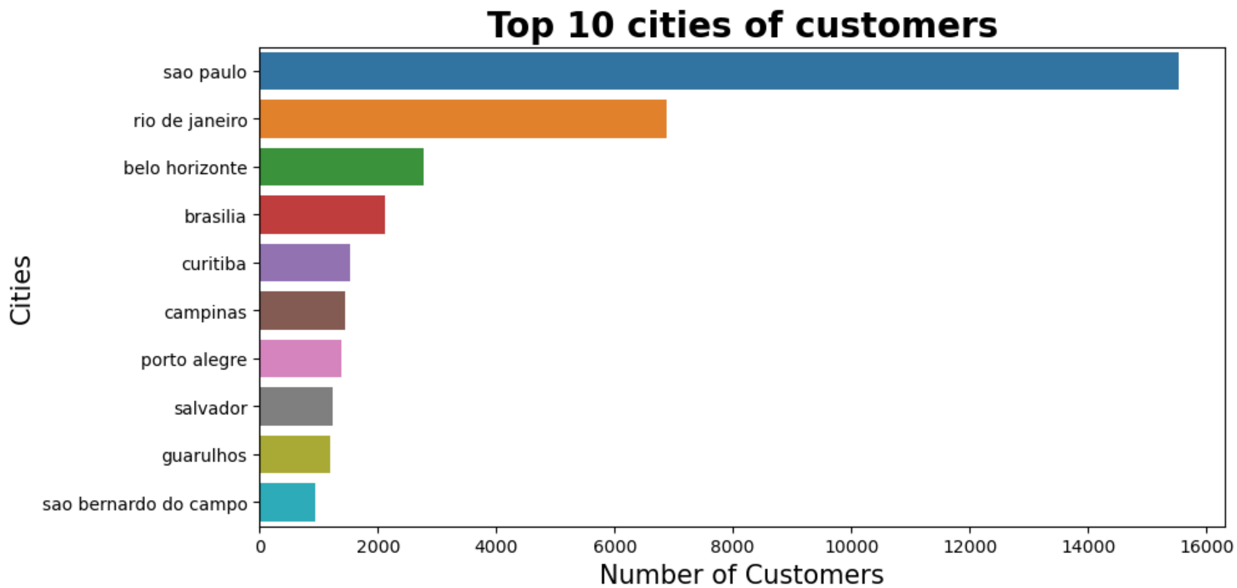
observations:

1. The **total count of customer unique ID** is **99441**, while the **count of unique customer unique ID** is **96096**. We could observe that **almost all of the customers are one time visitors**, i.e., the **frequency of their visit would be 1**.
2. The customers come from **14994 unique zip code locations**, and the **most number of customers**, **142**, belong to the zip code **22790**, which is **Rio de Janeiro**, **Brazil**.
3. The **top city** to which customers belong to is **Sao Paulo** and the **top state** to which our customers belong is **Sao Paulo**.

Visualization of top 10 cities

```
customerCity = customers.customer_city.value_counts(normalize = True)
[:10] * 100
print('The top 10 cities from which customers come are: \n',
customerCity)

The top 10 cities from which customers come are:
 sao paulo                15.627357
rio de janeiro           6.920687
belo horizonte           2.788588
brasilia                 2.142979
curitiba                 1.529550
campinas                 1.452117
porto alegre             1.386752
salvador                 1.251999
guarulhos                1.195684
sao bernardo do campo    0.943273
Name: customer_city, dtype: float64

plt.figure(figsize=(10, 5))
sns.barplot(y = customers.customer_city.value_counts().index[:10], x =
customers.customer_city.value_counts().values[:10])
```

```
plt.xlabel('Number of Customers',color='black',fontsize=15)
plt.ylabel('Cities',color='black',fontsize=15)
plt.title('Top 10 cities of
customers',color='black',fontsize=20,fontweight='bold')
plt.show()
```



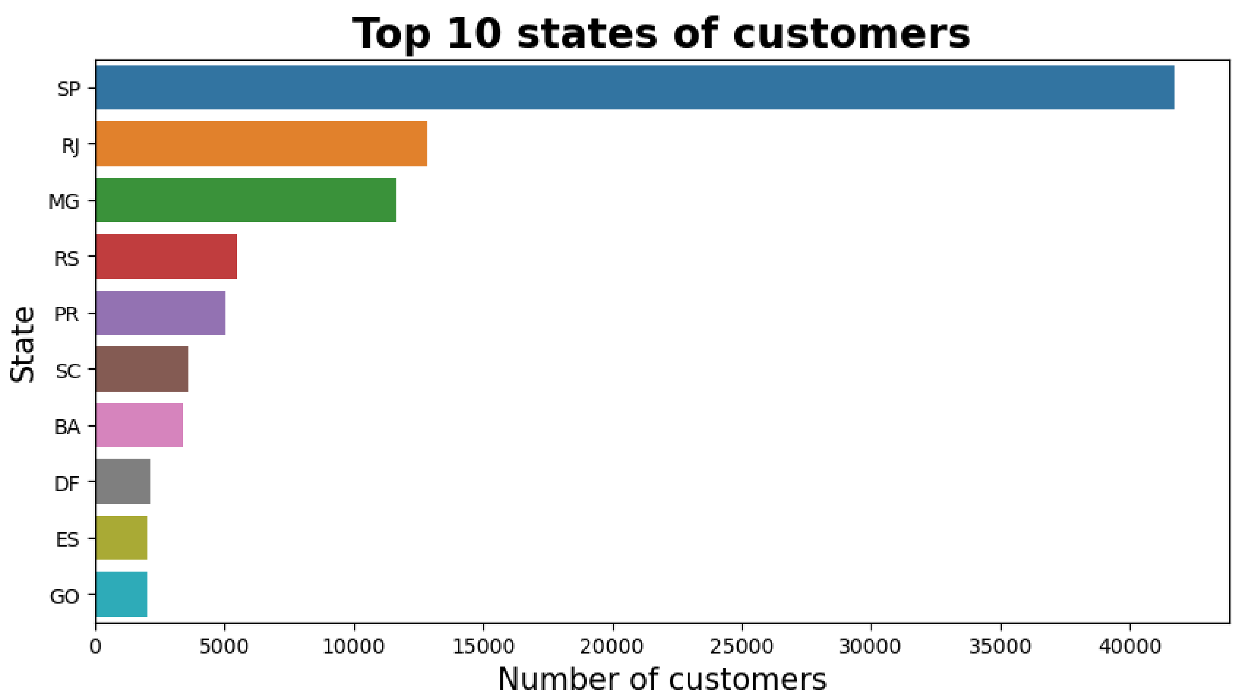
observations:

1. The **top city** to which the customers belong is **Sao Paulo**, which account to **15.62% of customers**.
2. This is followed by **Rio De Janeiro**, which accounts to **6.92% of customers**.
3. The **least city** to which the customers belong to **among the top 10** is from **Sao Bernardo Do Campo**, which accounts to just **0.94%**.

Visualization of top 10 States

```
customerState = customers.customer_state.value_counts(normalize=True)
[:10] * 100
print('The top 10 cities from which customers come are: \n',
customerState)

The top 10 cities from which customers come are:
 SP    41.980672
RJ    12.924247
MG    11.700405
RS     5.496727
PR     5.073360
SC     3.657445
BA     3.399000
DF     2.152030
ES     2.044428
```

```
GO      2.031355
Name: customer_state, dtype: float64

plt.figure(figsize=(10, 5))
sns.barplot(y = customers.customer_state.value_counts().index[:10], x
= customers.customer_state.value_counts().values[:10])
plt.xlabel('Number of customers',color='black',fontsize=15)
plt.ylabel('State',color='black',fontsize=15)
plt.title('Top 10 states of
customers',color='black',fontsize=20,fontweight='bold')
plt.show()
```



observations:

1. The **top state** to which customers belong is **Sao Paulo**, from where **41.98%** of customers come from.
2. This is followed by **Rio De Janeiro**, which accounts to **12.92% of customers**.

Visualization of Geolocation of Customers

```
incorrectLocation = geolocation[(geolocation.geolocation_lat > 10) &
(geolocation.geolocation_lng < -18)]
incorrectLocation

        geolocation_zip_code_prefix  geolocation_lat  geolocation_lng
\
538512                        29654        29.409252       -98.484121

538557                        29654        21.657547      -101.466766
```

```
585242                           35179        25.995203       -98.078544

585260                           35179        25.995245       -98.078533


              geolocation_city geolocation_state
538512  santo antônio do canaã                ES
538557  santo antonio do canaa                ES
585242      santana do paraíso                MG
585260      santana do paraiso                MG

geolocation.drop(index = [538512, 538557, 585242, 585260], inplace = 
True)
```

Observations:

1. There are some records in the geolocation data for which the **geolocation latitude and longitude are pointing to locations in the sea**, which will lead to **inappropriate visualization of the geolocation**, when aggregation is applied to the fields.
2. So such records are alone **dropped** from the data.
3. Those records include **geolocation zipcodes 29654** and **35179**, for which the latitude and longitude values for certain records are incorrectly given.

4. **Latitude greater than 10 degrees** and **longitude lesser than -18 degrees** point to the sea.

```
geolocationMean = geolocation.groupby('geolocation_zip_code_prefix', 
as_index = False).agg({'geolocation_lat'  : 'max', 

'geolocation_lng'  : 'max'})
geolocationMean.head()

   geolocation_zip_code_prefix  geolocation_lat  geolocation_lng
0                         1001       -23.549292       -46.633559
1                         1002       -23.544641       -46.633180
2                         1003       -23.548901       -46.634862
3                         1004       -23.549181       -46.634057
4                         1005       -23.548758       -46.634768
```

Observation:

1. Since there are many geographical coordinates given for a single geolocation zipcode, we consider the **maximum value of the coordinate for a particular zipcode**.

```
customerDensity = customers.merge(geolocationMean, left_on = 
'customer_zip_code_prefix', right_on = 'geolocation_zip_code_prefix', 
how = 'left')[['customer_unique_id', 'customer_zip_code_prefix', 
'geolocation_lat', 'geolocation_lng']]
customerDensity.head()
```

```
                  customer_unique_id  customer_zip_code_prefix  
geolocation_lat  \
0  861eff4711a542e4b93843c6dd7febb0                     14409        -
20.468849   
1  290c77bc529b7ac935b93aa66c333dc3                      9790        -
23.659702   
2  060e732b5b29e8181a18229c7b0b2b5e                      1151        -
23.527788   
3  259dac757896d24d7702b9acbbff3f3c                      8775        -
23.493944   
4  345ecd01c38d18a9036ed96c73b8d066                     13056        -
22.961980   

   geolocation_lng  
0       -47.382173  
1       -46.530264  
2       -46.652997  
3       -46.172406  
4       -47.125767  

customerDensity.dropna(inplace = True)
```

observations:

1. The **customer zip codes are mapped with the geolocation zip code's latitude and longidute**, so as to visualise from which region our customers are more densly concentrated.
2. There are some **zip codes for which the latitude and longitude values are not available** in the data, so we **drop such records** for visualization.

```
# create a map centered on your coordinates
m = folium.Map(location = customerDensity[['geolocation_lat', 
'geolocation_lng']].values.tolist()[0], zoom_start = 13)

# create a list of coordinates
coordinates = customerDensity[['geolocation_lat', 
'geolocation_lng']].values.tolist()

# create a heatmap layer with the list of coordinates
heat_layer = HeatMap(coordinates)

# add the heatmap layer to the map
heat_layer.add_to(m)

# display the map
m

<folium.folium.Map at 0x7b9a66828090>
```

observation:

1. From the heatmap, we could see that **most of the customers are based out of South America**, while **some are from the Europe**.

4.3. Exploratory Data Analysis On OrderItems dataframe

```
orderItems.head(3)
```

```
                           order_id  order_item_id  \
0  00010242fe8c5a6d1ba2dd792cb16214              1
1  00018f77f2f0320c557190d7a144bdd3              1
2  000229ec398224ef6ca0657da4fc703e              1

                         product_id                         seller_id
\
0  4244733e06e7ecb4970a6e2683c13e61  48436dade18ac8b2bce089ec2a041202

1  e5f2d52b802189ee658865ca93d83a8f  dd7ddc04e1b6c2c614352b383efe2d36

2  c777355d18b72b67abbeef9df44fd0fd  5b51032eddd242adc84c38acab88f23d


   shipping_limit_date  price  freight_value
0  2017-09-19 09:45:35   58.9          13.29
1  2017-05-03 11:05:13  239.9          19.93
2  2018-01-18 14:48:30  199.0          17.87
```

```
orderItems.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 112650 entries, 0 to 112649
Data columns (total 7 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   order_id             112650 non-null  object
 1   order_item_id        112650 non-null  int64
 2   product_id           112650 non-null  object
 3   seller_id            112650 non-null  object
 4   shipping_limit_date  112650 non-null  object
 5   price                112650 non-null  float64
 6   freight_value        112650 non-null  float64
dtypes: float64(2), int64(1), object(4)
memory usage: 6.0+ MB
```

```
orderItems['shipping_limit_date'] =
pd.to_datetime(orderItems.shipping_limit_date)

orderItems.isna().sum() / len(orderItems) * 100
```

```
order_id                0.0
order_item_id           0.0
```

```
product_id             0.0
seller_id              0.0
shipping_limit_date    0.0
price                  0.0
freight_value          0.0
dtype: float64
```

```
orderItems.describe(exclude = np.number)
```

```
                                order_id
product_id  \
count                             112650
112650
unique                             98666
32951
top     8272b63d03f5f79c56e9e4120aec44ef
aca2eb7d00ea1a7b8ebd4e68314663af
freq                                  21
527
first                                NaN
NaN
last                                 NaN
NaN

                               seller_id  shipping_limit_date
count                             112650               112650
unique                              3095                93318
top     6560211a19b47992c3666cc44a7e94c0  2017-07-21 18:25:23
freq                                2033                   21
first                                NaN  2016-09-19 00:15:34
last                                 NaN  2020-04-09 22:35:08
```

```
orderItems.describe()
```

```
       order_item_id          price  freight_value
count  112650.000000  112650.000000  112650.000000
mean        1.197834     120.653739      19.990320
std         0.705124     183.633928      15.806405
min         1.000000       0.850000       0.000000
25%         1.000000      39.900000      13.080000
50%         1.000000      74.990000      16.260000
75%         1.000000     134.900000      21.150000
max        21.000000    6735.000000     409.680000
```

Observations:

1. The order items dataframe consist of all the orders placed by the customers and the details of the products in that order.

2. There are **98666 unique orders** placed with the business and the order with **most number of items** is **8272b63d03f5f79c56e9e4120aec44ef**, which has **21 items in a single order**.
3. **32951 unique products** were ordered during the taken time period and the **most ordered product** is **aca2eb7d00ea1a7b8ebd4e68314663af**, which was ordered **527 times**. During the further stages of analysis, the product will be analysed mapping the ID with the products dataframe.
4. Similarly there are **3095 unique sellers** for the product and the **seller who sells most of the product** is **6560211a19b47992c3666cc44a7e94c0**. This data is also masked but we can combine this with geolocation and find which state or city the sellers belong to and do further analysis.
5. The **average price of the products** ordered is **120.65 Brazilian Reals**. The price of the products ordered is **highly right skewed**, as the **costliest product ordered** is priced at **6735 Brazilian Reals**.
6. Similarly the **freight value** of the order **on an average for each order** is **19.99 Brazilian Reals**, and the **expensive freight value** is **409.68 Brazilian Reals**. The particular orders whose freight values are higher will be studied later in the course of analysis.

Visualization of Top 10 orders

```
topOrders = orderItems.groupby('order_id', as_index =
False).agg({'price'          : 'sum',

'freight_value' : 'sum'})
topOrders['total_price'] = topOrders.price + topOrders.freight_value
top10Orders = topOrders.sort_values(by = 'total_price', ascending =
False)[:10]
top10Orders
```

	order_id	price	freight_value	total_price
1455	03caa2c082116e1d31e67e9ae3700499	13440.0	224.08	13664.08
44467	736e1922ae60d0d6a89247b851902527	7160.0	114.88	7274.88
3130	0812eb902a67711a1cb742b3cdaa65ae	6735.0	194.31	6929.31
98298	fefacc66af859508bf1a7934eab1e97f	6729.0	193.21	6922.21
94439	f5136e38d1a14a4dbd87dff67da82701	6499.0	227.66	6726.66
17114	2cc9089445046817a7539d90805e6e5a	5934.6	146.94	6081.54
65046	a96610ab360d42a2e5335a3998b4718a	4799.0	151.34	4950.34
69531	b4c4b76c642808cbe472a32b86cddc95	4599.9	209.54	4809.44
9868	199af31afc78c699f0dbf71fb178d4d4	4690.0	74.34	4764.34

```
54353  8dbc85d1447242f3b127dda390d56e19   4590.0          91.78
4681.78
```

Visualization of top sellers of the orders placed by customers

```
topSellers = orderItems.seller_id.value_counts()
topSellers.head()
```

```
6560211a19b47992c3666cc44a7e94c0    2033
4a3ca9315b744ce9f8e9374361493884    1987
1f50f920176fa81dab994f9023523100    1931
cc419e0650a3c5ba77189a1882b7556a    1775
da8622b14eb17ae2831f4ac5b9dab84a    1551
Name: seller_id, dtype: int64
```

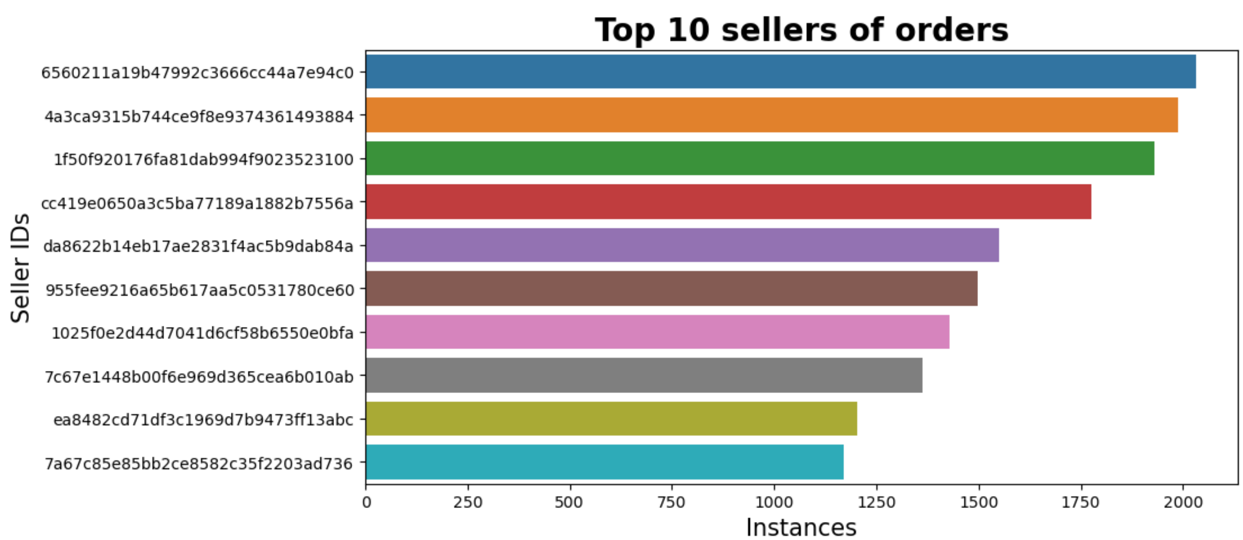
```
topSellers = pd.DataFrame({'seller_id'     : topSellers.index,
                           'instances'     : topSellers.values})
topSellers.head()
```

```
                          seller_id  instances
0  6560211a19b47992c3666cc44a7e94c0       2033
1  4a3ca9315b744ce9f8e9374361493884       1987
2  1f50f920176fa81dab994f9023523100       1931
3  cc419e0650a3c5ba77189a1882b7556a       1775
4  da8622b14eb17ae2831f4ac5b9dab84a       1551
```

```
topSellersOfOrders = topSellers.merge(sellers, on =
'seller_id').merge(geolocationMean, left_on =
'seller_zip_code_prefix', right_on =
'geolocation_zip_code_prefix').drop(columns =
['geolocation_zip_code_prefix'], axis = 1).sort_values('instances',
ascending = False)
topSellersOfOrders.head()
```

```
                           seller_id  instances
seller_zip_code_prefix  \
0   6560211a19b47992c3666cc44a7e94c0       2033
5849
2   4a3ca9315b744ce9f8e9374361493884       1987
14940
51  1f50f920176fa81dab994f9023523100       1931
15025
55  cc419e0650a3c5ba77189a1882b7556a       1775
9015
58  da8622b14eb17ae2831f4ac5b9dab84a       1551
13405

              seller_city seller_state  geolocation_lat
geolocation_lng
0                sao paulo           SP       -23.649432       -
```

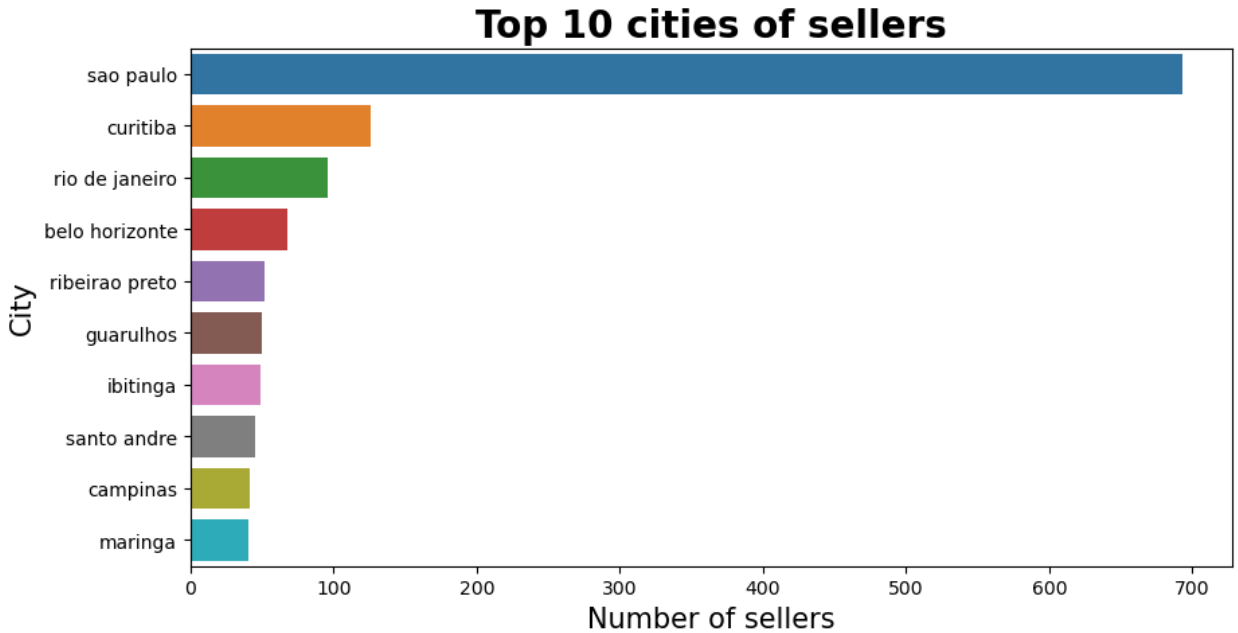
```
46.753466
2                 ibitinga             SP         -21.734663        -
48.809349
51  sao jose do rio preto             SP         -20.793902        -
49.376768
55              santo andre             SP         -23.653394        -
46.513267
58               piracicaba             SP         -22.692313        -
47.653256

plt.figure(figsize=(10, 5))
sns.barplot(x = topSellers.instances[:10], y =
topSellers.seller_id[:10])
plt.xlabel('Instances',color='black',fontsize=15)
plt.ylabel('Seller IDs',color='black',fontsize=15)
plt.title('Top 10 sellers of
orders',color='black',fontsize=20,fontweight='bold')
plt.show()
```



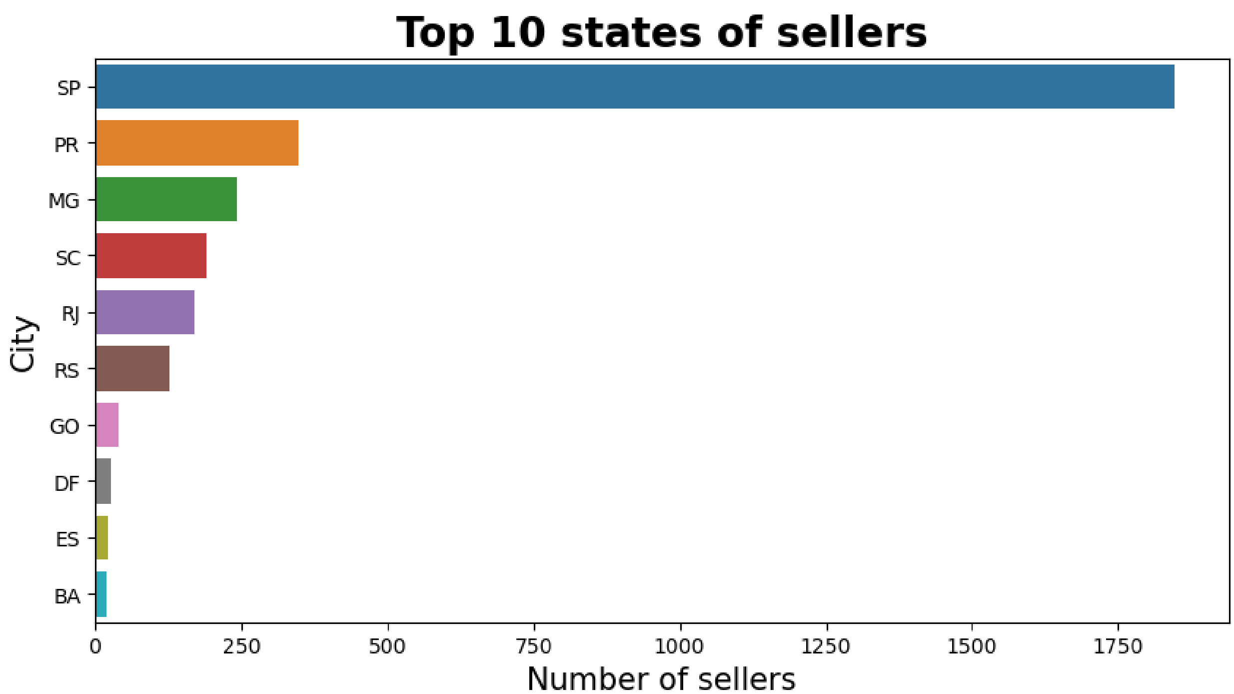
Observations:

1. Since the **seller IDs are masked**, we could not make out from what the seller ID means.
2. So we use the location and city of the sellers to draw inferences.

```
plt.figure(figsize=(10, 5))
sns.barplot(y =
topSellersOfOrders.seller_city.value_counts().index[:10], x =
topSellersOfOrders.seller_city.value_counts().values[:10])
plt.xlabel('Number of sellers',color='black',fontsize=15)
plt.ylabel('City',color='black',fontsize=15)
plt.title('Top 10 cities of
sellers',color='black',fontsize=20,fontweight='bold')
plt.show()
```




```
plt.figure(figsize=(10, 5))
sns.barplot(y =
topSellersOfOrders.seller_state.value_counts().index[:10], x =
topSellersOfOrders.seller_state.value_counts().values[:10])
plt.xlabel('Number of sellers',color='black',fontsize=15)
plt.ylabel('City',color='black',fontsize=15)
plt.title('Top 10 states of
sellers',color='black',fontsize=20,fontweight='bold')
plt.show()
```



Observations:

1. The **sellers of orders** are mostly from the **city** of **Sao Paulo**, followed by **Curitiba** and **Rio De Janeiro**.
2. The sellers of orders are mostly from the **state** of **Sao Paulo**.
3. This is obvious as most of the customers are from the same state and city of Sao Paulo.

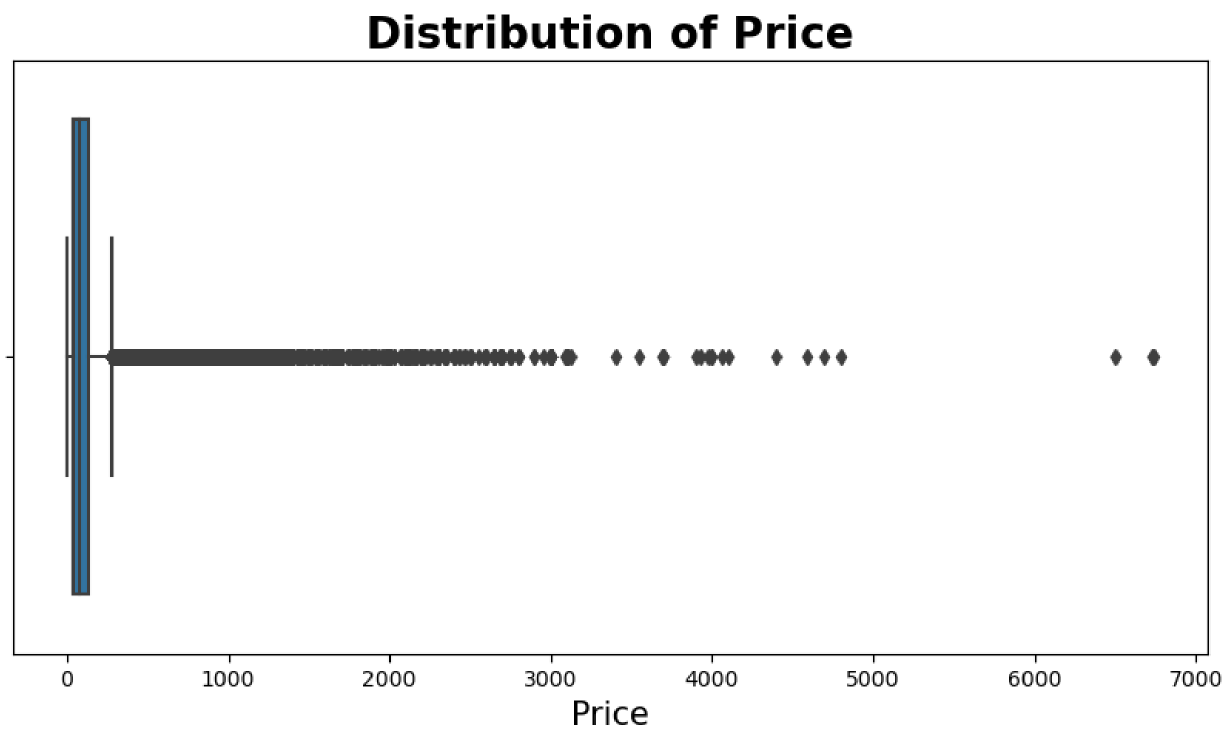
```
# create a map centered on your coordinates
m = folium.Map(location = topSellersOfOrders[['geolocation_lat',
'geolocation_lng']].values.tolist()[0], zoom_start = 13)

# create a list of coordinates
coordinates = topSellersOfOrders[['geolocation_lat',
'geolocation_lng']].values.tolist()

# create a heatmap layer with the list of coordinates
heat_layer = HeatMap(coordinates)

# add the heatmap layer to the map
heat_layer.add_to(m)

# display the map
m

<folium.folium.Map at 0x7b9a5a5eb210>
```

Observation:

1. From the heatmap of the sellers based on their latitudes and longitudes, we could infer the **concentration of sellers are only in South America**. They carter to all of our customers spread in Europe and South America.

Distribution of price of the orders

```
plt.figure(figsize=(10, 5))
sns.boxplot(x='price', data=orderItems)
plt.xlabel('Price',color='black',fontsize=15)
plt.title('Distribution of
Price',color='black',fontsize=20,fontweight='bold')
plt.show()
```



Observations:

1. From the boxplot we could infer that the **price of the products** ordered is highly **right skewed**.
2. So as to view the spread of the price more clearly we will ignore the outliers and then find the distribution.

```
Q1 = np.quantile(orderItems.price, 0.25)
Q3 = np.quantile(orderItems.price, 0.75)
IQR = Q3 - Q1
priceDistribution = orderItems[~((orderItems.price < Q1 - 1.5 * IQR) |
(orderItems.price > Q3 + 1.5 * IQR))]
priceDistribution.head()
```

```
                             order_id  order_item_id  \
0  00010242fe8c5a6d1ba2dd792cb16214              1
1  00018f77f2f0320c557190d7a144bdd3              1
2  000229ec398224ef6ca0657da4fc703e              1
3  00024acbcdf0a6daa1e931b038114c75              1
4  00042b26cf59d7ce69dfabb4e55b4fd9              1

                         product_id                         seller_id
\
0  4244733e06e7ecb4970a6e2683c13e61  48436dade18ac8b2bce089ec2a041202

1  e5f2d52b802189ee658865ca93d83a8f  dd7ddc04e1b6c2c614352b383efe2d36

2  c777355d18b72b67abbeef9df44fd0fd  5b51032eddd242adc84c38acab88f23d

3  7634da152a4610f1595efa32f14722fc  9d7a1d34a5052409006425275ba1c2b4

4  ac6c3623068f30de03045865e4e10089  df560393f3a51e74553ab94004ba5c87


  shipping_limit_date   price  freight_value
0 2017-09-19 09:45:35   58.90          13.29
1 2017-05-03 11:05:13  239.90          19.93
2 2018-01-18 14:48:30  199.00          17.87
3 2018-08-15 10:10:18   12.99          12.79
4 2017-02-13 13:57:51  199.90          18.14
```

```
plt.figure(figsize=(10, 5))
sns.distplot(priceDistribution.price)
plt.axvline(priceDistribution.price.mean(), c = 'red')
plt.axvline(priceDistribution.price.median(), c = 'black')
plt.xlabel('Price',color='black',fontsize=15)
plt.title('Distribution of Price without
outliers',color='black',fontsize=20,fontweight='bold')
plt.show()
```


```
priceDistribution.price.describe()
```

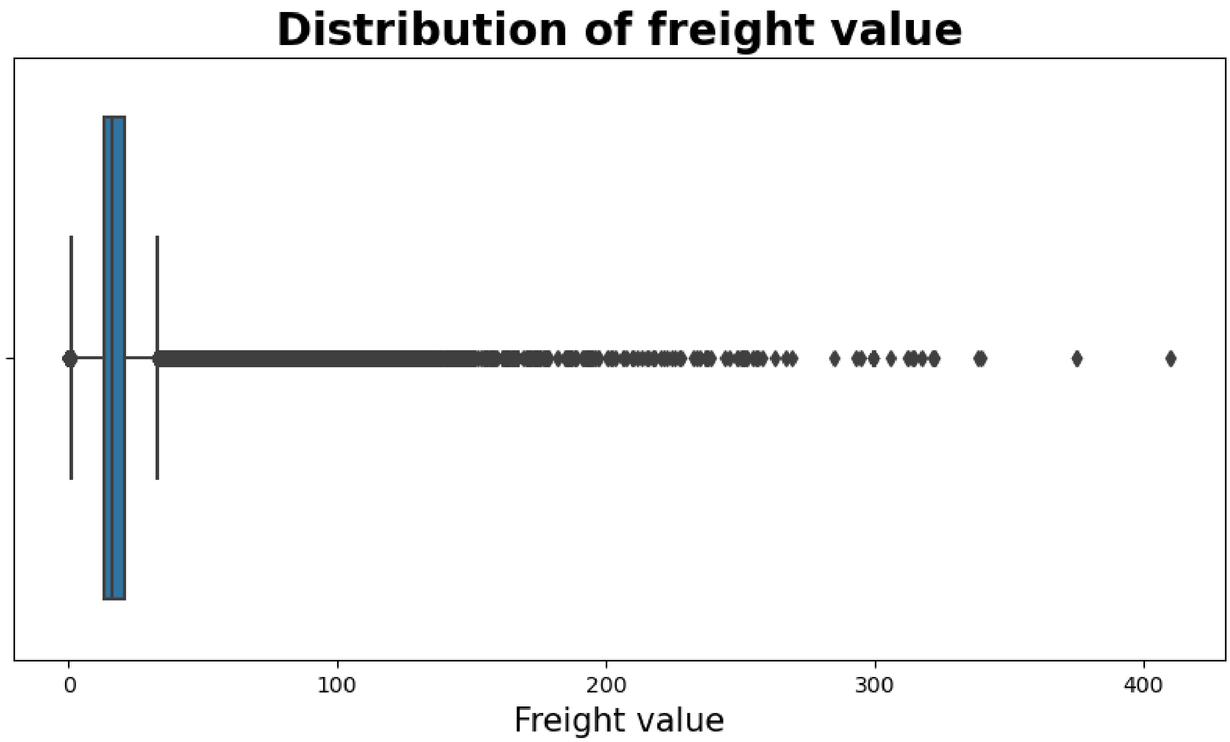
```
count    104223.000000
mean         83.974668
std          58.580002
min           0.850000
25%          38.500000
50%          69.000000
75%         118.990000
max         277.300000
Name: price, dtype: float64
```

Observations:

1. The price of the products within the interquartile range are spread mostly between 0 and 100 Brazilian Reals, which could be seen in the distribution plot.
2. The **average price of the products** is **83.97 Brazilian Reals**.

Visualization of freight value of the orders

```
plt.figure(figsize=(10, 5))
sns.boxplot(x='freight_value', data=orderItems)
plt.xlabel('Freight value',color='black',fontsize=15)
plt.title('Distribution of freight
value',color='black',fontsize=20,fontweight='bold')
plt.show()
```



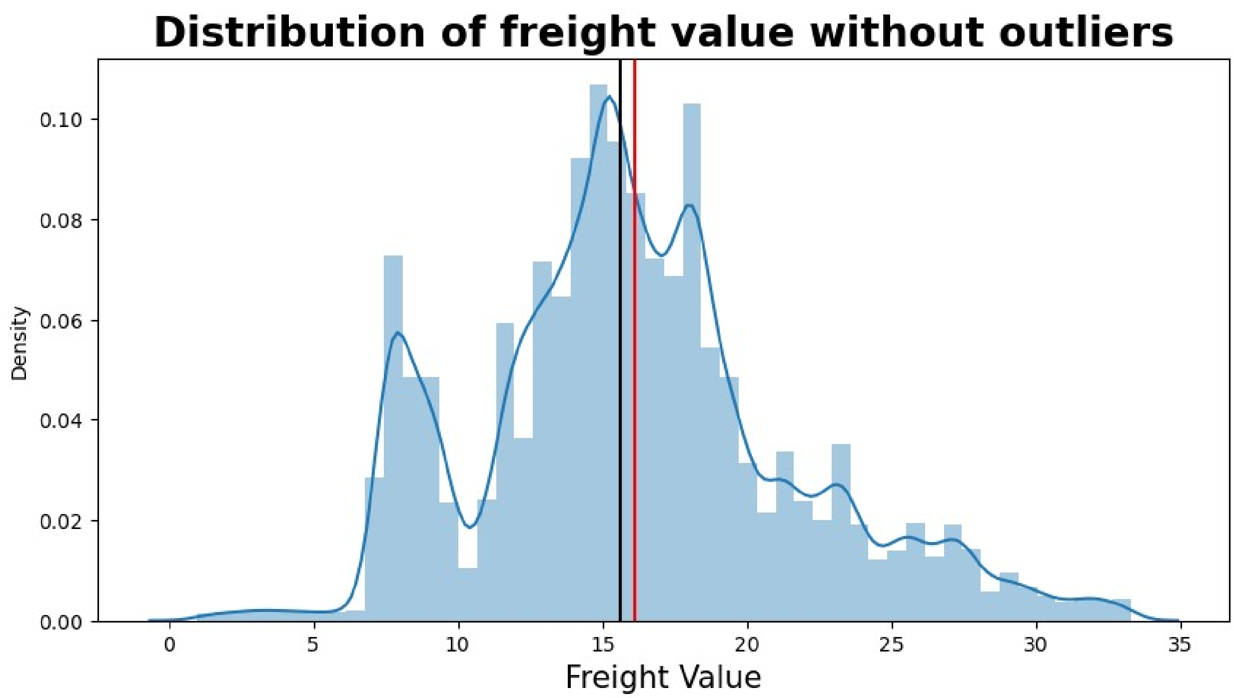
Observations:

1. From the boxplot we could infer that the **freight value of the product** ordered is highly **right skewed**.
2. So as to view the spread of the freight value more clearly we will ignore the outliers and then find the distribution.

```
Q1 = np.quantile(orderItems.freight_value, 0.25)
Q3 = np.quantile(orderItems.freight_value, 0.75)
IQR = Q3 - Q1
freightValueDistribution = orderItems[~((orderItems.freight_value < Q1
- 1.5 * IQR) | (orderItems.freight_value > Q3 + 1.5 * IQR))]
freightValueDistribution.head()

                           order_id  order_item_id  \
0  00010242fe8c5a6d1ba2dd792cb16214              1
1  00018f77f2f0320c557190d7a144bdd3              1
2  000229ec398224ef6ca0657da4fc703e              1
3  00024acbcdf0a6daa1e931b038114c75              1
4  00042b26cf59d7ce69dfabb4e55b4fd9              1

                         product_id                         seller_id
\
0  4244733e06e7ecb4970a6e2683c13e61  48436dade18ac8b2bce089ec2a041202

1  e5f2d52b802189ee658865ca93d83a8f  dd7ddc04e1b6c2c614352b383efe2d36

2  c777355d18b72b67abbeef9df44fd0fd  5b51032eddd242adc84c38acab88f23d
```

```
3  7634da152a4610f1595efa32f14722fc  9d7a1d34a5052409006425275ba1c2b4

4  ac6c3623068f30de03045865e4e10089  df560393f3a51e74553ab94004ba5c87


  shipping_limit_date   price  freight_value
0 2017-09-19 09:45:35   58.90          13.29
1 2017-05-03 11:05:13  239.90          19.93
2 2018-01-18 14:48:30  199.00          17.87
3 2018-08-15 10:10:18   12.99          12.79
4 2017-02-13 13:57:51  199.90          18.14
```

```
plt.figure(figsize=(10, 5))
sns.distplot(freightValueDistribution.freight_value)
plt.axvline(freightValueDistribution.freight_value.mean(), c = 'red')
plt.axvline(freightValueDistribution.freight_value.median(), c =
'black')
plt.xlabel('Freight Value',color='black',fontsize=15)
plt.title('Distribution of freight value without
outliers',color='black',fontsize=20,fontweight='bold')
plt.show()
```




```
freightValueDistribution.freight_value.describe()

count    100516.000000
mean         16.125685
std           5.468564
```

```
min           0.980000
25%          12.760000
50%          15.620000
75%          18.800000
max          33.250000
Name: freight_value, dtype: float64
```

Observations:

1. The freight values of the products within the interquartile range are spread mostly between 5 and 25, which could be seen in the distribution plot. We could infer that such orders were within the continent of South America.
2. The **average freight value** of the products is **16.12 Brazilian Reals**.

4.4. Exploratory Data Analysis on Payments DataFrame

```
payments.head(3)
```

```
                           order_id  payment_sequential
payment_type  \
0  b81ef226f3fe1789b1e8b2acac839d17                   1  credit_card

1  a9810da82917af2d9aefd1278f1dcfa0                   1  credit_card

2  25e8ea4e93396b6fa0d3dd708e76c1bd                   1  credit_card


   payment_installments  payment_value
0                     8          99.33
1                     1          24.39
2                     1          65.71
```

```
print('Number of Records:',payments.shape[0])
print('Number of Columns:',payments.shape[1])
```

```
Number of Records: 103886
Number of Columns: 5
```

```
payments.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103886 entries, 0 to 103885
Data columns (total 5 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   order_id              103886 non-null  object
 1   payment_sequential    103886 non-null  int64
 2   payment_type          103886 non-null  object
 3   payment_installments  103886 non-null  int64
```

```
 4   payment_value         103886 non-null  float64
dtypes: float64(1), int64(2), object(2)
memory usage: 4.0+ MB
```

```
payments.isna().sum()
```

```
order_id                0
payment_sequential      0
payment_type            0
payment_installments    0
payment_value           0
dtype: int64
```

```
payments.describe(include = np.number)
```

```
       payment_sequential  payment_installments  payment_value
count       103886.000000         103886.000000  103886.000000
mean             1.092679              2.853349     154.100380
std              0.706584              2.687051     217.494064
min              1.000000              0.000000       0.000000
25%              1.000000              1.000000      56.790000
50%              1.000000              1.000000     100.000000
75%              1.000000              4.000000     171.837500
max             29.000000             24.000000   13664.080000
```

```
payments.describe(exclude = np.number)
```

```
                                order_id payment_type
count                             103886       103886
unique                             99440            5
top     fa65dad1b0e818e3ccc5cb0e39231352  credit_card
freq                                  29        76795
```

Observations:

1. There is **no presence of Null values** in the payments dataframe.
2. Most of the payements were made through **credit cards**.
3. The **average number of payment installments** was **1**, since it is highly right skewed, the mean is not considered. **24 was the maximum number of payment installments** for an order.
4. The payment value of the orders is also highly right skewed. The **average payment value** is **154.1 Brazilian Reals**.

Visulaization Of Different Payment types

```
payments.payment_type.value_counts(normalize = True) * 100
```

```
credit_card    73.922376
boleto         19.043952
voucher         5.558978
debit_card      1.471806
```

```
not_defined     0.002888
Name: payment_type, dtype: float64
```

Observations:

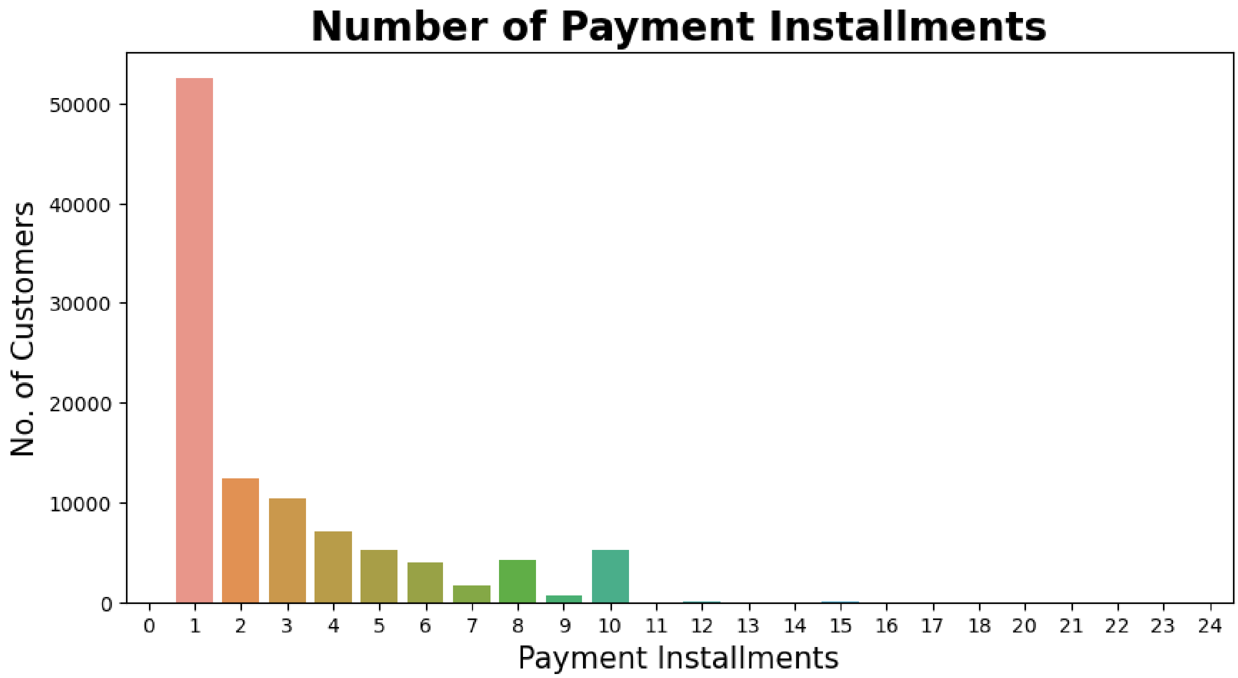
1. From the count plot, we cound clearly see that **credit card** accounts for **73.9% of payments**, which is the **most preferred payment type**, followed by **boleto**, **voucher** and **debit card**.
2. There is imbalance present in the data as most of the payment types are of credit cards.

Distribution of Number of Payment Installments

```
payments.payment_installments.value_counts(normalize = True)[:10] *
100
```

```
1     50.580444
2     11.948675
3     10.069692
4      6.832489
10     5.128699
5      5.043028
8      4.108350
6      3.773367
7      1.565177
9      0.619910
Name: payment_installments, dtype: float64
```

```
plt.figure(figsize=(10, 5))
sns.countplot(x='payment_installments',data=payments)
plt.title('Number of Payment
Installments',fontweight='bold',fontsize=20)
plt.xlabel('Payment Installments',fontsize=15,color='black')
plt.ylabel('No. of Customers',fontsize=15,color='black')
plt.show()
```

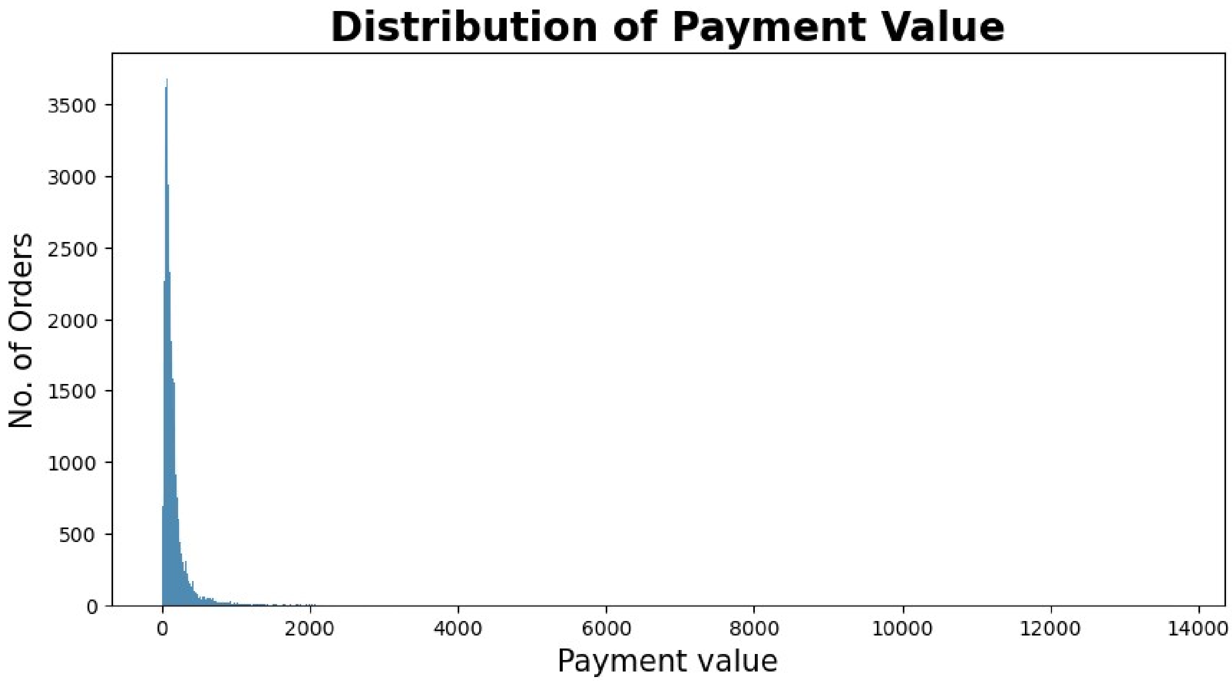


Observations:

1. Most customers prefered to pay for the order in a **single installment**. However, customers also opted for more than one installment, the number is not insignificant.
2. For further analysis, we could **convert the installments to an object datatype** as we could not consider it as a numeric column.

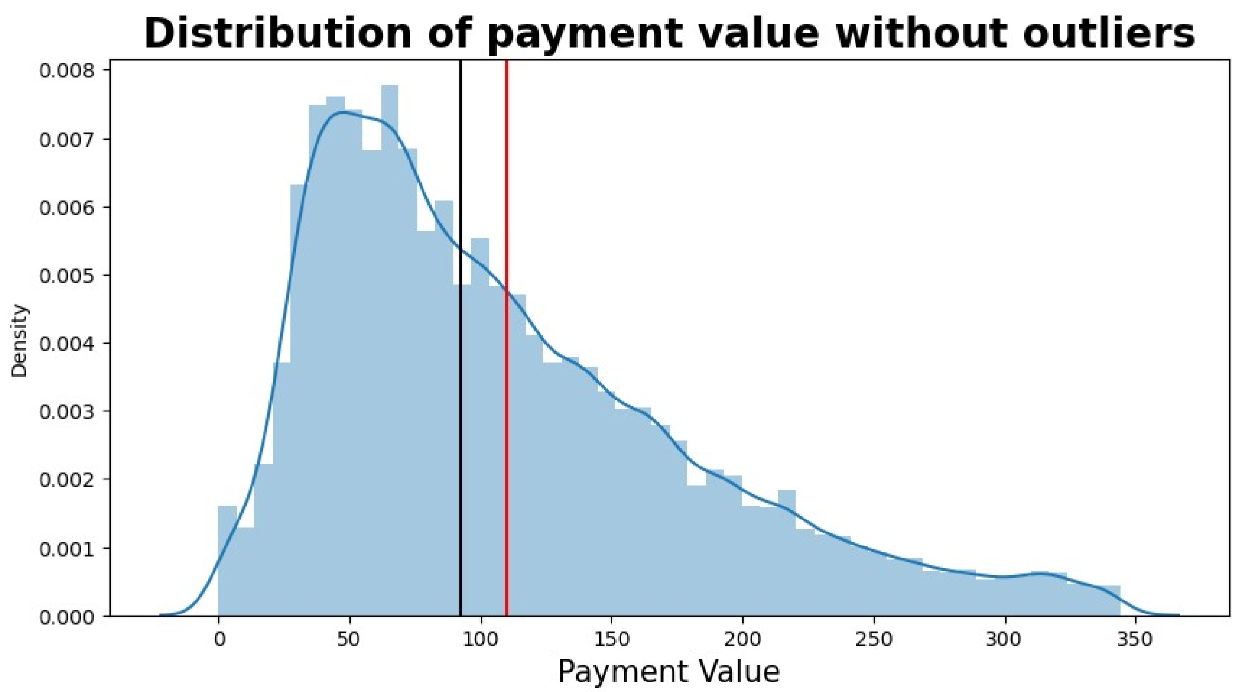
Distribution of the payment value of the orders

```
plt.figure(figsize=(10, 5))
sns.histplot(x='payment_value', data=payments)
plt.title('Distribution of Payment
Value',fontweight='bold',fontsize=20)
plt.xlabel('Payment value',fontsize=15)
plt.ylabel('No. of Orders',fontsize=15)
plt.show()
```




```
Q1 = np.quantile(payments.payment_value, 0.25)
Q3 = np.quantile(payments.payment_value, 0.75)
IQR = Q3 - Q1
paymentValueDistribution = payments[~((payments.payment_value < Q1 -
1.5 * IQR) | (payments.payment_value > Q3 + 1.5 * IQR))]
paymentValueDistribution.head()

                           order_id  payment_sequential
payment_type  \
0  b81ef226f3fe1789b1e8b2acac839d17                   1  credit_card

1  a9810da82917af2d9aefd1278f1dcfa0                   1  credit_card

2  25e8ea4e93396b6fa0d3dd708e76c1bd                   1  credit_card

3  ba78997921bbcdc1373bb41e913ab953                   1  credit_card

4  42fdf880ba16b47b59251dd489d4441a                   1  credit_card


   payment_installments  payment_value
0                     8          99.33
1                     1          24.39
2                     1          65.71
3                     8         107.78
4                     2         128.45

plt.figure(figsize=(10, 5))
sns.distplot(paymentValueDistribution.payment_value)
```

```
plt.axvline(paymentValueDistribution.payment_value.mean(), c = 'red')
plt.axvline(paymentValueDistribution.payment_value.median(), c =
'black')
plt.xlabel('Payment Value',color='black',fontsize=15)
plt.title('Distribution of payment value without
outliers',color='black',fontsize=20,fontweight='bold')
plt.show()
```




```
paymentValueDistribution.payment_value.describe()

count    95905.000000
mean       110.062133
std         72.785054
min          0.000000
25%         54.000000
50%         92.200000
75%        150.580000
max        344.340000
Name: payment_value, dtype: float64
```

Observations:

1. The payment values of the orders within the interquartile range are spread mostly between 0 and 200, which could be seen in the distribution plot.
2. The **average payment value** for the orders is **110.06 Brazilian Reals**.

4.5. Exploratory DataAnalysis On Order reviews dataframe

```
orderReviews.head(3)
```

```
                          review_id                          order_id
\
0  7bc2406110b926393aa56f80a40eba40  73fc7af87114b39712e6da79b0a377eb

1  80e641a11e56f04c1ad469d5645fdfde  a548910a1c6147796b98fdf73dbeba33

2  228ce5500dc1d8e020d8d1322874b6f0  f9e4b658b201a9f2ecdecbb34bed034b


   review_score review_comment_title review_comment_message  \
0             4                  NaN                    NaN
1             5                  NaN                    NaN
2             5                  NaN                    NaN

  review_creation_date review_answer_timestamp
0  2018-01-18 00:00:00     2018-01-18 21:46:59
1  2018-03-10 00:00:00     2018-03-11 03:05:13
2  2018-02-17 00:00:00     2018-02-18 14:36:24
```

```
print('Number of records:',orderReviews.shape[0])
print('number of columns:',orderReviews.shape[1])
```

```
Number of records: 99224
number of columns: 7
```

```
orderReviews['review_answer_timestamp'] =
pd.to_datetime(orderReviews.review_answer_timestamp)
orderReviews['review_creation_date'] =
pd.to_datetime(orderReviews.review_creation_date)
```

```
orderReviews.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99224 entries, 0 to 99223
Data columns (total 7 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   review_id                99224 non-null  object
 1   order_id                 99224 non-null  object
 2   review_score             99224 non-null  int64
 3   review_comment_title     11568 non-null  object
 4   review_comment_message   40977 non-null  object
 5   review_creation_date     99224 non-null  datetime64[ns]
 6   review_answer_timestamp  99224 non-null  datetime64[ns]
dtypes: datetime64[ns](2), int64(1), object(4)
memory usage: 5.3+ MB
```

```
orderReviews.isna().sum()[orderReviews.isna().sum() > 0] / 
len(orderReviews) * 100

review_comment_title      88.341530
review_comment_message    58.702532
dtype: float64
```

Observations:

1. There are **88.34%** of `review_comment_title` and **58.7%** of `review_comment_message` as **null values**.
2. We are **dropping** the null values.

```
orderReviews.dropna(inplace = True)

reviewScore = orderReviews.review_score.value_counts(normalize = True)
* 100
reviewScore

5    55.107226
1    18.182742
4    14.564488
3     7.490599
2     4.654945
Name: review_score, dtype: float64
```

Observations:

1. From the count plot of review score, we could clearly see that for about **57.77%** of orders, the **review score is 5**, which is the maximum review score.
2. From this we could clearly see that customers were mostly satisfied by the products and the business.

Comparision of review scores of on-time and late deliveries

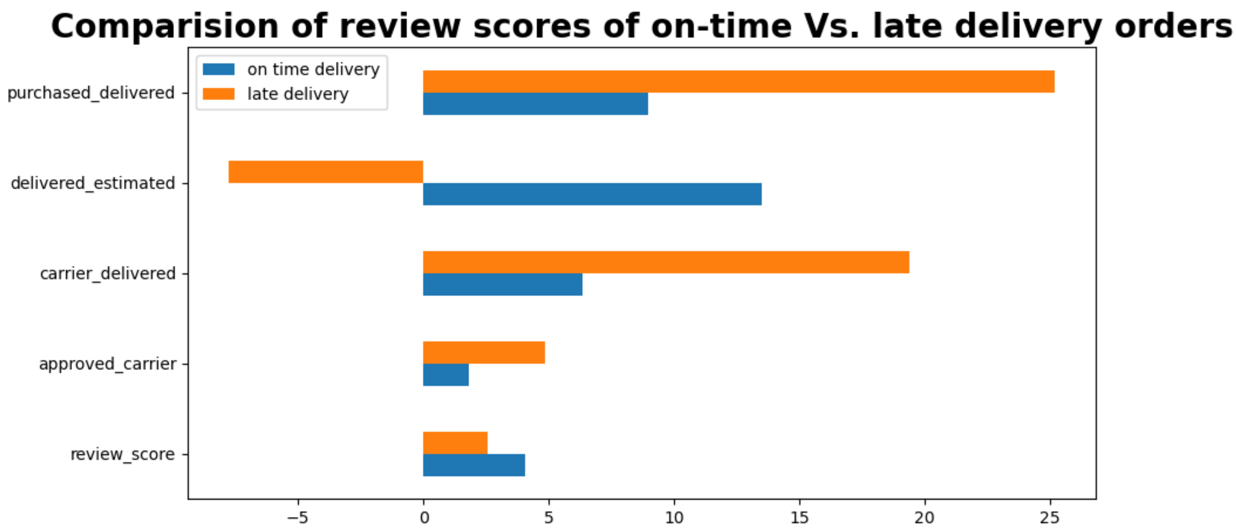
```
reviewScoreAnalysis = orderReviews[['order_id', 
'review_score']].merge(orders[['order_id', 'purchased_approved', 
'approved_carrier', 'carrier_delivered', 'delivered_estimated', 
'purchased_delivered']], on = 'order_id')
reviewScoreAnalysis.head()

                           order_id  review_score  purchased_approved
\
0  b9bf720beb4ab3728760088589c62129             4                 525

1  e51478e7e277a83743b6f9991dbfa3fb             5                 883

2  37e7875cdce5a9e5b3a692971f370151             4                3042

3  e029f708df3cc108b3264558771605c6             5                1221
```

```
4  e2e6ee1ed2d7f2f36b05d234983bd7a0             5               74123


   approved_carrier  carrier_delivered  delivered_estimated  \
0                 0                  6                   15
1                 0                  3                   15
2                 3                 16                    7
3                 4                  7                   16
4                 2                  7                    7

   purchased_delivered
0                    7
1                    3
2                   19
3                   11
4                   11
```

```
ontimeDelivery_review =
reviewScoreAnalysis[reviewScoreAnalysis.delivered_estimated > 0]
[['review_score', 'purchased_approved', 'approved_carrier',
'carrier_delivered', 'delivered_estimated',
'purchased_delivered']].mean()
lateDelivery_review =
reviewScoreAnalysis[reviewScoreAnalysis.delivered_estimated < 0]
[['review_score', 'purchased_approved', 'approved_carrier',
'carrier_delivered', 'delivered_estimated',
'purchased_delivered']].mean()
comparision_review = pd.DataFrame([ontimeDelivery_review,
lateDelivery_review]).T
comparision_review.rename(columns = {0 : 'on time delivery', 1 : 'late
delivery'}, inplace = True)
comparision_review
```

```
                     on time delivery  late delivery
review_score                 4.040577       2.577267
purchased_approved       14923.547788   18692.007663
approved_carrier             1.810071       4.840358
carrier_delivered            6.335004      19.363985
delivered_estimated         13.512100      -7.748404
purchased_delivered          8.939012      25.163474
```

```
comparision_review.drop('purchased_approved').plot(kind = 'barh',
figsize = (10, 5))
plt.title('Comparision of review scores of on-time Vs. late delivery
orders',fontweight='bold',fontsize=20)
plt.show()
```



Observations:

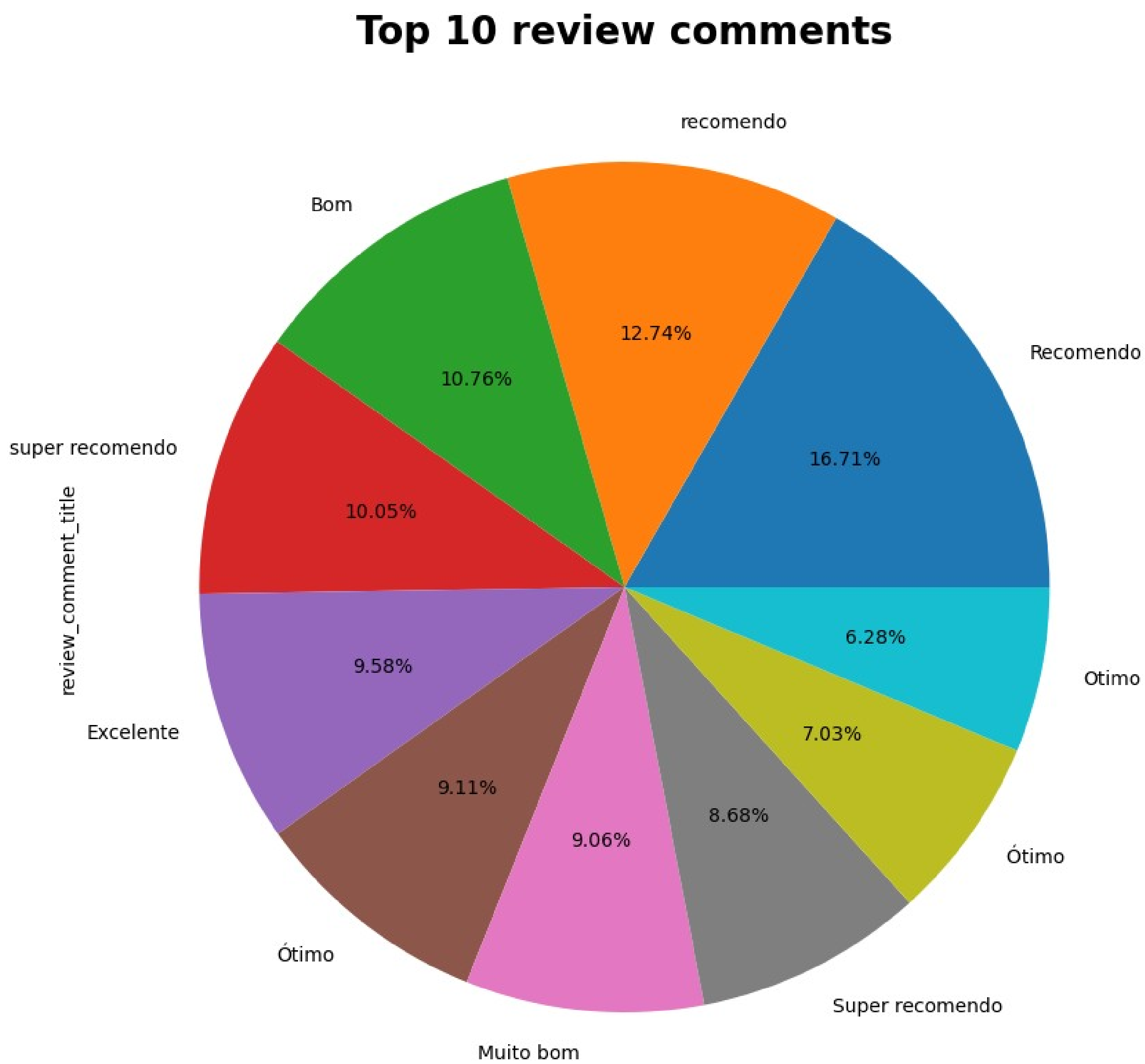
1. The **review scores of late deliveries was 2.5** while for **on-time deliveries it was 4** on an average.
2. It took **25 days on an average** for the **orders to get delivered** to the customers for **late delivery orders**, while it took just **9 days** for **on-time delivery orders**.
3. On an average, orders were delivered **14 days before the estimated date of delivery** for **on-time delivered orders**.
4. It also took **extra hour** for the **orders to get approved** for orders which were **delivered late**.

Top comments by the customers

```
topComments = orderReviews.review_comment_title.value_counts()[:10]
print('The top 20 comments by the customer are:',topComments,sep='\n')
```

```
The top 20 comments by the customer are:
Recomendo           354
recomendo           270
Bom                 228
super recomendo     213
Excelente           203
Ótimo               193
Muito bom           192
Super recomendo     184
Ótimo               149
Otimo               133
Name: review_comment_title, dtype: int64
```

```
topComments.plot(kind="pie",autopct="%2.2f%%",figsize=(10, 10))
plt.title('Top 10 review comments',fontweight='bold',fontsize=20)
plt.show()
```



Observations:

1. The most occuring comment is **Recomendo**, **Bom**, **super recomendo** and **excelente**.
2. **Recommedo** is about **11.93%**.

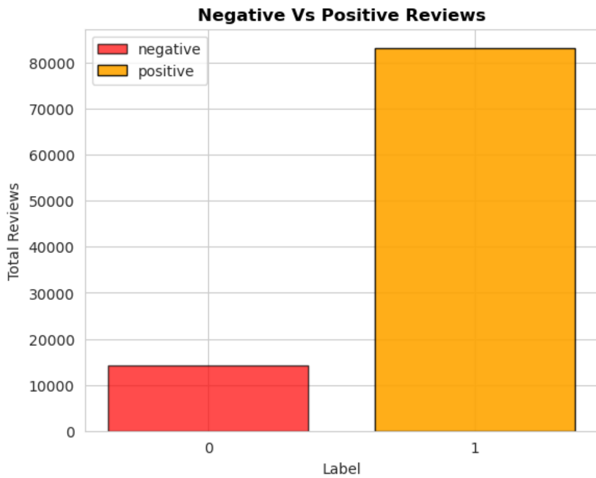
```
def partition(x):
    if x < 3:
        return 0
    return 1

orderReviewsAnalysis = orderReviews.copy()
orderReviewsAnalysis['review_score']=orderReviewsAnalysis['review_scor
e'].map(lambda cw : partition(cw) )
```

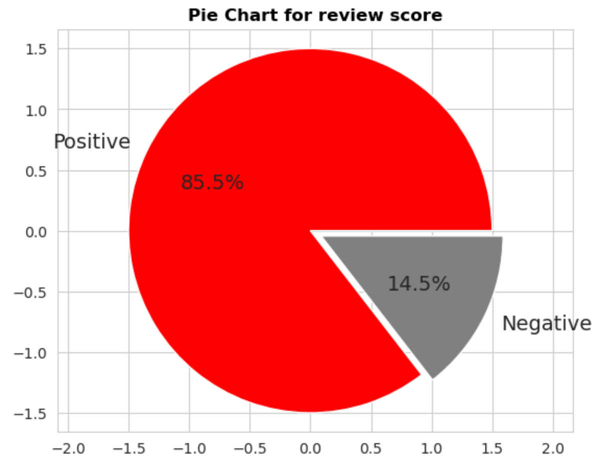
```
# checking the review score now
orderReviewsAnalysis.review_score.value_counts()
```

```
1    7592
0    2247
Name: review_score, dtype: int64
```

```
#counting the review score with 1 and 0
y_value_counts = orderReviewsAnalysis.review_score.value_counts()

#calculating the percentage of each review type
print("Total Positive Reviews :", y_value_counts[1], ", (",
(y_value_counts[1]/(y_value_counts[1]+y_value_counts[0]))*100,"%)")
print("Total Negative Reviews :", y_value_counts[0], ", (",
(y_value_counts[0]/(y_value_counts[1]+y_value_counts[0]))*100,"%)")
print('\n')

#plotting bar-plot and pie chart
%matplotlib inline
sns.set_style("whitegrid")
plt.figure(figsize=(14,5))
plt.subplot(1,2,1)
plt.ylabel('Total Reviews')
plt.xlabel('Label')
plt.title('Negative Vs Positive
Reviews',color='black',fontweight='bold')
plt.xticks([10,10.20],['0','1'])
#creating bar plots
plt.bar(10,14112, color = 'red', width =
0.15,alpha=0.7,label='negative',edgecolor='black')
plt.bar(10.20,83143,color = 'orange', width =
0.15,alpha=0.9,label='positive',edgecolor='black')
plt.legend()

plt.subplot(1,2,2)
labels = ['Positive','Negative']
sizes = [83143,14112]
explode = (0, 0.1)  # only "explode" the 2nd slice (i.e. 'Hogs')
color={'Red','grey'}
plt.pie(sizes,explode=explode ,colors=color,labels=labels,
autopct='%1.1f%%',shadow=False,
startangle=0,radius=1.5,labeldistance=1.1,textprops={'fontsize':
14},frame=True, )
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a
circle.
plt.title('Pie Chart for review
score',color='black',fontweight='bold')
plt.show()
```

```
Total Positive Reviews : 7592 , ( 77.16231324321578 %)
Total Negative Reviews : 2247 , ( 22.837686756784226 %)
```





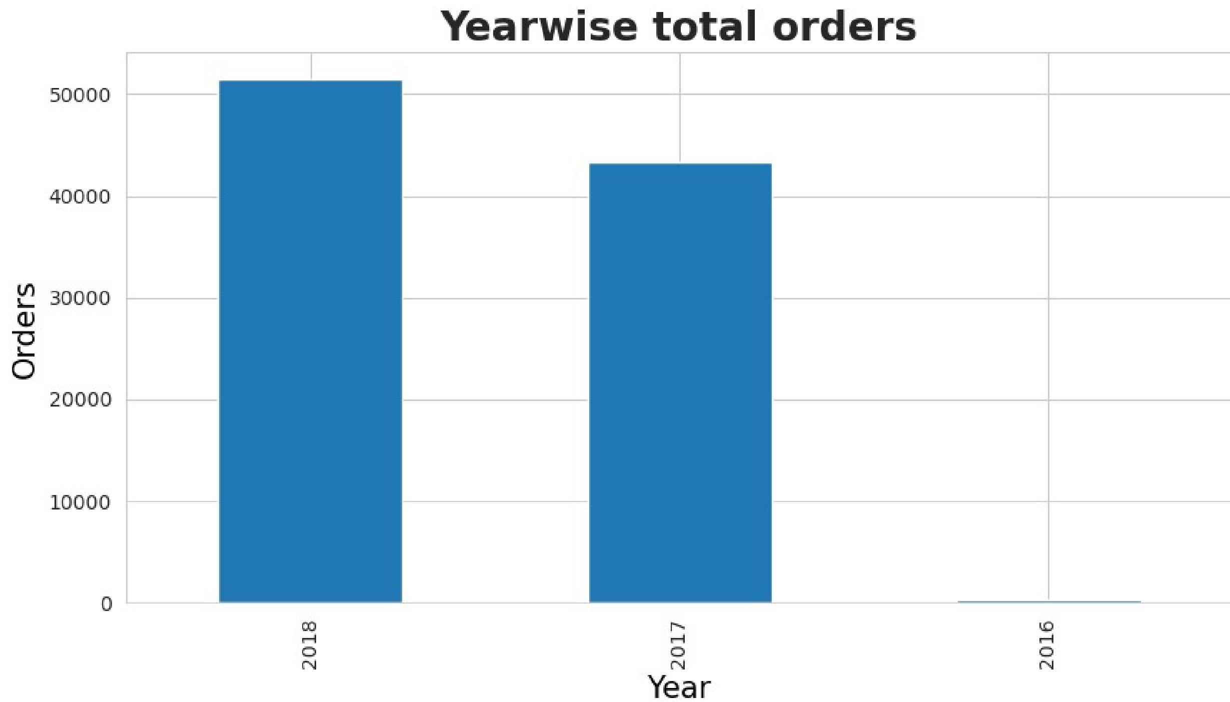
Observations:

1. Review scores **below 3** are considered as **negative reviews** and **above 3** are said to be **positive reviews**.
2. We can observe from the above plots **85.5%** of the total reviews are **positive** and only **14.5%** reviews are **negative**.

4.6. Revenue Generated

Year-wise number of orders

```
plt.figure(figsize=(10, 5))
pd.to_datetime(orders.order_purchase_timestamp).dt.year.value_counts()
.plot(kind='bar')
plt.title('Yearwise total orders',fontweight='bold',fontsize=20)
plt.xlabel('Year',fontsize=15,color='black')
plt.ylabel('Orders',fontsize=15,color='black')
plt.show()
```



Observation:

1. The year of **2018** is when **most orders were placed**.

Month-wise revenue for the years 2017 and 2018

```
def is_late_delivery(Days):
    if Days < 0:
        return 1
    else:
        return 0

def is_ontime_delivery(Days):
    if Days > 0:
        return 1
    else:
        return 0

year2016 = orders[orders.order_purchase_timestamp.dt.year ==
2016].merge(orderItems, on = 'order_id')
year2016['Month'] = year2016.order_purchase_timestamp.dt.month
year2016['isLateDelivery'] =
year2016['delivered_estimated'].apply(is_late_delivery)
year2016['isOnTimeDelivery'] =
year2016['delivered_estimated'].apply(is_ontime_delivery)
revenue2016 = year2016.groupby('Month').agg({'order_id' : 'nunique',
'price' : 'sum', 'freight_value' : 'sum', 'purchased_approved' :
'mean', 'carrier_delivered' : 'mean', 'delivered_estimated' : 'mean',
'purchased_delivered' : 'mean', 'isLateDelivery' : 'sum',
```

```
'isOnTimeDelivery' : 'sum'})
revenue2016['total_revenue'] = revenue2016.price +
revenue2016.freight_value
revenue2016['lateDeliveryRate'] = revenue2016['isLateDelivery'] /
(revenue2016['isLateDelivery'] + revenue2016['isOnTimeDelivery'])
revenue2016

       order_id     price  freight_value  purchased_approved  \
Month
9             1    134.97           8.49            0.000000
10          261  39738.17        6093.65        31555.386364
12            1     10.90           8.72          890.000000

       carrier_delivered  delivered_estimated  purchased_delivered  \
Month
9                1.00000           -37.000000            54.000000
10               5.62013            35.798701            19.198052
12               1.00000            21.000000             4.000000

       isLateDelivery  isOnTimeDelivery  total_revenue
lateDeliveryRate
Month

9                   3                 0         143.46
1.000000
10                  3               304       45831.82
0.009772
12                  0                 1          19.62
0.000000

year2017 = orders[orders.order_purchase_timestamp.dt.year ==
2017].merge(orderItems, on = 'order_id')
year2017['Month'] = year2017.order_purchase_timestamp.dt.month
year2017['isLateDelivery'] =
year2017['delivered_estimated'].apply(is_late_delivery)
year2017['isOnTimeDelivery'] =
year2017['delivered_estimated'].apply(is_ontime_delivery)
revenue2017 = year2017.groupby('Month').agg({'order_id' : 'nunique',
'price' : 'sum', 'freight_value' : 'sum', 'purchased_approved' :
'mean', 'carrier_delivered' : 'mean', 'delivered_estimated' : 'mean',
'purchased_delivered' : 'mean', 'isLateDelivery' : 'sum',
'isOnTimeDelivery' : 'sum'})
revenue2017['total_revenue'] = revenue2017.price +
revenue2017.freight_value
revenue2017['lateDeliveryRate'] = revenue2017['isLateDelivery'] /
(revenue2017['isLateDelivery'] + revenue2017['isOnTimeDelivery'])
revenue2017

       order_id      price  freight_value  purchased_approved  \
Month
```

```
1           749  111609.71       15666.01       14288.871570
2          1650  233716.91       36938.42       11139.714517
3          2545  359109.85       55107.03        6177.327807
4          2279  338839.16       49652.13       13151.595351
5          3531  488010.45       77258.11       13569.175069
6          3130  421310.97       68013.90       13466.575079
7          3841  478598.50       83898.01       13519.357536
8          4190  553928.41       90976.11       12527.191103
9          4137  604764.74       93400.02       12330.243381
10         4478  648247.65      102869.36       13479.104910
11         7288  987510.37      165582.29       14508.177956
12         5508  725558.51      116955.07       14256.016502

       carrier_delivered  delivered_estimated  purchased_delivered  \
Month
1               8.701427            26.734358            12.072448
2               9.002698            18.165677            12.634107
3               9.364421            11.439724            12.427634
4              10.679669            12.108747            14.328211
5               7.937296            12.395535            10.899172
6               8.357450            11.719782            11.451622
7               7.850893            11.586578            11.021530
8               7.345447            12.344612            10.482038
9               8.105910            10.435077            11.404787
10              7.766206            10.992712            11.264097
11             10.384470             7.281449            14.579301
12             10.947581            12.104352            14.781427

       isLateDelivery  isOnTimeDelivery  total_revenue
lateDeliveryRate
Month

1                  26               885      127275.72
0.028540
2                  62              1787      270655.33
0.033532
3                 163              2717      414216.88
0.056597
4                 191              2322      388491.29
0.076005
5                 151              3810      565268.56
0.038122
6                 130              3332      489324.87
0.037551
7                 160              4175      562496.51
0.036909
8                 151              4603      644904.52
0.031763
9                 242              4414      698164.76
0.051976
```

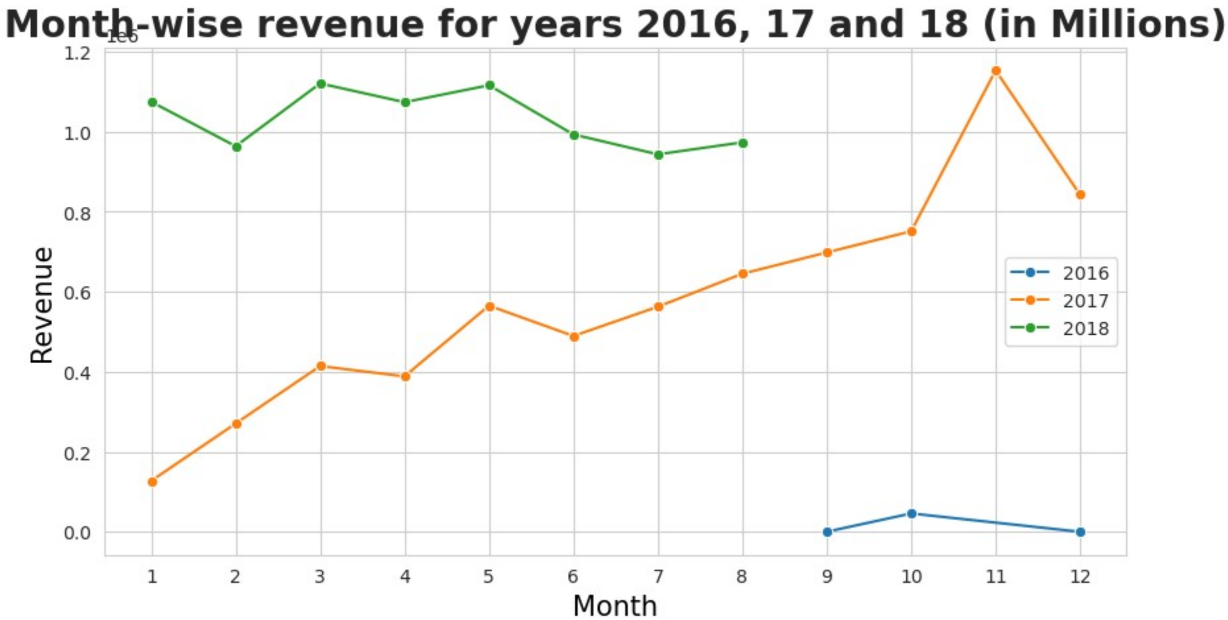
```
10                   264                 4898      751117.01
0.051143
11                  1172                 7138     1153092.66
0.141035
12                   504                 5619      842513.58
0.082313
```

```
year2018 = orders[orders.order_purchase_timestamp.dt.year ==
2018].merge(orderItems, on = 'order_id')
year2018['Month'] = year2018.order_purchase_timestamp.dt.month
year2018['isLateDelivery'] =
year2018['delivered_estimated'].apply(is_late_delivery)
year2018['isOnTimeDelivery'] =
year2018['delivered_estimated'].apply(is_ontime_delivery)
revenue2018 = year2018.groupby('Month').agg({'order_id' : 'nunique',
'price' : 'sum', 'freight_value' : 'sum', 'purchased_approved' :
'mean', 'carrier_delivered' : 'mean', 'delivered_estimated' : 'mean',
'purchased_delivered' : 'mean', 'isLateDelivery' : 'sum',
'isOnTimeDelivery' : 'sum'})
revenue2018['total_revenue'] = revenue2018.price +
revenue2018.freight_value
revenue2018['lateDeliveryRate'] = revenue2018['isLateDelivery'] /
(revenue2018['isLateDelivery'] + revenue2018['isOnTimeDelivery'])
revenue2018
```

```
       order_id      price  freight_value  purchased_approved  \
Month
1          7045  922192.60      152670.38        15841.367146
2          6543  824207.87      139455.59        14366.830757
3          7001  953311.25      167215.46        13605.120274
4          6409  923081.83      150642.10        17088.306233
5          6681  966547.76      149446.94        14948.900233
6          5976  840156.23      152896.15        12594.163708
7          5596  797173.38      146234.44        17851.038383
8          6265  828540.84      144748.47        14523.856960

       carrier_delivered  delivered_estimated  purchased_delivered  \
Month
1               9.854841            12.010618            13.656090
2              12.700693             7.361940            16.481210
3              12.128759             5.799750            15.604741
4               8.035366            11.935772            11.014770
5               8.282220            11.342262            10.878106
6               6.197031            18.297293             8.667055
7               5.668773            10.189228             8.623914
8               4.817653             7.402441             7.262097

       isLateDelivery  isOnTimeDelivery  total_revenue
lateDeliveryRate
Month
```

```
1                      525                 7405     1074862.98
0.066204
2                     1183                 6173      963663.46
0.160821
3                     1641                 6190     1120526.71
0.209552
4                      368                 6948     1073723.93
0.050301
5                      618                 6980     1115994.70
0.081337
6                       93                 6771      993052.38
0.013549
7                      294                 5949      943407.82
0.047093
8                      735                 5908      973289.31
0.110643
```

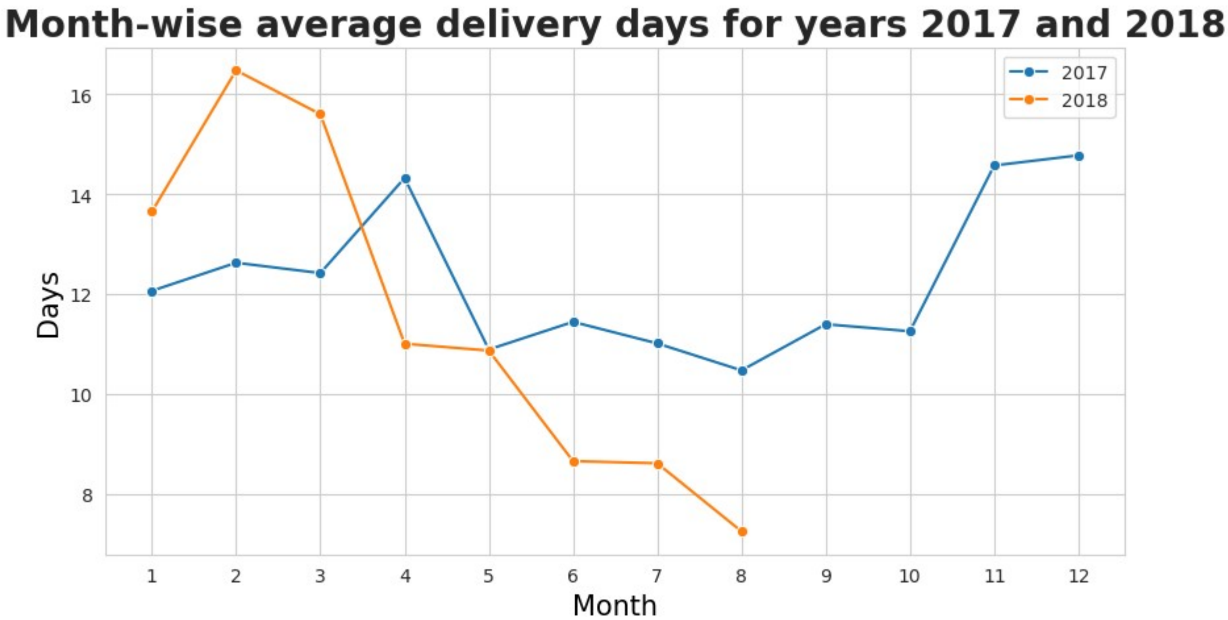
```
plt.figure(figsize=(10, 5))
sns.lineplot(y = revenue2016['total_revenue'], x = revenue2016.index,
marker = 'o', label = '2016')
sns.lineplot(y = revenue2017['total_revenue'], x = revenue2017.index,
marker = 'o', label = '2017')
sns.lineplot(y = revenue2018['total_revenue'], x = revenue2018.index,
marker = 'o', label = '2018')
plt.title('Month-wise revenue for years 2016, 17 and 18 (in
Millions)',fontweight='bold',fontsize=20)
plt.xlabel('Month',fontsize=15,color='black')
plt.ylabel('Revenue',fontsize=15,color='black')
plt.xticks([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
plt.legend()
plt.show()
```



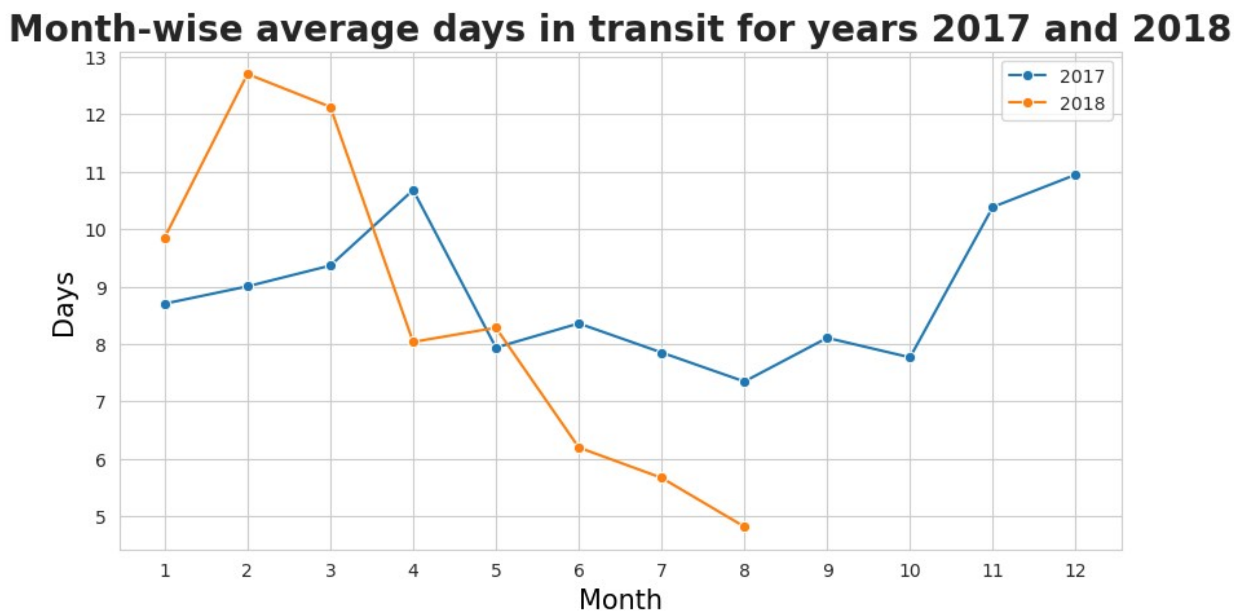
Observations:

1. There are **not many records available for the year 2016**, so the revenue is also less. Therefore we consider only the records from the year 2017 to the available records upto August of 2018 for our analysis.
2. From the available data, it is clearly evident that the revenue grew constantly all throughout the year 2017, starting from **127K Brazilian Real** all the way upto **1.15M Brazilian Real** during the month of **November 2017**.
3. There was a dip in the revenue of around **310K Brazilian Real** in the month of **December 2017**.
4. The year **2018 saw a constant revenue flow** which was in the range of **966K - 1.13M Brazilian Real**.
5. The revenue is in **correspondance with the number of orders placed**.

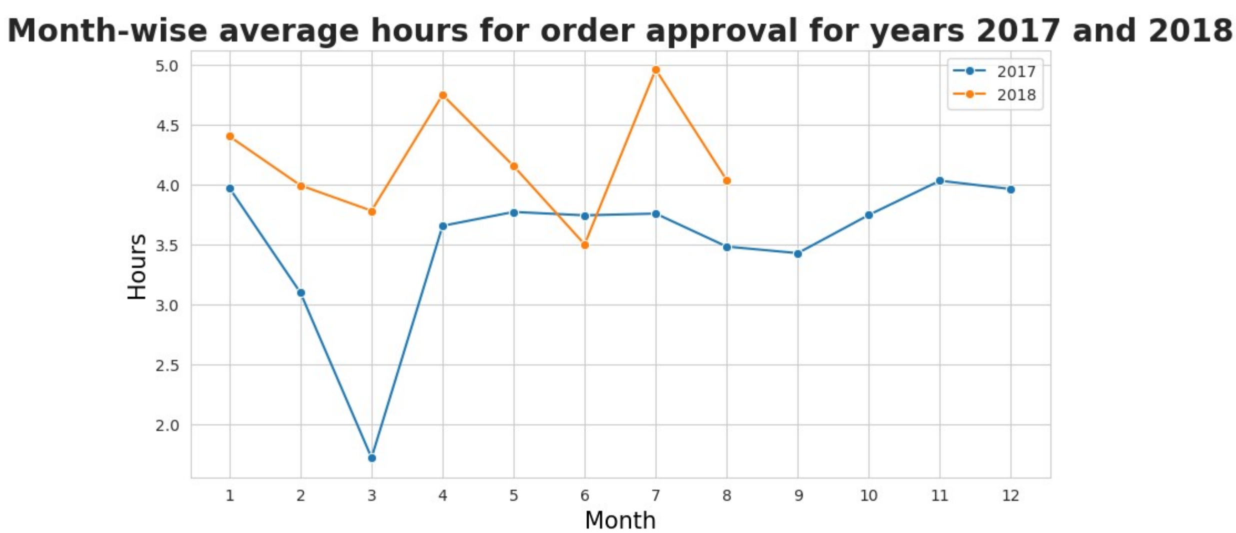
```
plt.figure(figsize=(10, 5))
sns.lineplot(y = revenue2017['purchased_delivered'], x =
revenue2017.index, marker = 'o', label = '2017')
sns.lineplot(y = revenue2018['purchased_delivered'], x =
revenue2018.index, marker = 'o', label = '2018')
plt.title('Month-wise average delivery days for years 2017 and
2018',fontweight='bold',fontsize=20)
plt.xlabel('Month',fontsize=15,color='black')
plt.ylabel('Days',fontsize=15,color='black')
plt.xticks([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
plt.legend()
plt.show()
```



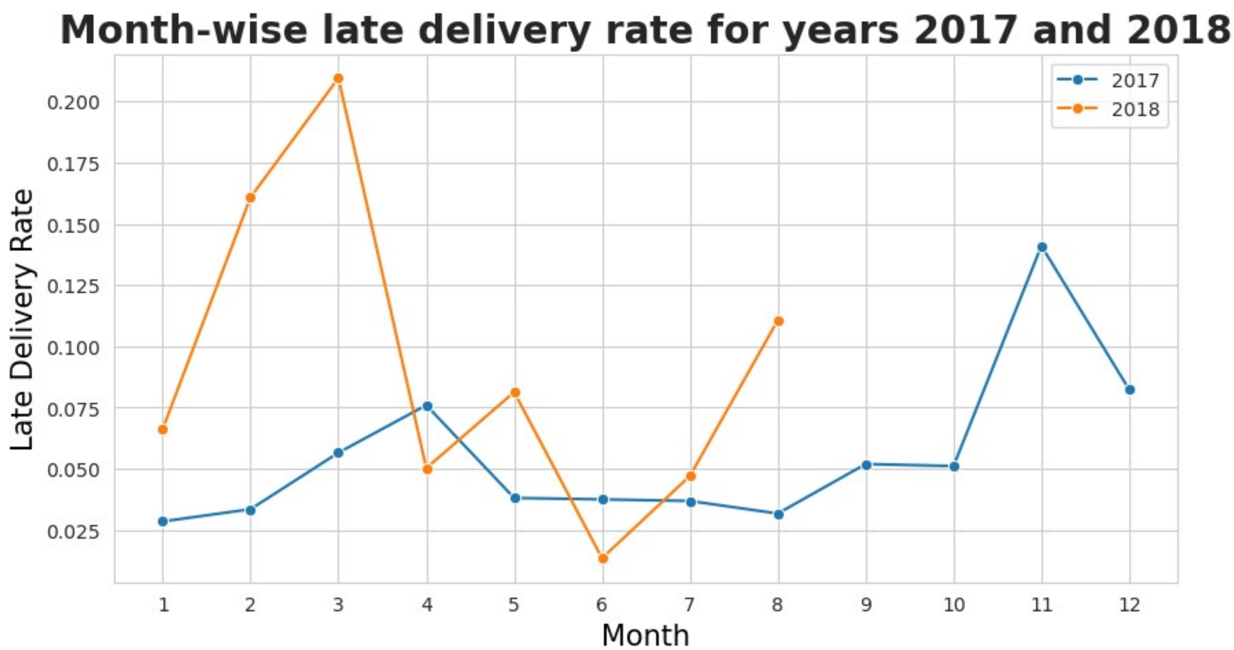

```python
plt.figure(figsize=(10, 5))
sns.lineplot(y = revenue2017['carrier_delivered'], x =
revenue2017.index, marker = 'o', label = '2017')
sns.lineplot(y = revenue2018['carrier_delivered'], x =
revenue2018.index, marker = 'o', label = '2018')
plt.title('Month-wise average days in transit for years 2017 and
2018',fontweight='bold',fontsize=20)
plt.xlabel('Month',fontsize=15,color='black')
plt.ylabel('Days',fontsize=15,color='black')
plt.xticks([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
plt.legend()
plt.show()
```




```
plt.figure(figsize=(10, 5))
sns.lineplot(y = revenue2017['purchased_approved']/3600, x =
revenue2017.index, marker = 'o', label = '2017')
sns.lineplot(y = revenue2018['purchased_approved']/3600, x =
revenue2018.index, marker = 'o', label = '2018')
plt.title('Month-wise average hours for order approval for years 2017
and 2018',fontweight='bold',fontsize=20)
plt.xlabel('Month',fontsize=15,color='black')
plt.ylabel('Hours',fontsize=15,color='black')
plt.xticks([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
plt.legend()
plt.show()
```



```
plt.figure(figsize=(10, 5))
sns.lineplot(y = revenue2017['lateDeliveryRate'], x =
revenue2017.index, marker = 'o', label = '2017')
sns.lineplot(y = revenue2018['lateDeliveryRate'], x =
revenue2018.index, marker = 'o', label = '2018')
plt.title('Month-wise late delivery rate for years 2017 and
2018',fontweight='bold',fontsize=20)
plt.xlabel('Month',fontsize=15,color='black')
plt.ylabel('Late Delivery Rate',fontsize=15,color='black')
plt.xticks([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
plt.legend()
plt.show()
```



Observations:

1. The data for the **year 2016 was very less** so we do **not consider** it for interpretation.
2. The rise in revenue is in **accordance with the number of days** it took on an average for the **orders to get delivered** to the customers and also the **number of days** it took on an average **while the orders were in transit**.
3. This clearly indicates that the **business thrives only based on the less number of days it takes for the order to get delivered**.
4. **Optimising the delivery days** would actually help in **increasing the revenue** and help sustain the business over years.
5. The graphs clearly indicate that on periods **when there were huge numbers of orders**, the **average delivery time was also comparatively high**, which indicates that proper measures should be undertaken to carter fast delivery of products.
6. The only viable method would be to **invest in transit and delivery partners**.
7. Hours taken for the order to get approved does not have any impact on the business.

Business Recommendations:

1. **Increase cross-docking centres** for **first mile delivery**.
2. Introduce **product traceability**.
3. **Optimize the inventory management** for **fast approval of orders**.
4. **Know target customers** and **increase their satisfaction**.
5. Invest in **delivery partners** and **transit**.

Quarter-wise revenue

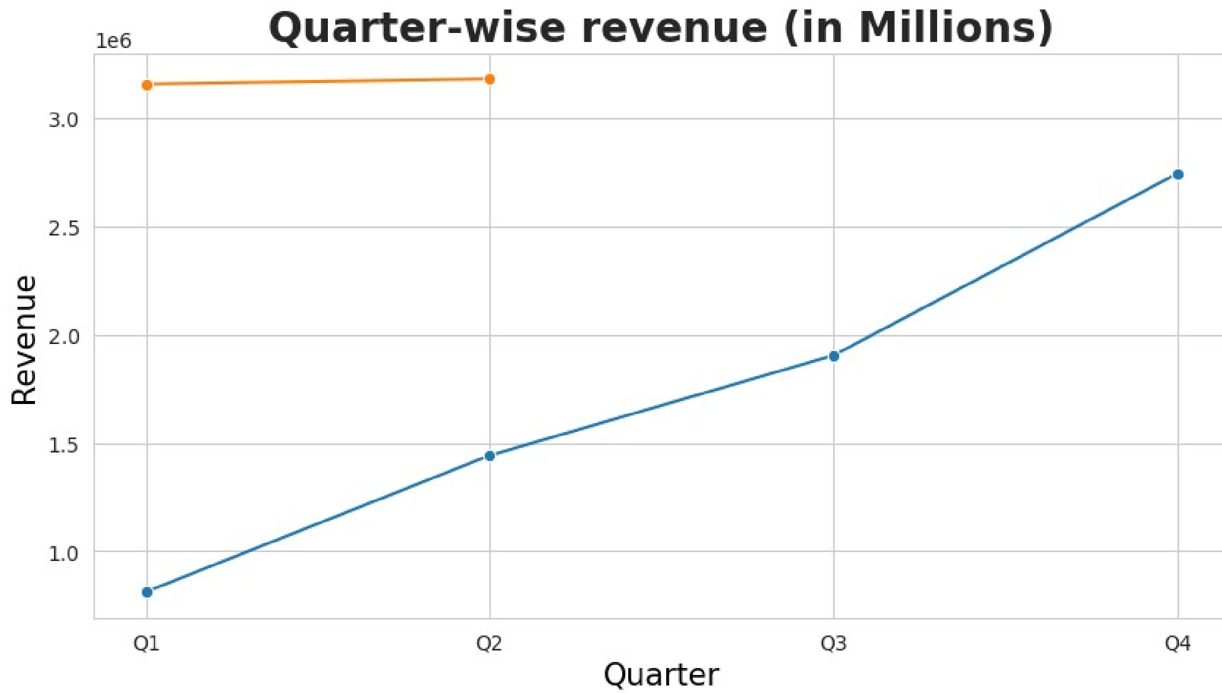
```
quarters2017 = pd.DataFrame(columns = ['total_revenue'])
quarters2018 = pd.DataFrame(columns = ['total_revenue'])
quarters2017.loc['Q1'] = [sum(revenue2017.total_revenue[:3])]
quarters2017.loc['Q2'] = [sum(revenue2017.total_revenue[3:6])]
quarters2017.loc['Q3'] = [sum(revenue2017.total_revenue[6:9])]
quarters2017.loc['Q4'] = [sum(revenue2017.total_revenue[9:])]
quarters2018.loc['Q1'] = [sum(revenue2018.total_revenue[:3])]
quarters2018.loc['Q2'] = [sum(revenue2018.total_revenue[3:6])]

quarters2017
```

	total_revenue
Q1	812147.93
Q2	1443084.72
Q3	1905565.79
Q4	2746723.25

```
quarters2018
```

	total_revenue
Q1	3159053.15
Q2	3182771.01

```
plt.figure(figsize=(10, 5))
sns.lineplot(y = quarters2017['total_revenue'], x =
quarters2017.index, marker = 'o')
sns.lineplot(y = quarters2018['total_revenue'], x =
quarters2018.index, marker = 'o')
plt.title('Quarter-wise revenue (in
Millions)',fontweight='bold',fontsize=20)
plt.xlabel('Quarter',fontsize=15,color='black')
plt.ylabel('Revenue',fontsize=15,color='black')
plt.show()
```



Observations:

1. We only see the records for the quarters Q1 of FY2017 to Q2 of FY2018 as they are the available records.
2. The revenue was on the rise during this period, which stood at a high of **3.27M Brazilian Real** at **Q2 of FY2018**.
3. Comparing the first and second quarters of financial years 2017 and 2018 respectively, we find that the **revenue increased very drastically**, which says the business is on the uprising.

4.7. Black Friday Sale

Analysis of sales during November 2017

Observations:

1. The sales during the **month of November and December 2017** is alone studied extensively because it was the month that **saw the highest revenue generated**, and which was followed by a sudden dip in revenue the very next month.
2. It is also in connection with the **Black Friday Sale** which was on **Friday, 24th of November 2017**.

```
november2017 = year2017[year2017.order_purchase_timestamp.dt.month ==
11]
november2017['Date'] = november2017.order_purchase_timestamp.dt.day
november2017.head()
```

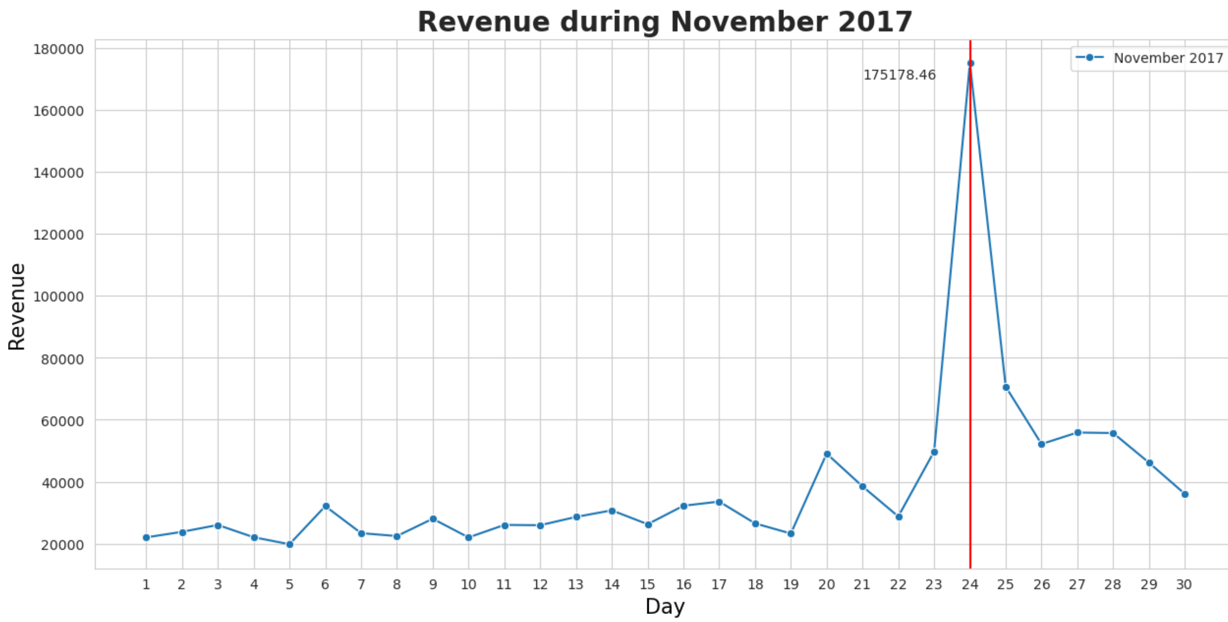
```
                             order_id                       customer_id  \
1   949d5b44dbf5de918fe9c16f97b45f8a  f88197465ea7920adcdbec7375364d82

10  85ce859fd6dc634de8d2f1e290444043  059f7fc5719c7da6cbafe370971a8d70

17  6ea2f835b4556291ffdc53fa0b3b95e8  c7340080e394356141681bd4c9b8fe31

26  68873cf91053cd11e6b49a766db5af1a  4632eb5a8f175f6fe020520ae0c678f3

27  8f06cc6465925031568537b815f1198d  9916715c2ab6ee1710c9c32f0a534ad2


   order_status order_purchase_timestamp   order_approved_at  \
1     delivered      2017-11-18 19:28:06 2017-11-18 19:45:59
10    delivered      2017-11-21 00:03:41 2017-11-21 00:14:22
17    delivered      2017-11-24 21:27:48 2017-11-25 00:21:09
26    delivered      2017-11-30 22:02:15 2017-12-02 02:51:18
27    delivered      2017-11-15 11:31:41 2017-11-15 11:46:42

   order_delivered_carrier_date order_delivered_customer_date  \
1           2017-11-22 13:39:59           2017-12-02 00:28:42
10          2017-11-23 21:32:26           2017-11-27 18:28:00
17          2017-12-13 21:14:05           2017-12-28 18:59:23
26          2017-12-04 22:07:01           2017-12-05 20:28:40
27          2017-11-16 22:03:00           2017-11-22 22:41:07

   order_estimated_delivery_date  purchased_approved  approved_carrier  \
1                     2017-12-15                1073                 3

10                    2017-12-11                 641                 2

17                    2017-12-21               10401                18

26                    2017-12-18               17343                 2

27                    2017-12-05                 901                 1


    carrier_delivered  delivered_estimated  purchased_delivered  \
1                   9                   12                   13
10                  3                   13                    6
17                 14                   -8                   33
26                  0                   12                    4
27                  6                   12                    7

    order_item_id                        product_id  \
1               1  d0b61bfb1de832b15ba9d266ca96e5b0
10              1  cce679660c66e6fbd5c8091dfd29e9cd
17              1  be021417a6acb56b9b50d3fd2714baa8
```

```
26               1  15a9e834e89eab39d973492882c658d6
27               1  12087840651e83b48206b82c213b76fd

                           seller_id shipping_limit_date  price  \
1   66922902710d126a0e7d26b0e3805106 2017-11-23 19:45:59   45.0
10  d2374cbcbb3ca4ab1086534108cc3ab7 2017-11-29 00:14:22   17.9
17  f5f46307a4d15880ca14fab4ad9dfc9b 2017-11-30 00:21:09  339.0
26  a673821011d0cec28146ea42f5ab767f 2017-12-07 02:51:18   79.9
27  5b925e1d006e9476d738aa200751b73b 2017-11-21 11:46:42  299.0

    freight_value  Month  isLateDelivery  isOnTimeDelivery  Date
1           27.20     11               0                 1    18
10          11.85     11               0                 1    21
17          17.12     11               1                 0    24
26          11.76     11               0                 1    30
27          18.34     11               0                 1    15

blackfriday = november2017[november2017['Date']==24]
blackfriday.head()

                             order_id
customer_id  \
17   6ea2f835b4556291ffdc53fa0b3b95e8
c7340080e394356141681bd4c9b8fe31
59   b01875821b8dcb6abc61776f0f971bce
818596f5b68adfe2c11498ebb6d39e02
60   b01875821b8dcb6abc61776f0f971bce
818596f5b68adfe2c11498ebb6d39e02
115  c263211bd219538f7c031591e87ef0d7
ed8c52327eecff596e141636d5b556d2
116  c263211bd219538f7c031591e87ef0d7
ed8c52327eecff596e141636d5b556d2

    order_status order_purchase_timestamp   order_approved_at  \
17     delivered      2017-11-24 21:27:48 2017-11-25 00:21:09
59     delivered      2017-11-24 21:55:22 2017-11-25 01:31:43
60     delivered      2017-11-24 21:55:22 2017-11-25 01:31:43
115    delivered      2017-11-24 16:56:46 2017-11-28 03:48:24
116    delivered      2017-11-24 16:56:46 2017-11-28 03:48:24

    order_delivered_carrier_date order_delivered_customer_date  \
17           2017-12-13 21:14:05           2017-12-28 18:59:23
59           2017-11-28 22:37:15           2017-12-01 21:11:40
60           2017-11-28 22:37:15           2017-12-01 21:11:40
115          2017-12-08 23:28:26           2017-12-18 20:24:54
116          2017-12-08 23:28:26           2017-12-18 20:24:54

    order_estimated_delivery_date  purchased_approved
approved_carrier  \
17                     2017-12-21               10401
```

```
18
59                     2017-12-15                  12981
3
60                     2017-12-15                  12981
3
115                    2017-12-19                  39098
10
116                    2017-12-19                  39098
10

     carrier_delivered  delivered_estimated  purchased_delivered  \
17                  14                   -8                   33
59                   2                   13                    6
60                   2                   13                    6
115                  9                    0                   24
116                  9                    0                   24

     order_item_id                        product_id  \
17               1  be021417a6acb56b9b50d3fd2714baa8
59               1  a6ad77b15e566298a4e8ee2011ab1255
60               2  a6ad77b15e566298a4e8ee2011ab1255
115              1  028b0b0277744a9eaa2c4f57c24dcb68
116              2  028b0b0277744a9eaa2c4f57c24dcb68

                            seller_id shipping_limit_date  price  \
17   f5f46307a4d15880ca14fab4ad9dfc9b 2017-11-30 00:21:09  339.0
59   1025f0e2d44d7041d6cf58b6550e0bfa 2017-12-01 00:38:17   31.8
60   1025f0e2d44d7041d6cf58b6550e0bfa 2017-12-01 00:38:17   31.8
115  1025f0e2d44d7041d6cf58b6550e0bfa 2017-12-05 03:48:24  359.7
116  1025f0e2d44d7041d6cf58b6550e0bfa 2017-12-05 03:48:24  359.7

     freight_value  Month  isLateDelivery  isOnTimeDelivery  Date
17           17.12     11               1                 0    24
59           39.28     11               0                 1    24
60           39.28     11               0                 1    24
115          17.27     11               0                 0    24
116          17.27     11               0                 0    24
```

```
revenueNovember2017 = november2017.groupby('Date').agg({'order_id' :
'nunique', 'price' : 'sum', 'freight_value' : 'sum'})
revenueNovember2017['total_revenue'] = revenueNovember2017.price +
revenueNovember2017.freight_value

plt.figure(figsize=(15, 7))
sns.lineplot(y = revenueNovember2017['total_revenue'], x =
revenueNovember2017.index, marker = 'o', label = 'November 2017')
plt.title('Revenue during November
2017',fontweight='bold',fontsize=20)
plt.axvline(24, c = 'r')
plt.annotate(revenueNovember2017.loc[24].total_revenue, (21, 170000))
```

```
plt.xlabel('Day',fontsize=15,color='black')
plt.ylabel('Revenue',fontsize=15,color='black')
plt.xticks(range(1, 31))
plt.legend()
plt.show()
```



Observations:

1. **Black Friday Sale** fell on **24th of November** during the year **2017**, during which the highest number of orders, **1147 orders were placed**.
2. This generated the **maximum revenue for a single day**, which was around **175K Brazilian Real**.
3. During the further sales in later years, this should be tapped in to increase the revenue and compare with other players in the same industry.
4. The **peak and trought seen in the revenue** during the months of November and December corresponds to Black Friday Sale, and the dip in sales is not necessarily due to any specific reasons. This is said because the December's revenue is still higher than that of November's. So the **trought is not due to any wrongdoings in the business**.

Late delivering sellers on Black Friday

```
def deliveryType(Date):
    if Date < 0:
        return 'Late'
    else:
        return 'OnTime'

blackFriday = november2017[november2017.Date == 24]
blackFriday['Delivery'] =
```

```
blackFriday['delivered_estimated'].apply(deliveryType)
blackFriday.head()
```

```
                                 order_id
customer_id  \
17   6ea2f835b4556291ffdc53fa0b3b95e8
c7340080e394356141681bd4c9b8fe31
59   b01875821b8dcb6abc61776f0f971bce
818596f5b68adfe2c11498ebb6d39e02
60   b01875821b8dcb6abc61776f0f971bce
818596f5b68adfe2c11498ebb6d39e02
115  c263211bd219538f7c031591e87ef0d7
ed8c52327eecff596e141636d5b556d2
116  c263211bd219538f7c031591e87ef0d7
ed8c52327eecff596e141636d5b556d2

    order_status order_purchase_timestamp   order_approved_at  \
17     delivered      2017-11-24 21:27:48 2017-11-25 00:21:09
59     delivered      2017-11-24 21:55:22 2017-11-25 01:31:43
60     delivered      2017-11-24 21:55:22 2017-11-25 01:31:43
115    delivered      2017-11-24 16:56:46 2017-11-28 03:48:24
116    delivered      2017-11-24 16:56:46 2017-11-28 03:48:24

    order_delivered_carrier_date order_delivered_customer_date  \
17           2017-12-13 21:14:05           2017-12-28 18:59:23
59           2017-11-28 22:37:15           2017-12-01 21:11:40
60           2017-11-28 22:37:15           2017-12-01 21:11:40
115          2017-12-08 23:28:26           2017-12-18 20:24:54
116          2017-12-08 23:28:26           2017-12-18 20:24:54

    order_estimated_delivery_date  purchased_approved
approved_carrier  \
17                      2017-12-21               10401
18
59                      2017-12-15               12981
3
60                      2017-12-15               12981
3
115                     2017-12-19               39098
10
116                     2017-12-19               39098
10

     carrier_delivered  delivered_estimated  purchased_delivered  \
17                  14                   -8                   33
59                   2                   13                    6
60                   2                   13                    6
115                  9                    0                   24
116                  9                    0                   24
```

```
     order_item_id                        product_id  \
17               1  be021417a6acb56b9b50d3fd2714baa8
59               1  a6ad77b15e566298a4e8ee2011ab1255
60               2  a6ad77b15e566298a4e8ee2011ab1255
115              1  028b0b0277744a9eaa2c4f57c24dcb68
116              2  028b0b0277744a9eaa2c4f57c24dcb68

                            seller_id shipping_limit_date  price  \
17   f5f46307a4d15880ca14fab4ad9dfc9b 2017-11-30 00:21:09  339.0
59   1025f0e2d44d7041d6cf58b6550e0bfa 2017-12-01 00:38:17   31.8
60   1025f0e2d44d7041d6cf58b6550e0bfa 2017-12-01 00:38:17   31.8
115  1025f0e2d44d7041d6cf58b6550e0bfa 2017-12-05 03:48:24  359.7
116  1025f0e2d44d7041d6cf58b6550e0bfa 2017-12-05 03:48:24  359.7

     freight_value  Month  isLateDelivery  isOnTimeDelivery  Date
Delivery
17           17.12     11               1                 0    24
Late
59           39.28     11               0                 1    24
OnTime
60           39.28     11               0                 1    24
OnTime
115          17.27     11               0                 0    24
OnTime
116          17.27     11               0                 0    24
OnTime
```

```
blackFriday.order_id.nunique()
```

```
1147
```

```
year2017.head()
```

```
                           order_id                       customer_id
\
0  e481f51cbdc54678b7cc49136f2d6af7  9ef432eb6251297304e76186b10a928d

1  949d5b44dbf5de918fe9c16f97b45f8a  f88197465ea7920adcdbec7375364d82

2  a4591c265e18cb1dcee52889e2d8acc3  503740e9ca751ccdda7ba28e9ab8f608

3  6514b8ad8028c9f2cc2374ded245783f  9bdf08b4b3b52b5526ff42d37d47f222

4  76c6e866289321a7c93b82b54852dc33  f54a9f0e6b351c431402b8461ea51999


  order_status order_purchase_timestamp   order_approved_at  \
0    delivered      2017-10-02 10:56:33 2017-10-02 11:07:15
1    delivered      2017-11-18 19:28:06 2017-11-18 19:45:59
2    delivered      2017-07-09 21:57:05 2017-07-09 22:10:13
3    delivered      2017-05-16 13:10:30 2017-05-16 13:22:11
```

```
4    delivered      2017-01-23 18:29:09 2017-01-25 02:50:47

  order_delivered_carrier_date order_delivered_customer_date  \
0          2017-10-04 19:55:00           2017-10-10 21:25:13
1          2017-11-22 13:39:59           2017-12-02 00:28:42
2          2017-07-11 14:58:04           2017-07-26 10:57:55
3          2017-05-22 10:07:46           2017-05-26 12:55:51
4          2017-01-26 14:16:31           2017-02-02 14:08:10

  order_estimated_delivery_date  purchased_approved  approved_carrier
\
0                    2017-10-18                 642                 2

1                    2017-12-15                1073                 3

2                    2017-08-01                 788                 1

3                    2017-06-07                 701                 5

4                    2017-03-06               30098                 1


   carrier_delivered  delivered_estimated  purchased_delivered
order_item_id  \
0                  6                    7                    8
1
1                  9                   12                   13
1
2                 14                    5                   16
1
3                  4                   11                    9
1
4                  6                   31                    9
1

                         product_id                         seller_id
\
0  87285b34884572647811a353c7ac498a  3504c0cb71d7fa48d967e0e4c94d59d9

1  d0b61bfb1de832b15ba9d266ca96e5b0  66922902710d126a0e7d26b0e3805106

2  060cb19345d90064d1015407193c233d  8581055ce74af1daba164fdbd55a40de

3  4520766ec412348b8d4caa5e8a18c464  16090f2ca825584b5a147ab24aa30c86

4  ac1789e492dcd698c5c10b97a671243a  63b9ae557efed31d1f7687917d248a8d


  shipping_limit_date   price  freight_value  Month  isLateDelivery  \
0 2017-10-06 11:07:15   29.99           8.72     10               0
1 2017-11-23 19:45:59   45.00          27.20     11               0
```

```
2 2017-07-13 22:10:13  147.90          27.36      7                0
3 2017-05-22 13:22:11   59.99          15.17      5                0
4 2017-01-27 18:29:09   19.90          16.05      1                0

   isOnTimeDelivery
0                 1
1                 1
2                 1
3                 1
4                 1

lateDeliveringSellers_blackFriday =
blackFriday[blackFriday.delivered_estimated < 0]['seller_id']
lateDeliveringSellers_blackFriday.value_counts().to_frame()

                                  seller_id
8160255418d5aaa7dbdc9f4c64ebda44         22
1f50f920176fa81dab994f9023523100         18
1025f0e2d44d7041d6cf58b6550e0bfa         18
4a3ca9315b744ce9f8e9374361493884         12
54965bbe3e4f07ae045b90b0b8541f52         11
...                                     ...
1da3aeb70d7989d1e6d9b0e887f97c23          1
7b07b3c7487f0ea825fc6df75abd658b          1
c864036feaab8c1659f65ea4faebe1da          1
712e6ed8aa4aa1fa65dab41fed5737e4          1
2c9e548be18521d1c43cde1c582c6de8          1

[114 rows x 1 columns]

print('Number of sellers who delivered late during black friday: ',
blackFriday[blackFriday.delivered_estimated < 0]
['seller_id'].nunique())

Number of sellers who delivered late during black friday:  114

averageLateDeliveringSellers =
november2017[november2017.delivered_estimated <
0].groupby('Date').agg({'seller_id' :
'nunique'}).drop(24).seller_id.mean()
print('Average late delivering sellers over the months: ',
round(averageLateDeliveringSellers))

Average late delivering sellers over the months:  22

lateDeliveringSellers_blackFriday =
blackFriday[blackFriday.delivered_estimated < 0]['seller_id']
lateDeliveringSellers_blackFriday.value_counts()
[lateDeliveringSellers_blackFriday.value_counts() > 5]
```

```
8160255418d5aaa7dbdc9f4c64ebda44    22
1f50f920176fa81dab994f9023523100    18
1025f0e2d44d7041d6cf58b6550e0bfa    18
4a3ca9315b744ce9f8e9374361493884    12
54965bbe3e4f07ae045b90b0b8541f52    11
ea8482cd71df3c1969d7b9473ff13abc    10
Name: seller_id, dtype: int64
```

Observations:

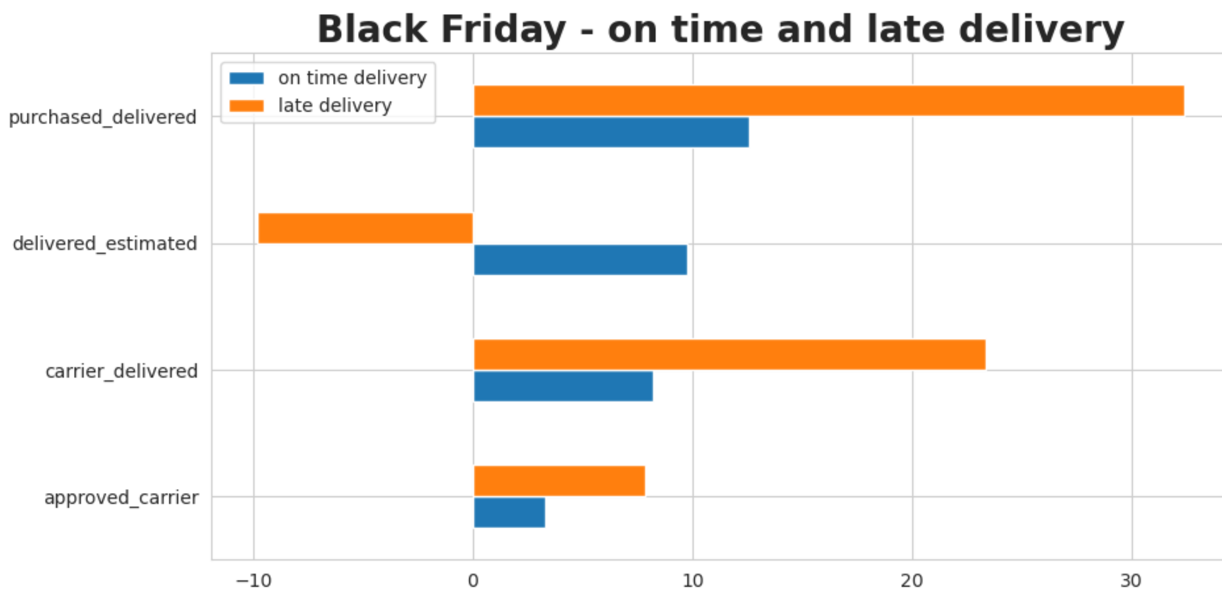
1. As the number of orders increased, late deliveries was also on the rise which indicates **inability to handle huge volume of orders**.
2. During peak sales days, such late delivering sellers should be avoided or they should be told to **increase their delivery performance**.

Late deliveries on Black Friday Sale

```
ontimeDelivery_bf = blackFriday[blackFriday.delivered_estimated > 0]
[['purchased_approved', 'approved_carrier', 'carrier_delivered',
'delivered_estimated', 'purchased_delivered']].mean()
lateDelivery_bf = blackFriday[blackFriday.delivered_estimated < 0]
[['purchased_approved', 'approved_carrier', 'carrier_delivered',
'delivered_estimated', 'purchased_delivered']].mean()
comparision = pd.DataFrame([ontimeDelivery_bf, lateDelivery_bf]).T
comparision.rename(columns = {0 : 'on time delivery', 1 : 'late
delivery'}, inplace = True)
comparision
```

	on time delivery	late delivery
purchased_approved	15799.711174	18235.150000
approved_carrier	3.282197	7.869231
carrier_delivered	8.235795	23.346154
delivered_estimated	9.737689	-9.788462
purchased_delivered	12.554924	32.380769

```
comparision.drop('purchased_approved').plot(kind = 'barh', figsize =
(10, 5))
plt.title('Black Friday - on time and late
delivery',fontweight='bold',fontsize=20)
plt.show()
```



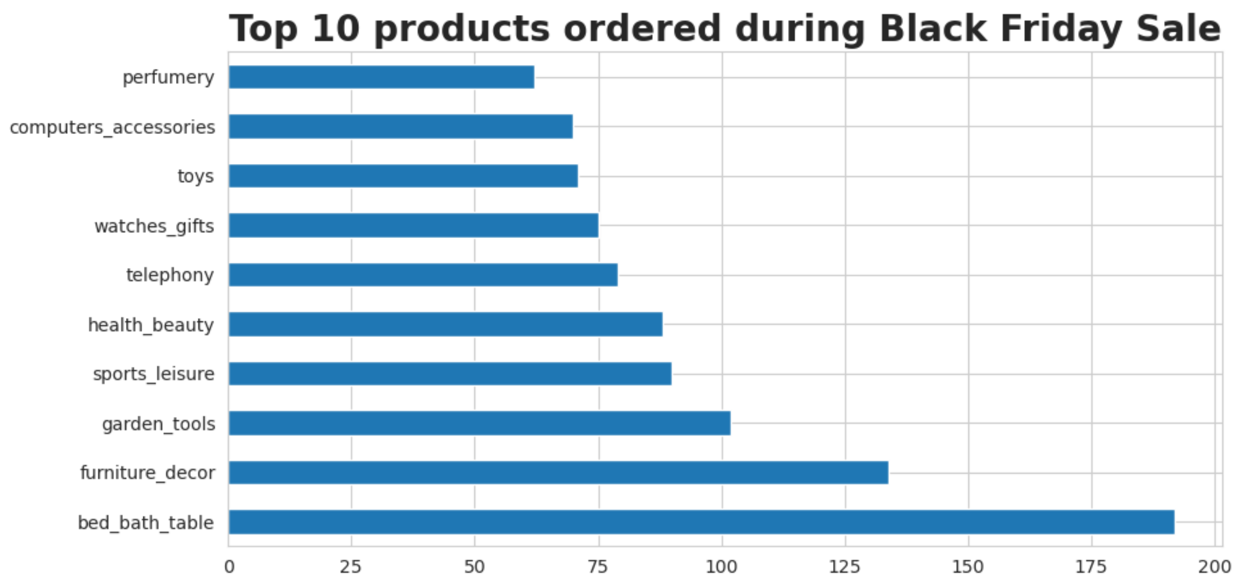

```
blackFriday.Delivery.value_counts(normalize = True) * 100

OnTime    80.669145
Late      19.330855
Name: Delivery, dtype: float64
```

Observations:

1. Inability to handle huge volume of orders (1147) as **19.33%** of orders **delivered late** compared to an **overall 8.12% late deliveries**.
2. **Increase delivery performance** to attract more sales during successive offers.
3. Understand customer preference and market those products extensively on sale days.

Products ordered on Black Friday Sale

```
blackFridayProducts = blackFriday.merge(products[['product_id',
'product_category_name']], on =
'product_id').merge(productCategoryTranslation, on =
'product_category_name')
plt.figure(figsize = (10, 5))
blackFridayProducts.product_category_name_english.value_counts()
[:10].plot(kind = 'barh')
plt.title('Top 10 products ordered during Black Friday
Sale',fontweight='bold',fontsize=20)
plt.show()
```



Observations:

1. **Customer preferences**, **regional demands**, **market trends** should be considered during future sale days so as to increase revenue.
2. Customer preferences could be seen from the above bar plot, which gives the top products ordered during the black friday sale.
3. **Bed bath table** constituted the **most orders during that day**.

4.8. Analysis of Late Deliveries

```
def is_late(Days):
    if Days < -10:
        return 'delayed by >10 days'
    elif Days < -5 and Days >= -10:
        return 'delayed by 6-10 days'
    elif Days < 0 and Days >= -5:
        return 'delayed by 1-5 days'
    else:
        return 'on time'

lateDelivery = orders[['order_id', 'order_purchase_timestamp',
'order_delivered_customer_date', 'order_estimated_delivery_date',
'delivered_estimated']].merge(orderReviews[['order_id',
'review_score']], on = 'order_id', how = 'left')
lateDelivery['is_late'] =
lateDelivery['delivered_estimated'].apply(is_late)
lateDelivery.head()
```

```
                           order_id order_purchase_timestamp  \
0  e481f51cbdc54678b7cc49136f2d6af7      2017-10-02 10:56:33
```

```
1  53cdb2fc8bc7dce0b6741e2150273451      2018-07-24 20:41:37
2  47770eb9100c2d0c44946d9cf07ec65d      2018-08-08 08:38:49
3  949d5b44dbf5de918fe9c16f97b45f8a      2017-11-18 19:28:06
4  ad21c59c0840e6cb83a9ceb5573f8159      2018-02-13 21:18:39

  order_delivered_customer_date order_estimated_delivery_date  \
0           2017-10-10 21:25:13                    2017-10-18
1           2018-08-07 15:27:45                    2018-08-13
2           2018-08-17 18:06:29                    2018-09-04
3           2017-12-02 00:28:42                    2017-12-15
4           2018-02-16 18:17:02                    2018-02-26

   delivered_estimated  review_score  is_late
0                    7           NaN  on time
1                    5           4.0  on time
2                   17           NaN  on time
3                   12           NaN  on time
4                    9           NaN  on time
```

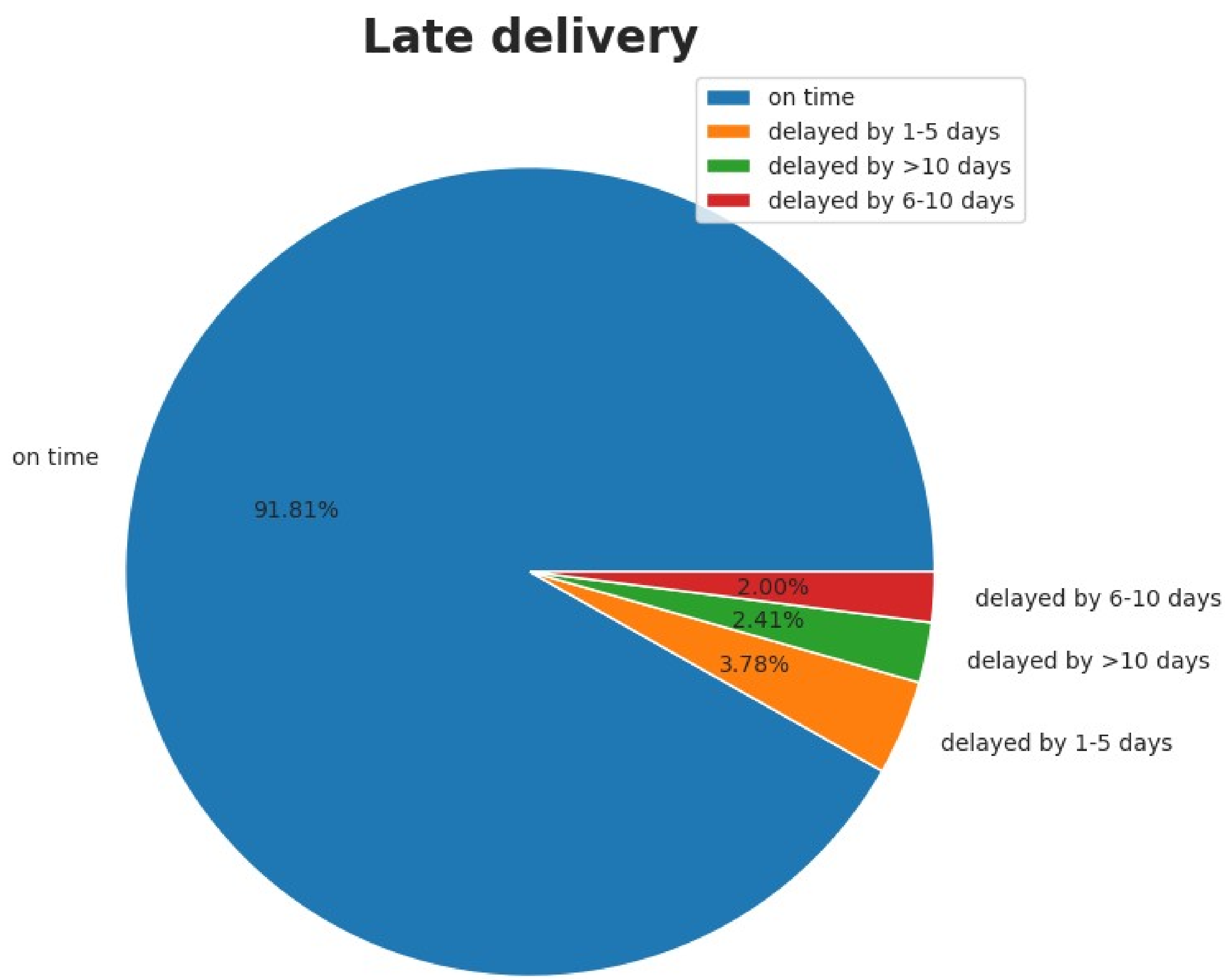
```
lateDelivery.is_late.value_counts()
```

```
on time                 87320
delayed by 1-5 days      3596
delayed by >10 days      2294
delayed by 6-10 days     1904
Name: is_late, dtype: int64
```

```
lateDelivery.is_late.value_counts(normalize = True) * 100
```

```
on time                 91.805623
delayed by 1-5 days      3.780726
delayed by >10 days      2.411843
delayed by 6-10 days     2.001808
Name: is_late, dtype: float64
```

```
plt.figure(figsize = (10, 8))
plt.pie(lateDelivery.is_late.value_counts(), autopct = '%0.2f%%',
labels = lateDelivery.is_late.value_counts().index)
plt.title('Late delivery',fontweight='bold',fontsize=20)
plt.legend()
plt.show()
```



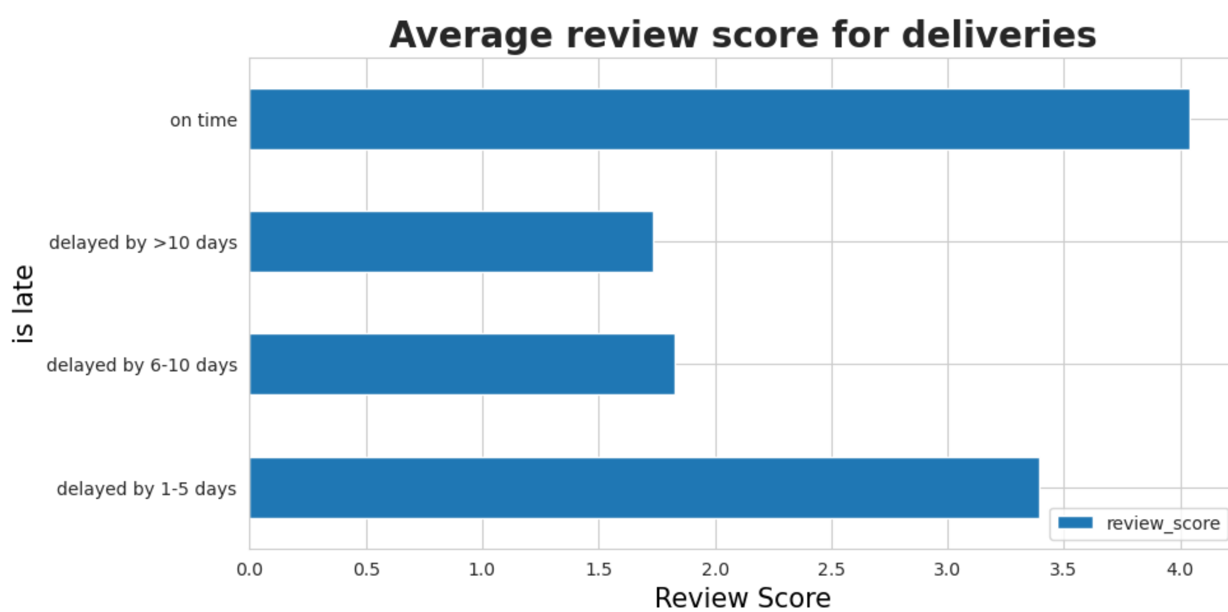
Observations:

1. To find out if the order was delivered late than the expected date of delivery, we took the `order_delivered_customer_date` and the `order_estimated_delivery_date` and **subtracted them to get the required number of days**.
2. If the value was in **positive**, it denotes that the products were **delivered before the estimated date of delivery**, which are mapped to **on time**.
3. Late deliveries upto 5 days are mapped to **delayed by 1-5 days**, while late deliveries between 5-10 days are mapped to **delayed by 6-10 days** and late deliveries greater than 10 are mapped to **delayed by >10 days**.
4. Of all the orders, **91.89%** of orders were **delivered on time**, whereas, only **8.11%** of deliveries were **delivered late**. But this level of late deliveries should also be minimized in order to retain more customers, as they could potentially move to other e-commerce platforms.

```
reviewScore_lateDelivery =
lateDelivery.groupby('is_late').agg({'review_score' : 'mean'})
reviewScore_lateDelivery
```

	review_score
is_late	
delayed by 1-5 days	3.393782
delayed by 6-10 days	1.824645
delayed by >10 days	1.736559
on time	4.042449

```
reviewScore_lateDelivery.plot(kind = 'barh', figsize = (10, 5))
plt.title('Average review score for
deliveries',fontweight='bold',fontsize=20)
plt.xlabel('Review Score',fontsize=15,color='black')
plt.ylabel('is late',fontsize=15,color='black')
plt.show()
```



Observations:

1. The delivery time with respect to the expected date of delivery is correlated with the **review score** that the customers give.
2. For instance, orders which were **delivered on time** recieved on an average of **4** as their review score, while orders which were **delivered late by more than 10 days** recieved an average review score of **1.7**.
3. This could be a clear indication that the **customers were dissatisfied by the late deliveries**, and this needs to be minimized to a greater extent to retain customers.

```
lateDeliveringSellers = lateDelivery[lateDelivery.is_late != 'on
time'].merge(orderItems[['seller_id', 'product_id', 'order_id',
'product_id']], on = 'order_id', how = 'left')
```

```
lateDeliveringSellersAnalysis =
lateDeliveringSellers.groupby('seller_id').agg({'order_id' : 'count',
'delivered_estimated' : 'mean'}).sort_values(by = 'order_id',
ascending = False)[:11]
lateDeliveringSellersAnalysis['delivered_estimated'] =
lateDeliveringSellersAnalysis['delivered_estimated'].round()
lateDeliveringSellersAnalysis
```

	order_id	delivered_estimated
seller_id		
4a3ca9315b744ce9f8e9374361493884	214	-11.0
1f50f920176fa81dab994f9023523100	182	-10.0
4869f7a5dfa277a7dca6462dcf3b52b2	133	-9.0
1025f0e2d44d7041d6cf58b6550e0bfa	130	-6.0
7c67e1448b00f6e969d365cea6b010ab	130	-11.0
ea8482cd71df3c1969d7b9473ff13abc	123	-8.0
6560211a19b47992c3666cc44a7e94c0	122	-7.0
955fee9216a65b617aa5c0531780ce60	119	-7.0
da8622b14eb17ae2831f4ac5b9dab84a	113	-11.0
cc419e0650a3c5ba77189a1882b7556a	103	-8.0
8b321bb669392f5163d04c59e235e066	103	-9.0

Observations:

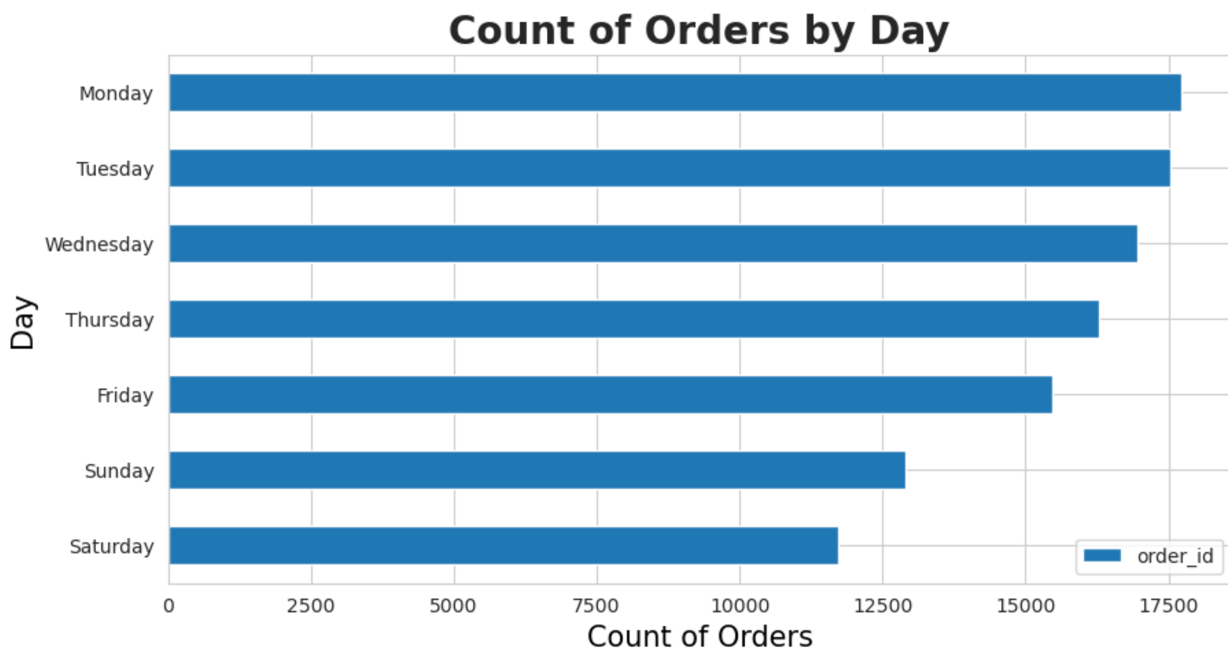
1. The list of sellers who were involved in late deliveries of more than 100 orders, and the `delivered_estimated` field is the average number of days taken for late delivery of such orders.
2. If we could make these sellers deliver on time, we could further avoid customer dissatisfaction, which was reflected in the low review rating.

4.9. Golden hours for business

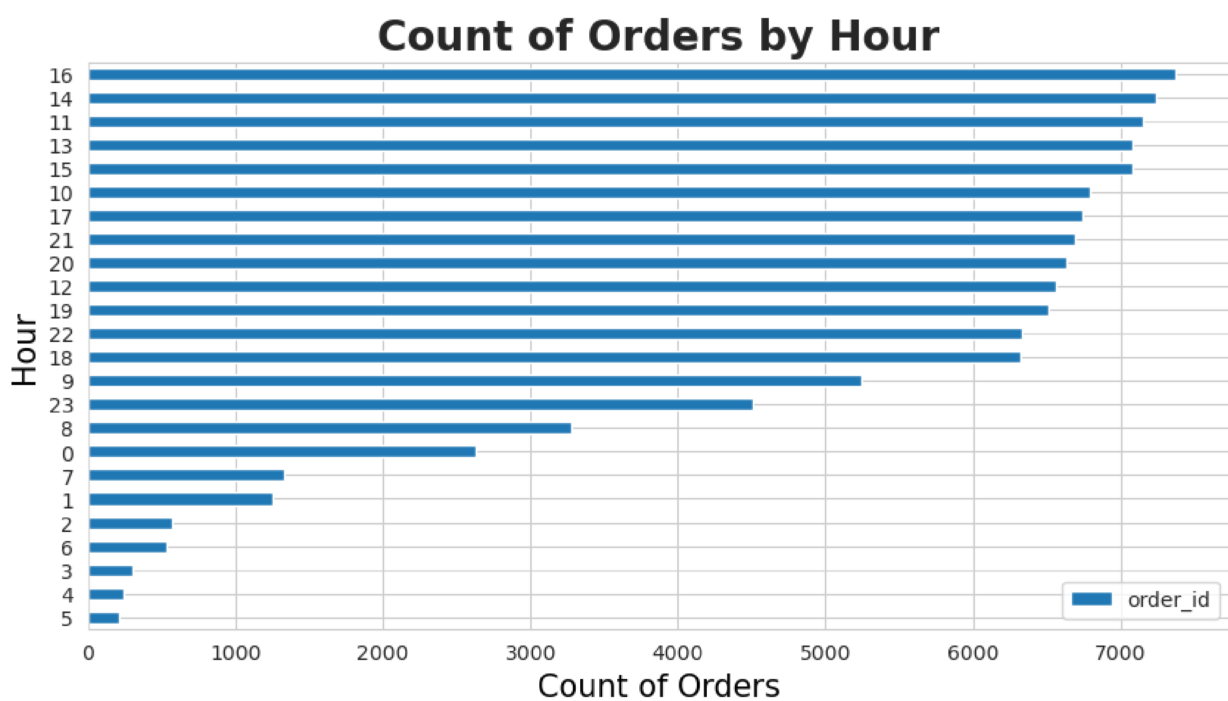
```
def weekend(dayName):
    if dayName == 'Saturday' or dayName == 'Sunday':
        return 'weekend'
    else:
        return 'weekday'

ordersTimeAnalysis = orders.copy().merge(orderItems, on = 'order_id')
ordersTimeAnalysis['Hour'] =
ordersTimeAnalysis.order_purchase_timestamp.dt.hour
ordersTimeAnalysis['day_name'] =
ordersTimeAnalysis.order_purchase_timestamp.dt.day_name()
ordersTimeAnalysis['is_weekend'] =
ordersTimeAnalysis.day_name.apply(weekend)
ordersTimeAnalysis['total_revenue'] = ordersTimeAnalysis.price +
ordersTimeAnalysis.freight_value
ordersTimeAnalysis.head()
```

```
                           order_id                       customer_id  \
0  e481f51cbdc54678b7cc49136f2d6af7  9ef432eb6251297304e76186b10a928d   
1  53cdb2fc8bc7dce0b6741e2150273451  b0830fb4747a6c6d20dea0b8c802d7ef   
2  47770eb9100c2d0c44946d9cf07ec65d  41ce2a54c0b03bf3443c3d931a367089   
3  949d5b44dbf5de918fe9c16f97b45f8a  f88197465ea7920adcdbec7375364d82   
4  ad21c59c0840e6cb83a9ceb5573f8159  8ab97904e6daea8866dbdbc4fb7aad2c   

  order_status order_purchase_timestamp   order_approved_at  \
0    delivered      2017-10-02 10:56:33 2017-10-02 11:07:15   
1    delivered      2018-07-24 20:41:37 2018-07-26 03:24:27   
2    delivered      2018-08-08 08:38:49 2018-08-08 08:55:23   
3    delivered      2017-11-18 19:28:06 2017-11-18 19:45:59   
4    delivered      2018-02-13 21:18:39 2018-02-13 22:20:29   

  order_delivered_carrier_date order_delivered_customer_date  \
0          2017-10-04 19:55:00           2017-10-10 21:25:13   
1          2018-07-26 14:31:00           2018-08-07 15:27:45   
2          2018-08-08 13:50:00           2018-08-17 18:06:29   
3          2017-11-22 13:39:59           2017-12-02 00:28:42   
4          2018-02-14 19:46:34           2018-02-16 18:17:02   

  order_estimated_delivery_date  purchased_approved  approved_carrier  \
0                    2017-10-18                 642                 2   
1                    2018-08-13               24170                 0   
2                    2018-09-04                 994                 0   
3                    2017-12-15                1073                 3   
4                    2018-02-26                3710                 0   

   carrier_delivered  delivered_estimated  purchased_delivered  order_item_id  \
0                  6                    7                    8              1   
1                 12                    5                   13              1   
2                  9                   17                    9              1   
3                  9                   12                   13              1   
4                  1                    9                    2
```

```
1

                           product_id                          seller_id  \
0  87285b34884572647811a353c7ac498a  3504c0cb71d7fa48d967e0e4c94d59d9

1  595fac2a385ac33a80bd5114aec74eb8  289cdb325fb7e7f891c38608bf9e0962

2  aa4383b373c6aca5d8797843e5594415  4869f7a5dfa277a7dca6462dcf3b52b2

3  d0b61bfb1de832b15ba9d266ca96e5b0  66922902710d126a0e7d26b0e3805106

4  65266b2da20d04dbe00c5c2d3bb7859e  2c9e548be18521d1c43cde1c582c6de8


  shipping_limit_date   price  freight_value  Hour   day_name
is_weekend  \
0 2017-10-06 11:07:15   29.99           8.72    10     Monday
weekday
1 2018-07-30 03:24:27  118.70          22.76    20    Tuesday
weekday
2 2018-08-13 08:55:23  159.90          19.22     8  Wednesday
weekday
3 2017-11-23 19:45:59   45.00          27.20    19   Saturday
weekend
4 2018-02-19 20:31:37   19.90           8.72    21    Tuesday
weekday

   total_revenue
0          38.71
1         141.46
2         179.12
3          72.20
4          28.62

ordersTimeAnalysis.groupby(['day_name']).agg({'order_id' :
'count'}).sort_values('order_id').plot(kind = 'barh', figsize = (10,
5))
plt.title('Count of Orders by Day',fontweight='bold',fontsize=20)
plt.xlabel('Count of Orders',fontsize=15,color='black')
plt.ylabel('Day',fontsize=15,color='black')
plt.show()
```




```
ordersTimeAnalysis.groupby(['Hour']).agg({'order_id' :
'count'}).sort_values('order_id').plot(kind = 'barh', figsize = (10,
5))
plt.title('Count of Orders by Hour',fontweight='bold',fontsize=20)
plt.xlabel('Count of Orders',fontsize=15,color='black')
plt.ylabel('Hour',fontsize=15,color='black')
plt.show()
```



Observations:

1. The above plots represent the **peak hours** and **peak days** during which the customers order products.
2. The **customer traffic is more during the weekdays compared to the weekends**, with **Monday** and **Tuesday** being the days when most orders were placed.
3. Similarly, the **peak time** during which most number of orders were placed were between **11 AM** to **4 PM** in the afternoon.
4. We could improve our sales and revenue if we could tap in this information and target the customers with attractive offers.

Business recommendations:

1. **Increase weekend sales** by **strong digital presence** and **extensive marketing**.
2. **Attractive offers** during peak hour business.
3. Targeting customers through personalised advertisements of products they prefer.
4. **Loyal customers benefits** and **improve customer support**.

4.10. Exploratory Data Analysis On Products dataframe

```
products.head()
```

```
                         product_id  product_category_name  \
0  1e9e8ef04dbcff4541ed26657ea517e5             perfumaria
1  3aa071139cb16b67ca9e5dea641aaa2f                  artes
2  96bd76ec8810374ed1b65e291975717f          esporte_lazer
3  cef67bcfe19066a932b7673e239eb23d                  bebes
4  9dc1a7de274444849c219cff195d0b71  utilidades_domesticas

   product_name_lenght  product_description_lenght  product_photos_qty
\
0                 40.0                       287.0                 1.0

1                 44.0                       276.0                 1.0

2                 46.0                       250.0                 1.0

3                 27.0                       261.0                 1.0

4                 37.0                       402.0                 4.0


   product_weight_g  product_length_cm  product_height_cm
product_width_cm
0             225.0               16.0               10.0
14.0
1            1000.0               30.0               18.0
20.0
2             154.0               18.0                9.0
```

```
15.0
3              371.0                   26.0                    4.0
26.0
4              625.0                   20.0                   17.0
13.0

print('Number of records:',products.shape[0])
print('Number of Columns:',products.shape[1])

Number of records: 32951
Number of Columns: 9

products.isna().sum()

product_id                      0
product_category_name         610
product_name_lenght           610
product_description_lenght    610
product_photos_qty            610
product_weight_g                2
product_length_cm               2
product_height_cm               2
product_width_cm                2
dtype: int64

products.dropna(inplace = True)
```

Observation:

1. Since the **product IDs are masked**, if they do not have any category name, we could not interpret anything from the data, so **dropping such records** will be the best way to proceed with the analysis.

```
orderedProducts = products.merge(orderItems, on =
'product_id').merge(productCategoryTranslation, on =
'product_category_name')[['product_id',
'product_category_name_english', 'product_name_lenght',
'product_description_lenght', 'product_photos_qty',
'product_weight_g', 'product_length_cm', 'product_height_cm',
'product_width_cm', 'order_id', 'price', 'freight_value']]
orderedProducts['total_revenue'] = orderedProducts.price +
orderedProducts.freight_value
orderedProducts.head()

                         product_id product_category_name_english  \
0  1e9e8ef04dbcff4541ed26657ea517e5                     perfumery
1  6a2fb4dd53d2cdb88e0432f1284a004c                     perfumery
2  6a2fb4dd53d2cdb88e0432f1284a004c                     perfumery
3  0d009643171aee696f4733340bc2fdd0                     perfumery
4  0d009643171aee696f4733340bc2fdd0                     perfumery
```

```
   product_name_lenght  product_description_lenght  product_photos_qty  \
0                 40.0                       287.0                 1.0   

1                 39.0                       346.0                 2.0   

2                 39.0                       346.0                 2.0   

3                 52.0                       150.0                 1.0   

4                 52.0                       150.0                 1.0   


   product_weight_g  product_length_cm  product_height_cm  
product_width_cm  \
0             225.0               16.0               10.0              
14.0   
1             400.0               27.0                5.0              
20.0   
2             400.0               27.0                5.0              
20.0   
3             422.0               21.0               16.0              
18.0   
4             422.0               21.0               16.0              
18.0   

                           order_id   price  freight_value  
total_revenue  
0  e17e4f88e31525f7deef66779844ddce   10.91           7.39          
18.30  
1  048cc42e03ca8d43c729adf6962cb348   16.90           7.78          
24.68  
2  5fa78e91b5cb84b6a8ccc42733f95742   16.90           7.78          
24.68  
3  24b1c4d88fdb7a2dc87f8ecc7d8f47f1  339.00          17.13         
356.13  
4  7b13c77c64a9a956500cbf1a9a23798d  275.00          23.48         
298.48  

orderedProductsAnalysis = 
orderedProducts.groupby('product_category_name_english', as_index = 
False).agg({
                                                        'product_id'            
: 'count',
                                                        'order_id'              
: 'count',
                                                        'price'                 
: 'sum',
                                                        
'freight_value'                   : 'sum',
```

```
'total_revenue'                   : 'sum'})
orderedProductsAnalysis.head()
```

```
  product_category_name_english  product_id  order_id     price  \
0    agro_industry_and_commerce         212       212  72530.47
1              air_conditioning         297       297  55024.96
2                           art         209       209  24202.64
3         arts_and_craftmanship          24        24   1814.01
4                         audio         364       364  50688.50

   freight_value  total_revenue
0        5843.60       78374.07
1        6749.23       61774.19
2        4045.17       28247.81
3         370.13        2184.14
4        5710.44       56398.94
```

```
orderedProductsAnalysis.select_dtypes(include = np.number).describe()
```

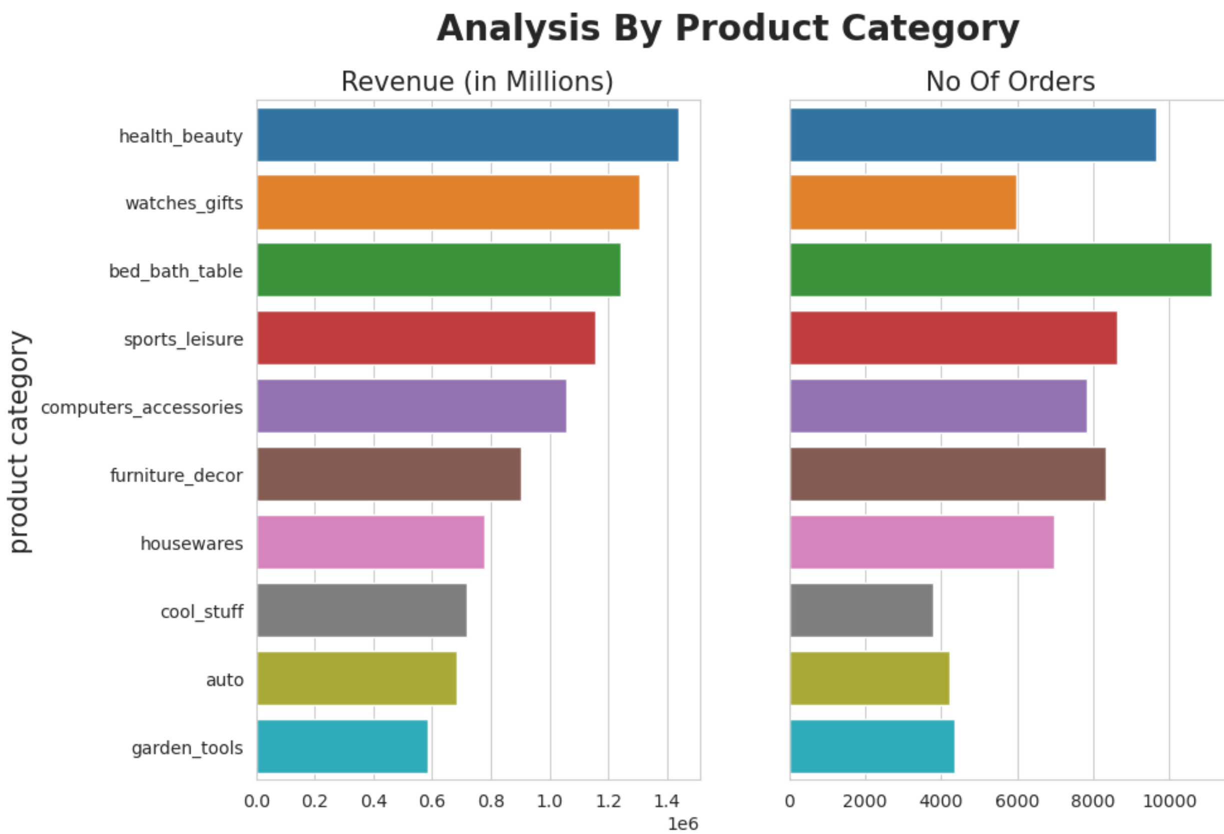
```
         product_id      order_id         price  freight_value
total_revenue
count     71.000000     71.000000  7.100000e+01      71.000000
7.100000e+01
mean    1563.690141   1563.690141  1.887980e+05   31313.653521
2.201117e+05
std     2606.537422   2606.537422  3.036850e+05   50281.462423
3.515343e+05
min        2.000000      2.000000  2.832900e+02      41.220000
3.245100e+02
25%       93.000000     93.000000  9.171185e+03    1973.205000
1.174393e+04
50%      281.000000    281.000000  4.685688e+04    6749.230000
5.605240e+04
75%     1819.000000   1819.000000  2.029071e+05   35505.620000
2.214684e+05
max    11115.000000  11115.000000  1.258681e+06  204693.040000
1.441248e+06
```

```
top10revenueGenerating = orderedProductsAnalysis.sort_values(by =
'total_revenue', ascending = False)[:10]
top10revenueGenerating
```

```
   product_category_name_english  product_id  order_id       price  \
43                  health_beauty        9670      9670  1258681.34
70                  watches_gifts        5991      5991  1205005.68
7                  bed_bath_table       11115     11115  1036988.68
65                 sports_leisure        8641      8641   988048.97
15          computers_accessories        7827      7827   911954.32
39                furniture_decor        8334      8334   729762.49
```

```
49                           housewares         6964       6964   632248.66
20                           cool_stuff         3796       3796   635290.85
5                                  auto         4235       4235   592720.11
42                         garden_tools         4347       4347   485256.46

    freight_value  total_revenue
43      182566.73     1441248.07
70      100535.93     1305541.61
7       204693.04     1241681.72
65      168607.51     1156656.48
15      147318.08     1059272.40
39      172749.30      902511.79
49      146149.11      778397.77
20       84039.10      719329.95
5        92664.21      685384.32
42       98962.75      584219.21
```

```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10, 7), sharey=True)
fig.suptitle('Analysis By Product Category', fontsize=20, fontweight =
'bold')

sns.barplot(ax=ax[0], x='total_revenue', y=
top10revenueGenerating.product_category_name_english, data =
top10revenueGenerating)
ax[0].set_title('Revenue (in Millions)', fontsize = 15)
ax[0].set_ylabel('product category', fontsize = 15)

sns.barplot(ax=ax[1], x='order_id', y =
top10revenueGenerating.product_category_name_english, data =
top10revenueGenerating)
ax[1].set_title('No Of Orders', fontsize = 15)

for i in range(0,2):
    ax[i].set(xlabel=None)

for i in range(1,2):
    ax[i].set(ylabel=None)
```



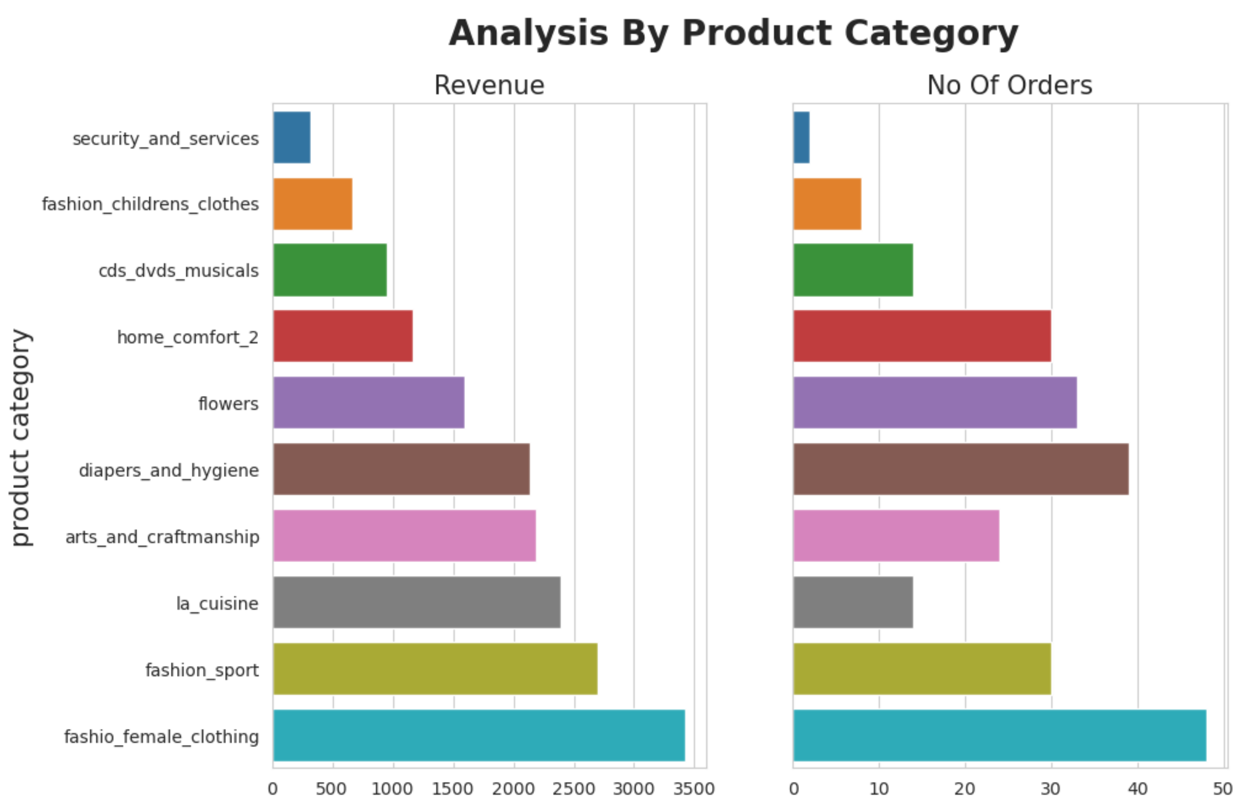

```
bottom10revenueGenerating = orderedProductsAnalysis.sort_values(by =
'total_revenue', ascending = True)[:10]
bottom10revenueGenerating
```

	product_category_name_english	product_id	order_id	price
61	security_and_services	2	2	283.29
29	fashion_childrens_clothes	8	8	569.85
11	cds_dvds_musicals	14	14	730.00
46	home_comfort_2	30	30	760.27
35	flowers	33	33	1110.04
23	diapers_and_hygiene	39	39	1567.59
3	arts_and_craftmanship	24	24	1814.01
52	la_cuisine	14	14	2054.99
32	fashion_sport	30	30	2119.51
27	fashio_female_clothing	48	48	2803.64

\

	freight_value	total_revenue
61	41.22	324.51
29	95.51	665.36
11	224.99	954.99
46	410.31	1170.58
35	488.87	1598.91
23	573.68	2141.27
3	370.13	2184.14

```
52          333.55         2388.54
32          578.13         2697.64
27          621.75         3425.39

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10, 7), sharey=True)
fig.suptitle('Analysis By Product Category', fontsize=20, fontweight =
'bold')

sns.barplot(ax=ax[0], x='total_revenue', y=
bottom10revenueGenerating.product_category_name_english, data =
bottom10revenueGenerating)
ax[0].set_title('Revenue', fontsize = 15)
ax[0].set_ylabel('product category', fontsize = 15)

sns.barplot(ax=ax[1], x='order_id', y =
bottom10revenueGenerating.product_category_name_english, data =
bottom10revenueGenerating)
ax[1].set_title('No Of Orders', fontsize = 15)

for i in range(0,2):
    ax[i].set(xlabel=None)

for i in range(1,2):
    ax[i].set(ylabel=None)
```



Observations:

1. The main inference from the analysis of products ordered is, the total revenue each product category generated.
2. The minimum revenue generated products were, **security and services**, **fashion childrens clothes** and **cds dvds musicals**.
3. While the maximum revenue generated products were **health beauty**, **watches gifts** and **bed bath table**.
4. **security and services** is the least ordered product, while **bed bath table** is the most ordered product.

4.11. Overseas Customers

```
overseasCustomers = customerDensity[customerDensity.geolocation_lat > 
10]
overseasCustomers.head()
```

```
                      customer_unique_id  customer_zip_code_prefix  \
3830   3fbfe90197db709a78d7e0eaabe0aac0                     47310   
4887   a8563d0be40211e2527f8b80c24f4845                     28595   
5111   aef278d3c4350b0d32907d429421f071                     68447   
14955  c037aa753c0787f6e28b2d5c5e40d997                     68447   
16444  f570b38fd1007c094f293aadb09bcedf                     68447   

       geolocation_lat  geolocation_lng  
3830         38.268205        -7.803886  
4887         43.684961        -7.411080  
5111         42.428884        -6.873344  
14955        42.428884        -6.873344  
16444        42.428884        -6.873344  
```

```
# create a map centered on your coordinates
m = folium.Map(location = overseasCustomers[['geolocation_lat', 
'geolocation_lng']].values.tolist()[0], zoom_start = 13)

# create a list of coordinates
coordinates = overseasCustomers[['geolocation_lat', 
'geolocation_lng']].values.tolist()

# create a heatmap layer with the list of coordinates
heat_layer = HeatMap(coordinates)

# add the heatmap layer to the map
heat_layer.add_to(m)

# display the map
m
```

```
<folium.folium.Map at 0x7b9a51761ed0>
```

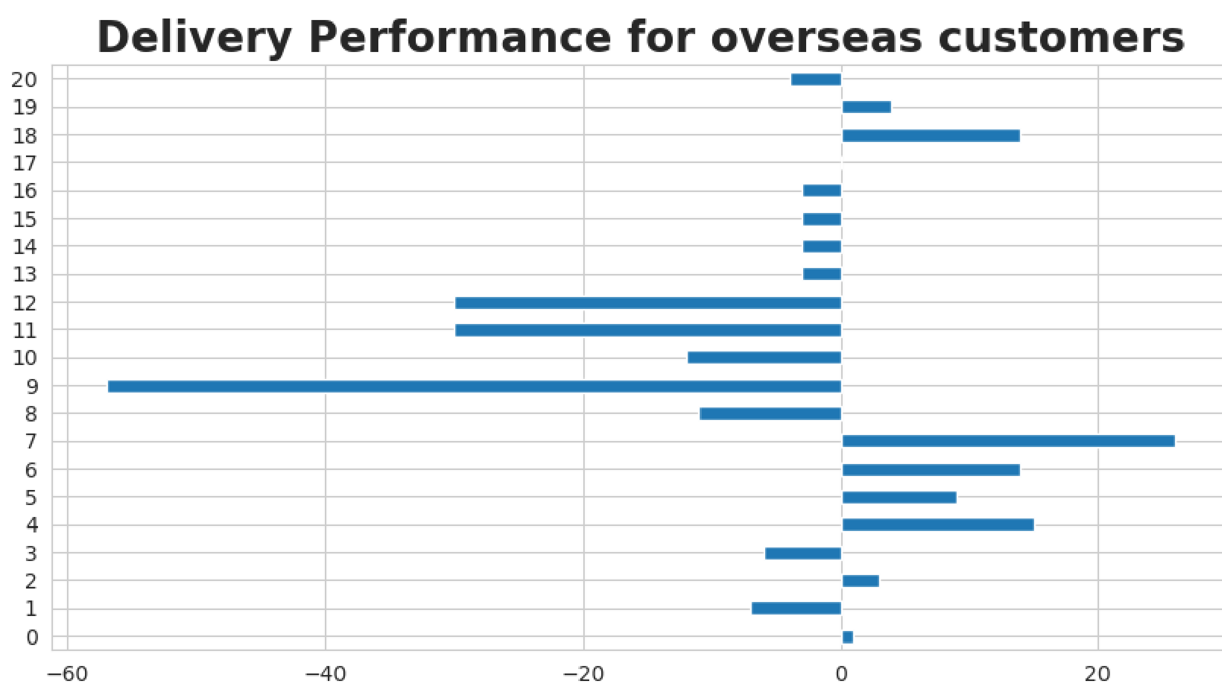
```
overseasAnalysis =
overseasCustomers[['customer_unique_id']].merge(customers, on =
'customer_unique_id').merge(orders, on =
'customer_id').merge(orderItems, on = 'order_id').merge(products, on =
'product_id').merge(productCategoryTranslation, on =
'product_category_name')
overseasAnalysis.head()
```

```
                 customer_unique_id                       customer_id
\
0  3fbfe90197db709a78d7e0eaabe0aac0  d92a2fbf56a1e0f231a58f7a1e9ca540

1  a8563d0be40211e2527f8b80c24f4845  4457d60c844b9cec4abec3a9507f23a5

2  6e9d7c002cb4603011d3e83033b01878  2dd769df72fbd8448297d18c48df7b92

3  aef278d3c4350b0d32907d429421f071  d90af5c00814430fc3e212e8163bf2b8

4  2a4b1192846ec238d62df3838257bad9  88aac7b0942dcdb41ebabf7811b106fc


  customer_zip_code_prefix       customer_city customer_state  \
0                    47310  santana do sobrado             BA
1                    28595             portela             RJ
2                    46560            ibiajara             BA
3                    68447    vila dos cabanos             PA
4                    68275     porto trombetas             PA

                           order_id order_status
order_purchase_timestamp  \
0  ed7774b614a7ad220649f09dc6a4c043    delivered      2017-11-16
23:27:21
1  a85ce89cbcc514dfe135de0036be45db    delivered      2017-08-21
16:17:56
2  897ec6416d50126a9061626f0fc2d658    delivered      2017-04-20
15:05:38
3  72fb560d115ecf3b15de9b853c02e505    delivered      2018-04-19
14:04:23
4  4d5abe7999d76d1fb6237d3677706af0    delivered      2017-11-23
18:13:30

     order_approved_at order_delivered_carrier_date  \
0 2017-11-16 23:50:57          2017-11-17 22:32:25
1 2017-08-23 02:50:25          2017-08-23 15:33:02
2 2017-04-20 15:21:31          2017-04-24 07:52:21
3 2018-04-19 14:34:54          2018-04-23 09:57:00
4 2017-11-23 18:55:39          2017-11-28 20:07:50

  order_delivered_customer_date order_estimated_delivery_date  \
0           2017-12-11 14:14:54                    2017-12-13
```

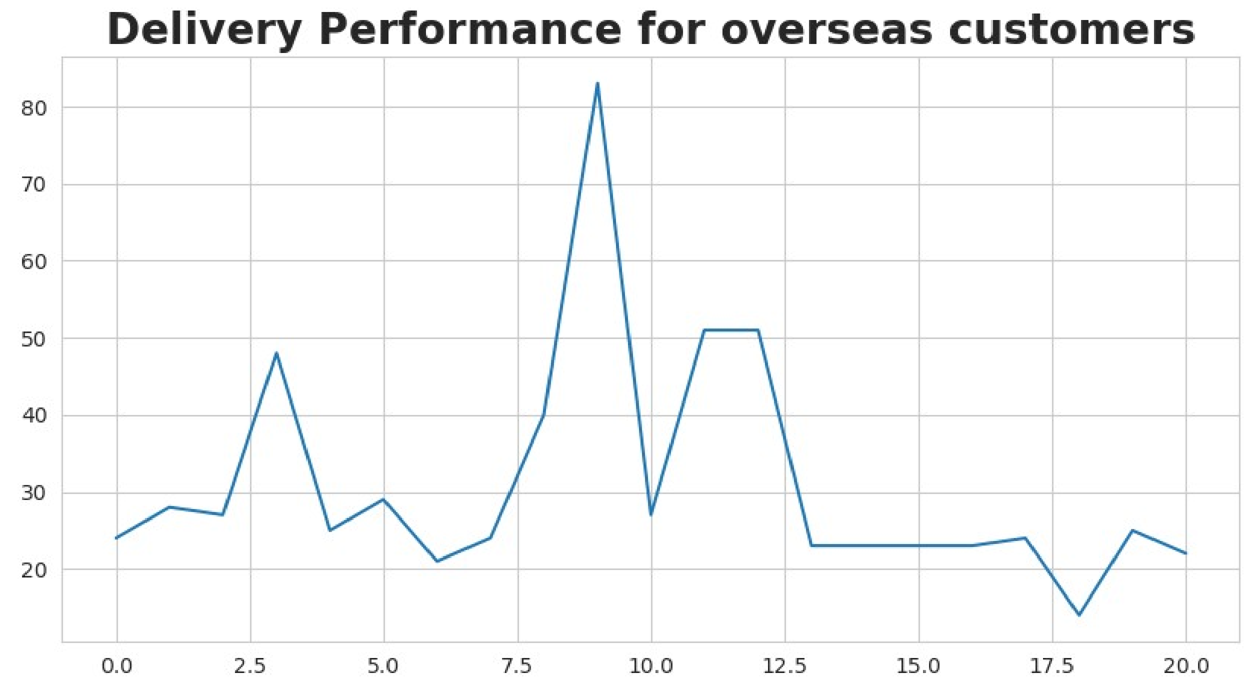
```
1          2017-09-19 10:52:56                         2017-09-13
2          2017-05-18 08:06:47                         2017-05-22
3          2018-06-06 20:32:22                         2018-06-01
4          2017-12-19 08:58:58                         2018-01-04

   purchased_approved  approved_carrier  carrier_delivered  \
0                1416                 0                 23
1               37949                 0                 26
2                 953                 3                 24
3                1831                 3                 44
4                2529                 5                 20

   delivered_estimated  purchased_delivered  order_item_id  \
0                    1                   24              1
1                   -7                   28              1
2                    3                   27              1
3                   -6                   48              1
4                   15                   25              1

                         product_id                         seller_id
\
0  1a980a10bed1d765e2eb2ad3608a63a1  dbc22125167c298ef99da25668e1011f

1  7a10781637204d8d10485c71a6108a2e  4869f7a5dfa277a7dca6462dcf3b52b2

2  1d54b96972338247c7341a2069e2bd96  6560211a19b47992c3666cc44a7e94c0

3  3fbc0ef745950c7932d5f2a446189725  06a2c3af7b3aee5d69171b0e14f0ee87

4  187e7d92b8168c3661824809d0c5dffb  431af27f296bc6519d890aa5a05fdb11


  shipping_limit_date   price  freight_value product_category_name  \
0 2017-11-22 23:50:57   36.90          17.92      malas_acessorios
1 2017-08-29 02:50:25  229.90          16.36    relogios_presentes
2 2017-04-27 15:21:31   45.00          20.80    relogios_presentes
3 2018-04-25 14:31:42   64.99          18.33          beleza_saude
4 2017-11-29 18:31:09  119.90          29.24          beleza_saude

   product_name_lenght  product_description_lenght  product_photos_qty
\
0                 45.0                       217.0                 1.0

1                 42.0                       236.0                 1.0

2                 59.0                       184.0                 1.0

3                 50.0                      1257.0                 1.0

4                 30.0                      1501.0                 1.0
```

```
   product_weight_g  product_length_cm  product_height_cm
product_width_cm  \
0             850.0               45.0               10.0
31.0
1             342.0               18.0               13.0
15.0
2             150.0               16.0                2.0
20.0
3             350.0               19.0               12.0
13.0
4            1900.0               27.0                9.0
18.0

  product_category_name_english
0           luggage_accessories
1                 watches_gifts
2                 watches_gifts
3                 health_beauty
4                 health_beauty
```

```
overseasAnalysis.delivered_estimated.plot(kind = 'barh', figsize =
(10, 5))
plt.title('Delivery Performance for overseas customers', fontsize=20,
fontweight = 'bold')
plt.show()
```



```
overseasAnalysis.purchased_delivered.plot(kind = 'line', figsize =
(10, 5))
plt.title('Delivery Performance for overseas customers', fontsize=20,
fontweight = 'bold')
plt.show()
```




```
overseasAnalysis.product_category_name_english.value_counts()

stationery             6
health_beauty          3
watches_gifts          2
auto                   2
luggage_accessories    1
art                    1
home_appliances        1
furniture_decor        1
bed_bath_table         1
cool_stuff             1
telephony              1
home_appliances_2      1
Name: product_category_name_english, dtype: int64
```

Business Recommendations:

1. **Overseas customers** mostly ordered **from 2018**.
2. **More than 50% of orders** were **delivered late** than the estimated delivery date.
3. Very **poor shipment delivery rate** should be handled by **opting for a new logistic partner**.

4. **Promoting indigenous products** especially **among overseas customers** to increase sales and revenue.
5. Focus on **company branding** and **prominency in the origin region**, to help create trust among customers.
6. Focus on **CX (Customer Experience)** throughout the process of order and **offer customer support**.

5. Merging the individual datasets

```
merged = customers.merge(orders, on = 'customer_id').merge(orderItems,
on = 'order_id').merge(products, on =
'product_id').merge(geolocationMean, left_on =
'customer_zip_code_prefix', right_on =
'geolocation_zip_code_prefix').merge(payments, on =
'order_id').merge(sellers, on =
'seller_id').merge(productCategoryTranslation, on =
'product_category_name').merge(orderReviews, on = 'order_id', how =
'left')
merged.head()
```

```
                        customer_id                customer_unique_id
\
0  06b8999e2fba1a1fbc88172c00ba8bc7  861eff4711a542e4b93843c6dd7febb0

1  8912fc0c3bbf1e2fbf35819e21706718  9eae34bbd3a474ec5d07949ca7de67c0

2  8912fc0c3bbf1e2fbf35819e21706718  9eae34bbd3a474ec5d07949ca7de67c0

3  f0ac8e5a239118859b1734e1087cbb1f  3c799d181c34d51f6d44bbbc563024db

4  6bc8d08963a135220ed6c6d098831f84  23397e992b09769faf5e66f9e171a241


  customer_zip_code_prefix    customer_city customer_state  \
0                    14409           franca             SP
1                    68030         santarem             PA
2                    68030         santarem             PA
3                    92480  nova santa rita             RS
4                    25931             mage             RJ

                           order_id order_status
order_purchase_timestamp  \
0  00e7ee1b050b8499577073aeb2a297a1    delivered      2017-05-16
15:05:35
1  c1d2b34febe9cd269e378117d6681172    delivered      2017-11-09
00:50:13
2  c1d2b34febe9cd269e378117d6681172    delivered      2017-11-09
```

```
00:50:13
3  b1a5d5365d330d10485e0203d54ab9e8    delivered      2017-05-07
20:11:26
4  2e604b3614664aa66867856dba7e61b7    delivered      2018-02-03
19:45:40

    order_approved_at order_delivered_carrier_date  \
0 2017-05-16 15:22:12          2017-05-23 10:47:57
1 2017-11-10 00:47:48          2017-11-22 01:43:37
2 2017-11-10 00:47:48          2017-11-22 01:43:37
3 2017-05-08 22:22:56          2017-05-19 20:16:31
4 2018-02-04 22:29:19          2018-02-19 18:21:47

  order_delivered_customer_date order_estimated_delivery_date  \
0           2017-05-25 10:35:35                    2017-06-05
1           2017-11-28 00:09:50                    2017-12-19
2           2017-11-28 00:09:50                    2017-12-19
3           2017-05-26 09:54:04                    2017-06-12
4           2018-02-28 21:09:00                    2018-03-22

   purchased_approved  approved_carrier  carrier_delivered  \
0                 997                 6                  1
1               86255                12                  5
2               86255                12                  5
3                7890                10                  6
4                9819                14                  9

   delivered_estimated  purchased_delivered  order_item_id  \
0                   10                    8              1
1                   20                   18              1
2                   20                   18              2
3                   16                   18              1
4                   21                   25              1

                         product_id                         seller_id
\
0  a9516a079e37a9c9c36b9b78b10169e8  7c67e1448b00f6e969d365cea6b010ab

1  a9516a079e37a9c9c36b9b78b10169e8  7c67e1448b00f6e969d365cea6b010ab

2  a9516a079e37a9c9c36b9b78b10169e8  7c67e1448b00f6e969d365cea6b010ab

3  a9516a079e37a9c9c36b9b78b10169e8  7c67e1448b00f6e969d365cea6b010ab

4  a9516a079e37a9c9c36b9b78b10169e8  7c67e1448b00f6e969d365cea6b010ab


  shipping_limit_date   price  freight_value product_category_name  \
0 2017-05-22 15:22:12  124.99          21.88     moveis_escritorio
1 2017-11-23 00:47:18  112.99          24.90     moveis_escritorio
```

```
2 2017-11-23 00:47:18  112.99          24.90     moveis_escritorio
3 2017-05-22 22:22:56  124.99          15.62     moveis_escritorio
4 2018-02-18 21:29:19  106.99          30.59     moveis_escritorio

   product_name_lenght  product_description_lenght  product_photos_qty
\
0                 41.0                      1141.0                 1.0

1                 41.0                      1141.0                 1.0

2                 41.0                      1141.0                 1.0

3                 41.0                      1141.0                 1.0

4                 41.0                      1141.0                 1.0


   product_weight_g  product_length_cm  product_height_cm
product_width_cm  \
0            8683.0               54.0               64.0
31.0
1            8683.0               54.0               64.0
31.0
2            8683.0               54.0               64.0
31.0
3            8683.0               54.0               64.0
31.0
4            8683.0               54.0               64.0
31.0

   geolocation_zip_code_prefix  geolocation_lat  geolocation_lng  \
0                        14409       -20.468849       -47.382173
1                        68030        -2.430314       -54.693217
2                        68030        -2.430314       -54.693217
3                        92480       -29.826454       -51.245676
4                        25931       -22.604835       -43.026500

   payment_sequential payment_type  payment_installments
payment_value  \
0                   1  credit_card                     2
146.87
1                   1  credit_card                     1
275.79
2                   1  credit_card                     1
275.79
3                   1  credit_card                     7
140.61
4                   1  credit_card                    10
137.58
```

```
   seller_zip_code_prefix      seller_city seller_state  \
0                    8577  itaquaquecetuba           SP
1                    8577  itaquaquecetuba           SP
2                    8577  itaquaquecetuba           SP
3                    8577  itaquaquecetuba           SP
4                    8577  itaquaquecetuba           SP

  product_category_name_english review_id  review_score
review_comment_title  \
0              office_furniture       NaN           NaN
NaN
1              office_furniture       NaN           NaN
NaN
2              office_furniture       NaN           NaN
NaN
3              office_furniture       NaN           NaN
NaN
4              office_furniture       NaN           NaN
NaN

  review_comment_message review_creation_date review_answer_timestamp

0                    NaN                  NaT                     NaT

1                    NaN                  NaT                     NaT

2                    NaN                  NaT                     NaT

3                    NaN                  NaT                     NaT

4                    NaN                  NaT                     NaT
```

```
merged.shape
```

```
(111468, 48)
```

Observation:

1. The merged dataframe is obtained from merging all the individual dataframes. We will use the merged dataframe for our further analysis.

```
merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 111468 entries, 0 to 111467
Data columns (total 48 columns):
 #   Column                         Non-Null Count   Dtype
---  ------                         --------------   -----
 0   customer_id                    111468 non-null  object
 1   customer_unique_id             111468 non-null  object
```

```
 2   customer_zip_code_prefix       111468 non-null  object
 3   customer_city                  111468 non-null  object
 4   customer_state                 111468 non-null  object
 5   order_id                       111468 non-null  object
 6   order_status                   111468 non-null  object
 7   order_purchase_timestamp       111468 non-null  datetime64[ns]
 8   order_approved_at              111468 non-null  datetime64[ns]
 9   order_delivered_carrier_date   111468 non-null  datetime64[ns]
 10  order_delivered_customer_date  111468 non-null  datetime64[ns]
 11  order_estimated_delivery_date  111468 non-null  datetime64[ns]
 12  purchased_approved             111468 non-null  int64
 13  approved_carrier               111468 non-null  int64
 14  carrier_delivered              111468 non-null  int64
 15  delivered_estimated            111468 non-null  int64
 16  purchased_delivered            111468 non-null  int64
 17  order_item_id                  111468 non-null  int64
 18  product_id                     111468 non-null  object
 19  seller_id                      111468 non-null  object
 20  shipping_limit_date            111468 non-null  datetime64[ns]
 21  price                          111468 non-null  float64
 22  freight_value                  111468 non-null  float64
 23  product_category_name          111468 non-null  object
 24  product_name_lenght            111468 non-null  float64
 25  product_description_lenght     111468 non-null  float64
 26  product_photos_qty             111468 non-null  float64
 27  product_weight_g               111468 non-null  float64
 28  product_length_cm              111468 non-null  float64
 29  product_height_cm              111468 non-null  float64
 30  product_width_cm               111468 non-null  float64
 31  geolocation_zip_code_prefix    111468 non-null  int64
 32  geolocation_lat                111468 non-null  float64
 33  geolocation_lng                111468 non-null  float64
 34  payment_sequential             111468 non-null  int64
 35  payment_type                   111468 non-null  object
 36  payment_installments           111468 non-null  int64
 37  payment_value                  111468 non-null  float64
 38  seller_zip_code_prefix         111468 non-null  int64
 39  seller_city                    111468 non-null  object
 40  seller_state                   111468 non-null  object
 41  product_category_name_english  111468 non-null  object
 42  review_id                      11110 non-null   object
 43  review_score                   11110 non-null   float64
 44  review_comment_title           11110 non-null   object
 45  review_comment_message         11110 non-null   object
 46  review_creation_date           11110 non-null   datetime64[ns]
 47  review_answer_timestamp        11110 non-null   datetime64[ns]
dtypes: datetime64[ns](8), float64(13), int64(10), object(17)
memory usage: 41.7+ MB
```

```
merged.drop(columns = ['order_status', 'order_item_id',
'order_approved_at', 'order_delivered_carrier_date',
'order_delivered_customer_date', 'order_estimated_delivery_date',
'approved_carrier', 'carrier_delivered', 'seller_id',
'shipping_limit_date', 'product_category_name', 'product_name_lenght',
'product_description_lenght', 'product_photos_qty',
'geolocation_zip_code_prefix', 'payment_sequential',
'seller_zip_code_prefix', 'review_id', 'review_comment_title',
'review_comment_message', 'review_creation_date',
'review_answer_timestamp', 'seller_city', 'seller_state'], axis = 1,
inplace = True)
merged.head()
```

```
                        customer_id                customer_unique_id
\
0  06b8999e2fba1a1fbc88172c00ba8bc7  861eff4711a542e4b93843c6dd7febb0

1  8912fc0c3bbf1e2fbf35819e21706718  9eae34bbd3a474ec5d07949ca7de67c0

2  8912fc0c3bbf1e2fbf35819e21706718  9eae34bbd3a474ec5d07949ca7de67c0

3  f0ac8e5a239118859b1734e1087cbb1f  3c799d181c34d51f6d44bbbc563024db

4  6bc8d08963a135220ed6c6d098831f84  23397e992b09769faf5e66f9e171a241


  customer_zip_code_prefix    customer_city customer_state  \
0                    14409           franca             SP
1                    68030         santarem             PA
2                    68030         santarem             PA
3                    92480  nova santa rita             RS
4                    25931             mage             RJ

                           order_id order_purchase_timestamp  \
0  00e7ee1b050b8499577073aeb2a297a1      2017-05-16 15:05:35
1  c1d2b34febe9cd269e378117d6681172      2017-11-09 00:50:13
2  c1d2b34febe9cd269e378117d6681172      2017-11-09 00:50:13
3  b1a5d5365d330d10485e0203d54ab9e8      2017-05-07 20:11:26
4  2e604b3614664aa66867856dba7e61b7      2018-02-03 19:45:40

   purchased_approved  delivered_estimated  purchased_delivered  \
0                 997                   10                    8
1               86255                   20                   18
2               86255                   20                   18
3                7890                   16                   18
4                9819                   21                   25

                         product_id   price  freight_value
product_weight_g  \
0  a9516a079e37a9c9c36b9b78b10169e8  124.99          21.88
```

```
8683.0
1  a9516a079e37a9c9c36b9b78b10169e8  112.99          24.90
8683.0
2  a9516a079e37a9c9c36b9b78b10169e8  112.99          24.90
8683.0
3  a9516a079e37a9c9c36b9b78b10169e8  124.99          15.62
8683.0
4  a9516a079e37a9c9c36b9b78b10169e8  106.99          30.59
8683.0

   product_length_cm  product_height_cm  product_width_cm
geolocation_lat  \
0               54.0               64.0              31.0        -
20.468849
1               54.0               64.0              31.0         -
2.430314
2               54.0               64.0              31.0         -
2.430314
3               54.0               64.0              31.0        -
29.826454
4               54.0               64.0              31.0        -
22.604835

   geolocation_lng payment_type  payment_installments
payment_value  \
0       -47.382173  credit_card                     2         146.87

1       -54.693217  credit_card                     1         275.79

2       -54.693217  credit_card                     1         275.79

3       -51.245676  credit_card                     7         140.61

4       -43.026500  credit_card                    10         137.58


  product_category_name_english  review_score
0              office_furniture           NaN
1              office_furniture           NaN
2              office_furniture           NaN
3              office_furniture           NaN
4              office_furniture           NaN
```

6. Creating a grouped-by dataframe based on individual customers

```
final = merged.groupby('customer_unique_id',
as_index=False).agg({'customer_zip_code_prefix'      : 'max',

'customer_city'                   : 'max',

'customer_state'                  : 'max',

'order_id'                        : 'nunique',

'purchased_approved'              : 'mean',

'delivered_estimated'             : 'min',

'purchased_delivered'             : 'mean',

'product_id'                      : 'nunique',

'price'                           : 'sum',

'freight_value'                   : 'sum',

'product_weight_g'                : 'sum',

'product_length_cm'               : 'sum',

'product_height_cm'               : 'sum',

'product_width_cm'                : 'sum',

'geolocation_lat'                 : 'mean',

'geolocation_lng'                 : 'mean',

'payment_type'                    : 'max',

'payment_installments'            : 'max',

'payment_value'                   : 'sum',

'review_score'                    : 'mean'})

final.head()
```

```
                  customer_unique_id  customer_zip_code_prefix
customer_city  \
```

```
0  0000366f3b9a7992bf8c76cfdf3221e2                        7787
cajamar
1  0000b849f77a49e4a4ce2b2a4ca5be3f                        6053
osasco
2  0000f46a3911fa3c0805444483337064                       88115      sao
jose
3  0000f6ccb0745a6a4b88665a16c9f078                       66812
belem
4  0004aac84e0df4da2b147fca70cf8255                       18040
sorocaba

  customer_state  order_id  purchased_approved  delivered_estimated  \
0             SP         1               891.0                    4
1             SP         1             26057.0                    4
2             SC         1                 0.0                    1
3             PA         1              1176.0                   11
4             SP         1              1270.0                    7

   purchased_delivered  product_id   price  freight_value
product_weight_g  \
0                  6.0           1  129.90          12.00
1500.0
1                  3.0           1   18.90           8.29
375.0
2                 25.0           1   69.00          17.22
1500.0
3                 20.0           1   25.99          17.63
150.0
4                 13.0           1  180.00          16.89
6050.0

   product_length_cm  product_height_cm  product_width_cm
geolocation_lat  \
0               34.0                7.0              32.0       -
23.333580
1               26.0               11.0              18.0       -
23.545029
2               25.0               50.0              35.0       -
27.532246
3               19.0                5.0              11.0        -
1.304189
4               16.0                3.0              11.0       -
23.496567

   geolocation_lng payment_type  payment_installments
payment_value  \
0       -46.823060  credit_card                     8         141.90

1       -46.781482  credit_card                     1          27.19
```

```
2       -48.618667  credit_card                     8          86.22

3       -48.476339  credit_card                     4          43.62

4       -47.462811  credit_card                     6         196.89


   review_score
0           5.0
1           NaN
2           NaN
3           NaN
4           NaN
```

```
final.rename(columns = {'order_id' : 'no_of_orders', 'product_id' :
'no_of_products'}, inplace = True)
```

```
final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90528 entries, 0 to 90527
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   customer_unique_id        90528 non-null  object
 1   customer_zip_code_prefix  90528 non-null  int64
 2   customer_city             90528 non-null  object
 3   customer_state            90528 non-null  object
 4   no_of_orders              90528 non-null  int64
 5   purchased_approved        90528 non-null  float64
 6   delivered_estimated       90528 non-null  int64
 7   purchased_delivered       90528 non-null  float64
 8   no_of_products            90528 non-null  int64
 9   price                     90528 non-null  float64
 10  freight_value             90528 non-null  float64
 11  product_weight_g          90528 non-null  float64
 12  product_length_cm         90528 non-null  float64
 13  product_height_cm         90528 non-null  float64
 14  product_width_cm          90528 non-null  float64
 15  geolocation_lat           90528 non-null  float64
 16  geolocation_lng           90528 non-null  float64
 17  payment_type              90528 non-null  object
 18  payment_installments      90528 non-null  int64
 19  payment_value             90528 non-null  float64
 20  review_score              8963 non-null   float64
dtypes: float64(12), int64(5), object(4)
memory usage: 14.5+ MB
```

```
final['customer_zip_code_prefix'] =
final.customer_zip_code_prefix.astype('object')
```

```
final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90528 entries, 0 to 90527
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   customer_unique_id        90528 non-null  object 
 1   customer_zip_code_prefix  90528 non-null  object 
 2   customer_city             90528 non-null  object 
 3   customer_state            90528 non-null  object 
 4   no_of_orders              90528 non-null  int64  
 5   purchased_approved        90528 non-null  float64
 6   delivered_estimated       90528 non-null  int64  
 7   purchased_delivered       90528 non-null  float64
 8   no_of_products            90528 non-null  int64  
 9   price                     90528 non-null  float64
 10  freight_value             90528 non-null  float64
 11  product_weight_g          90528 non-null  float64
 12  product_length_cm         90528 non-null  float64
 13  product_height_cm         90528 non-null  float64
 14  product_width_cm          90528 non-null  float64
 15  geolocation_lat           90528 non-null  float64
 16  geolocation_lng           90528 non-null  float64
 17  payment_type              90528 non-null  object 
 18  payment_installments      90528 non-null  int64  
 19  payment_value             90528 non-null  float64
 20  review_score              8963 non-null   float64
dtypes: float64(12), int64(4), object(5)
memory usage: 14.5+ MB
```

```
# to save the grouped-by dataframe as a new csv for future usage.
#final.to_csv('final.csv')
#merged.to_csv('merged.csv')
```

7. RMF Analysis

RFM analysis is a data driven customer behavior segmentation technique.

RFM stands for recency, frequency, and monetary value.

The idea is to segment customers based on when their last purchase was, how often they’ve purchased in the past, and how much they’ve spent overall. All three of these measures have proven to be effective predictors of a customer's willingness to engage in marketing messages and offers.

7.1. Recency

```
recency = merged.groupby('customer_unique_id', as_index=False)
['order_purchase_timestamp'].max()
recency.rename(columns={'order_purchase_timestamp':'LastPurchaseDate'}
,inplace = True)
recency.head()
```

```
                 customer_unique_id    LastPurchaseDate
0  0000366f3b9a7992bf8c76cfdf3221e2 2018-05-10 10:56:27
1  0000b849f77a49e4a4ce2b2a4ca5be3f 2018-05-07 11:11:27
2  0000f46a3911fa3c0805444483337064 2017-03-10 21:05:03
3  0000f6ccb0745a6a4b88665a16c9f078 2017-10-12 20:29:41
4  0004aac84e0df4da2b147fca70cf8255 2017-11-14 19:45:42
```

```
recent_date = merged['order_purchase_timestamp'].dt.date.max()
print('The last recent date in the available dataset is: ',
recent_date)
```

```
The last recent date in the available dataset is:  2018-08-29
```

```
recency['Recency'] = recency['LastPurchaseDate'].dt.date.apply(lambda
x: (recent_date - x).days)
recency.head()
```

```
                 customer_unique_id    LastPurchaseDate  Recency
0  0000366f3b9a7992bf8c76cfdf3221e2 2018-05-10 10:56:27      111
1  0000b849f77a49e4a4ce2b2a4ca5be3f 2018-05-07 11:11:27      114
2  0000f46a3911fa3c0805444483337064 2017-03-10 21:05:03      537
3  0000f6ccb0745a6a4b88665a16c9f078 2017-10-12 20:29:41      321
4  0004aac84e0df4da2b147fca70cf8255 2017-11-14 19:45:42      288
```

Observations:

1. The last purchase date of every individual customer is taken using the group by function.
2. **Recency** is calculated by **subtracting the last recent date available** in the dataset with **every customer's last purchase date**.

7.2. Frequency

```
frequency =
merged.groupby(["customer_unique_id"]).agg({"order_id":"nunique"}).res
et_index()
frequency.rename(columns={'order_id':'Frequency'},inplace=True)
frequency.head()
```

```
                 customer_unique_id  Frequency
0  0000366f3b9a7992bf8c76cfdf3221e2          1
1  0000b849f77a49e4a4ce2b2a4ca5be3f          1
```

```
2   0000f46a3911fa3c0805444483337064          1
3   0000f6ccb0745a6a4b88665a16c9f078          1
4   0004aac84e0df4da2b147fca70cf8255          1
```

Observation:

1. **Frequency** is calculated by selecting the **number of `unique order_id`** or orders placed by each individual customer.

7.3. Monetary

```
monetary = merged.groupby('customer_unique_id', as_index=False)
['payment_value'].sum()
monetary.rename(columns={'payment_value':'Monetary'},inplace=True)
monetary.head()
```

	customer_unique_id	Monetary
0	0000366f3b9a7992bf8c76cfdf3221e2	141.90
1	0000b849f77a49e4a4ce2b2a4ca5be3f	27.19
2	0000f46a3911fa3c0805444483337064	86.22
3	0000f6ccb0745a6a4b88665a16c9f078	43.62
4	0004aac84e0df4da2b147fca70cf8255	196.89

```
rfm = recency.merge(frequency, on='customer_unique_id')
rfm = rfm.merge(monetary,
on='customer_unique_id').drop(columns='LastPurchaseDate')
rfm.head()
```

	customer_unique_id	Recency	Frequency	Monetary
0	0000366f3b9a7992bf8c76cfdf3221e2	111	1	141.90
1	0000b849f77a49e4a4ce2b2a4ca5be3f	114	1	27.19
2	0000f46a3911fa3c0805444483337064	537	1	86.22
3	0000f6ccb0745a6a4b88665a16c9f078	321	1	43.62
4	0004aac84e0df4da2b147fca70cf8255	288	1	196.89

Observation:

1. **Monetary** is calculated by **summing up the payment value of each individual customer** who placed one or more orders.

7.4. Analysing the RFM data

```
rfm[rfm.Recency == 0]
```

	customer_unique_id	Recency	Frequency	Monetary
1463	0421e7a23f21e5d54efed456aedbc513	0	1	119.42
4454	0c6d7218d5f3fa14514fd29865269993	0	1	178.25

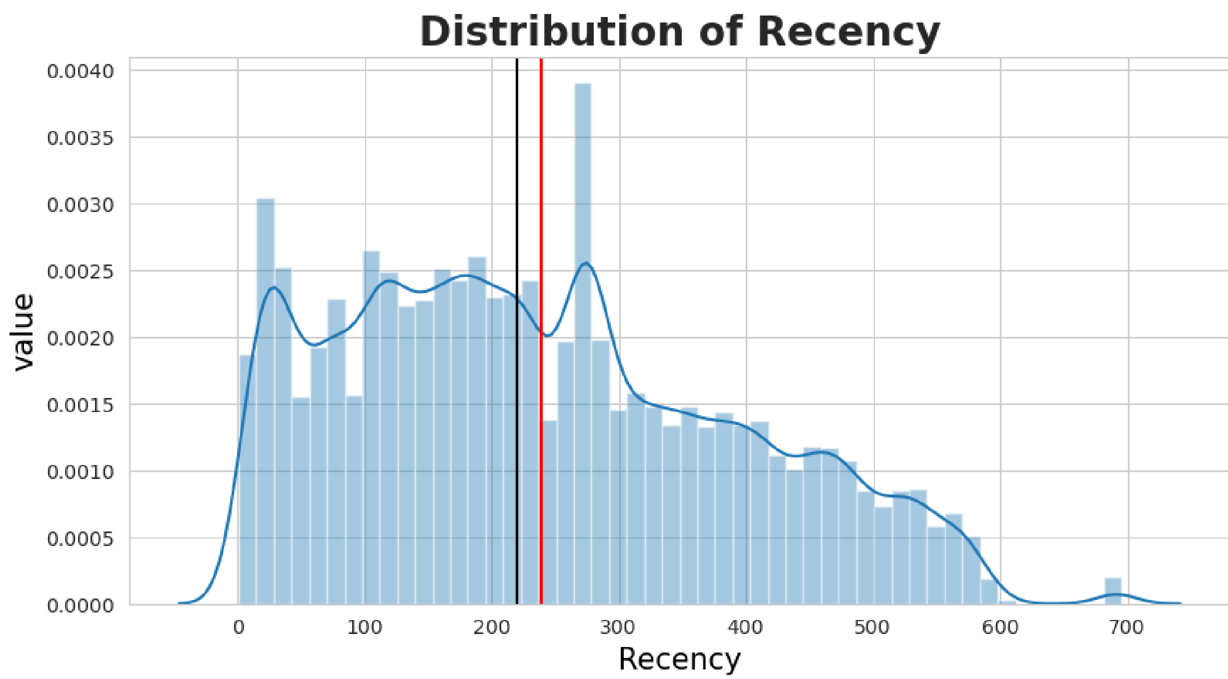
```
12062  21dbe8eabd00b34492a939c540e2b1a7        0           1     14.29
13032  24ac2b4327e25baf39f2119e4228976a        0           1     93.75
32785  5c58de6fb80e93396e2f35642666b693        0           1   1021.92
43195  7a22d14aa3c3599238509ddca4b93b01        0           1     73.10
45280  7febafa06d9d8f232a900a2937f04338        0           1     61.29
62249  afbcfd0b9c5233e7ccc73428526fbb52        0           1   2486.25
64024  b4dcade04bc548b7e3b0243c801f8c26        0           1    106.95
64767  b701bebbdf478f5500348f03aff62121        0           1     33.23
87738  f80013faf776e37bcea7634d59c2181e        0           1     74.21
```

```
rfm['Recency'] = rfm.Recency.apply(lambda x: 1 if x == 0 else x)
```

Observations:

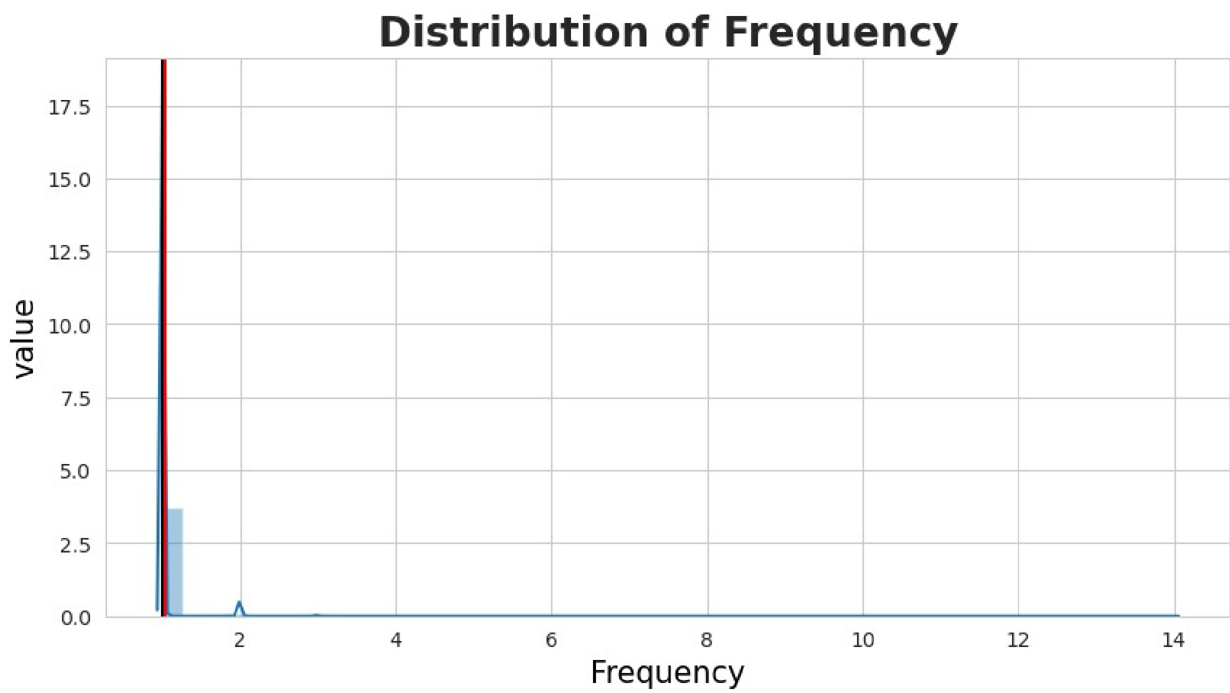
1. The recency column had values 0, i.e., a customer came at the last day of the date which we took as the threshold to calculate recency.
2. 0 in recency should be treated or removed for creating the target variable, i.e., Churn and for further process of scaling or normalization, so the **0 is converted to 1 for our convenience**.

```
plt.figure(figsize = (10, 5))
sns.distplot(rfm.Recency)
plt.axvline(rfm.Recency.mean(), c = 'red')
plt.axvline(rfm.Recency.median(), c = 'black')
plt.title('Distribution of Recency',fontweight='bold',fontsize=20)
plt.xlabel('Recency',fontsize=15,color='black')
plt.ylabel('value',fontsize=15,color='black')
plt.show()
print('Mean of recency: ', rfm.Recency.mean())
print('Median of recency: ', rfm.Recency.median())
print('Skewness of recency: ', rfm.Recency.skew())
```




```
Mean of recency:  238.73377297631671
Median of recency:  220.0
Skewness of recency:  0.43585883202493925
```

```python
plt.figure(figsize = (10, 5))
sns.distplot(rfm.Frequency)
plt.axvline(rfm.Frequency.mean(), c = 'red')
plt.axvline(rfm.Frequency.median(), c = 'black')
plt.title('Distribution of Frequency',fontweight='bold',fontsize=20)
plt.xlabel('Frequency',fontsize=15,color='black')
plt.ylabel('value',fontsize=15,color='black')
plt.show()
print('Mean of frequency: ', rfm.Frequency.mean())
print('Median of frequency: ', rfm.Frequency.median())
print('Skewness of frequency: ', rfm.Frequency.skew())
```

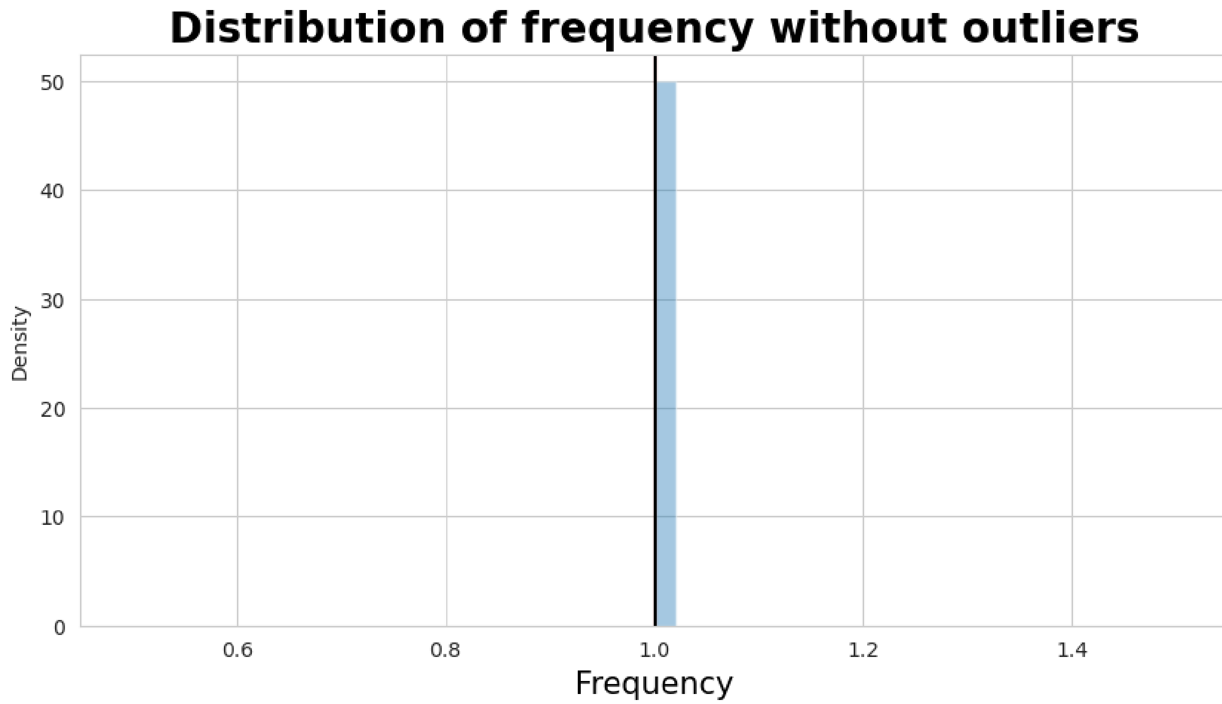



```
Mean of frequency:  1.0328958996111701
Median of frequency:  1.0
Skewness of frequency:  10.676600298052568
```

```
Q1 = np.quantile(rfm.Frequency, 0.25)
Q3 = np.quantile(rfm.Frequency, 0.75)
IQR = Q3 - Q1
frequencyDistribution = rfm[~((rfm.Frequency < Q1 - 1.5 * IQR) |
(rfm.Frequency > Q3 + 1.5 * IQR))]
frequencyDistribution.head()
```

	customer_unique_id	Recency	Frequency	Monetary
0	0000366f3b9a7992bf8c76cfdf3221e2	111	1	141.90
1	0000b849f77a49e4a4ce2b2a4ca5be3f	114	1	27.19
2	0000f46a3911fa3c0805444483337064	537	1	86.22
3	0000f6ccb0745a6a4b88665a16c9f078	321	1	43.62
4	0004aac84e0df4da2b147fca70cf8255	288	1	196.89

```
plt.figure(figsize=(10, 5))
sns.distplot(frequencyDistribution.Frequency)
plt.axvline(frequencyDistribution.Frequency.mean(), c = 'red')
plt.axvline(frequencyDistribution.Frequency.median(), c = 'black')
plt.xlabel('Frequency',color='black',fontsize=15)
plt.title('Distribution of frequency without
outliers',color='black',fontsize=20,fontweight='bold')
plt.show()
```



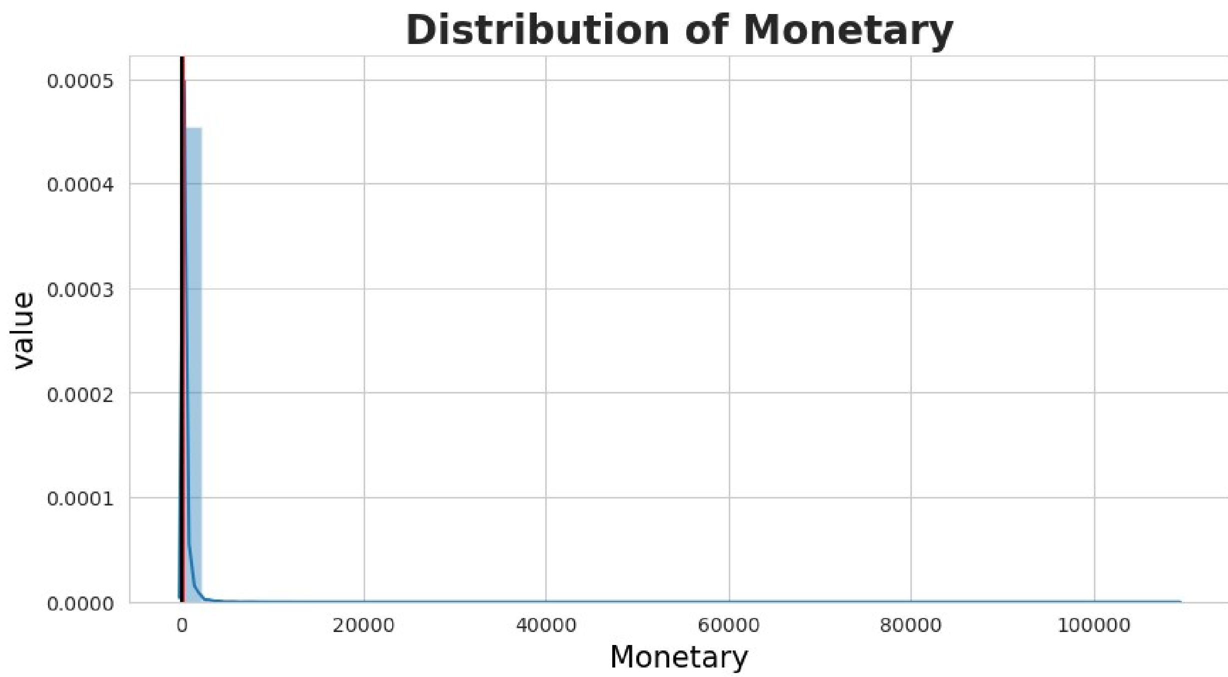

```
frequencyDistribution.Frequency.describe()

count    87850.0
mean         1.0
std          0.0
min          1.0
25%          1.0
50%          1.0
75%          1.0
max          1.0
Name: Frequency, dtype: float64
```

Observations:

1. The **frequency** from RFM analysis without outliers has a **standard deviation of 0**, that is, **all the values are only 1**.
2. So the **frequency will not help in our analysis** and also to segment the customers.

```
plt.figure(figsize = (10, 5))
sns.distplot(rfm.Monetary)
plt.axvline(rfm.Monetary.mean(), c = 'red')
plt.axvline(rfm.Monetary.median(), c = 'black')
plt.title('Distribution of Monetary',fontweight='bold',fontsize=20)
plt.xlabel('Monetary',fontsize=15,color='black')
plt.ylabel('value',fontsize=15,color='black')
plt.show()
print('Mean of monetary: ', rfm.Monetary.mean())
```

```
print('Median of monetary: ', rfm.Monetary.median())
print('Skewness of monetary: ', rfm.Monetary.skew())
```

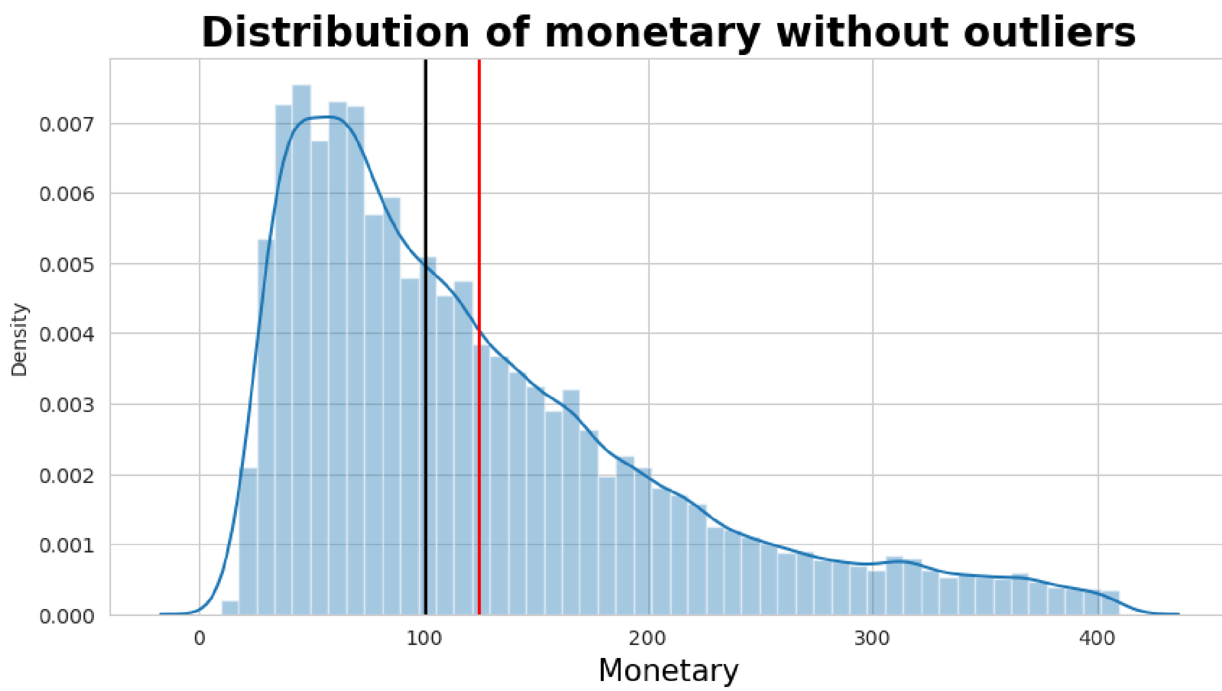



```
Mean of monetary:  212.23630898727467
Median of monetary:  112.83
Skewness of monetary:  70.4949829190865
```

```
Q1 = np.quantile(rfm.Monetary, 0.25)
Q3 = np.quantile(rfm.Monetary, 0.75)
IQR = Q3 - Q1
monetaryDistribution = rfm[~((rfm.Monetary < Q1 - 1.5 * IQR) |
(rfm.Monetary > Q3 + 1.5 * IQR))]
monetaryDistribution.head()
```

	customer_unique_id	Recency	Frequency	Monetary
0	0000366f3b9a7992bf8c76cfdf3221e2	111	1	141.90
1	0000b849f77a49e4a4ce2b2a4ca5be3f	114	1	27.19
2	0000f46a3911fa3c0805444483337064	537	1	86.22
3	0000f6ccb0745a6a4b88665a16c9f078	321	1	43.62
4	0004aac84e0df4da2b147fca70cf8255	288	1	196.89

```
plt.figure(figsize=(10, 5))
sns.distplot(monetaryDistribution.Monetary)
plt.axvline(monetaryDistribution.Monetary.mean(), c = 'red')
plt.axvline(monetaryDistribution.Monetary.median(), c = 'black')
plt.xlabel('Monetary',color='black',fontsize=15)
plt.title('Distribution of monetary without
outliers',color='black',fontsize=20,fontweight='bold')
plt.show()
```




```
monetaryDistribution.Monetary.describe()

count    81643.000000
mean       124.744198
std         85.108001
min          9.590000
25%         60.000000
50%        101.220000
75%        166.710000
max        409.610000
Name: Monetary, dtype: float64
```

Observations:

1. The average monetary value after outlier treatement is **124.74 Brazilian Real**, while the median value is **101.25 Brazilian Real**.
2. The middle 50% of values of monetary lie between **60 and 166.71 Brazilian Real**.

8. Customer Segmentation

8.1. Labels for Recency

```
ll_r = rfm.Recency.quantile(0.25)
mid_r = rfm.Recency.quantile(0.50)
ul_r = rfm.Recency.quantile(0.75)
print(ll_r, mid_r, ul_r)
```

```
115.0 220.0 347.0
```

```
def recency_label(recent):
    if recent <= ll_r:
        return 1
    elif (recent > ll_r) and (recent <= mid_r):
        return 2
    elif (recent > mid_r) and (recent <= ul_r):
        return 3
    elif recent > ul_r:
        return 4

rfm['recency_label'] = rfm.Recency.apply(recency_label)
rfm.head()
```

```
                 customer_unique_id  Recency  Frequency  Monetary  \
0  0000366f3b9a7992bf8c76cfdf3221e2      111          1    141.90
1  0000b849f77a49e4a4ce2b2a4ca5be3f      114          1     27.19
2  0000f46a3911fa3c0805444483337064      537          1     86.22
3  0000f6ccb0745a6a4b88665a16c9f078      321          1     43.62
4  0004aac84e0df4da2b147fca70cf8255      288          1    196.89

   recency_label
0              1
1              1
2              4
3              3
4              3
```

Recency label breakdown: 1 - These are the customers who whose visit date(s) are the most recent. (Recency value within the 25% quantile) 2 - These are the customers who whose visit date(s) are not very recent. (Recency value between 25% and 50% quantile) 3 - These are the customers who whose visit date(s) are somewhat recent. (Recency value between 50% and 75% quantile) 4 - These are the customers who whose visit date(s) are the oldest. (Recency value more than 75% quantile)

8.2. Labels for Monetary

```
ll_m = rfm.Monetary.quantile(0.25)
mid_m = rfm.Monetary.quantile(0.50)
ul_m = rfm.Monetary.quantile(0.75)
print(ll_m, mid_m, ul_m)
```

```
63.79 112.83 202.1225

def monetary_label(money):
    if money <= ll_m:
        return 4
    elif (money > ll_m) and (money <= mid_m):
        return 3
    elif (money > mid_m) and (money <= ul_m):
        return 2
    elif money > ul_m:
        return 1

rfm['monetary_label'] = rfm.Monetary.apply(monetary_label)
rfm.head()

                 customer_unique_id  Recency  Frequency  Monetary  \
0  0000366f3b9a7992bf8c76cfdf3221e2      111          1    141.90
1  0000b849f77a49e4a4ce2b2a4ca5be3f      114          1     27.19
2  0000f46a3911fa3c0805444483337064      537          1     86.22
3  0000f6ccb0745a6a4b88665a16c9f078      321          1     43.62
4  0004aac84e0df4da2b147fca70cf8255      288          1    196.89

   recency_label  monetary_label
0              1               2
1              1               4
2              4               3
3              3               4
4              3               2
```

Monetary label breakdown: 1 - These are the customers who spend large amount. (Monetary value within the 25% quantile) 2 - These are the customers who spend good amount. (Monetary value between 25% and 50% quantile) 3 - These are the customers who spend moderately. (Monetary value between 50% and 75% quantile) 4 - These are the customers who spend the least. (Monetary value more than 75% quantile)

8.3. Labels for Frequency

```
rfm.Frequency.value_counts()

1    87850
2     2462
3      171
4       28
5        9
6        3
7        3
9        1
```

```
14        1
Name: Frequency, dtype: int64
```

```
def frequency_label(frequent):
    if frequent == 1:
        return 4
    elif frequent == 2:
        return 3
    elif frequent == 3:
        return 2
    elif frequent > 3:
        return 1

rfm['frequency_label'] = rfm.Frequency.apply(frequency_label)
rfm.head()
```

```
                 customer_unique_id  Recency  Frequency  Monetary  \
0  0000366f3b9a7992bf8c76cfdf3221e2      111          1    141.90
1  0000b849f77a49e4a4ce2b2a4ca5be3f      114          1     27.19
2  0000f46a3911fa3c0805444483337064      537          1     86.22
3  0000f6ccb0745a6a4b88665a16c9f078      321          1     43.62
4  0004aac84e0df4da2b147fca70cf8255      288          1    196.89

   recency_label  monetary_label  frequency_label
0              1               2                4
1              1               4                4
2              4               3                4
3              3               4                4
4              3               2                4
```

Frequency label breakdown: 1 - These are the most frequent customers. (Frequency > 3) 2 - These are the frequent frequent customers. (Frequency = 3) 3 - These are the somewhat frequent customers. (Frequency = 2) 4 - These are the least frequent customers. (Frequency = 1)

```
rfm['Rank'] = list(zip(rfm.recency_label, rfm.monetary_label,
rfm.frequency_label))
rfm.head()
```

```
                 customer_unique_id  Recency  Frequency  Monetary  \
0  0000366f3b9a7992bf8c76cfdf3221e2      111          1    141.90
1  0000b849f77a49e4a4ce2b2a4ca5be3f      114          1     27.19
2  0000f46a3911fa3c0805444483337064      537          1     86.22
3  0000f6ccb0745a6a4b88665a16c9f078      321          1     43.62
4  0004aac84e0df4da2b147fca70cf8255      288          1    196.89

   recency_label  monetary_label  frequency_label       Rank
0              1               2                4  (1, 2, 4)
1              1               4                4  (1, 4, 4)
2              4               3                4  (4, 3, 4)
```

```
3               3                4                 4  (3, 4, 4)
4               3                2                 4  (3, 2, 4)
```

```
rfm.recency_label.value_counts()
```

```
1    22754
4    22595
3    22594
2    22585
Name: recency_label, dtype: int64
```

```
rfm.frequency_label.value_counts()
```

```
4    87850
3     2462
2      171
1       45
Name: frequency_label, dtype: int64
```

```
rfm.monetary_label.value_counts()
```

```
4    22637
1    22632
2    22630
3    22629
Name: monetary_label, dtype: int64
```

Observation:

1. Since **most of the frequency class is 4**, we will use only **recency and monetary for customer segmentation**.

```
rfm['rank_rm'] = list(zip(rfm.recency_label, rfm.monetary_label))
rfm.head()
```

```
                 customer_unique_id  Recency  Frequency  Monetary  \
0  0000366f3b9a7992bf8c76cfdf3221e2      111          1    141.90
1  0000b849f77a49e4a4ce2b2a4ca5be3f      114          1     27.19
2  0000f46a3911fa3c0805444483337064      537          1     86.22
3  0000f6ccb0745a6a4b88665a16c9f078      321          1     43.62
4  0004aac84e0df4da2b147fca70cf8255      288          1    196.89

   recency_label  monetary_label  frequency_label       Rank rank_rm
0              1               2                4  (1, 2, 4)  (1, 2)
1              1               4                4  (1, 4, 4)  (1, 4)
2              4               3                4  (4, 3, 4)  (4, 3)
3              3               4                4  (3, 4, 4)  (3, 4)
4              3               2                4  (3, 2, 4)  (3, 2)
```

```
rfm.rank_rm.value_counts()
```

```
(1, 2)    5867
(3, 3)    5837
(4, 3)    5835
(1, 1)    5793
(2, 4)    5745
(4, 4)    5723
(2, 2)    5701
(3, 1)    5664
(2, 1)    5644
(1, 4)    5632
(3, 2)    5556
(3, 4)    5537
(4, 1)    5531
(4, 2)    5506
(2, 3)    5495
(1, 3)    5462
Name: rank_rm, dtype: int64
```

8.4. Meaning of ranks:

The most important and least important customers (Recency Rank, Monetary Rank):

- Comparing Recency and Monetary - Recency rank is of higher importance than Monetary rank

The most important ranks:

1. (Recency - 1, Monetary - 1) - They are very recent and have spend a lot of money
2. (Recency - 1, Monetary - 2) - They are very recent and have spend a good amount of money
3. (Recency - 2, Monetary - 1) - They are recent and have spend a lot of money
4. (Recency - 2, Monetary - 2) - They are recent and have spend a good of money
5. (Recency - 1, Monetary - 3) - They are very recent and have spend a decent of money

The least important ranks:

1. (Recency - 4, Monetary - 4) - They are not at all recent and spend a negligible amount of money
2. (Recency - 4, Monetary - 3) - They are not at all recent and spend a a decent amount of money
3. (Recency - 4, Monetary - 2) - They are not at all recent and spend a good amount of money
4. (Recency - 3, Monetary - 4) - They are not very recent and spend a negligible amount of money
5. (Recency - 3, Monetary - 3) - They are not very recent and spend a decent amount of money

8.5. Business Insights from RM analysis

Insights from Recency Ranks:

1. Customers can be incentivised to purchase more in our store using offers/discounts/events which will make them more recent and at the same time bring in more money
2. Customers will use our store if the website is user-friendly and quick. This will help make the customer's shopping experience smooth meaning they will continue coming back to our store/website for their purchasing needs
3. When advertising using digital marketing techniques:
    - Customers who have a low recency ranks should be targeted less or removed from advertisement lists as it will not bring as much or even returns/sales (This can also be done using customer's time spent on website but that will be for a future project)
    - Customers who have high recency ranks should be targeted more extensively as it will bring a lot of sales in return

Insights from Monetary Ranks:

1. Customer's monetary values can be increased with a better algorithm which will recommend similar/useful items when an item is added to cart

Insights from Frequency Ranks: 97% (89100 out of 91832) of the customers have the lowest frequency rank (4) meaning they are very infrequent in their purchases. In order to combat this:-

1. Local language can be used in the ecommerce platform/store
2. Extend special offers for repeated purchases
3. Encourage Loyalty programs
4. Lower the Product Pricing for Increased Customer Frequency

9. Creating a target variable

```
rfm['Churn'] = rfm.Recency.apply(lambda x: 1 if x > rfm.Recency.mean()
else 0)
rfm.head()
```

```
                 customer_unique_id  Recency  Frequency  Monetary  \
0  0000366f3b9a7992bf8c76cfdf3221e2      111          1    141.90
1  0000b849f77a49e4a4ce2b2a4ca5be3f      114          1     27.19
2  0000f46a3911fa3c0805444483337064      537          1     86.22
3  0000f6ccb0745a6a4b88665a16c9f078      321          1     43.62
4  0004aac84e0df4da2b147fca70cf8255      288          1    196.89

  recency_label  monetary_label  frequency_label      Rank  rank_rm
```

```
Churn
0                1               2                4  (1, 2, 4)  (1, 2)
0
1                1               4                4  (1, 4, 4)  (1, 4)
0
2                4               3                4  (4, 3, 4)  (4, 3)
1
3                3               4                4  (3, 4, 4)  (3, 4)
1
4                3               2                4  (3, 2, 4)  (3, 2)
1
```

Observations:

1. The **churn rate**, also known as the **rate of attrition** or customer churn, is the **rate at which customers stop doing business with an entity**.
2. We used the **recency column to frame the target variable.** If the **customer's recency falls above the average** value of recency, we consider such customers as **churned**. The **rest of the customers** as **not churned**.
3. We used the **mean of recency as the threshold** as the **recency is normally** or symmetrically distributed.
4. We will have to **impute the target variable to the main dataframe** and do the further classification algorithm.

10. Merging the target variable with our final dataframe

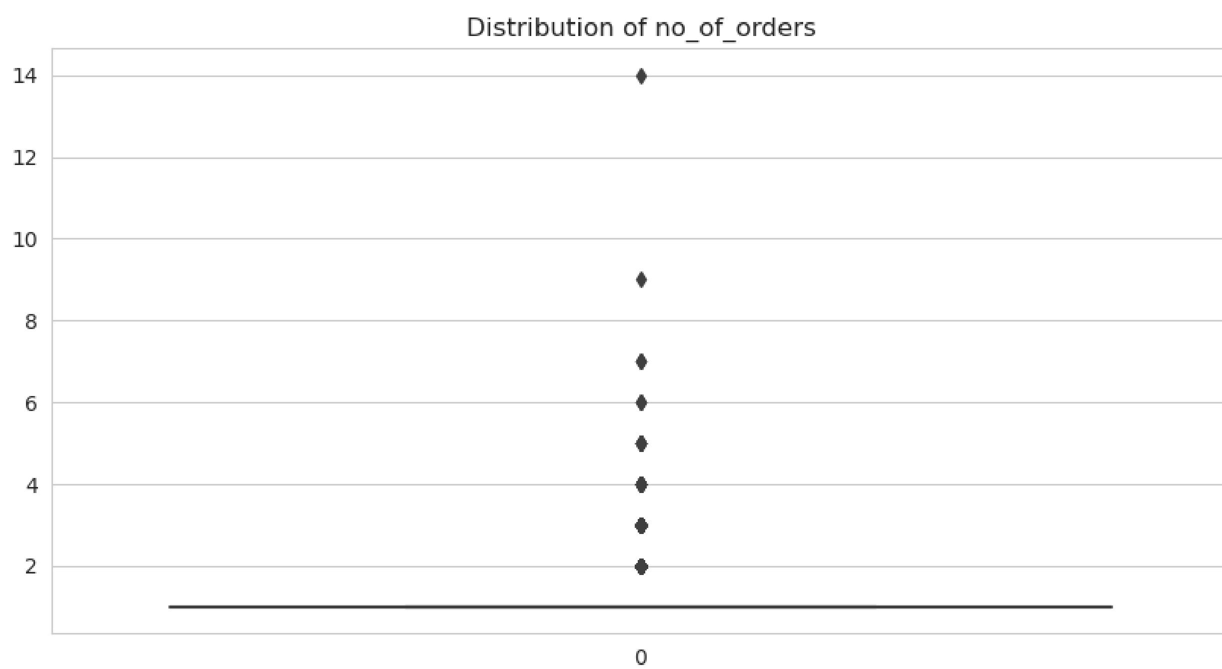
```
final = final.merge(rfm[['customer_unique_id', 'Recency', 'Monetary',
'Frequency', 'Churn']], on = 'customer_unique_id')
final.head()

                 customer_unique_id customer_zip_code_prefix
customer_city  \
0  0000366f3b9a7992bf8c76cfdf3221e2                     7787
cajamar
1  0000b849f77a49e4a4ce2b2a4ca5be3f                     6053
osasco
2  0000f46a3911fa3c0805444483337064                    88115      sao
jose
3  0000f6ccb0745a6a4b88665a16c9f078                    66812
belem
4  0004aac84e0df4da2b147fca70cf8255                    18040
sorocaba

  customer_state  no_of_orders  purchased_approved
```

```
delivered_estimated  \
0              SP              1               891.0
4
1              SP              1             26057.0
4
2              SC              1                 0.0
1
3              PA              1              1176.0
11
4              SP              1              1270.0
7

   purchased_delivered  no_of_products   price  freight_value  \
0                  6.0               1  129.90          12.00
1                  3.0               1   18.90           8.29
2                 25.0               1   69.00          17.22
3                 20.0               1   25.99          17.63
4                 13.0               1  180.00          16.89

   product_weight_g  product_length_cm  product_height_cm
product_width_cm  \
0            1500.0               34.0                7.0
32.0
1             375.0               26.0               11.0
18.0
2            1500.0               25.0               50.0
35.0
3             150.0               19.0                5.0
11.0
4            6050.0               16.0                3.0
11.0

   geolocation_lat  geolocation_lng payment_type  payment_installments
\
0       -23.333580       -46.823060  credit_card                     8

1       -23.545029       -46.781482  credit_card                     1

2       -27.532246       -48.618667  credit_card                     8

3        -1.304189       -48.476339  credit_card                     4

4       -23.496567       -47.462811  credit_card                     6


   payment_value  review_score  Recency  Monetary  Frequency  Churn
0         141.90           5.0      111    141.90          1      0
1          27.19           NaN      114     27.19          1      0
2          86.22           NaN      537     86.22          1      1
```

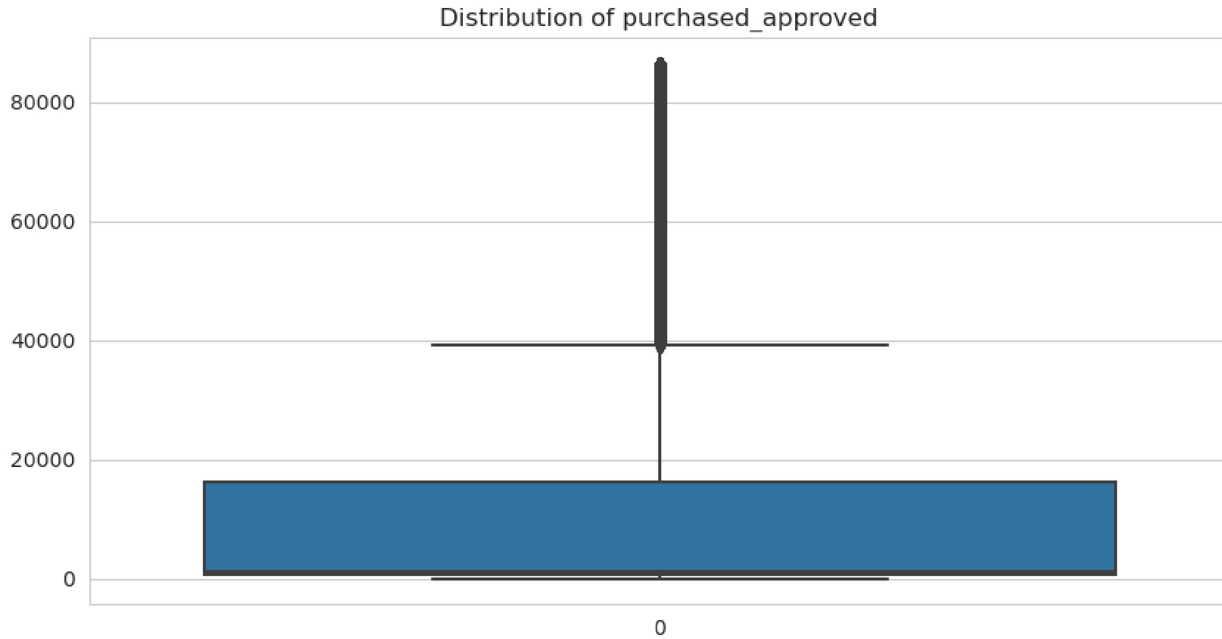
```
3            43.62              NaN       321      43.62             1        1
4           196.89              NaN       288     196.89             1        1

records, features = final.shape
print('Total number of unique records: ', records)
print('Total number of features: ', features)

Total number of unique records:  90528
Total number of features:  25

final['Churn'] = final.Churn.astype('object')
```

11. Outlier Treatement

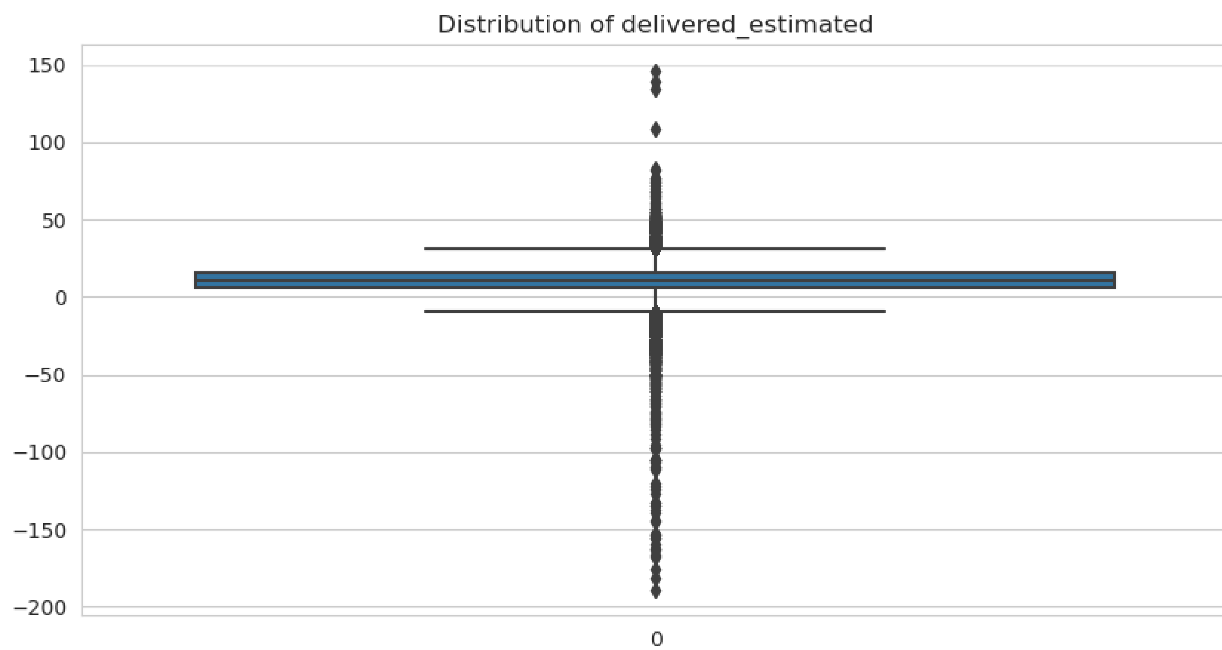
```
for col in final.select_dtypes(include = np.number).columns:
    plt.figure(figsize = (10, 5))
    print(f'Skewness of {col}: {final[col].skew()}')
    print(f'Standard deviation of {col}: {final[col].std()}')
    sns.boxplot(final[col])
    plt.title(f'Distribution of {col}')
    plt.show()

Skewness of no_of_orders: 10.676600298052568
Standard deviation of no_of_orders: 0.20649360862520988
```



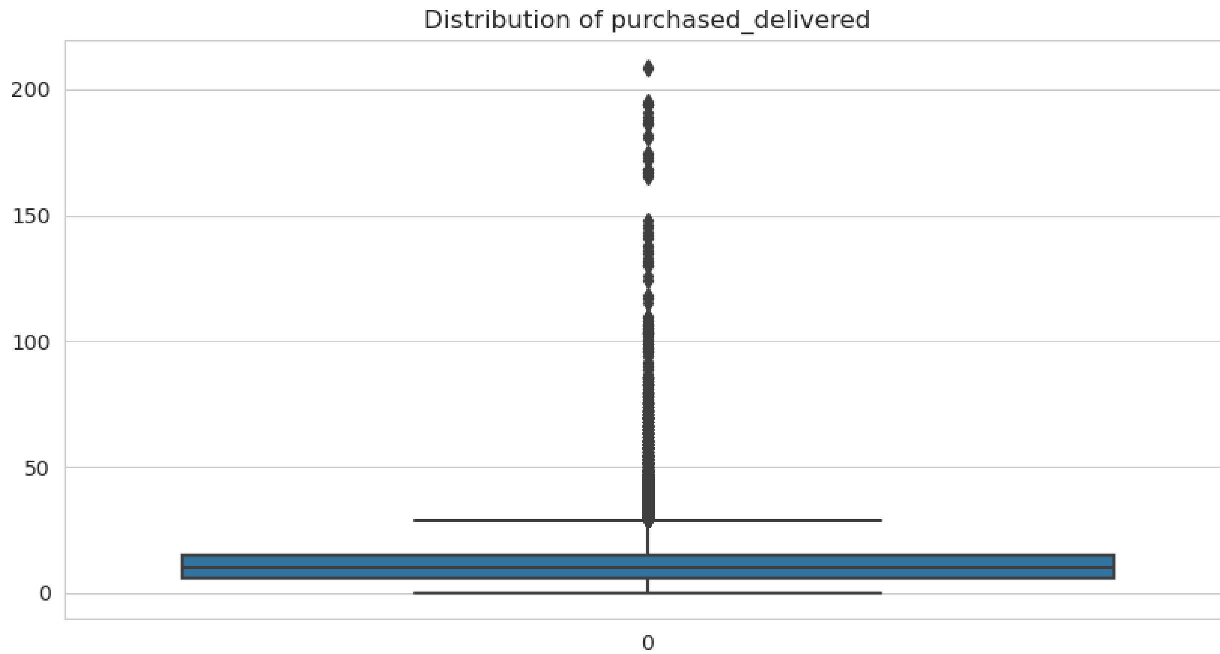
```
Skewness of purchased_approved: 1.6936517976235201
Standard deviation of purchased_approved: 23397.787779977294
```



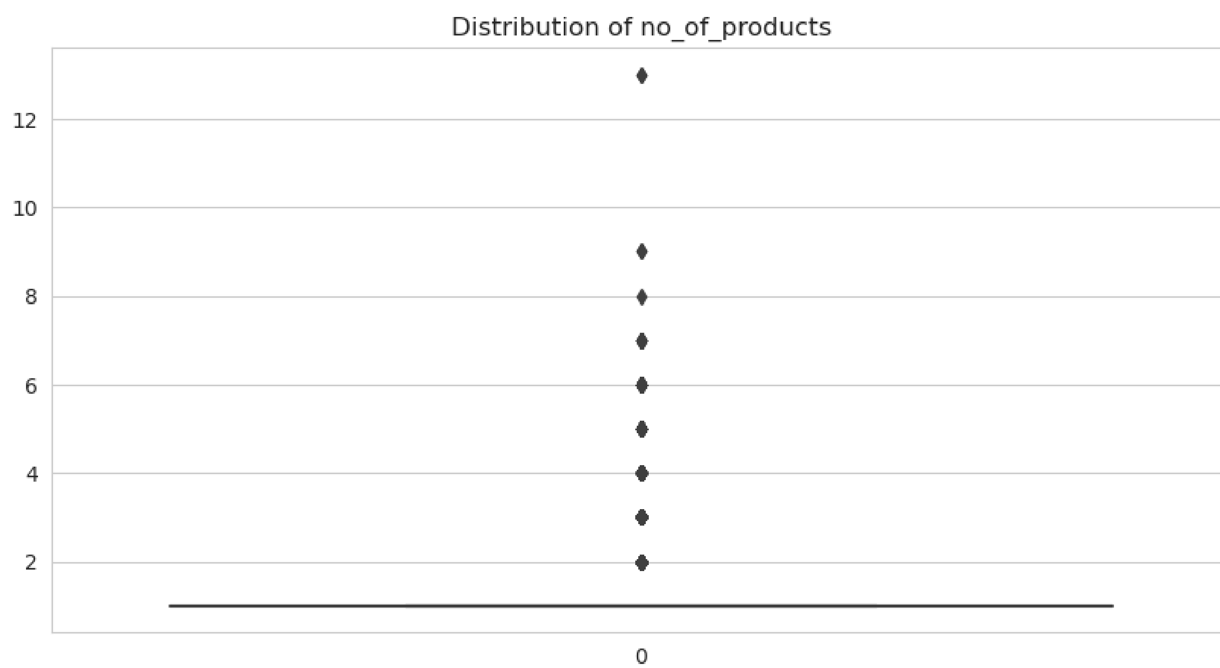

```
Skewness of delivered_estimated: -2.101764866389134
Standard deviation of delivered_estimated: 10.203242967048714
```



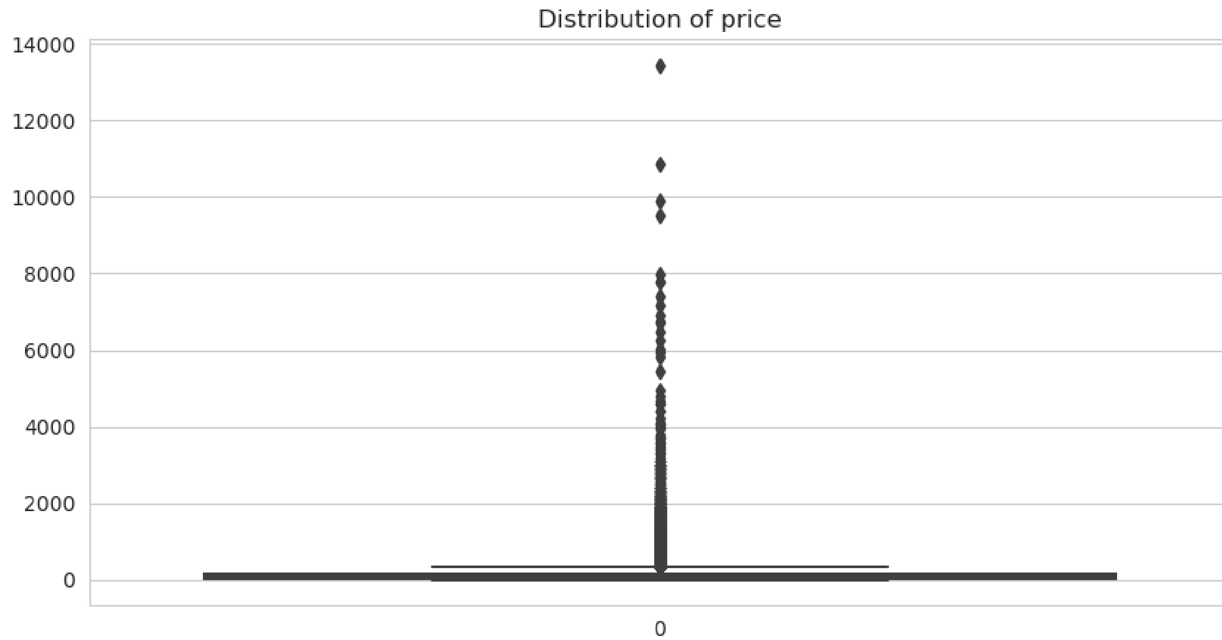

```
Skewness of purchased_delivered: 3.885615578737388
Standard deviation of purchased_delivered: 9.567765067052092
```



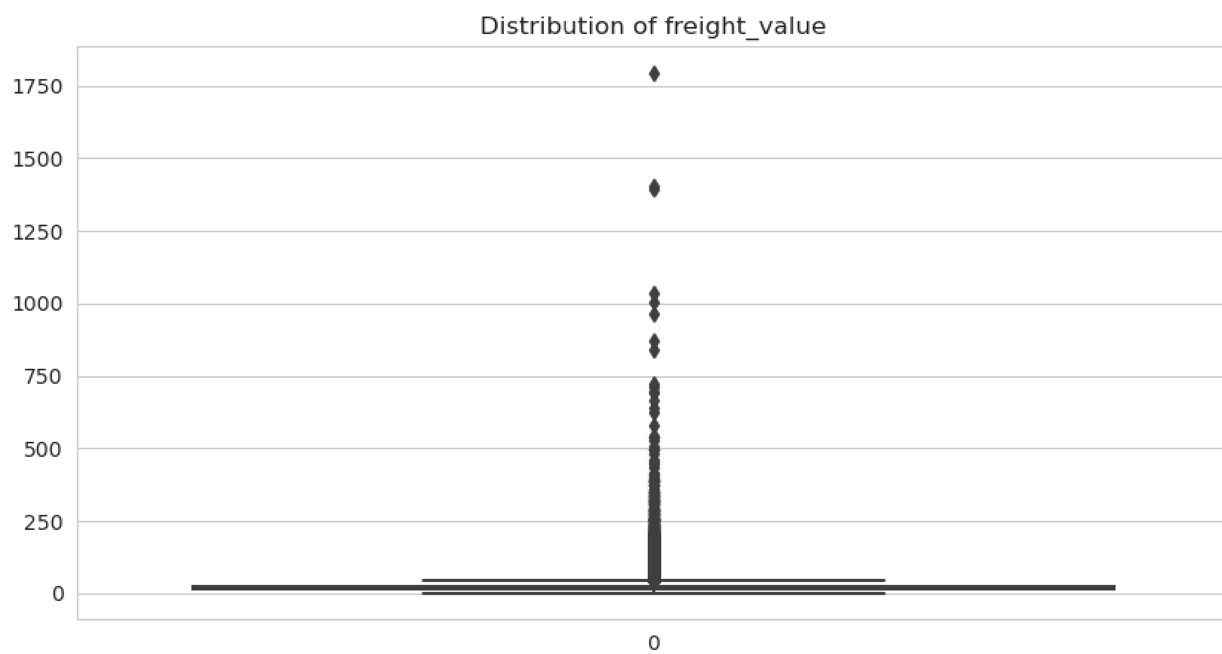

```
Skewness of no_of_products: 7.414378109080429
Standard deviation of no_of_products: 0.31373679944646404
```



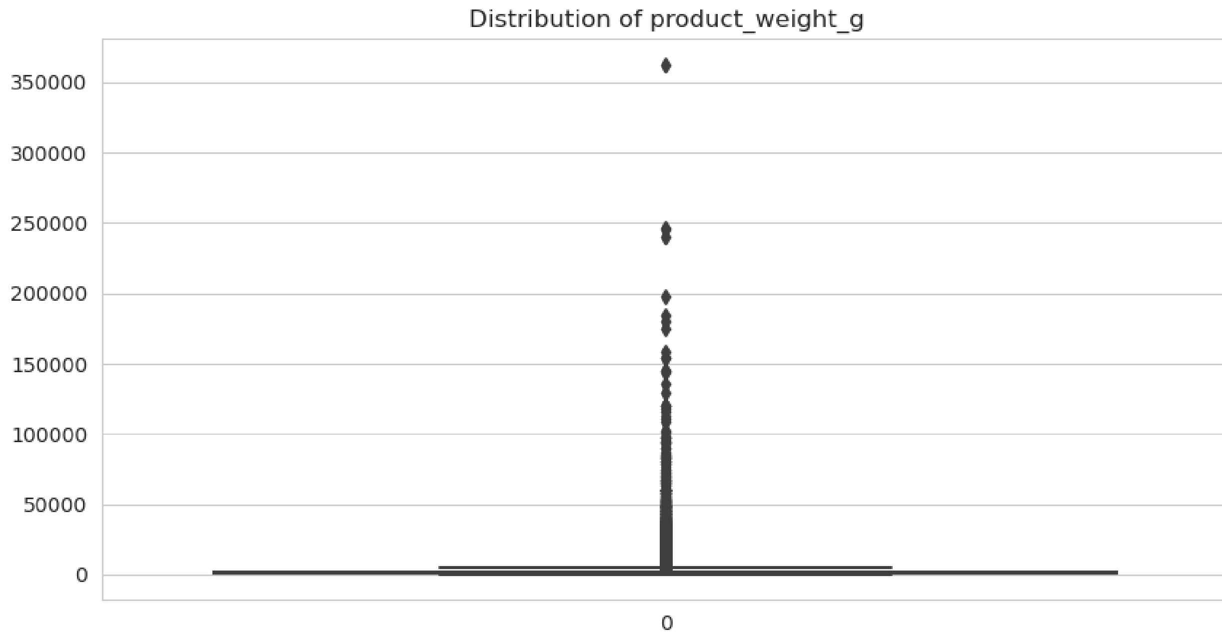

```
Skewness of price: 11.791837108894033
Standard deviation of price: 244.2877497694722
```



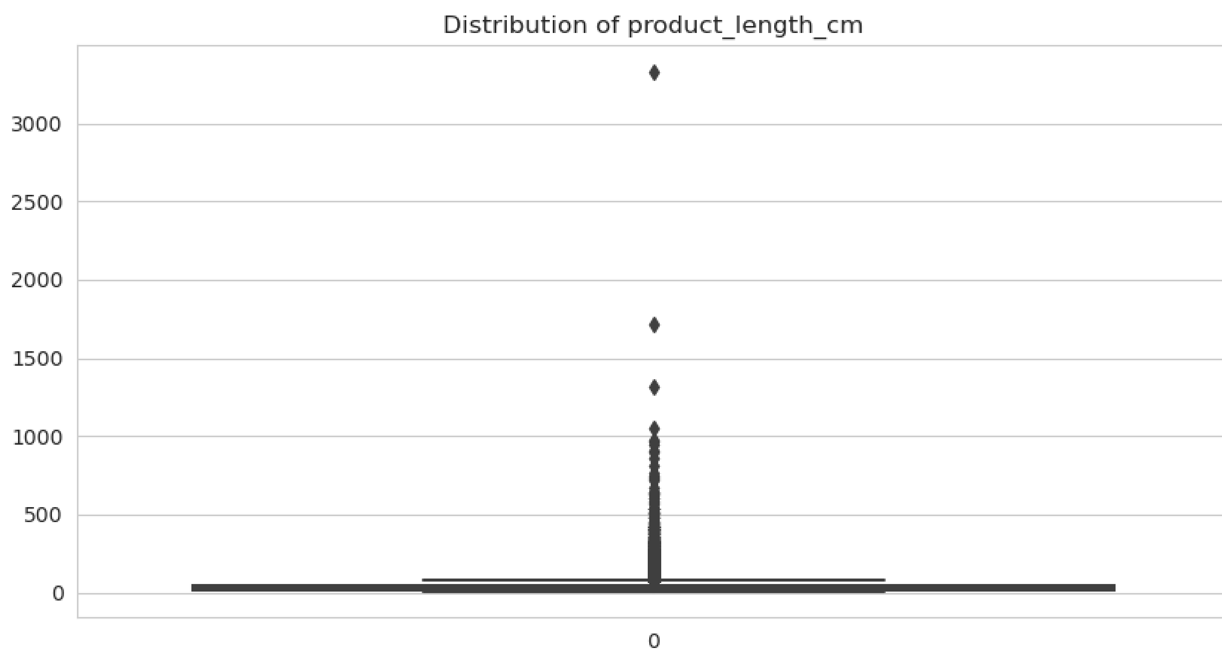

```
Skewness of freight_value: 13.696046608723156
Standard deviation of freight_value: 26.8905604707273
```



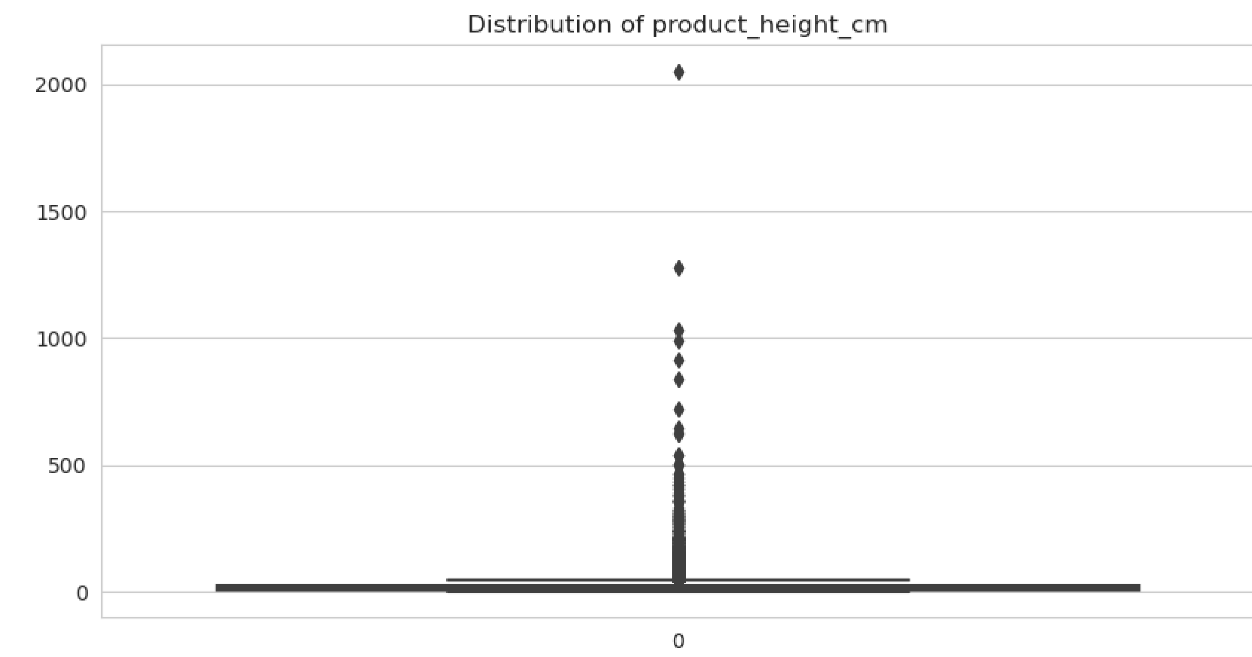

```
Skewness of product_weight_g: 12.131479466882134
Standard deviation of product_weight_g: 5812.313175955143
```



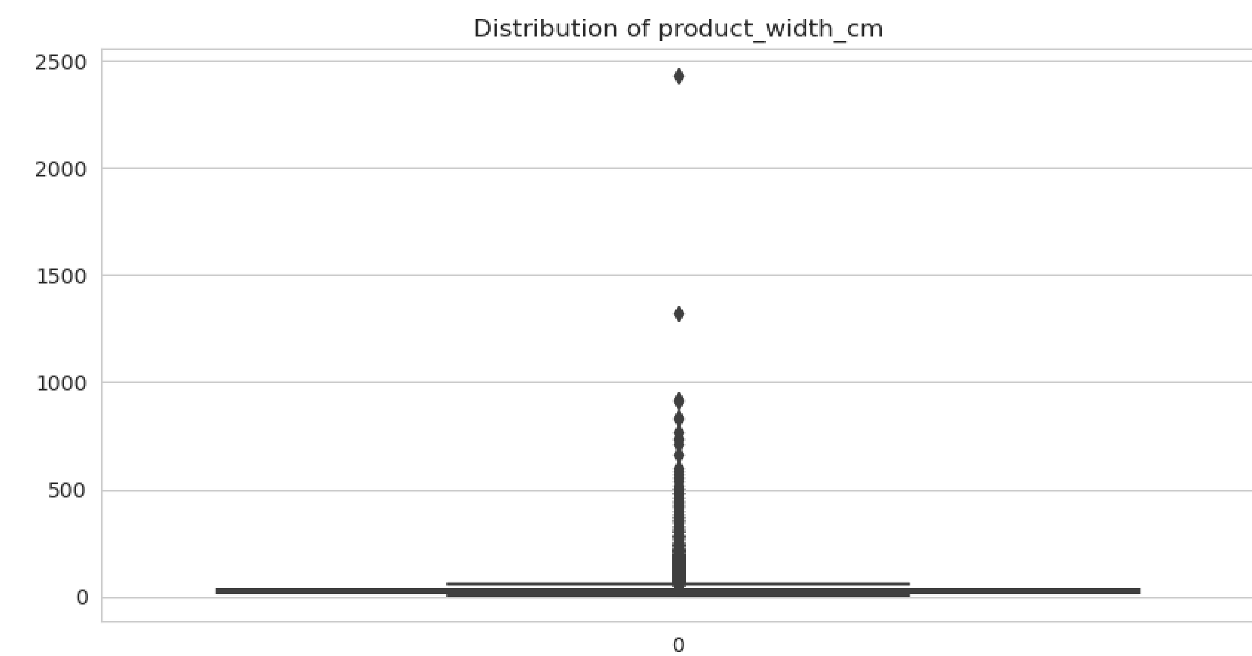

```
Skewness of product_length_cm: 16.000317045845396
Standard deviation of product_length_cm: 35.43155752809992
```



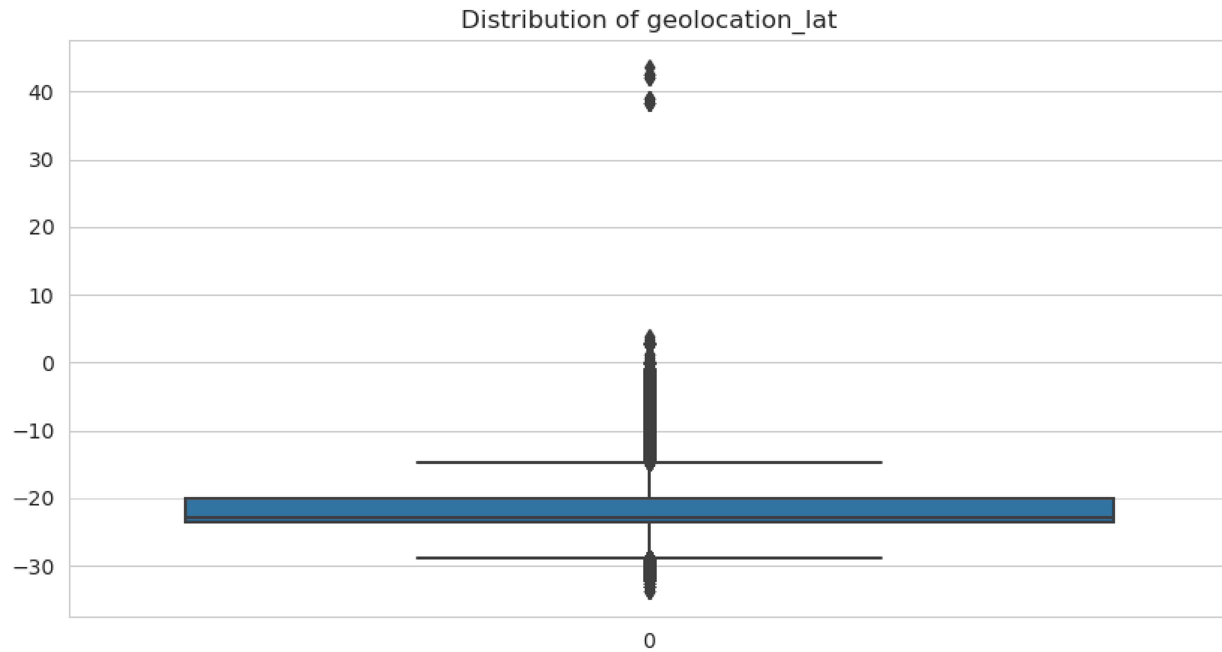

```
Skewness of product_height_cm: 14.445872079638715
Standard deviation of product_height_cm: 25.18795518390413
```



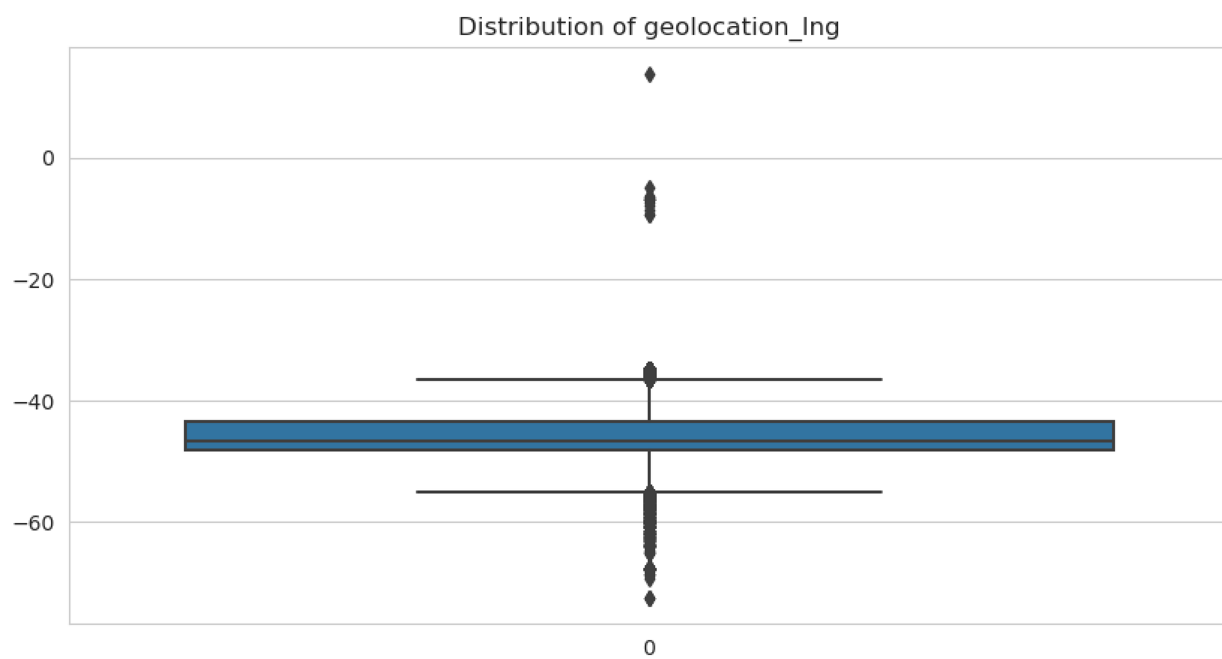

```
Skewness of product_width_cm: 16.47431670120788
Standard deviation of product_width_cm: 26.235366771941106
```



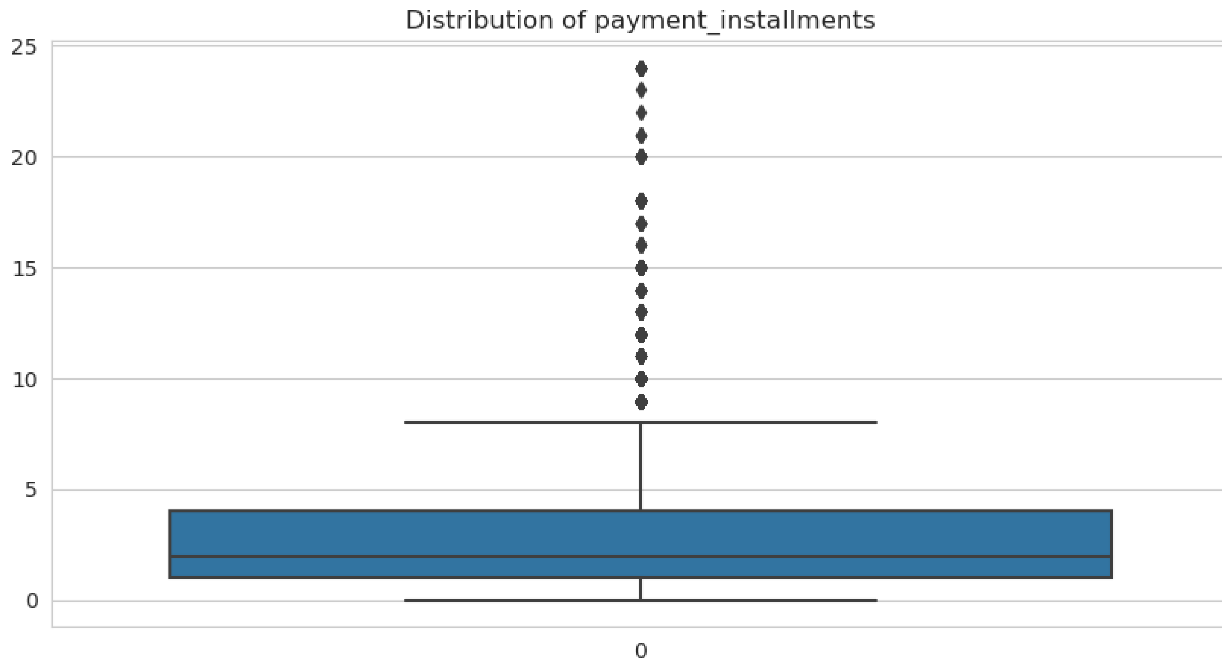

```
Skewness of geolocation_lat: 1.7731522011144614
Standard deviation of geolocation_lat: 5.683911480427562
```



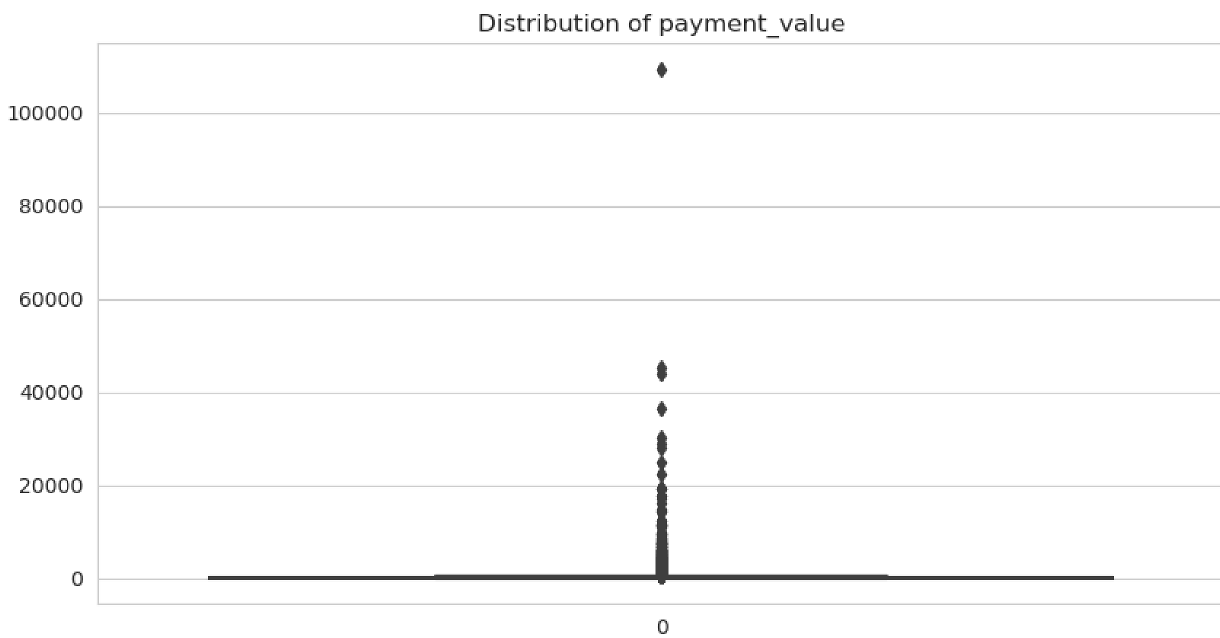

```
Skewness of geolocation_lng: 0.18920688857939136
Standard deviation of geolocation_lng: 4.095579090984354
```



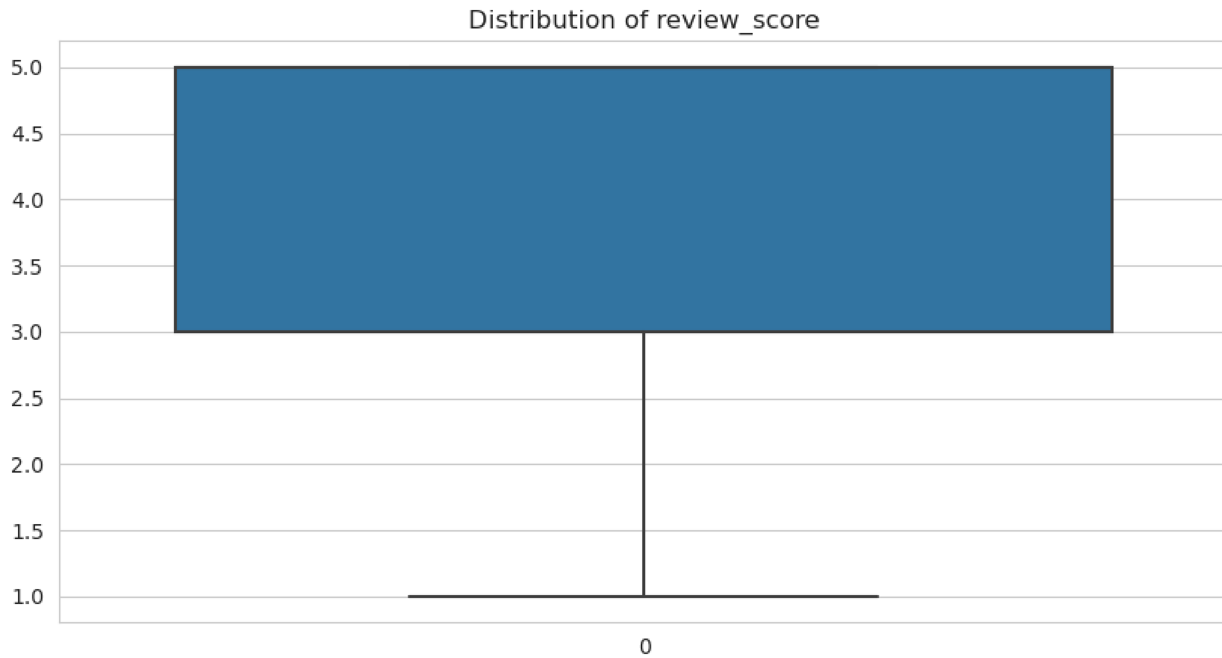

```
Skewness of payment_installments: 1.5985424567820286
Standard deviation of payment_installments: 2.728462973751188
```



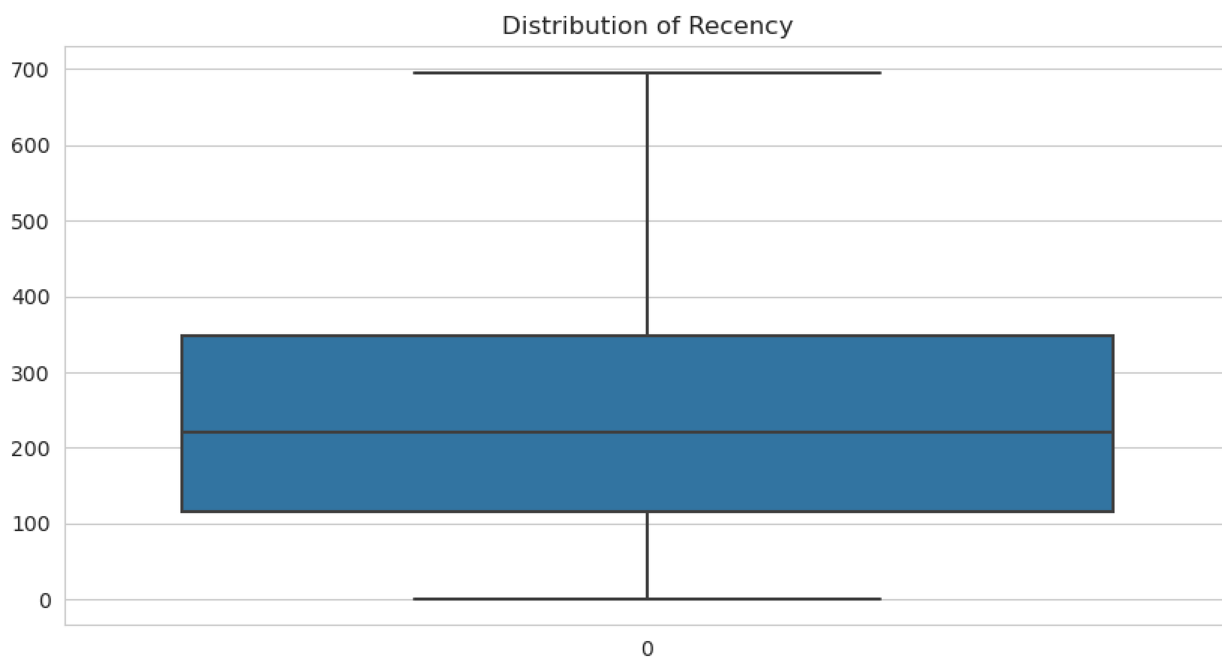

```
Skewness of payment_value: 70.4949829190865
Standard deviation of payment_value: 647.5936527572592
```



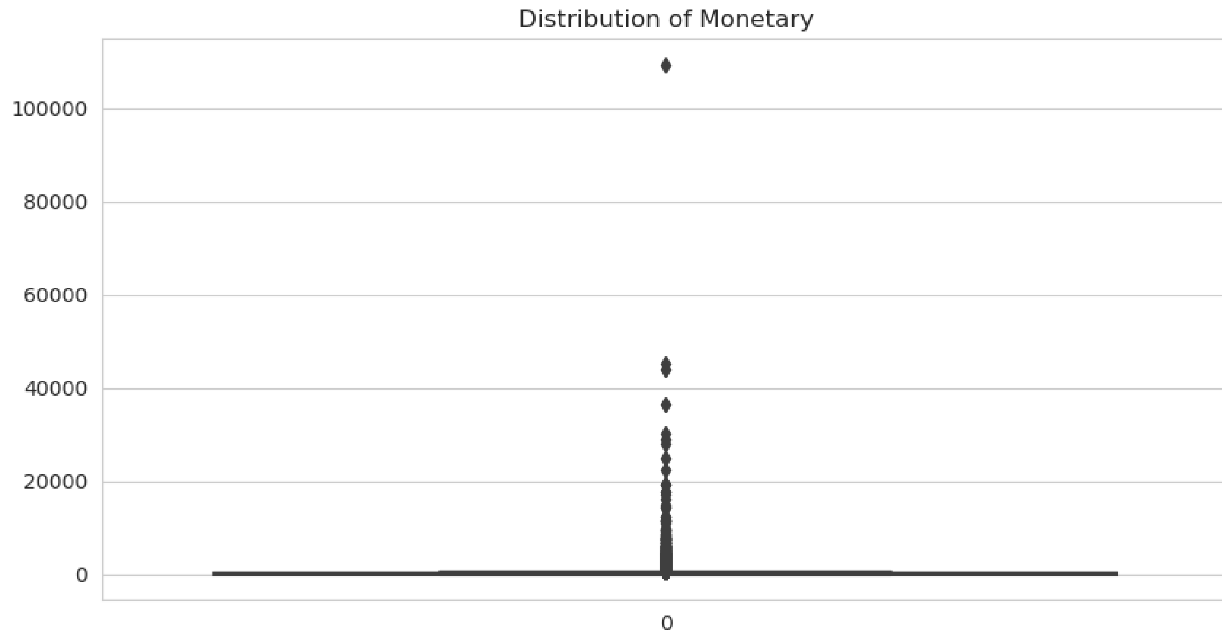

```
Skewness of review_score: -1.0689366055733671
Standard deviation of review_score: 1.5081853241987146
```



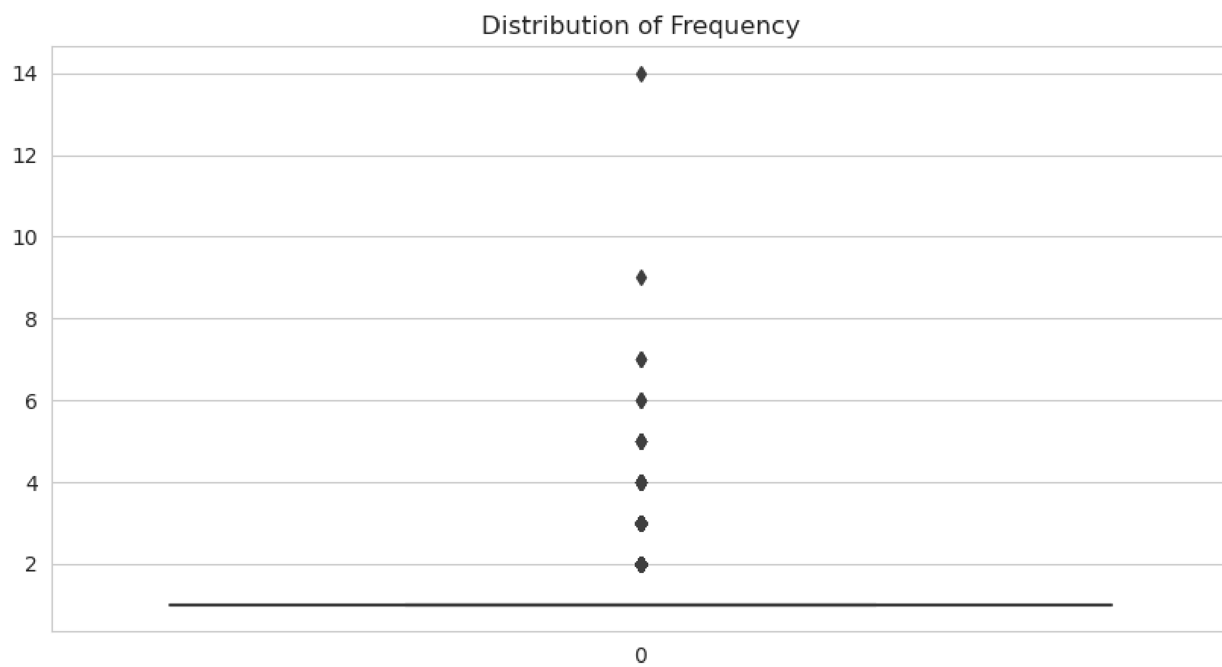

```
Skewness of Recency: 0.43585883202493925
Standard deviation of Recency: 152.38669351592222
```




```
Skewness of Monetary: 70.4949829190865
Standard deviation of Monetary: 647.5936527572592
```




```
Skewness of Frequency: 10.676600298052568
Standard deviation of Frequency: 0.20649360862520988
```

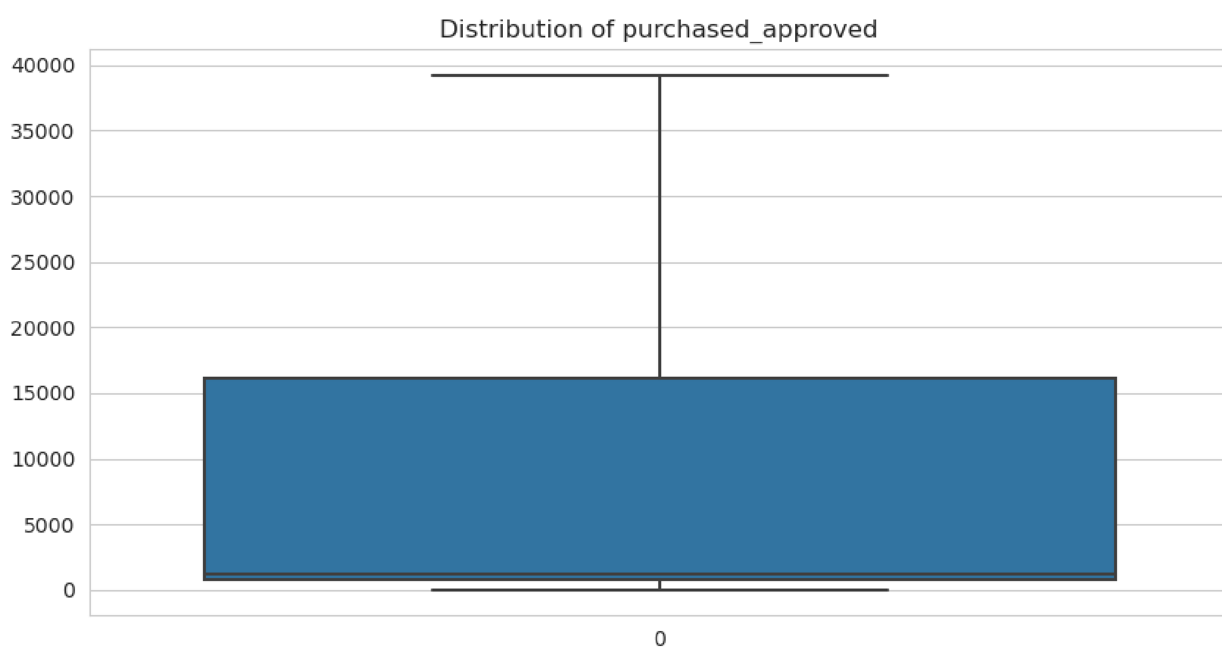



```
final.drop(columns = ['customer_zip_code_prefix', 'no_of_orders',
'no_of_products', 'Frequency'], axis = 1, inplace = True)
```

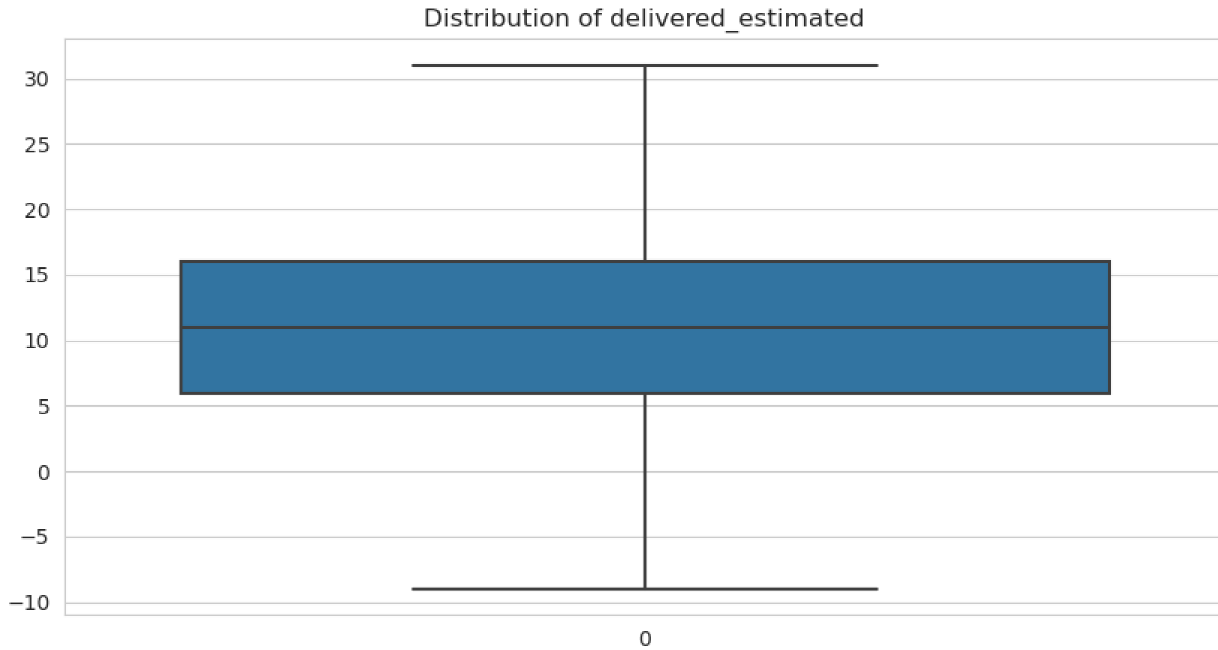
Observation:

1. Since the columns `no_of_orders`, `no_of_products` and `Frequency` has **standard deviation almost equal to 0**, we are **dropping those columns**, as it would **not add value to the model building**.

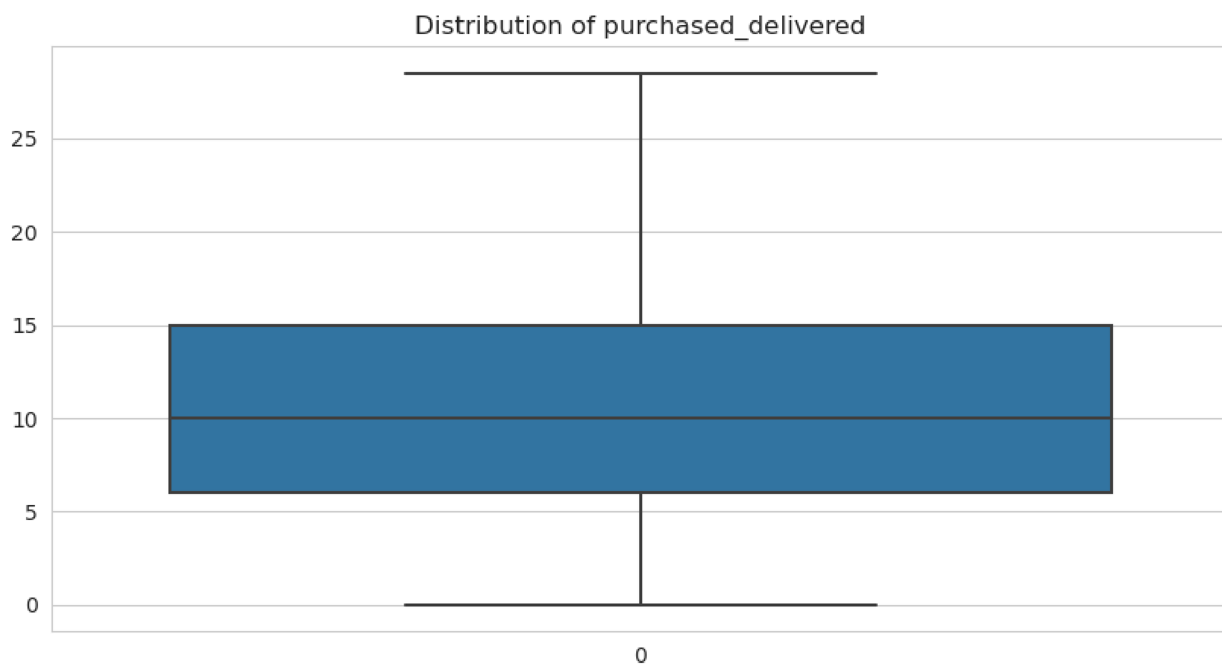
```
final_outlierTreated = final.copy()

for i in final_outlierTreated.select_dtypes(include = 
np.number).columns:
    q1 = final_outlierTreated[i].quantile(0.25)
    q3 = final_outlierTreated[i].quantile(0.75)
    iqr = q3 - q1
    ul = q3 + 1.5*iqr
    ll = q1 - 1.5*iqr
    final_outlierTreated[i] = 
np.where(final_outlierTreated[i]>ul,ul,final_outlierTreated[i])
    final_outlierTreated[i] = 
np.where(final_outlierTreated[i]<ll,ll,final_outlierTreated[i])

for col in final_outlierTreated.select_dtypes(include = 
np.number).columns:
    plt.figure(figsize = (10, 5))
    print(f'Skewness of {col}: {final_outlierTreated[col].skew()}')
    print(f'Standard deviation of {col}: 
{final_outlierTreated[col].std()}')
    sns.boxplot(final_outlierTreated[col])
    plt.title(f'Distribution of {col}')
    plt.show()

Skewness of purchased_approved: 1.216427542911808
Standard deviation of purchased_approved: 15172.739925537338
```



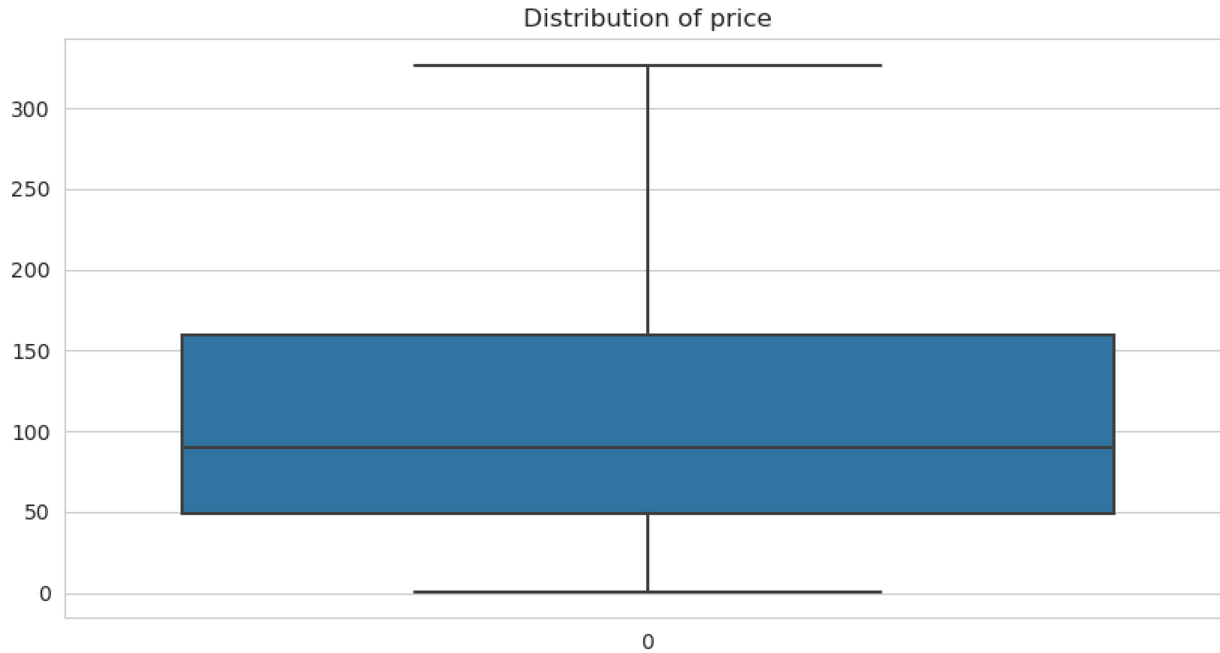
```
Skewness of delivered_estimated: -0.09874592372345704
Standard deviation of delivered_estimated: 8.274096249346677
```



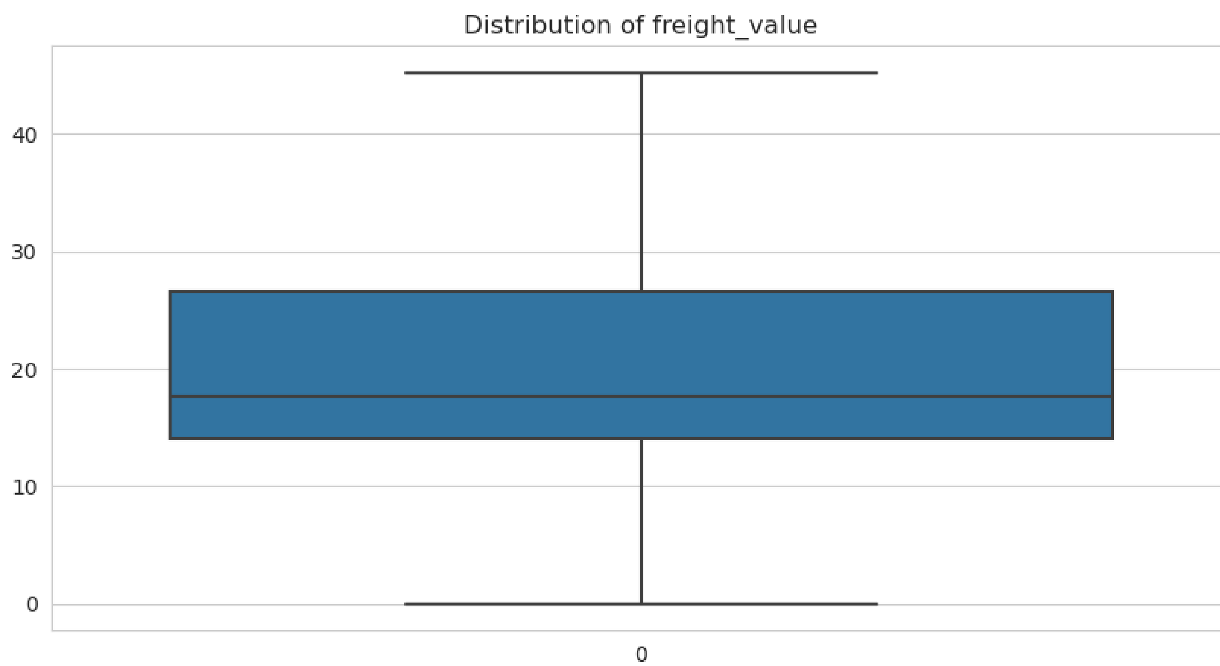

```
Skewness of purchased_delivered: 0.8756697985741126
Standard deviation of purchased_delivered: 7.115309691363529
```



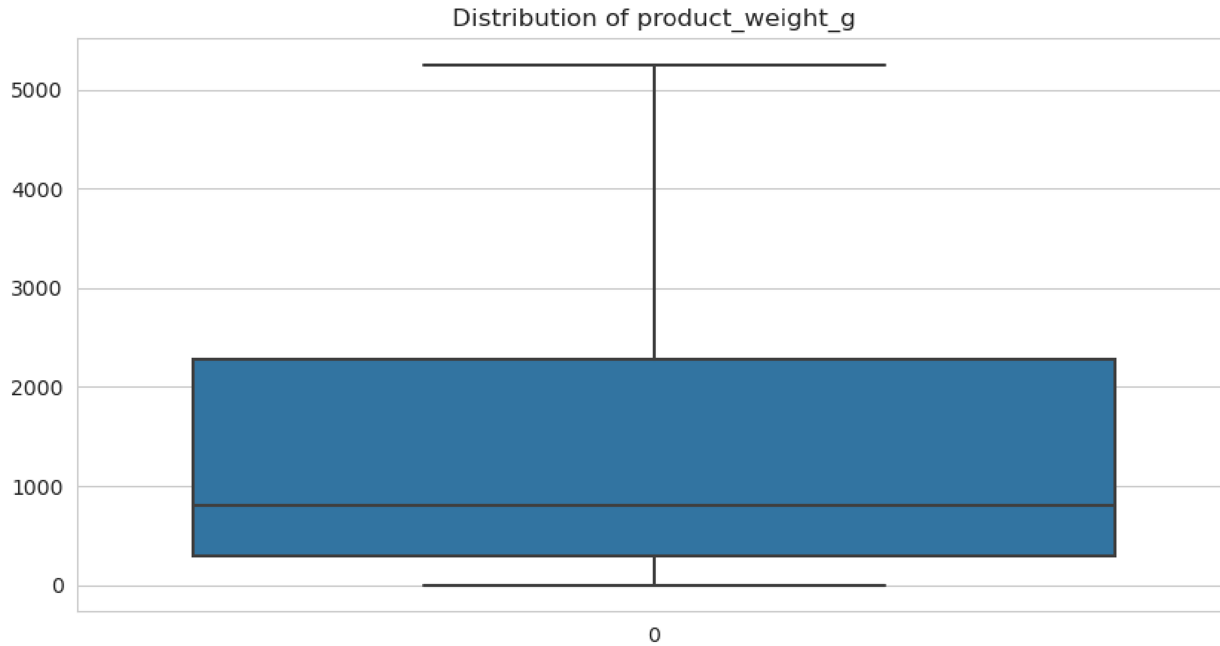
```
Skewness of price: 1.0621689422971194
Standard deviation of price: 92.20044361066198
```



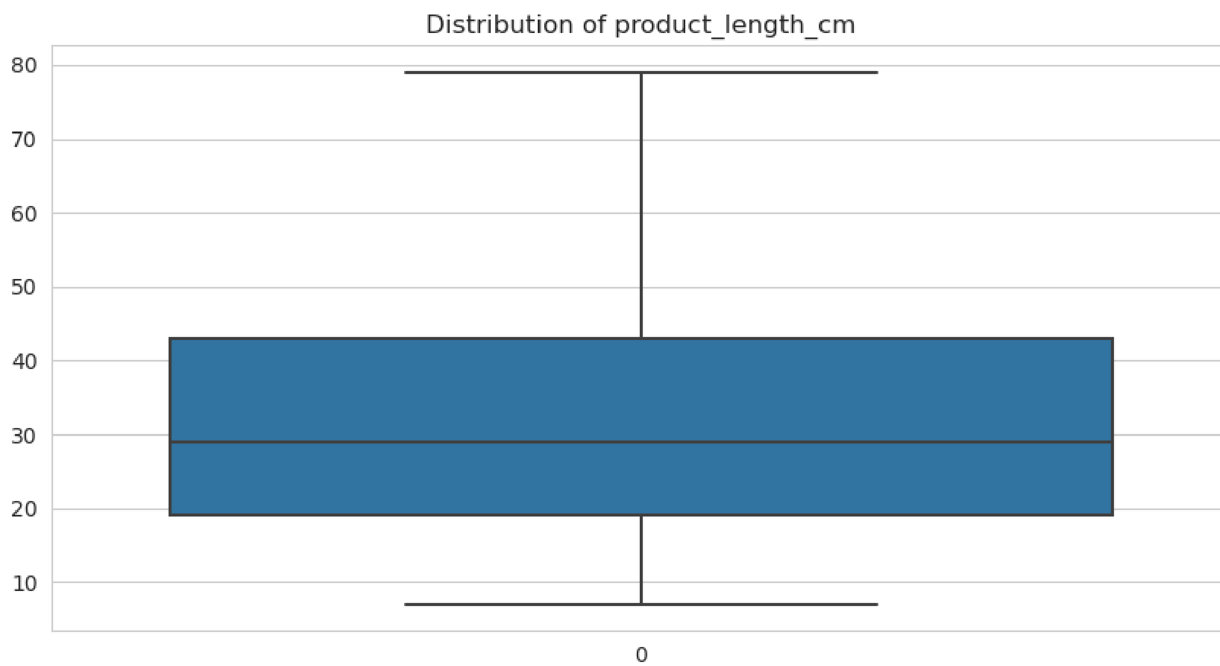

```
Skewness of freight_value: 0.9844226195345266
Standard deviation of freight_value: 11.097659947869786
```



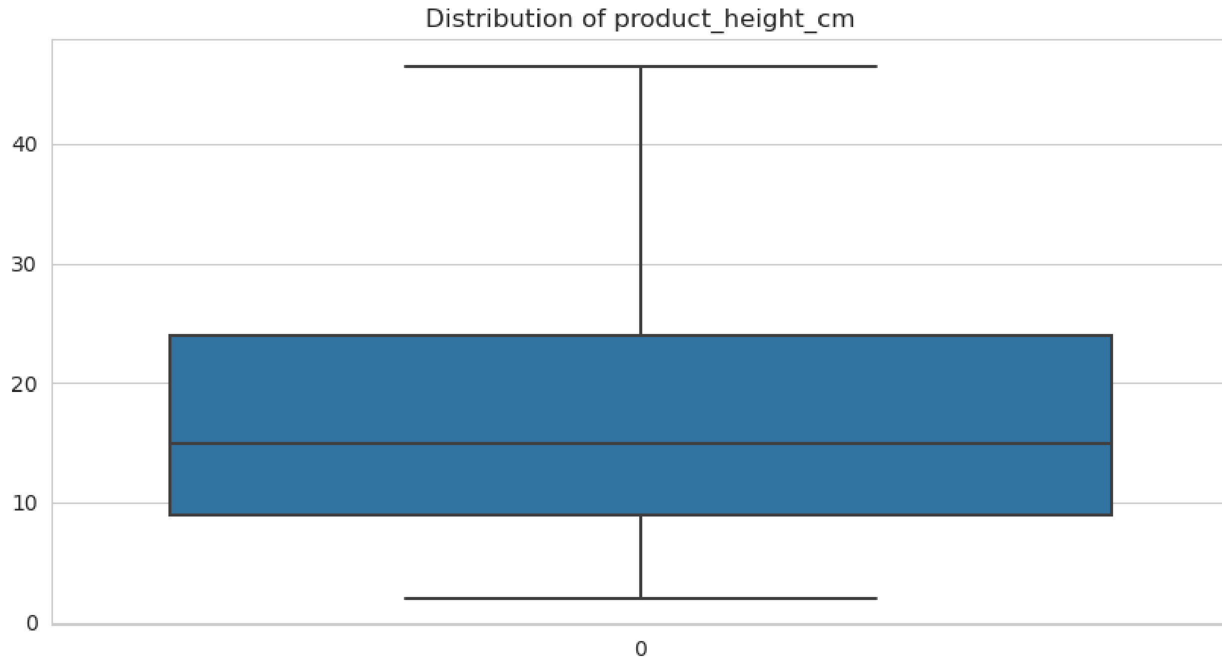
```
Skewness of product_weight_g: 1.184708672928979
Standard deviation of product_weight_g: 1768.577396432909
```



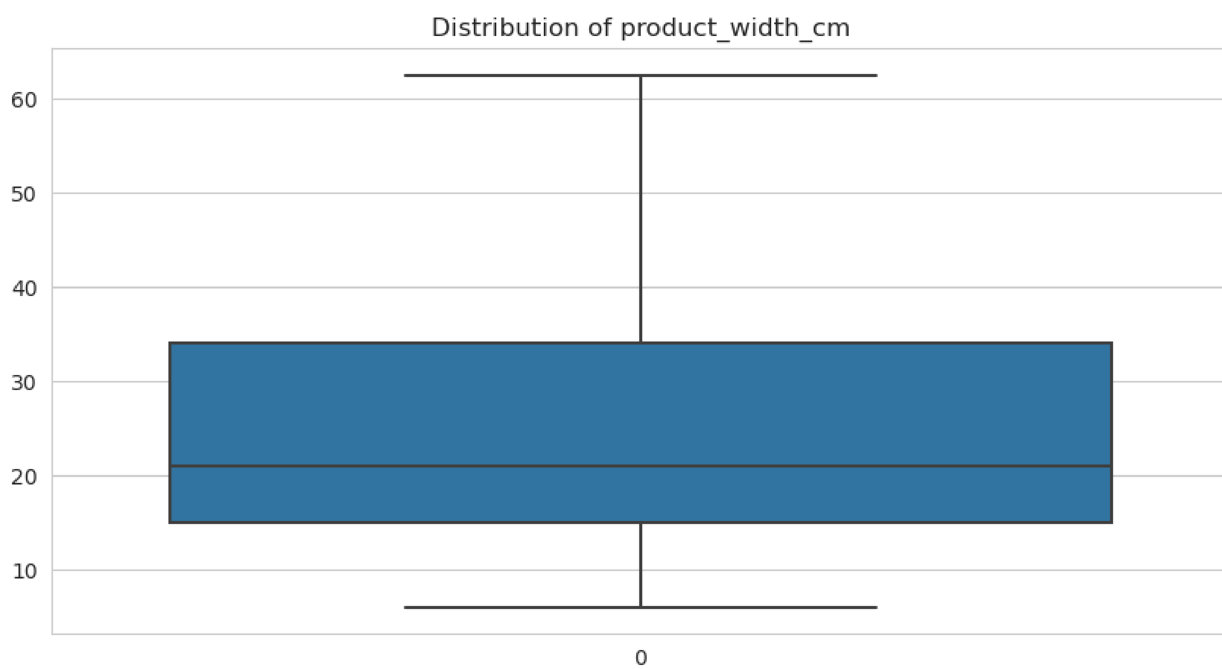

```
Skewness of product_length_cm: 1.0917311795460445
Standard deviation of product_length_cm: 18.785325900129585
```



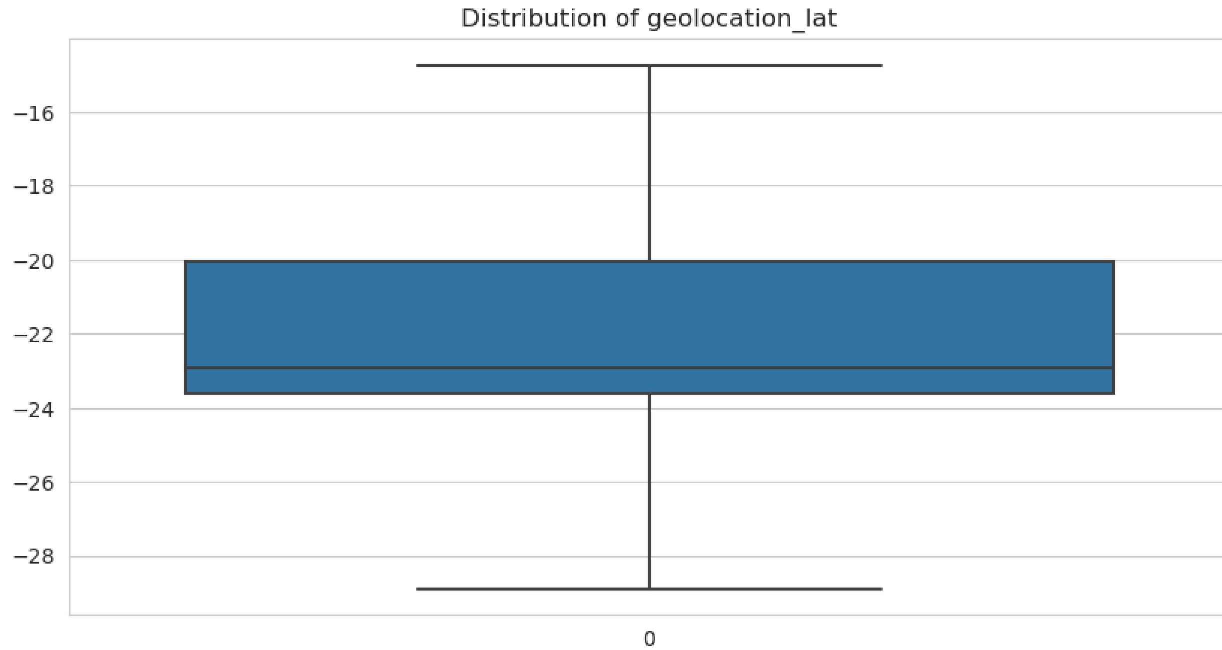
```
Skewness of product_height_cm: 0.9828445611757387
Standard deviation of product_height_cm: 12.625083800219741
```



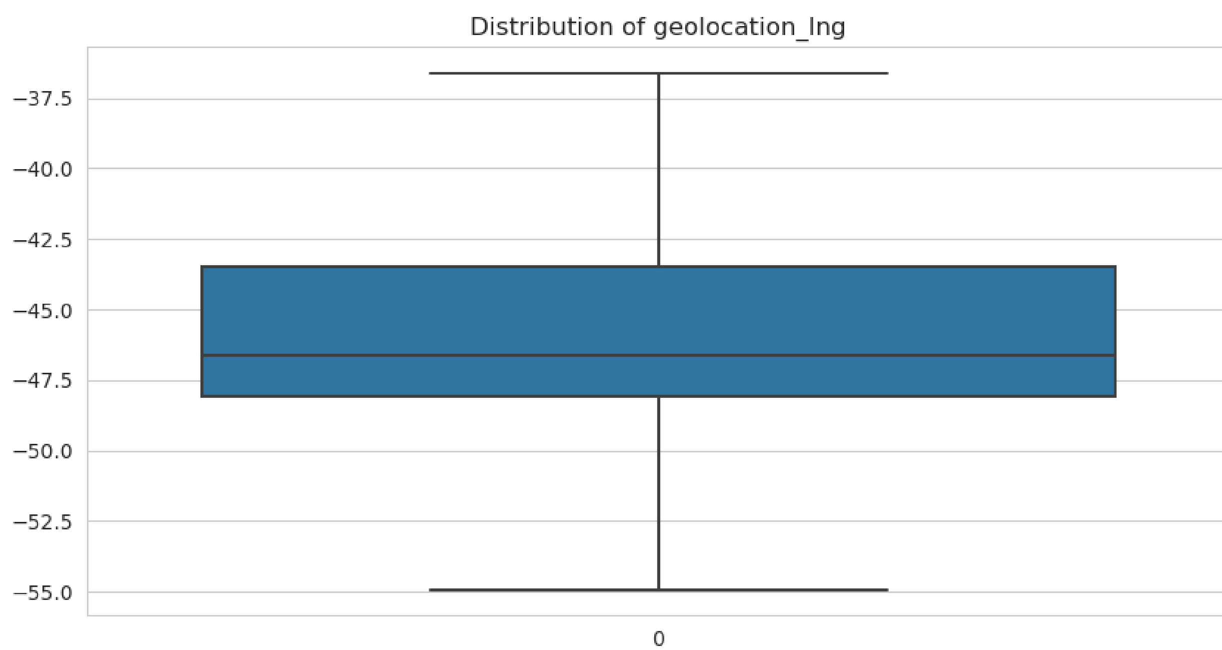

```
Skewness of product_width_cm: 1.125375095461402
Standard deviation of product_width_cm: 14.460754794476427
```



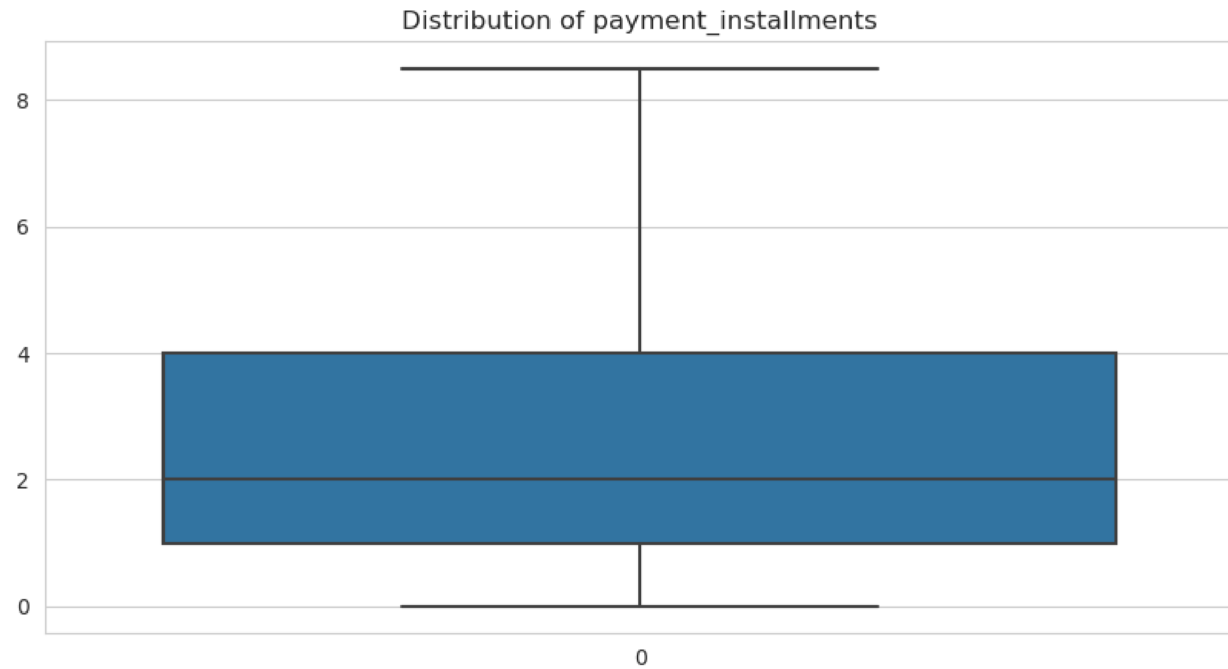
```
Skewness of geolocation_lat: 0.5304176813724053
Standard deviation of geolocation_lat: 3.6704632496030594
```



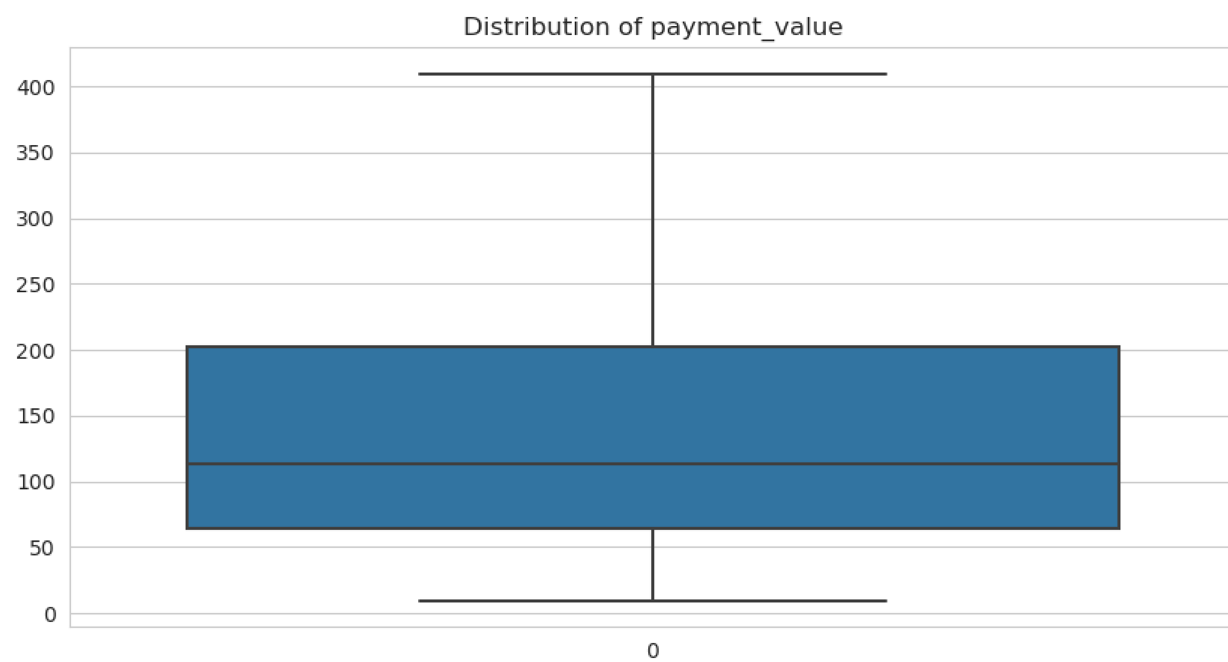

```
Skewness of geolocation_lng: 0.2797774883012845
Standard deviation of geolocation_lng: 3.8012245383733183
```



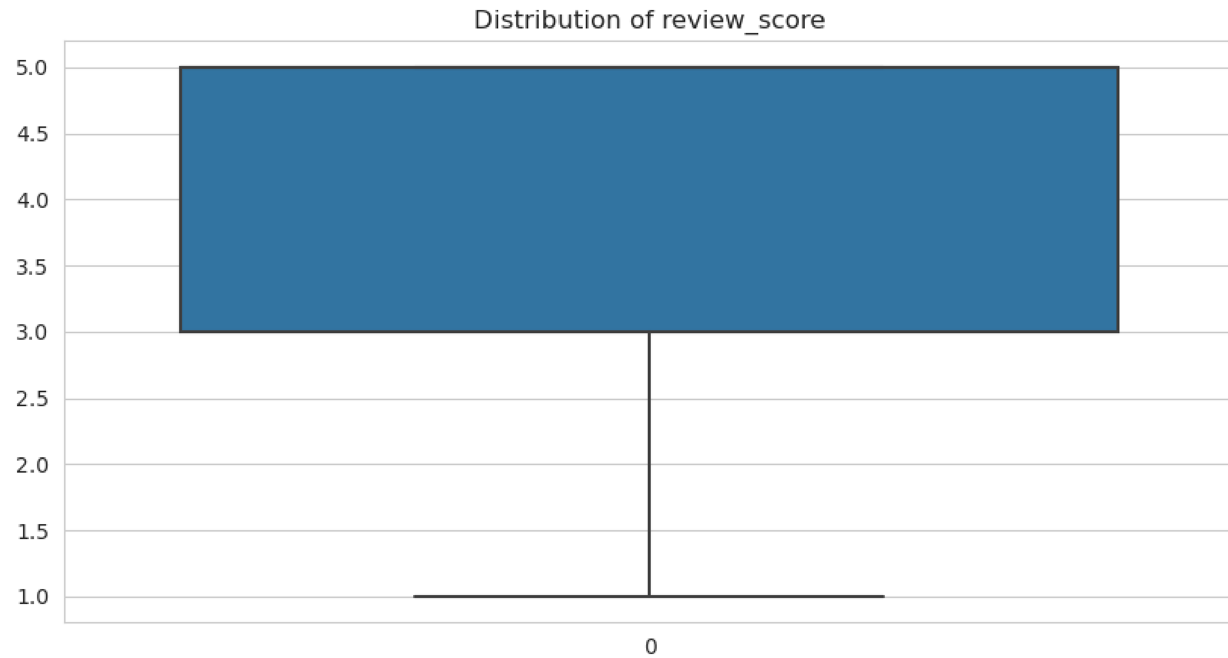

```
Skewness of payment_installments: 1.2118688690198518
Standard deviation of payment_installments: 2.4396707220778495
```



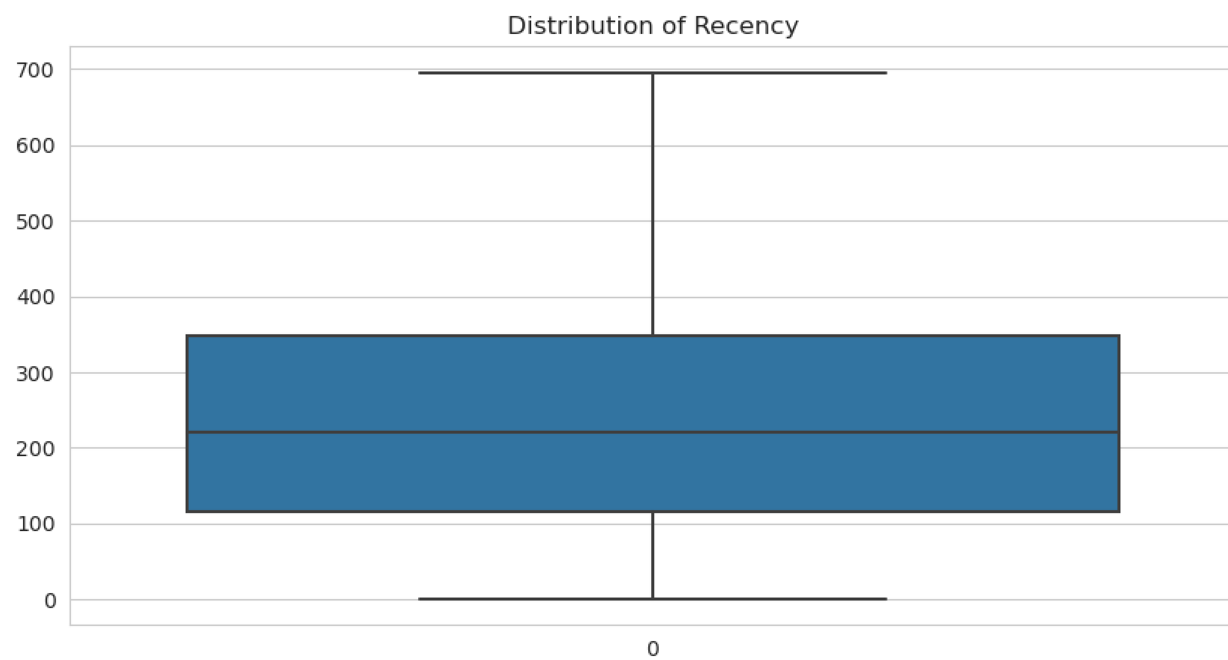

```
Skewness of payment_value: 1.0925860647703838
Standard deviation of payment_value: 117.11471507512535
```



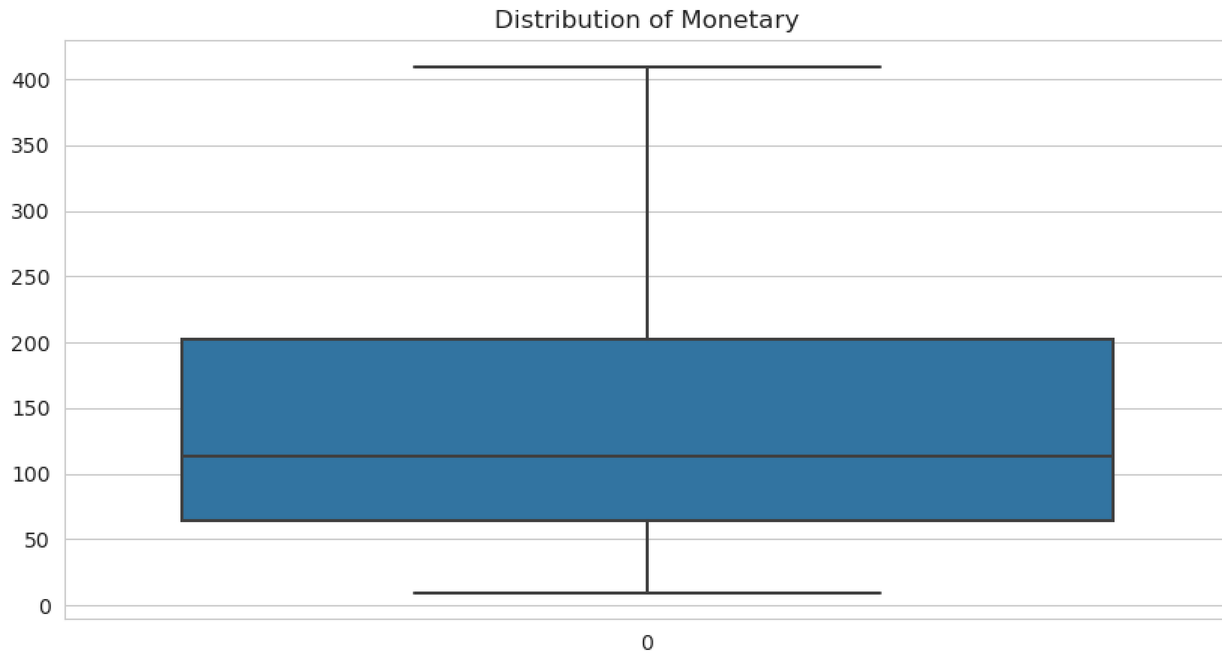

```
Skewness of review_score: -1.0689366055733671
Standard deviation of review_score: 1.5081853241987146
```




```
Skewness of Recency: 0.43585883202493925
Standard deviation of Recency: 152.38669351592222
```




```
Skewness of Monetary: 1.0925860647703838
Standard deviation of Monetary: 117.11471507512535
```




```
final_outlierTreated.shape
```

```
(90528, 21)
```

Observations:

1. The outliers are treated by the method of **capping**.
2. Values which fall outside of the upper and lower whisker are capped to the upper and lower whisker values respectively.
3. Since **dropping the values** would lead to **loss of huge volumes of data**, we prefer to cap the values.

12. Missing Value Treatement

```
final_outlierTreated.isna().sum() / len(final) * 100
```

```
customer_unique_id      0.000000
customer_city           0.000000
customer_state          0.000000
purchased_approved      0.000000
delivered_estimated     0.000000
purchased_delivered     0.000000
price                   0.000000
freight_value           0.000000
product_weight_g        0.000000
product_length_cm       0.000000
```

```
product_height_cm         0.000000
product_width_cm          0.000000
geolocation_lat           0.000000
geolocation_lng           0.000000
payment_type              0.000000
payment_installments      0.000000
payment_value             0.000000
review_score             90.099196
Recency                   0.000000
Monetary                  0.000000
Churn                     0.000000
dtype: float64
```

```
final_outlierTreated.drop(columns = ['review_score'], axis = 1,
inplace = True)
```

Observation:

1. Since more than **85%** of values are missing in the `review_score` feature, we are **dropping the column**.

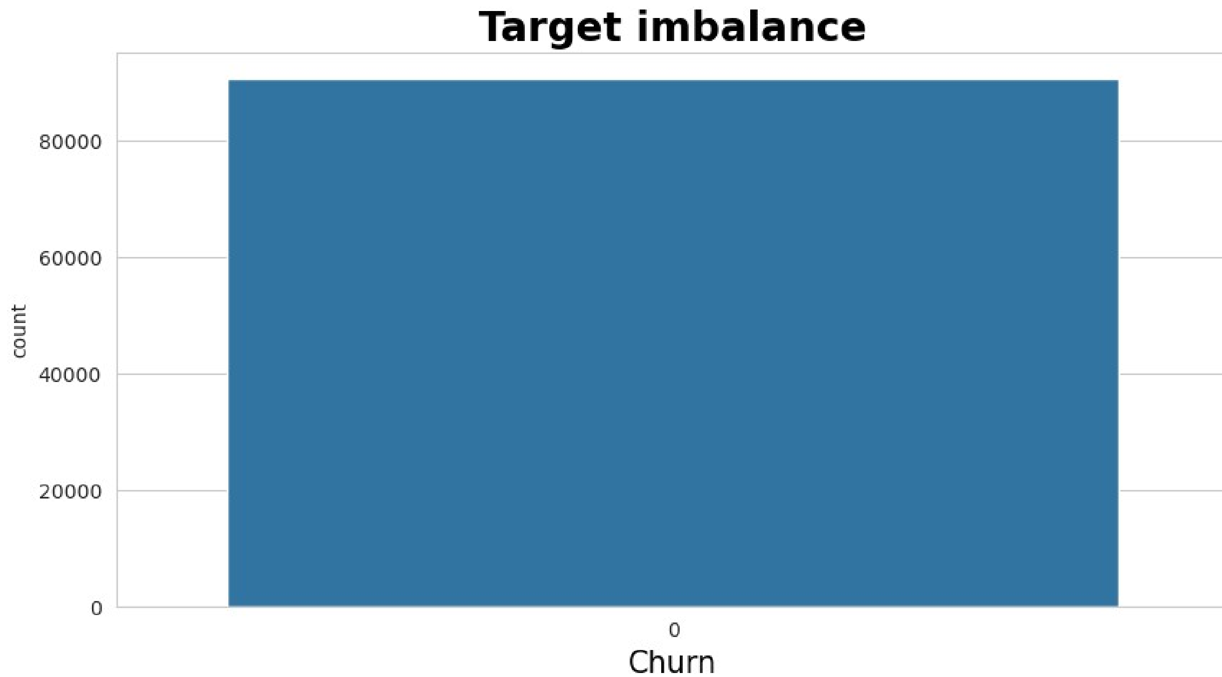
13. Multi-variate Analysis

13.1. Target imbalance

```
final_outlierTreated.Churn.value_counts(normalize = True) * 100
```

```
0    54.591949
1    45.408051
Name: Churn, dtype: float64
```

```
plt.figure(figsize=(10, 5))
sns.countplot(final_outlierTreated.Churn)
plt.xlabel('Churn',color='black',fontsize=15)
plt.title('Target
imbalance',color='black',fontsize=20,fontweight='bold')
plt.show()
```

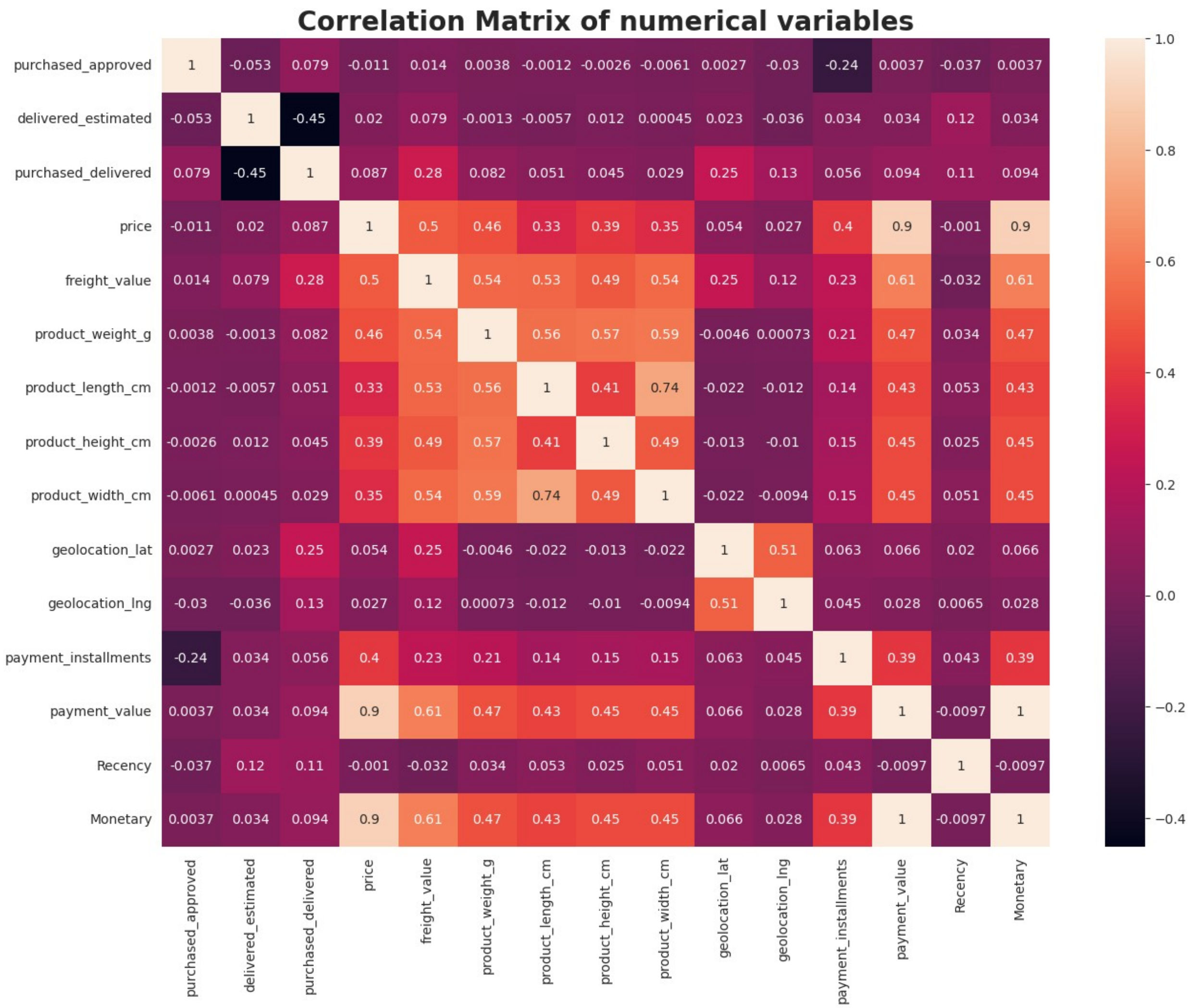


Observation:

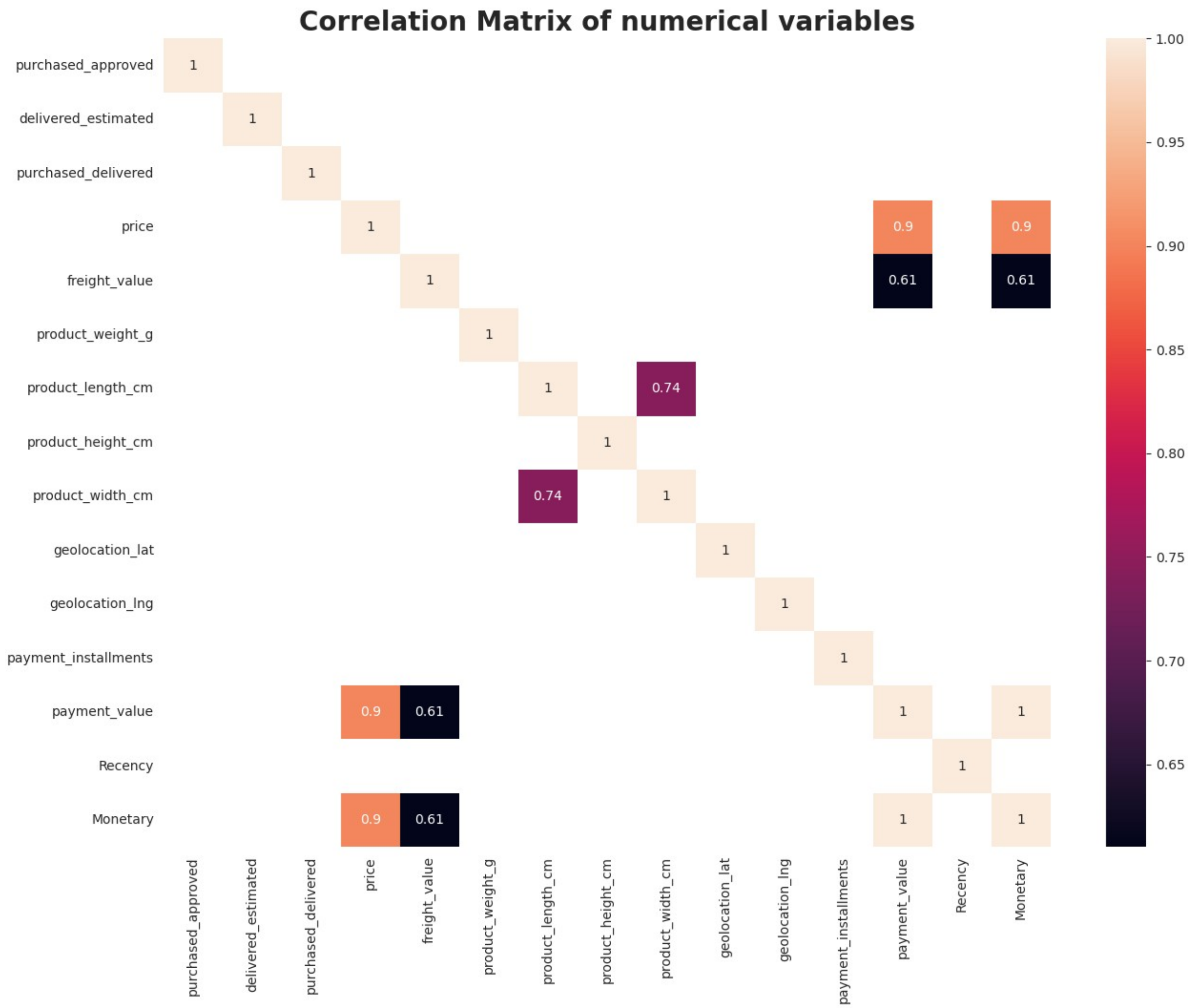
1. **Target variable is balanced**. So we **do not require upsampling** of the data using SMOTE.

13.2. Multivariate Analysis

```
plt.figure(figsize=(15,11))
sns.heatmap(final_outlierTreated.corr(), annot = True)
plt.title('Correlation Matrix of numerical
variables',fontsize=20,fontweight='bold')
plt.show()
```




```
plt.figure(figsize=(15,11))
sns.heatmap(final_outlierTreated.corr()[final_outlierTreated.corr() >
0.6], annot = True)
plt.title('Correlation Matrix of numerical
variables',fontsize=20,fontweight='bold')
plt.show()
```



Observations:

1. The above heatmap of the correlation coefficients between numerical variables shows which variables are moderately to highly correlated between themselves.
2. `product_width_cm` is **fairly correlated** with `product_length_cm`.
3. `freight_value` is **fairly correlated** with `Monetary` and `payment_value`, which both are the same. This variable would cause multi-collinearity, so it must be removed.
4. Similarly, `price` is **highly correlated** with `Monetary` and `payment_value`.

14. Statistical Tests

Statistical test for categorical and categorical variables

Chi-Squared test for Independence Hypothesis Null Hypothesis, H0: Variables are independent. **Alternate Hypothesis, Ha**: Variables are dependent.

```
def cat_cat(variable):
    dependent_variables = []
    independent_variables = []
    for var in variable:
        print(f'{var} and Churn')
        observed = pd.crosstab(final_outlierTreated[var], 
final_outlierTreated.Churn)
        chi_stats, pval, dof, expected = 
stats.chi2_contingency(observed)
        print('test statistics: ', chi_stats)
        print('p - value: ', pval)
        print('degrees of freedom: ', dof)
        if pval < 0.05:
            print(f'Reject Null Hypothesis. \nThe variables {var} and 
target variable, Churn are dependent.\n')
            dependent_variables.append(var)
        else:
            print(f'Failed to reject Null Hypothesis. \nThe variables 
{var} and target variable, Churn are independent.\n')
            independent_variables.append(var)
    print('Dependent variables: ', dependent_variables)
    print('Independent variables: ', independent_variables)

variable = ['customer_state', 'payment_type', 'payment_installments', 
'customer_city']
cat_cat(variable)
```

```
customer_state and Churn
test statistics:  353.9562373606318
p - value:  2.9132771252108942e-59
degrees of freedom:  26
Reject Null Hypothesis. 
The variables customer_state and target variable, Churn are dependent.

payment_type and Churn
test statistics:  266.16944819672017
p - value:  2.0805608001059732e-57
degrees of freedom:  3
Reject Null Hypothesis. 
The variables payment_type and target variable, Churn are dependent.

payment_installments and Churn
```

```
test statistics:  489.01783336833216
p - value:  1.2904748666154383e-99
degrees of freedom:  9
Reject Null Hypothesis.
The variables payment_installments and target variable, Churn are
dependent.

customer_city and Churn
test statistics:  4523.939055252141
p - value:  1.8256365995978932e-08
degrees of freedom:  4011
Reject Null Hypothesis.
The variables customer_city and target variable, Churn are dependent.

Dependent variables:  ['customer_state', 'payment_type',
'payment_installments', 'customer_city']
Independent variables:  []
```

Statistical test for categorical and numerical variables

ANOVA test for Independence Hypothesis Null Hypothesis, H0: Variables are not correlated with each other. **Alternate Hypothesis, Ha**: Variables are correlated with each other.

```
def num_cat(variable):
    correlated_variables = []
    noncorrelated_variables = []
    for var in variable:
        print(f'{var} Vs. target variable, Churn')
        churn = final[final.Churn == 1][var]
        not_churn = final[final.Churn == 0][var]
        test_stats, churn_pval = stats.shapiro(churn)
        test_stats, notchurn_pval = stats.shapiro(not_churn)
        if churn_pval < 0.05:
            print(f'churn of {var} is not normal')
        else:
            print(f'churn of {var} is normal')
        if notchurn_pval < 0.05:
            print(f'not churn of {var} is not normal')
        else:
            print(f'not churn of {var} is normal')
        levene_teststats, pval_levene = stats.levene(churn, not_churn)
        if pval_levene < 0.05:
            print(f'atleast one variance is not equal')
        else:
            print(f'all variances are equal')
        anova_teststats, pval_anova = stats.f_oneway(churn, not_churn)
        if pval_anova < 0.05:
            print(f'Reject Null Hypothesis. \nThe variables {var} and
target variable, Churn are correlated with each other.\n')
```

```
            correlated_variables.append(var)
        else:
            print(f'Failed to reject Null Hypothesis. \nThe variables
{var} and target variable, Churn are not correlated with each other.\
n')
            noncorrelated_variables.append(var)

    print('Correlated variables: ', correlated_variables)
    print('Non-correlated variables: ', noncorrelated_variables)


variable = ['purchased_approved', 'delivered_estimated',
'purchased_delivered', 'price', 'freight_value', 'product_weight_g',
'product_length_cm', 'product_height_cm', 'product_width_cm',
'geolocation_lat', 'geolocation_lng', 'Recency', 'Monetary']
num_cat(variable)
```

```
purchased_approved Vs. target variable, Churn
churn of purchased_approved is not normal
not churn of purchased_approved is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables purchased_approved and target variable, Churn are
correlated with each other.

delivered_estimated Vs. target variable, Churn
churn of delivered_estimated is not normal
not churn of delivered_estimated is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables delivered_estimated and target variable, Churn are
correlated with each other.

purchased_delivered Vs. target variable, Churn
churn of purchased_delivered is not normal
not churn of purchased_delivered is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables purchased_delivered and target variable, Churn are
correlated with each other.

price Vs. target variable, Churn
churn of price is not normal
not churn of price is not normal
all variances are equal
Failed to reject Null Hypothesis.
The variables price and target variable, Churn are not correlated with
each other.

freight_value Vs. target variable, Churn
```

```
churn of freight_value is not normal
not churn of freight_value is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables freight_value and target variable, Churn are correlated
with each other.

product_weight_g Vs. target variable, Churn
churn of product_weight_g is not normal
not churn of product_weight_g is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables product_weight_g and target variable, Churn are
correlated with each other.

product_length_cm Vs. target variable, Churn
churn of product_length_cm is not normal
not churn of product_length_cm is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables product_length_cm and target variable, Churn are
correlated with each other.

product_height_cm Vs. target variable, Churn
churn of product_height_cm is not normal
not churn of product_height_cm is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables product_height_cm and target variable, Churn are
correlated with each other.

product_width_cm Vs. target variable, Churn
churn of product_width_cm is not normal
not churn of product_width_cm is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables product_width_cm and target variable, Churn are
correlated with each other.

geolocation_lat Vs. target variable, Churn
churn of geolocation_lat is not normal
not churn of geolocation_lat is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables geolocation_lat and target variable, Churn are
correlated with each other.

geolocation_lng Vs. target variable, Churn
churn of geolocation_lng is not normal
not churn of geolocation_lng is not normal
```

```
atleast one variance is not equal
Reject Null Hypothesis.
The variables geolocation_lng and target variable, Churn are
correlated with each other.

Recency Vs. target variable, Churn
churn of Recency is not normal
not churn of Recency is not normal
atleast one variance is not equal
Reject Null Hypothesis.
The variables Recency and target variable, Churn are correlated with
each other.

Monetary Vs. target variable, Churn
churn of Monetary is not normal
not churn of Monetary is not normal
all variances are equal
Failed to reject Null Hypothesis.
The variables Monetary and target variable, Churn are not correlated
with each other.

Correlated variables:  ['purchased_approved', 'delivered_estimated',
'purchased_delivered', 'freight_value', 'product_weight_g',
'product_length_cm', 'product_height_cm', 'product_width_cm',
'geolocation_lat', 'geolocation_lng', 'Recency']
Non-correlated variables:  ['price', 'Monetary']
```

```
def non_parametric_tests(variable):
    correlated_variables = []
    noncorrelated_variables = []
    for var in variable:
        test_stats, pval =
stats.mannwhitneyu(final_outlierTreated[final_outlierTreated.Churn ==
1][var], final_outlierTreated[final_outlierTreated.Churn == 0][var])
        if pval < 0.05:
            print(f'Reject Null Hypothesis. \nThe variables {var} and
target variable, Churn are correlated with each other.\n')
            correlated_variables.append(var)
        else:
            print(f'Failed to reject Null Hypothesis. \nThe variables
{var} and target variable, Churn are not correlated with each other.\
n')
            noncorrelated_variables.append(var)
    print(f'Correlated variables: ', correlated_variables)
    print(f'Non correlated variables: ', noncorrelated_variables)

variable = ['purchased_approved', 'delivered_estimated',
'purchased_delivered', 'price', 'freight_value', 'product_weight_g',
'product_length_cm', 'product_height_cm', 'product_width_cm',
```

```
'geolocation_lat', 'geolocation_lng', 'Recency', 'Monetary']
non_parametric_tests(variable)
```

```
Reject Null Hypothesis.
The variables purchased_approved and target variable, Churn are
correlated with each other.

Reject Null Hypothesis.
The variables delivered_estimated and target variable, Churn are
correlated with each other.

Reject Null Hypothesis.
The variables purchased_delivered and target variable, Churn are
correlated with each other.

Failed to reject Null Hypothesis.
The variables price and target variable, Churn are not correlated with
each other.

Reject Null Hypothesis.
The variables freight_value and target variable, Churn are correlated
with each other.

Reject Null Hypothesis.
The variables product_weight_g and target variable, Churn are
correlated with each other.

Reject Null Hypothesis.
The variables product_length_cm and target variable, Churn are
correlated with each other.

Reject Null Hypothesis.
The variables product_height_cm and target variable, Churn are
correlated with each other.

Reject Null Hypothesis.
The variables product_width_cm and target variable, Churn are
correlated with each other.

Reject Null Hypothesis.
The variables geolocation_lat and target variable, Churn are
correlated with each other.

Reject Null Hypothesis.
The variables geolocation_lng and target variable, Churn are
correlated with each other.

Reject Null Hypothesis.
The variables Recency and target variable, Churn are correlated with
each other.
```

```
Reject Null Hypothesis.
The variables Monetary and target variable, Churn are correlated with each other.

Correlated variables:  ['purchased_approved', 'delivered_estimated', 'purchased_delivered', 'freight_value', 'product_weight_g', 'product_length_cm', 'product_height_cm', 'product_width_cm', 'geolocation_lat', 'geolocation_lng', 'Recency', 'Monetary']
Non correlated variables:  ['price']
```

Observations:

1. **All the categorical variables** are **dependant** on the **target variable**.
2. **The numerical variables**, which fail the normality test, when done non-parametric tests, are **all correlated** with the **target variable**, except for `price`.

15. Transformation of Data

```
transformed_data = final_outlierTreated.copy()
transformed_data['Churn'] = transformed_data['Churn'].astype('object')

transformed_data.skew()

purchased_approved       1.216428
delivered_estimated     -0.098746
purchased_delivered      0.875670
price                    1.062169
freight_value            0.984423
product_weight_g         1.184709
product_length_cm        1.091731
product_height_cm        0.982845
product_width_cm         1.125375
geolocation_lat          0.530418
geolocation_lng          0.279777
payment_installments     1.211869
payment_value            1.092586
Recency                  0.435859
Monetary                 1.092586
Churn                    0.184461
dtype: float64

transformed_data.describe()

       purchased_approved  delivered_estimated  purchased_delivered  \
count        90528.000000         90528.000000          90528.00000
mean         10218.436257            10.918180             11.54482
std          15172.739926             8.274096              7.11531
```

```
min            0.000000          -9.000000          0.00000
25%          756.000000           6.000000          6.00000
50%         1164.000000          11.000000         10.00000
75%        16142.250000          16.000000         15.00000
max        39221.625000          31.000000         28.50000

              price  freight_value  product_weight_g
product_length_cm  \
count  90528.000000   90528.000000      90528.000000
90528.000000
mean     118.080877      21.391276       1627.081113
34.209084
std       92.200444      11.097660       1768.577396
18.785326
min        0.850000       0.000000          0.000000
7.000000
25%       48.900000      14.100000        304.000000
19.000000
50%       89.900000      17.670000        800.000000
29.000000
75%      159.900000      26.550000       2283.000000
43.000000
max      326.400000      45.225000       5251.500000
79.000000

       product_height_cm  product_width_cm  geolocation_lat
geolocation_lng  \
count       90528.000000      90528.000000     90528.000000
90528.000000
mean           18.046422         26.419865       -21.859878        -
46.111407
std            12.625084         14.460755         3.670463
3.801225
min             2.000000          6.000000       -28.882827        -
54.921403
25%             9.000000         15.000000       -23.578469        -
48.060327
50%            15.000000         21.000000       -22.898404        -
46.614879
75%            24.000000         34.000000       -20.042230        -
43.486277
max            46.500000         62.500000       -14.737871        -
36.625202

       payment_installments  payment_value       Recency      Monetary

count          90528.000000   90528.000000  90528.000000  90528.000000

mean               2.837614     152.703864    238.733773    152.703864
```

std	2.439671	117.114715	152.386694	117.114715
min	0.000000	9.590000	1.000000	9.590000
25%	1.000000	63.790000	115.000000	63.790000
50%	2.000000	112.830000	220.000000	112.830000
75%	4.000000	202.122500	347.000000	202.122500
max	8.500000	409.621250	695.000000	409.621250

```
pt = PowerTransformer(method = 'yeo-johnson')
for var in transformed_data:
    if var in
['delivered_estimated','geolocation_lat','geolocation_lng']:
        transformed_data[var] =
pt.fit_transform(transformed_data[[var]])

pt = PowerTransformer(method='box-cox')
for var in transformed_data.select_dtypes(include=np.number):
    if var not in
['delivered_estimated','geolocation_lat','geolocation_lng']:
        transformed_data[var] = pt.fit_transform(0.001 +
transformed_data[[var]])

transformed_data.skew()
```

```
purchased_approved      0.136317
delivered_estimated     0.102573
purchased_delivered    -0.025024
price                  -0.029814
freight_value           0.177740
product_weight_g       -0.004216
product_length_cm       0.101678
product_height_cm      -0.033945
product_width_cm        0.070255
geolocation_lat         0.032696
geolocation_lng        -0.013325
payment_installments   -0.367193
payment_value          -0.000312
Recency                -0.161802
Monetary               -0.000312
Churn                   0.184461
dtype: float64
```

Observations:

1. The variables which have **negative values** are transformed using **yeo-johnson** method, as log of 0 or negative values would return infinite value.

2. The variables which has **only positive values** in it are transformed using **box-cox** method.

16. Classification Models

```
transformed_data.head()

                  customer_unique_id customer_city customer_state  \
0  0000366f3b9a7992bf8c76cfdf3221e2       cajamar             SP
1  0000b849f77a49e4a4ce2b2a4ca5be3f        osasco             SP
2  0000f46a3911fa3c0805444483337064      sao jose             SC
3  0000f6ccb0745a6a4b88665a16c9f078         belem             PA
4  0004aac84e0df4da2b147fca70cf8255      sorocaba             SP

   purchased_approved  delivered_estimated  purchased_delivered
price  \
0           -0.579563            -0.866609            -0.725370
0.452317
1            1.299464            -0.866609            -1.516359 -
1.663291
2           -3.569347            -1.214404             1.609794 -
0.307908
3           -0.452622            -0.016225             1.167662 -
1.352995
4           -0.416681            -0.506891             0.401717
0.872268

   freight_value  product_weight_g  product_length_cm
product_height_cm  \
0      -0.869439          0.460791           0.378968           -
0.913417
1      -1.410467         -0.678234          -0.167282           -
0.383337
2      -0.258318          0.460791          -0.253514
1.750517
3      -0.215367         -1.409315          -0.907027           -
1.272156
4      -0.293336          1.525512          -1.364730           -
1.764051

   product_width_cm  geolocation_lat  geolocation_lng payment_type  \
0          0.712075        -0.339009        -0.147663  credit_card
1         -0.427525        -0.403676        -0.136448  credit_card
2          0.867575        -1.742476        -0.641800  credit_card
3         -1.629117         1.762773        -0.601932  credit_card
4         -1.629117        -0.388799        -0.321518  credit_card
```

```
   payment_installments  payment_value   Recency  Monetary Churn
0              1.594216       0.278586 -0.750358  0.278586     0
1             -0.934791      -1.840386 -0.724705 -1.840386     0
2              1.594216      -0.360895  1.654413 -0.360895     1
3              0.923510      -1.234730  0.630258 -1.234730     1
4              1.333123       0.699222  0.449167  0.699222     1
```

```
def state_encoding(state):
    if state in ['RS', 'SC', 'PR']:
        return 'southern'
    elif state in ['SP', 'RJ', 'MG', 'ES']:
        return 'southeastern'
    elif state in ['MT', 'MS', 'GO', 'DF']:
        return 'centralwestern'
    elif state in ['MA', 'PI', 'CE', 'RN', 'PB', 'PE', 'AL', 'SE',
'BA']:
        return 'northeastern'
    else:
        return 'northern'

transformed_data['customer_state'] =
transformed_data['customer_state'].apply(state_encoding)
```

Observation:

1. Since the states are spread across the brazil, we are grouping the states based on the regions they are in, namely **southern**, **southeastern**, **centralwestern**, **northeastern** and **northern**.

```
features = transformed_data.copy()
features.head()
```

```
                 customer_unique_id customer_city customer_state  \
0  0000366f3b9a7992bf8c76cfdf3221e2       cajamar   southeastern
1  0000b849f77a49e4a4ce2b2a4ca5be3f        osasco   southeastern
2  0000f46a3911fa3c0805444483337064      sao jose       southern
3  0000f6ccb0745a6a4b88665a16c9f078         belem       northern
4  0004aac84e0df4da2b147fca70cf8255      sorocaba   southeastern

   purchased_approved  delivered_estimated  purchased_delivered
price  \
0           -0.579563            -0.866609            -0.725370
0.452317
1            1.299464            -0.866609            -1.516359 -
1.663291
2           -3.569347            -1.214404             1.609794 -
0.307908
3           -0.452622            -0.016225             1.167662 -
1.352995
4           -0.416681            -0.506891             0.401717
```

```
0.872268

   freight_value  product_weight_g  product_length_cm
product_height_cm  \
0      -0.869439          0.460791           0.378968          -
0.913417
1      -1.410467         -0.678234          -0.167282          -
0.383337
2      -0.258318          0.460791          -0.253514
1.750517
3      -0.215367         -1.409315          -0.907027          -
1.272156
4      -0.293336          1.525512          -1.364730          -
1.764051

   product_width_cm  geolocation_lat  geolocation_lng payment_type  \
0          0.712075        -0.339009        -0.147663  credit_card
1         -0.427525        -0.403676        -0.136448  credit_card
2          0.867575        -1.742476        -0.641800  credit_card
3         -1.629117         1.762773        -0.601932  credit_card
4         -1.629117        -0.388799        -0.321518  credit_card

   payment_installments  payment_value   Recency  Monetary Churn
0              1.594216       0.278586 -0.750358  0.278586     0
1             -0.934791      -1.840386 -0.724705 -1.840386     0
2              1.594216      -0.360895  1.654413 -0.360895     1
3              0.923510      -1.234730  0.630258 -1.234730     1
4              1.333123       0.699222  0.449167  0.699222     1
```

```
features.drop(columns = ['customer_unique_id', 'customer_city',
'payment_value'], axis = 1, inplace = True)
```

Observations:

1. Since the `payment_value` feature is same as that of the `Monetary` feature, the former is dropped.
2. Similarly, `customer_city` is a **multi-class feature**, so encoding it would be useless. So we drop the feature.

```
features.head(1)

  customer_state  purchased_approved  delivered_estimated  \
0   southeastern           -0.579563            -0.866609

   purchased_delivered     price  freight_value  product_weight_g  \
0             -0.72537  0.452317      -0.869439          0.460791

   product_length_cm  product_height_cm  product_width_cm
geolocation_lat  \
0           0.378968          -0.913417          0.712075         -
```

```
0.339009

   geolocation_lng payment_type  payment_installments   Recency
Monetary  \
0        -0.147663  credit_card              1.594216 -0.750358
0.278586

  Churn
0     0

independent = features.drop(columns = ['Churn'], axis = 1)
df_numeric = independent.select_dtypes(include = np.number)
df_categorical = independent.select_dtypes(exclude = np.number)
df_target = features['Churn'].astype('int')

encoded_data = pd.get_dummies(df_categorical, drop_first = True)

X = pd.concat([df_numeric, encoded_data], axis = 1)
X.drop(columns = ['Recency'], axis = 1, inplace = True)
```

Observation:

1. The `Recency` feature is dropped for the model building, as it is **used to create the target variable**. Predictions would be 100% accurate if the `Recency` feature is not dropped, which would be a good model.

16.1. Train-Test split

```
X_train, X_test, y_train, y_test =
train_test_split(sm.add_constant(X), df_target, random_state = 500,
test_size = 0.2)

# check the dimensions of the train & test subset using 'shape'
# print dimension of train set
print('X_train', X_train.shape)
print('y_train', y_train.shape)

# print dimension of test set
print('X_test', X_test.shape)
print('y_test', y_test.shape)

X_train (72422, 21)
y_train (72422,)
X_test (18106, 21)
y_test (18106,)
```

Statistically proving train & test are good representations of overall data A t-test independence on each column to show both have equal or similar representation. **Null**

Hypothesis, H0: Both sets have same mean, thus they have equal representation. **Alternate Hypothesis, Ha**: Both sets have unequal means, thus unequal representation.

```
tstats,pvals = stats.ttest_ind(X_train, X_test)
ref_df = pd.DataFrame(pvals,index=X_train.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

Observation:

1. As all the columns have **p-values greater than significance level of 0.05**, we **do not reject the null hypothesis** and we can conclude that **all independent features are properly represented both in train and test sets**.

16.2. Logit Regression

```
logreg = sm.Logit(y_train, X_train).fit()
print(logreg.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.657903
         Iterations 5
                           Logit Regression Results

======================================================================
========
Dep. Variable:                  Churn   No. Observations:
72422
Model:                          Logit   Df Residuals:
72401
Method:                           MLE   Df Model:
20
Date:                Mon, 17 Apr 2023   Pseudo R-squ.:
0.04488
Time:                        13:46:26   Log-Likelihood:
-47647.
converged:                       True   LL-Null:
-49886.
Covariance Type:            nonrobust   LLR p-value:
0.000
======================================================================
=========================
                                  coef    std err          z      P>|
z|      [0.025      0.975]
----------------------------------------------------------------------
-------------------------
```

```
const                                          0.5539      0.052     10.610
0.000       0.452       0.656
purchased_approved                            -0.4150      0.011    -36.712
0.000      -0.437      -0.393
delivered_estimated                            0.2954      0.009     33.278
0.000       0.278       0.313
purchased_delivered                            0.3527      0.010     34.941
0.000       0.333       0.372
price                                         -0.0526      0.027     -1.959
0.050      -0.105    3.78e-05
freight_value                                 -0.3367      0.013    -24.985
0.000      -0.363      -0.310
product_weight_g                               0.0826      0.013      6.570
0.000       0.058       0.107
product_length_cm                              0.1097      0.012      8.986
0.000       0.086       0.134
product_height_cm                              0.0398      0.010      4.032
0.000       0.020       0.059
product_width_cm                               0.0902      0.012      7.324
0.000       0.066       0.114
geolocation_lat                                0.0168      0.018      0.925
0.355      -0.019       0.052
geolocation_lng                                0.0249      0.014      1.812
0.070      -0.002       0.052
payment_installments                           0.1951      0.010     19.435
0.000       0.175       0.215
Monetary                                      -0.0287      0.029     -0.979
0.328      -0.086       0.029
customer_state_northeastern                    0.1071      0.056      1.908
0.056      -0.003       0.217
customer_state_northern                        0.2138      0.067      3.203
0.001       0.083       0.345
customer_state_southeastern                    0.0472      0.049      0.960
0.337      -0.049       0.144
customer_state_southern                        0.1064      0.065      1.642
0.100      -0.021       0.233
payment_type_credit_card                      -1.0318      0.030    -34.154
0.000      -1.091      -0.973
payment_type_debit_card                       -1.2875      0.072    -17.882
0.000      -1.429      -1.146
payment_type_voucher                          -0.5176      0.053     -9.800
0.000      -0.621      -0.414
======================================================================
=========================
```

```
print('Akaike information criterion (AIC):', logreg.aic)
```

```
Akaike information criterion (AIC): 95335.32324162214
```

Observations:

1. The Akaike Information Criteria (AIC) is a **relative measure of model evaluation** for a given dataset.
2. It is given by: **-2 ln(L) + 2K**, where, L - Log Likelihood, K - Parameters to be estimated.
3. The AIC gives a **trade-off between the model accuracy and model complexity**, i.e., it **prevents from overfitting**.

Interpret the odds for each variable

```
logreg.params
```

```
const                          0.553923
purchased_approved            -0.414969
delivered_estimated            0.295429
purchased_delivered            0.352659
price                         -0.052581
freight_value                 -0.336701
product_weight_g               0.082564
product_length_cm              0.109722
product_height_cm              0.039835
product_width_cm               0.090170
geolocation_lat                0.016818
geolocation_lng                0.024936
payment_installments           0.195125
Monetary                      -0.028668
customer_state_northeastern    0.107067
customer_state_northern        0.213828
customer_state_southeastern    0.047175
customer_state_southern        0.106366
payment_type_credit_card      -1.031811
payment_type_debit_card       -1.287465
payment_type_voucher          -0.517560
dtype: float64
```

```
df_odds = pd.DataFrame(np.exp(logreg.params), columns= ['Odds'])
df_odds
```

	Odds
const	1.740065
purchased_approved	0.660360
delivered_estimated	1.343703
purchased_delivered	1.422846
price	0.948778
freight_value	0.714122
product_weight_g	1.086068
product_length_cm	1.115968
product_height_cm	1.040639
product_width_cm	1.094360
geolocation_lat	1.016960
geolocation_lng	1.025250
payment_installments	1.215462

```
Monetary                        0.971739
customer_state_northeastern     1.113009
customer_state_northern         1.238409
customer_state_southeastern     1.048305
customer_state_southern         1.112229
payment_type_credit_card        0.356361
payment_type_debit_card         0.275969
payment_type_voucher            0.595973
```

Observations:

1. `const`: The **odds of customer churning** is **0.490694**, considering **all other variables take zero value**.
2. `purchased_delivered` = **1.41**, which implies that the **odds of customer churning increases by a factor of 1.41** due to **one unit increase in the days taken for order to get delivered to the customer from the date it was purchased**, keeping other variables constant.

Predict values

```
#train set
y_pred_prob_train = logreg.predict(X_train)
y_pred_train = [ 0 if x < 0.5 else 1 for x in y_pred_prob_train]

#test set
y_pred_prob = logreg.predict(X_test)
y_pred_prob.head()

68625    0.401219
64892    0.346073
83200    0.374344
66023    0.545440
17448    0.395183
dtype: float64

y_pred = [ 0 if x < 0.5 else 1 for x in y_pred_prob]
y_pred[0:5]

[0, 0, 0, 1, 0]
```

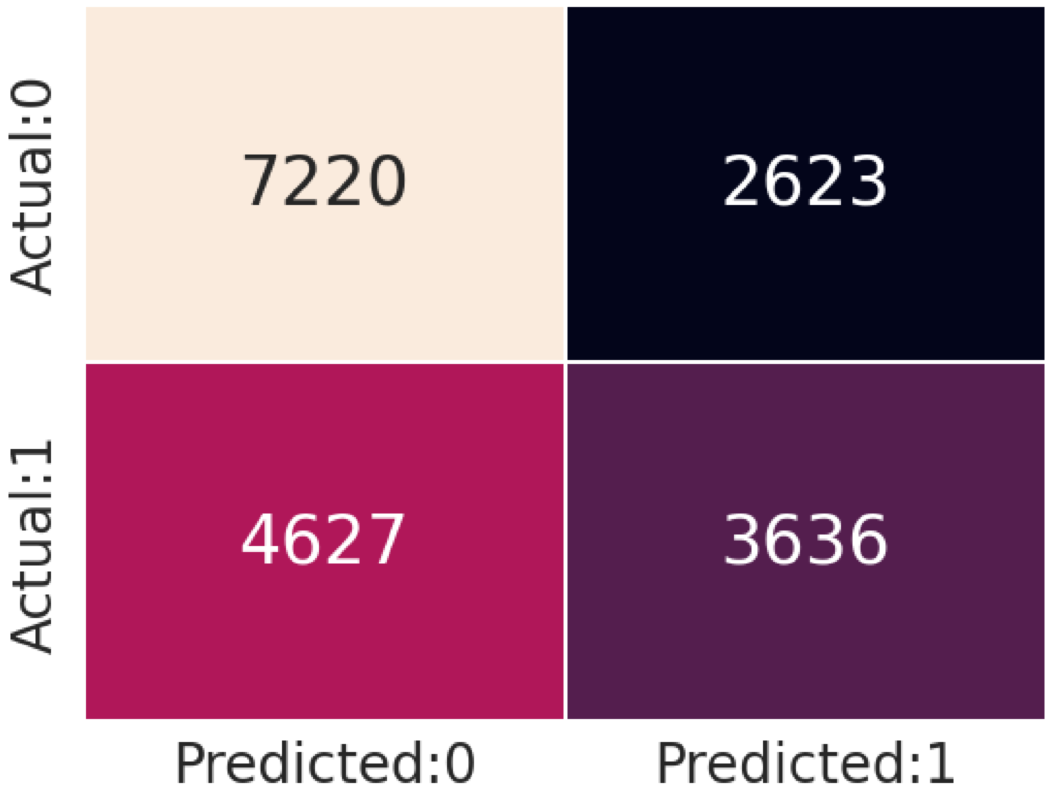
Observation:

1. Since the target variable can take only two values either 0 or 1. We decide the cut-off of 0.5, i.e., if `y_pred_prob` is less than 0.5, then consider it to be 0 else consider it to be 1.

Confusion Matrix

```
cm = confusion_matrix(y_test, y_pred)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
```

```
              linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```



Classification Report

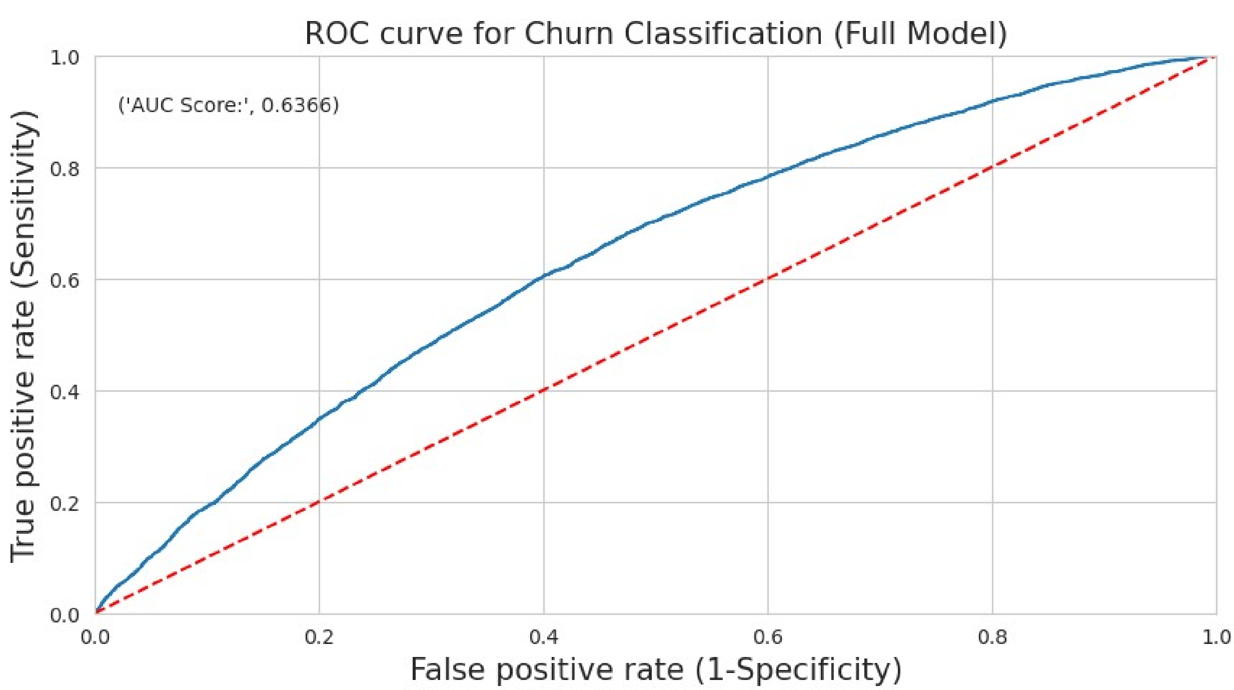
```
acc_table = classification_report(y_test, y_pred)
print(acc_table)

              precision    recall  f1-score   support

           0       0.61      0.73      0.67      9843
           1       0.58      0.44      0.50      8263

    accuracy                           0.60     18106
   macro avg       0.60      0.59      0.58     18106
weighted avg       0.60      0.60      0.59     18106


kappa = cohen_kappa_score(y_test, y_pred)
print('kappa value:',kappa)

kappa value: 0.176995345766783
```

Observations:

1. From the above output, we can infer that the **recall of the positive class** is known as **sensitivity** and the **recall of the negative class** is **specificity**.
2. **Support** is the **number of observations in the corresponding class**.
3. The **macro average** in the output is obtained by **averaging the unweighted mean per label** and the **weighted average** is given by **averaging the support-weighted mean per label**.
4. **Kappa score** is a **measure of inter-rater reliability**. For logistic regression, the actual and predicted values of the target variable are the raters.
5. As the kappa score for the full model (with cut-off probability 0.5) is **0.189**, we can say that there is **slight agreement between the actual and predicted values**.

ROC curve

```
plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve for Churn Classification (Full Model)', fontsize
= 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(y_test, y_pred_prob),4)))
plt.grid(True)
```



Observations:

1. ROC curve is plotted with the **true positive rate (tpr) on the y-axis** and **false positive rate (fpr) on the x-axis.** The area under this curve is used as a **measure of separability of the model**.
2. The **red dotted line** represents the ROC curve of a **purely random classifier**. A good classifier stays as far away from that line as possible (toward the top-left corner).
3. From the above plot, we can see that our classifier (logistic regression) is **near the dotted line**, with the **AUC score 0.644**.

```
cols = ['test_accuracy', 'train_accuracy', 'test_precision',
'train_precision','test_recall','train_recall', 'test_kappa',
'train_kappa', 'f1_score','roc_auc_score']
model_evaluation = pd.DataFrame(columns=cols)
model_evaluation.loc['Logit_FullModel'] =
[accuracy_score(y_test,y_pred), accuracy_score(y_train,y_pred_train),

precision_score(y_test,y_pred), precision_score(y_train,y_pred_train),
                                          recall_score(y_test,y_pred),
recall_score(y_train,y_pred_train),

cohen_kappa_score(y_test,y_pred),
cohen_kappa_score(y_train,y_pred_train),
                                          f1_score(y_test,y_pred),
roc_auc_score(y_test,y_pred_prob)]
model_evaluation
```

```
                 test_accuracy  train_accuracy  test_precision  \
Logit_FullModel        0.59958        0.604664        0.580923

                 train_precision  test_recall  train_recall
test_kappa  \
Logit_FullModel         0.585135     0.440034      0.440811
0.176995

                 train_kappa  f1_score  roc_auc_score
Logit_FullModel     0.185339  0.500757       0.636576
```

Identify the Best Cut-off Value - Youden's Index

```
youdens_table = pd.DataFrame({'TPR': tpr,
                             'FPR': fpr,
                             'Threshold': thresholds})
youdens_table['Difference'] = youdens_table.TPR - youdens_table.FPR
youdens_table = youdens_table.sort_values('Difference', ascending =
False).reset_index(drop = True)
youdens_table.head()
```

```
        TPR       FPR  Threshold  Difference
0  0.681956  0.474449   0.434289    0.207507
1  0.680988  0.473839   0.434408    0.207148
```

```
2  0.680867  0.473738   0.434422    0.207129
3  0.682077  0.474957   0.434159    0.207120
4  0.682198  0.475160   0.434126    0.207038
```

Observations:

1. Youden's Index is the classification cut-off probability for which the (Sensitivity + Specificity - 1) is maximized.
2. Youden's Index = max(Sensitivity + Specificity - 1) = max(TPR + TNR - 1) = max(TPR - FPR)
3. As we can see that the **optimal cut-off probability is approximately 0.455**. Let us consider this cut-off to predict the target values, i.e., if `y_pred_prob` is less than 0.455, then consider it to be 0 else consider it to be 1.
4. Model evaluation metrics are calculated with the cut-off value obtained from youden's cut-off value.

```
y_pred_train_youden = [ 0 if x < 0.455 else 1 for x in
y_pred_prob_train]
y_pred_youden = [ 0 if x < 0.455 else 1 for x in y_pred_prob]

model_evaluation.loc['Logit_FullModel'] =
[accuracy_score(y_test,y_pred_youden),
accuracy_score(y_train,y_pred_train_youden),

precision_score(y_test,y_pred_youden),
precision_score(y_train,y_pred_train_youden),

recall_score(y_test,y_pred_youden),
recall_score(y_train,y_pred_train_youden),

cohen_kappa_score(y_test,y_pred_youden),
cohen_kappa_score(y_train,y_pred_train_youden),

f1_score(y_test,y_pred_youden), roc_auc_score(y_test,y_pred_prob)]
model_evaluation

                 test_accuracy  train_accuracy  test_precision  \
Logit_FullModel       0.601513        0.604402        0.558365

                 train_precision  test_recall  train_recall
test_kappa  \
Logit_FullModel         0.558812      0.60668      0.606656
0.20245

                 train_kappa  f1_score  roc_auc_score
Logit_FullModel     0.207675  0.581521       0.636576
```

16.3. Decision Tree model

```
xtrain_dt, xtest_dt, ytrain_dt, ytest_dt = train_test_split(X,
df_target, test_size = 0.2, random_state = 500)
print('xtrain: ', xtrain_dt.shape)
print('ytrain: ', ytrain_dt.shape)
print('xtest: ', xtest_dt.shape)
print('ytest: ', ytest_dt.shape)
```

```
xtrain:  (72422, 20)
ytrain:  (72422,)
xtest:  (18106, 20)
ytest:  (18106,)
```

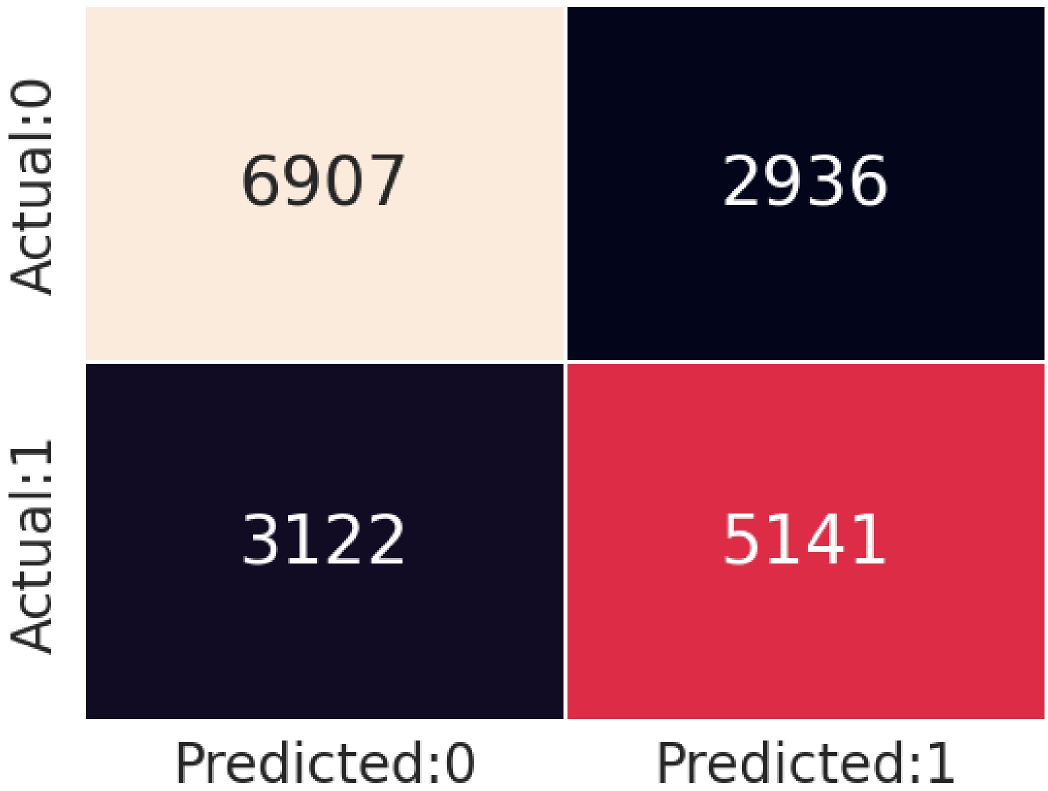
```
tstats,pvals = stats.ttest_ind(xtrain_dt, xtest_dt)
ref_df = pd.DataFrame(pvals,index=xtrain_dt.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

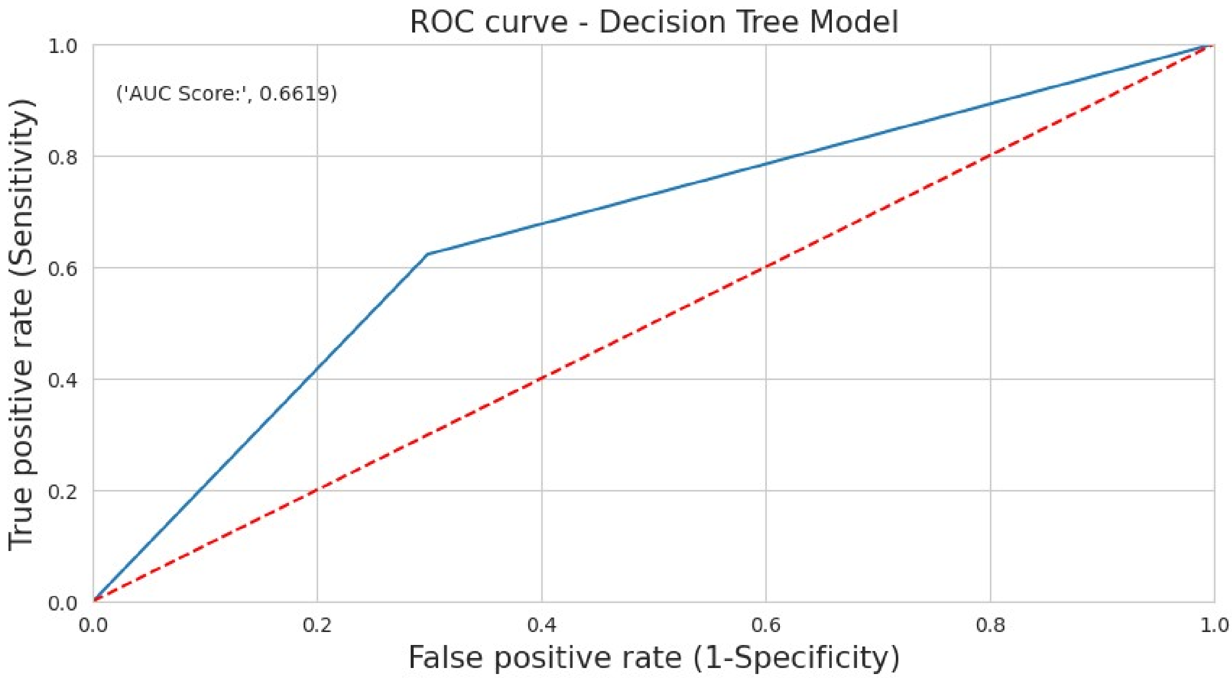
```
decisionTree = DecisionTreeClassifier()
decisionTree = decisionTree.fit(xtrain_dt, ytrain_dt)

ypred_proba_dt = decisionTree.predict(xtest_dt)

ypred_dt = [0 if i < 0.5 else 1 for i in ypred_proba_dt]
ypred_dt[:10]
```

```
[0, 0, 0, 0, 1, 0, 1, 0, 1, 1]
```

```
ypred_proba_dt_train = decisionTree.predict(xtrain_dt)
ypred_dt_train = [0 if i < 0.5 else 1 for i in ypred_proba_dt_train]

cm = confusion_matrix(ytest_dt, ypred_dt)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_dt, ypred_dt))

              precision    recall  f1-score   support

           0       0.69      0.70      0.70      9843
           1       0.64      0.62      0.63      8263

    accuracy                           0.67     18106
   macro avg       0.66      0.66      0.66     18106
weighted avg       0.66      0.67      0.67     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_dt, ypred_proba_dt)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - Decision Tree Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_dt, ypred_proba_dt),4)))
plt.grid(True)
```




```
model_evaluation.loc['DecisionTree'] = [accuracy_score(ytest_dt,
ypred_dt), accuracy_score(ytrain_dt, ypred_dt_train),
                                          precision_score(ytest_dt,
ypred_dt), precision_score(ytrain_dt, ypred_dt_train),
                                          recall_score(ytest_dt,
ypred_dt), recall_score(ytrain_dt, ypred_dt_train),
                                          cohen_kappa_score(ytest_dt,
ypred_dt), cohen_kappa_score(ytrain_dt, ypred_dt_train),
                                          f1_score(ytest_dt,
ypred_dt), roc_auc_score(ytest_dt, ypred_proba_dt)]
model_evaluation

                 test_accuracy  train_accuracy  test_precision  \
Logit_FullModel       0.601513        0.604402        0.558365
DecisionTree          0.665415        1.000000        0.636499

                 train_precision  test_recall  train_recall
test_kappa  \
Logit_FullModel         0.558812     0.606680      0.606656
0.202450
DecisionTree            1.000000     0.622171      1.000000
0.324474

                 train_kappa  f1_score  roc_auc_score
Logit_FullModel     0.207675  0.581521       0.636576
DecisionTree        1.000000  0.629253       0.661944
```

16.4. XG Boost Model

```
xtrain_xg, xtest_xg, ytrain_xg, ytest_xg = train_test_split(X,
df_target, test_size = 0.2, random_state = 500)
print('xtrain: ', xtrain_xg.shape)
print('ytrain: ', ytrain_xg.shape)
print('xtest: ', xtest_xg.shape)
print('ytest: ', ytest_xg.shape)
```

```
xtrain:  (72422, 20)
ytrain:  (72422,)
xtest:  (18106, 20)
ytest:  (18106,)
```

```
tstats,pvals = stats.ttest_ind(xtrain_xg, xtest_xg)
ref_df = pd.DataFrame(pvals,index=xtrain_xg.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

```
xgBoost = XGBClassifier()
xbBoost = xgBoost.fit(xtrain_xg, ytrain_xg)
```

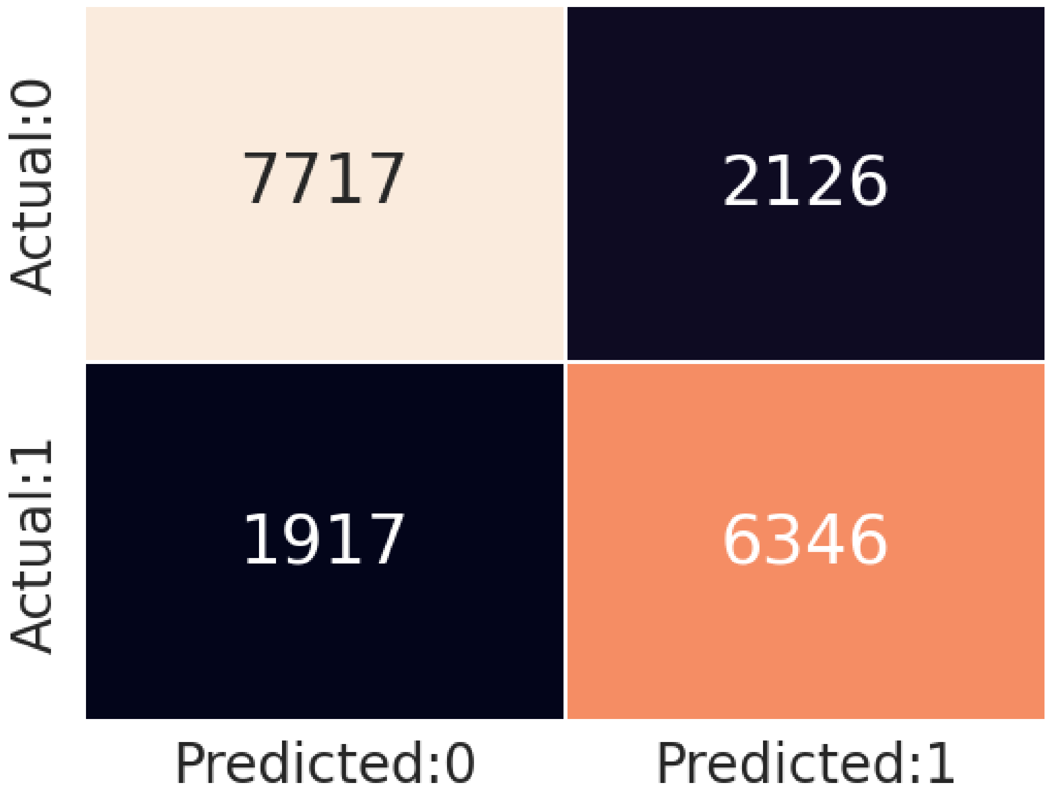
```
ypred_proba_xg = xgBoost.predict(xtest_xg)
```

```
ypred_xg = [0 if i < 0.5 else 1 for i in ypred_proba_xg]
ypred_xg[:10]
```

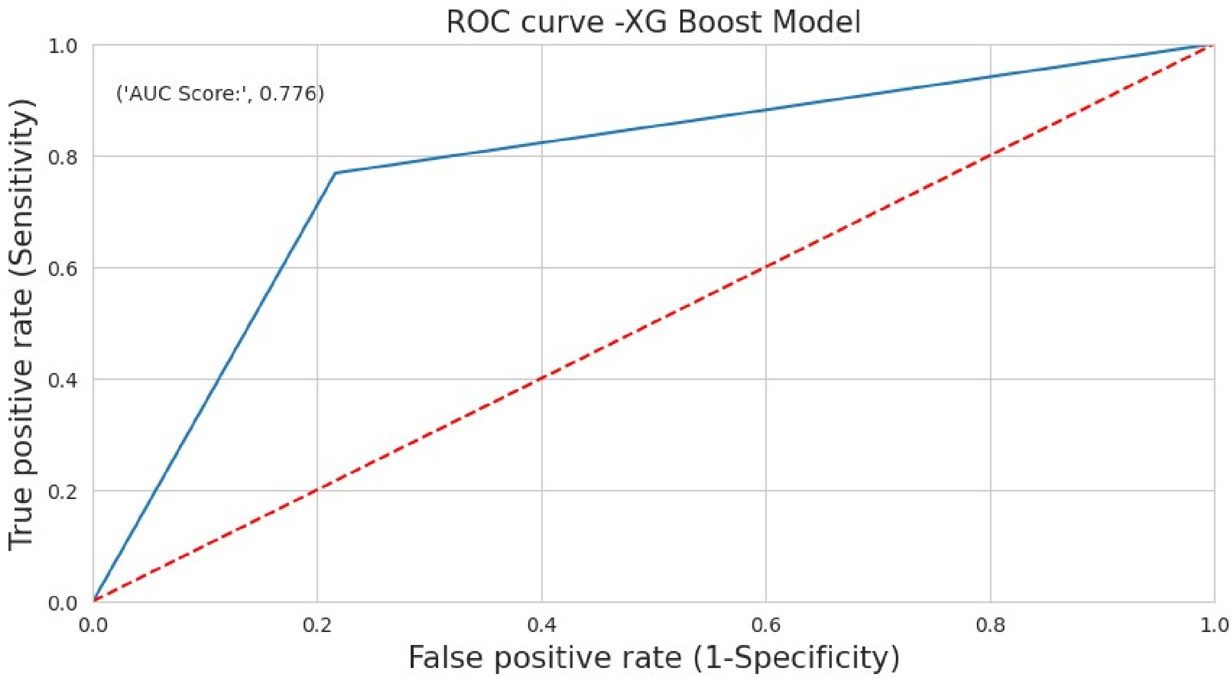
```
[0, 0, 0, 1, 1, 0, 1, 0, 1, 1]
```

```
ypred_proba_xg_train = xgBoost.predict(xtrain_xg)
ypred_xg_train = [0 if i < 0.5 else 1 for i in ypred_proba_xg_train]
```

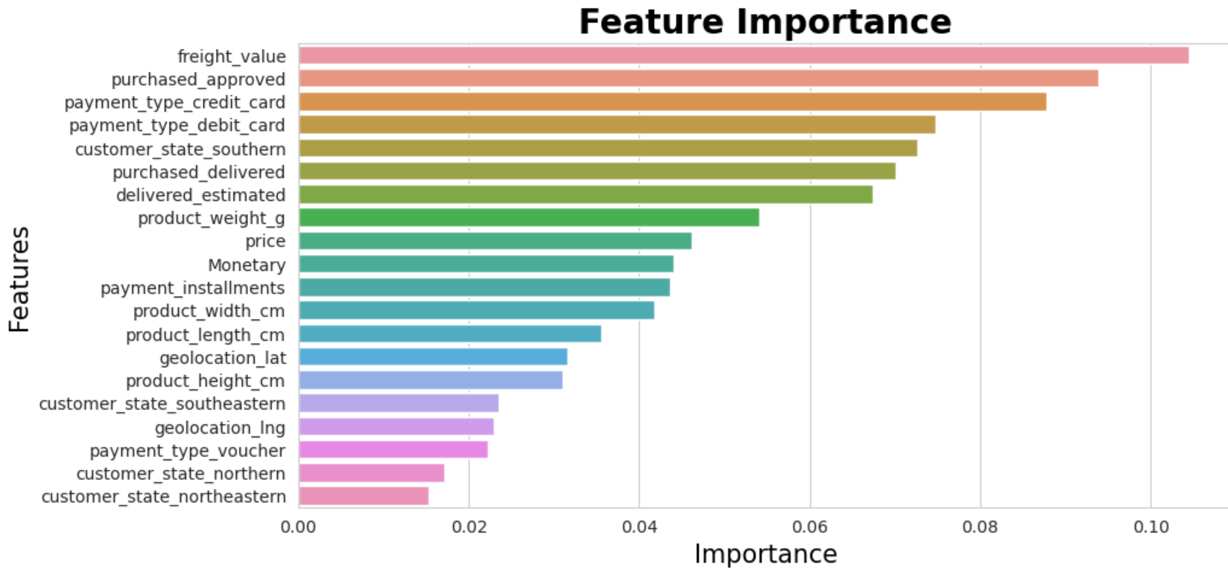
```
cm = confusion_matrix(ytest_xg, ypred_xg)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_xg, ypred_xg))

              precision    recall  f1-score   support

           0       0.80      0.78      0.79      9843
           1       0.75      0.77      0.76      8263

    accuracy                           0.78     18106
   macro avg       0.78      0.78      0.78     18106
weighted avg       0.78      0.78      0.78     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_xg, ypred_proba_xg)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve -XG Boost Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_xg, ypred_proba_xg),4)))
plt.grid(True)
```




```
plt.figure(figsize=(10, 5))
important_features = pd.DataFrame({'Features': xtrain_xg.columns,
                                   'Importance':
xbBoost.feature_importances_})
important_features = important_features.sort_values('Importance',
ascending = False)
sns.barplot(x = 'Importance', y = 'Features', data =
important_features)
plt.title('Feature
Importance',color='black',fontsize=20,fontweight='bold')
plt.xlabel('Importance',color='black',fontsize=15)
plt.ylabel('Features',color='black',fontsize=15)
plt.show()
```




```
model_evaluation.loc['XGBoost'] = [accuracy_score(ytest_xg, ypred_xg),
accuracy_score(ytrain_xg, ypred_xg_train),
                                   precision_score(ytest_xg,
ypred_xg), precision_score(ytrain_xg, ypred_xg_train),
                                   recall_score(ytest_xg,
ypred_xg), recall_score(ytrain_xg, ypred_xg_train),
                                   cohen_kappa_score(ytest_xg,
ypred_xg), cohen_kappa_score(ytrain_xg, ypred_xg_train),
                                   f1_score(ytest_xg,
ypred_xg), roc_auc_score(ytest_xg, ypred_proba_xg)]
model_evaluation
```

	test_accuracy	train_accuracy	test_precision	train_precision	test_recall	train_recall	test_kappa	train_kappa	f1_score	roc_auc_score
Logit_FullModel	0.601513	0.604402	0.558365	0.558812	0.606680	0.606656	0.202450	0.207675	0.581521	0.636576
DecisionTree	0.665415	1.000000	0.636499	1.000000	0.622171	1.000000	0.324474	1.000000	0.629253	0.661944
XGBoost	0.776704	0.834015	0.749056	0.805924	0.768002	0.835099	0.550893	0.666162	0.758411	0.776005

16.5. Random Forest Classifier

```
xtrain_random, xtest_random, ytrain_random, ytest_random =
train_test_split(X, df_target, test_size = 0.2, random_state = 500)
print('xtrain: ', xtrain_random.shape)
print('ytrain: ', ytrain_random.shape)
print('xtest: ', xtest_random.shape)
print('ytest: ', ytest_random.shape)
```

```
xtrain:  (72422, 20)
ytrain:  (72422,)
xtest:  (18106, 20)
ytest:  (18106,)
```

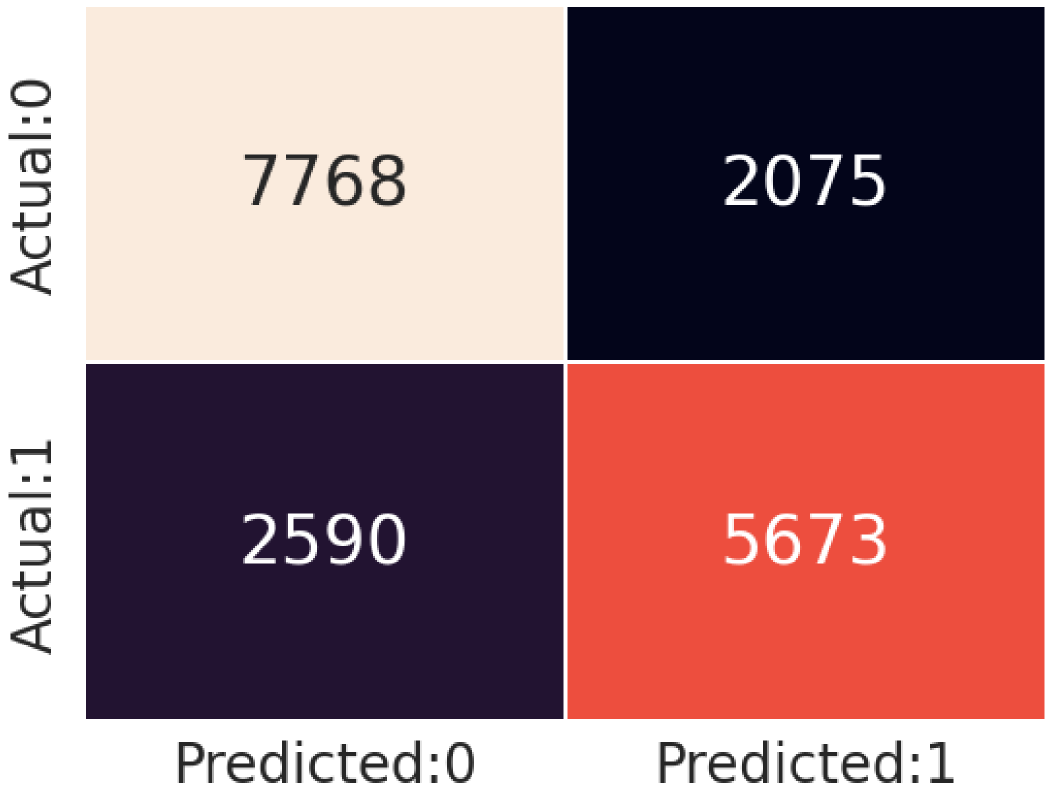
```
tstats,pvals = stats.ttest_ind(xtrain_random, xtest_random)
ref_df =
pd.DataFrame(pvals,index=xtrain_random.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

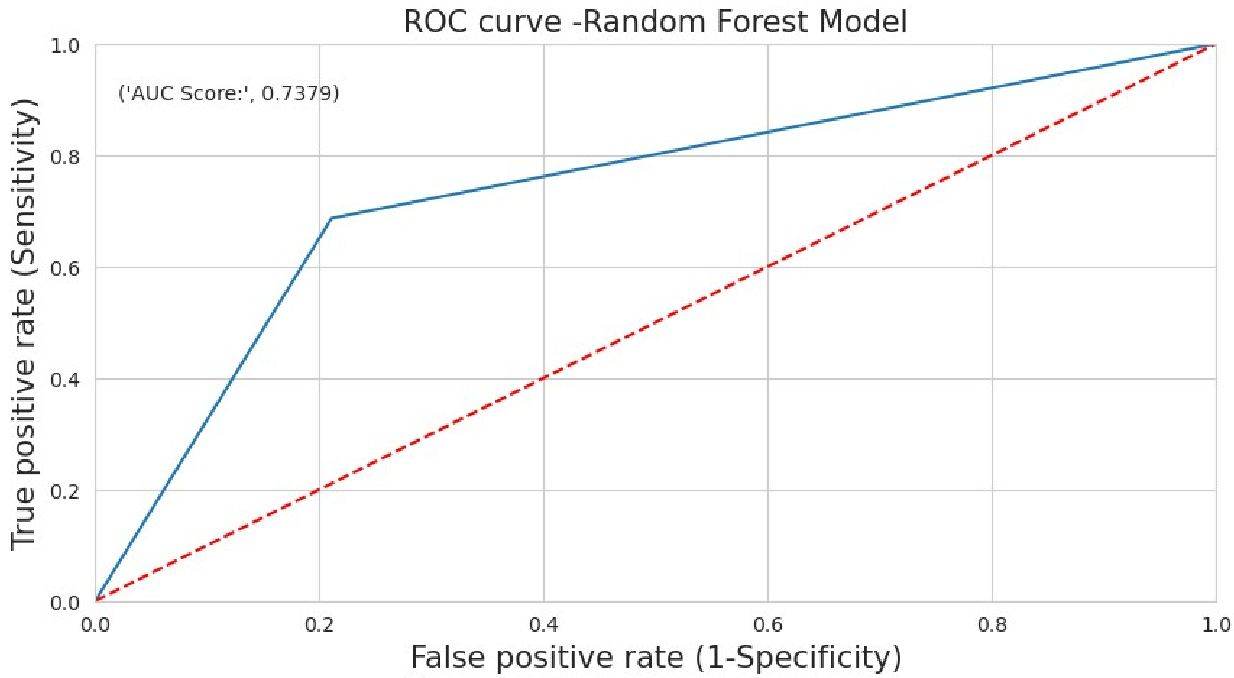
```
rand = RandomForestClassifier()
rand_model = rand.fit(xtrain_random,ytrain_random)

ypred_proba_random = rand_model.predict(xtest_random)

ypred_random = [0 if i < 0.5 else 1 for i in ypred_proba_random]
ypred_random[:10]
```

```
[0, 0, 0, 1, 1, 0, 1, 0, 1, 1]
```

```
ypred_proba_random_train = rand_model.predict(xtrain_random)
ypred_random_train = [0 if i < 0.5 else 1 for i in
ypred_proba_random_train]

cm = confusion_matrix(ytest_random, ypred_random)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_random, ypred_random))

              precision    recall  f1-score   support

           0       0.75      0.79      0.77      9843
           1       0.73      0.69      0.71      8263

    accuracy                           0.74     18106
   macro avg       0.74      0.74      0.74     18106
weighted avg       0.74      0.74      0.74     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_random, ypred_proba_random)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve -Random Forest Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_random, ypred_proba_random),4)))
plt.grid(True)
```




```
model_evaluation.loc['RandomForest Classifier'] =
[accuracy_score(ytest_random, ypred_random),
accuracy_score(ytrain_random, ypred_random_train),

precision_score(ytest_random, ypred_random),
precision_score(ytrain_random, ypred_random_train),
                                        recall_score(ytest_random,
ypred_random), recall_score(ytrain_random, ypred_random_train),

cohen_kappa_score(ytest_random, ypred_random),
cohen_kappa_score(ytrain_random, ypred_random_train),
                                        f1_score(ytest_random,
ypred_random), roc_auc_score(ytest_random, ypred_proba_random)]
model_evaluation
```

	test_accuracy	train_accuracy	test_precision \
Logit_FullModel	0.601513	0.604402	0.558365
DecisionTree	0.665415	1.000000	0.636499
XGBoost	0.776704	0.834015	0.749056
RandomForest Classifier	0.742351	1.000000	0.732189

	train_precision	test_recall	train_recall \
Logit_FullModel	0.558812	0.606680	0.606656
DecisionTree	1.000000	0.622171	1.000000

```
XGBoost                             0.805924     0.768002      0.835099
RandomForest Classifier             1.000000     0.686555      1.000000

                             test_kappa  train_kappa  f1_score
roc_auc_score
Logit_FullModel                0.202450     0.207675  0.581521
0.636576
DecisionTree                   0.324474     1.000000  0.629253
0.661944
XGBoost                        0.550893     0.666162  0.758411
0.776005
RandomForest Classifier        0.478137     1.000000  0.708638
0.737872
```

16.6. KNN 2 Clusters Model

```
xtrain_kn, xtest_kn, ytrain_kn, ytest_kn = train_test_split(X,
df_target, test_size = 0.2, random_state = 500)
print('xtrain: ', xtrain_kn.shape)
print('ytrain: ', ytrain_kn.shape)
print('xtest: ', xtest_kn.shape)
print('ytest: ', ytest_kn.shape)
```

```
xtrain:  (72422, 20)
ytrain:  (72422,)
xtest:  (18106, 20)
ytest:  (18106,)
```

```
tstats,pvals = stats.ttest_ind(xtrain_kn, xtest_kn)
ref_df = pd.DataFrame(pvals,index=xtrain_kn.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

```
knn = KNeighborsClassifier(n_neighbors=2)
knn_model = knn.fit(xtrain_kn,ytrain_kn)
```

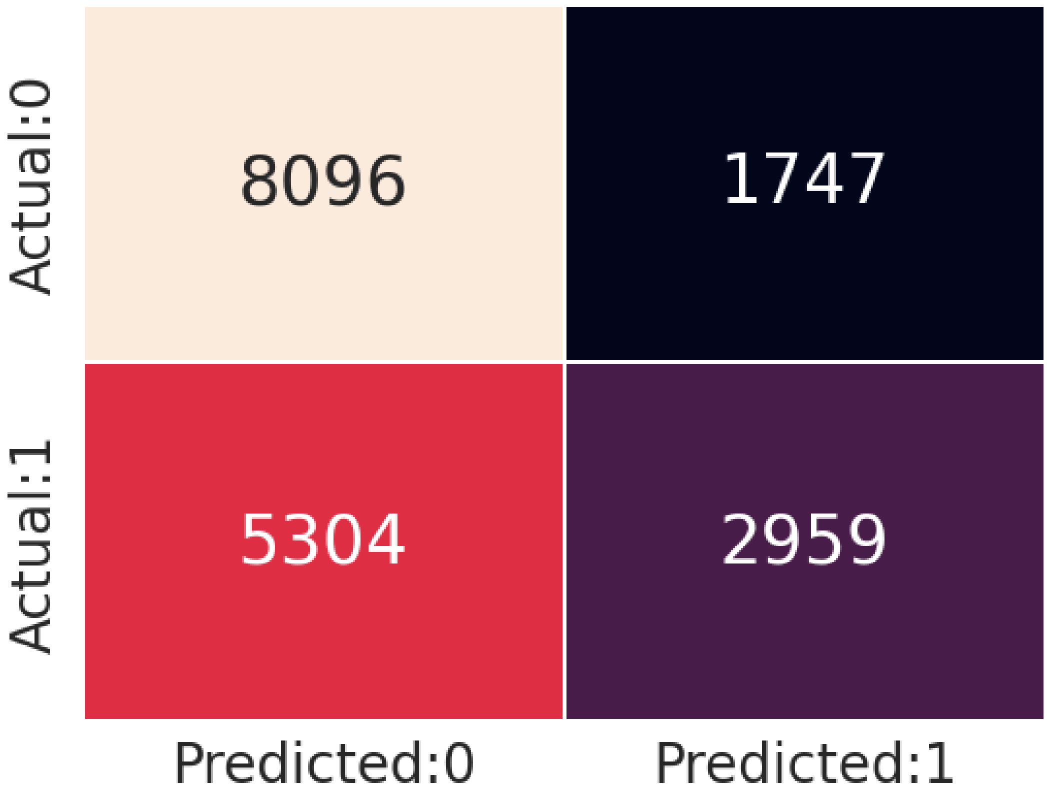
```
ypred_proba_knn = knn_model.predict(xtest_kn)
ypred_knn = [0 if i < 0.5 else 1 for i in ypred_proba_knn]
ypred_knn[:10]
```

```
[0, 0, 0, 0, 0, 0, 0, 0, 1, 1]
```

```
ypred_proba_knn_train = knn_model.predict(xtrain_kn)
ypred_knn_train = [0 if i < 0.5 else 1 for i in ypred_proba_knn_train]
```

```
cm = confusion_matrix(ytest_kn, ypred_knn)
conf_matrix = pd.DataFrame(data = cm,columns =
```

```
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```

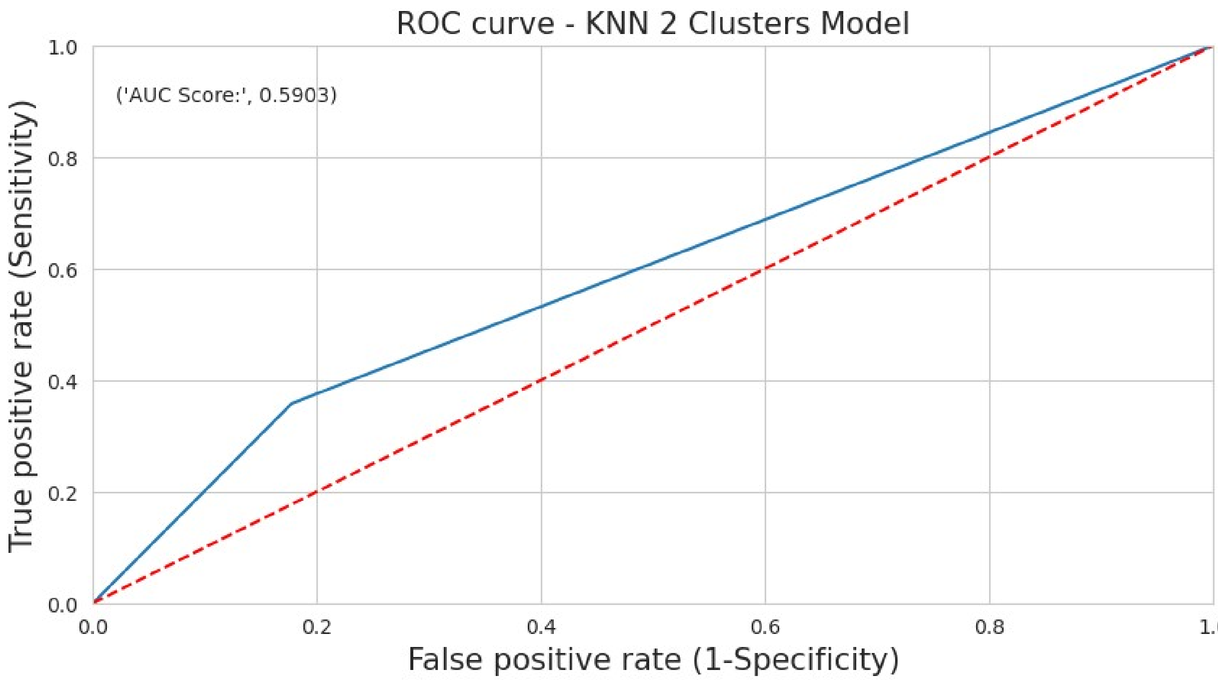



```
print(classification_report(ytest_kn, ypred_knn))
```

	precision	recall	f1-score	support
0	0.60	0.82	0.70	9843
1	0.63	0.36	0.46	8263
accuracy			0.61	18106
macro avg	0.62	0.59	0.58	18106
weighted avg	0.62	0.61	0.59	18106

```
plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_kn, ypred_proba_knn)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
```

```
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - KNN 2 Clusters Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_kn, ypred_proba_knn),4)))
plt.grid(True)
```




```
model_evaluation.loc['KNN 2 Cluster'] = [accuracy_score(ytest_kn,
ypred_knn), accuracy_score(ytrain_kn, ypred_knn_train),
                                         precision_score(ytest_kn,
ypred_knn), precision_score(ytrain_kn, ypred_knn_train),
                                         recall_score(ytest_kn,
ypred_knn), recall_score(ytrain_kn, ypred_knn_train),
                                         cohen_kappa_score(ytest_kn,
ypred_knn), cohen_kappa_score(ytrain_kn, ypred_knn_train),
                                         f1_score(ytest_kn,
ypred_knn), roc_auc_score(ytest_kn, ypred_proba_knn)]
model_evaluation
```

	test_accuracy	train_accuracy	test_precision \
Logit_FullModel	0.601513	0.604402	0.558365
DecisionTree	0.665415	1.000000	0.636499
XGBoost	0.776704	0.834015	0.749056

```
RandomForest Classifier        0.742351        1.000000        0.732189

KNN 2 Cluster                  0.610571        0.813040        0.628772


                         train_precision  test_recall  train_recall  \
Logit_FullModel                 0.558812     0.606680      0.606656
DecisionTree                    1.000000     0.622171      1.000000
XGBoost                         0.805924     0.768002      0.835099
RandomForest Classifier         1.000000     0.686555      1.000000
KNN 2 Cluster                   1.000000     0.358102      0.587748

                         test_kappa  train_kappa  f1_score
roc_auc_score
Logit_FullModel            0.202450     0.207675  0.581521
0.636576
DecisionTree               0.324474     1.000000  0.629253
0.661944
XGBoost                    0.550893     0.666162  0.758411
0.776005
RandomForest Classifier    0.478137     1.000000  0.708638
0.737872
KNN 2 Cluster              0.187079     0.609110  0.456319
0.590308
```

16.7. KNN 3 Clusters Model

```
xtrain_knn, xtest_knn, ytrain_knn, ytest_knn = train_test_split(X,
df_target, test_size = 0.2, random_state = 500)
print('xtrain: ', xtrain_knn.shape)
print('ytrain: ', ytrain_knn.shape)
print('xtest: ', xtest_knn.shape)
print('ytest: ', ytest_knn.shape)
```

```
xtrain:  (72422, 20)
ytrain:  (72422,)
xtest:  (18106, 20)
ytest:  (18106,)
```

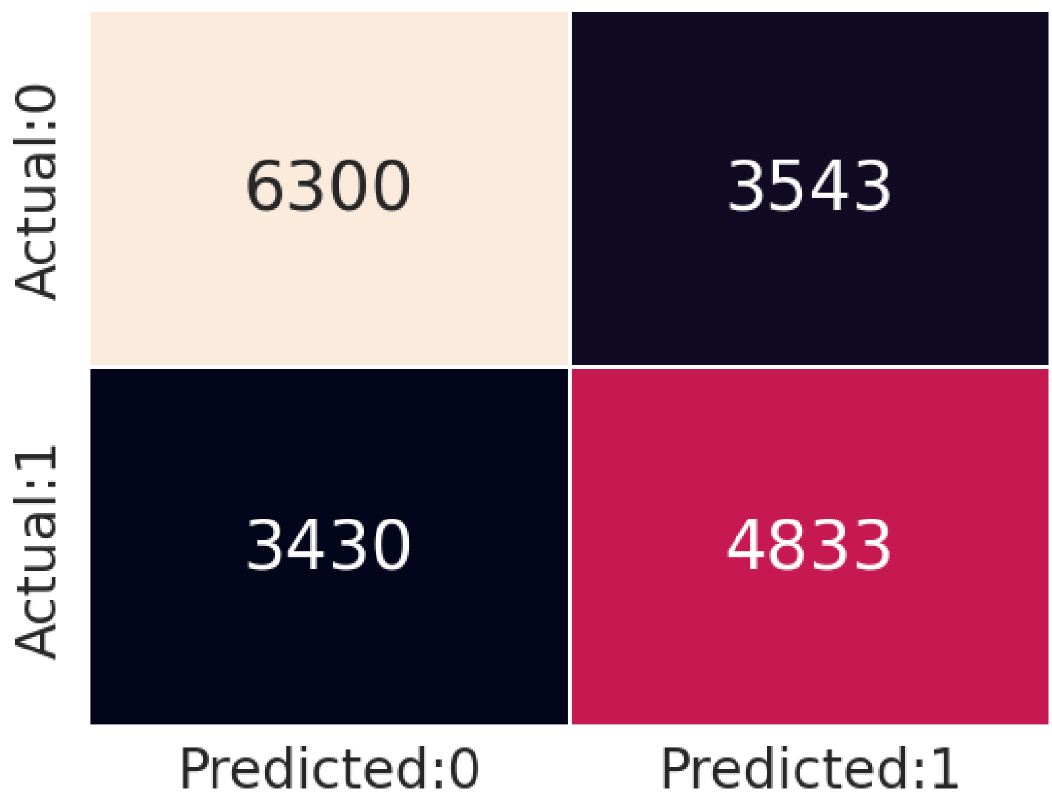
```
tstats,pvals = stats.ttest_ind(xtrain_knn, xtest_knn)
ref_df =
pd.DataFrame(pvals,index=xtrain_knn.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

```
knn = KNeighborsClassifier(n_neighbors=3)
knn_model = knn.fit(xtrain_knn,ytrain_knn)

ypred_proba_knn = knn_model.predict(xtest_knn)
ypred_knn = [0 if i < 0.5 else 1 for i in ypred_proba_knn]
ypred_knn[:10]
```

```
[1, 0, 0, 0, 1, 0, 0, 0, 1, 1]
```

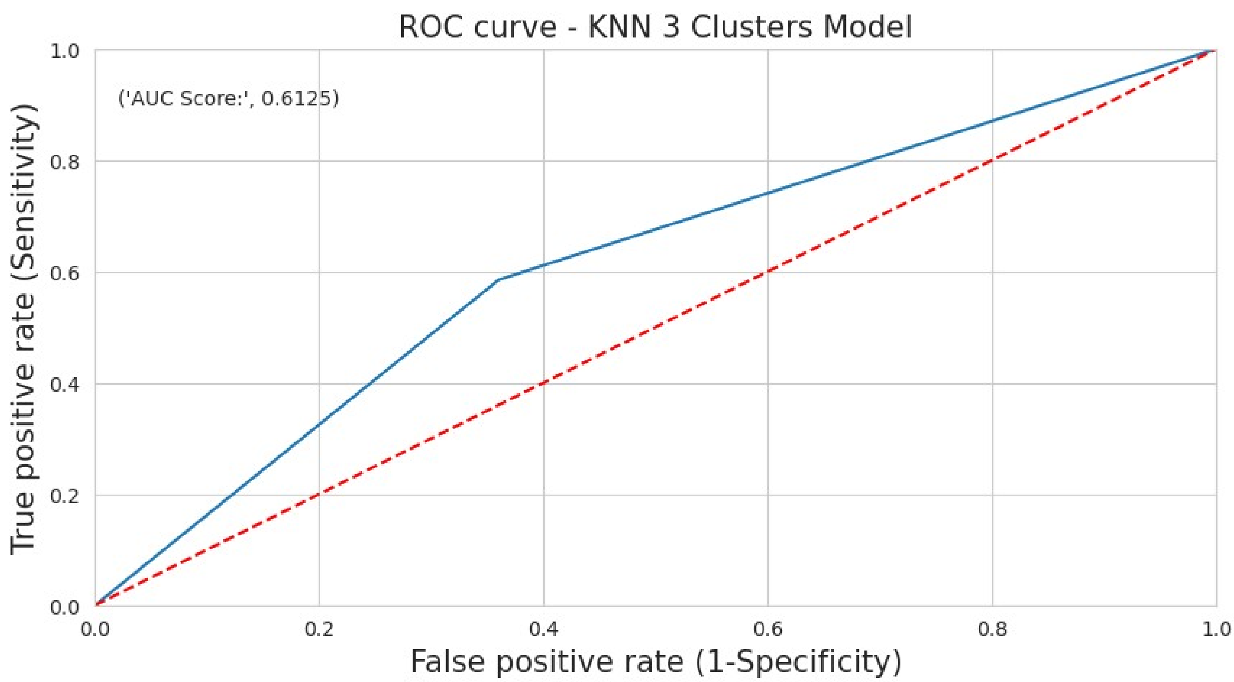
```
ypred_proba_knn_train = knn_model.predict(xtrain_knn)
ypred_knn_train = [0 if i < 0.5 else 1 for i in ypred_proba_knn_train]

cm = confusion_matrix(ytest_knn, ypred_knn)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_knn, ypred_knn))
```

```
              precision    recall  f1-score   support
```

```
           0       0.65      0.64      0.64      9843
           1       0.58      0.58      0.58      8263

    accuracy                           0.61     18106
   macro avg       0.61      0.61      0.61     18106
weighted avg       0.62      0.61      0.62     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_knn, ypred_proba_knn)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - KNN 3 Clusters Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_knn, ypred_proba_knn),4)))
plt.grid(True)
```




```
model_evaluation.loc['KNN 3 Cluster'] = [accuracy_score(ytest_knn,
ypred_knn), accuracy_score(ytrain_knn, ypred_knn_train),
                                          precision_score(ytest_knn,
ypred_knn), precision_score(ytrain_knn, ypred_knn_train),
                                          recall_score(ytest_knn,
ypred_knn), recall_score(ytrain_knn, ypred_knn_train),
                                          cohen_kappa_score(ytest_knn,
```

```
ypred_knn), cohen_kappa_score(ytrain_knn, ypred_knn_train),
                                          f1_score(ytest_knn,
ypred_knn), roc_auc_score(ytest_knn, ypred_proba_knn)]
model_evaluation
```

```
                         test_accuracy  train_accuracy  test_precision  \
Logit_FullModel               0.601513        0.604402        0.558365

DecisionTree                  0.665415        1.000000        0.636499

XGBoost                       0.776704        0.834015        0.749056

RandomForest Classifier       0.742351        1.000000        0.732189

KNN 2 Cluster                 0.610571        0.813040        0.628772

KNN 3 Cluster                 0.614879        0.809312        0.577006


                         train_precision  test_recall  train_recall  \
Logit_FullModel                 0.558812     0.606680      0.606656
DecisionTree                    1.000000     0.622171      1.000000
XGBoost                         0.805924     0.768002      0.835099
RandomForest Classifier         1.000000     0.686555      1.000000
KNN 2 Cluster                   1.000000     0.358102      0.587748
KNN 3 Cluster                   0.788499     0.584897      0.791956

                         test_kappa  train_kappa  f1_score
roc_auc_score
Logit_FullModel            0.202450     0.207675  0.581521
0.636576
DecisionTree               0.324474     1.000000  0.629253
0.661944
XGBoost                    0.550893     0.666162  0.758411
0.776005
RandomForest Classifier    0.478137     1.000000  0.708638
0.737872
KNN 2 Cluster              0.187079     0.609110  0.456319
0.590308
KNN 3 Cluster              0.224699     0.615442  0.580924
0.612473
```

16.8. Logistic Regression

```
xtrain_log, xtest_log, ytrain_log, ytest_log = train_test_split(X,
df_target, test_size = 0.2, random_state = 500)
print('xtrain: ', xtrain_log.shape)
```

```
print('ytrain: ', ytrain_log.shape)
print('xtest: ', xtest_log.shape)
print('ytest: ', ytest_log.shape)
```

```
xtrain:  (72422, 20)
ytrain:  (72422,)
xtest:  (18106, 20)
ytest:  (18106,)
```

```
tstats,pvals = stats.ttest_ind(xtrain_log, xtest_log)
ref_df =
pd.DataFrame(pvals,index=xtrain_log.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

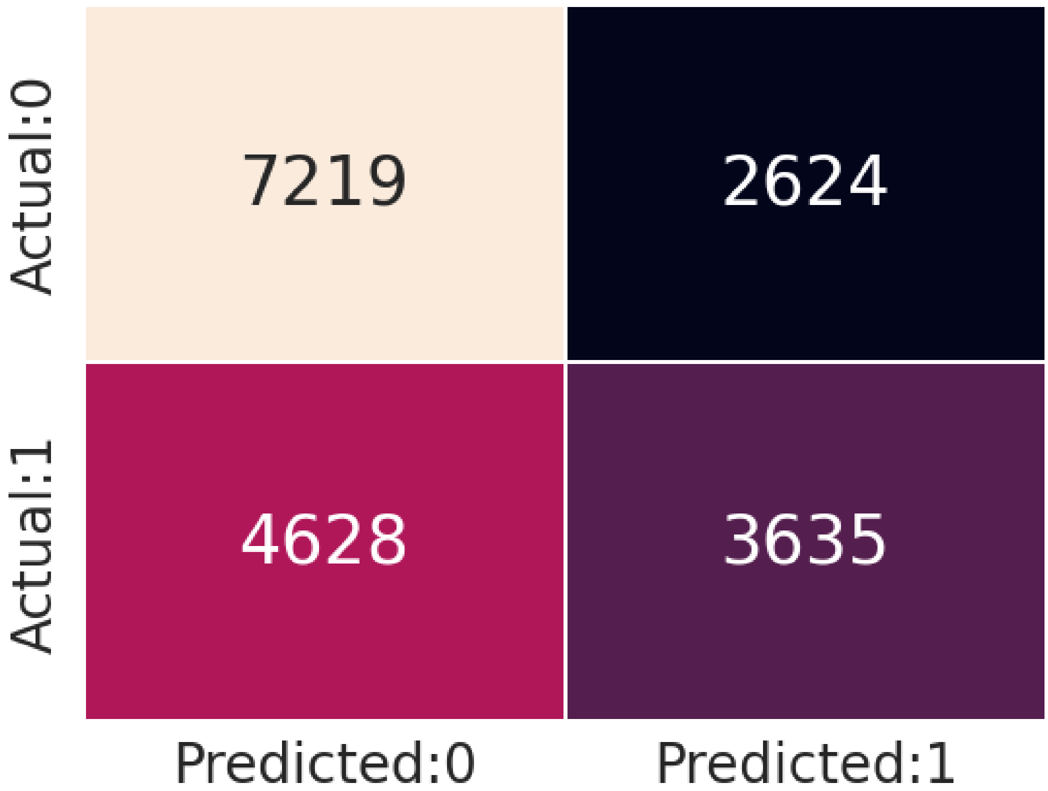
```
lr = LogisticRegression()
lr_model = lr.fit(xtrain_log,ytrain_log)
```

```
ypred_proba_log = lr_model.predict(xtest_log)
ypred_log = [0 if i < 0.5 else 1 for i in ypred_proba_log]
ypred_log[:10]
```

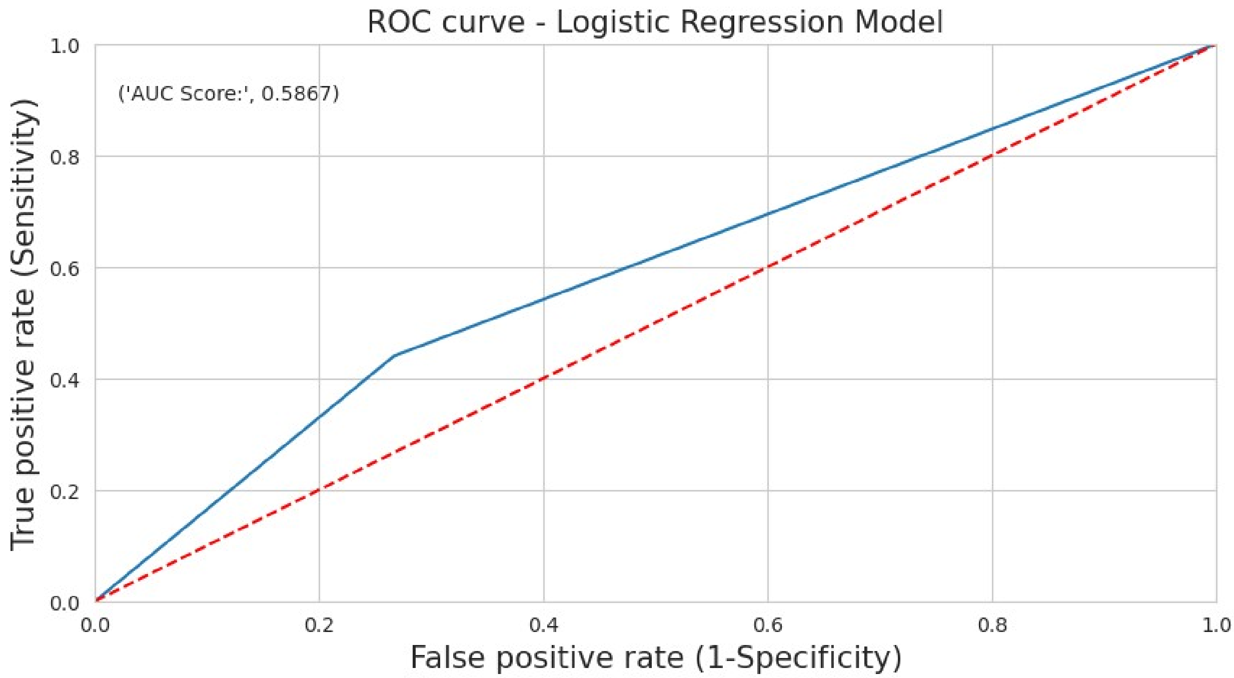
```
[0, 0, 0, 1, 0, 0, 1, 0, 1, 1]
```

```
ypred_proba_log_train = lr_model.predict(xtrain_log)
ypred_log_train = [0 if i < 0.5 else 1 for i in ypred_proba_log_train]
```

```
cm = confusion_matrix(ytest_log, ypred_log)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_log, ypred_log))

              precision    recall  f1-score   support

           0       0.61      0.73      0.67      9843
           1       0.58      0.44      0.50      8263

    accuracy                           0.60     18106
   macro avg       0.60      0.59      0.58     18106
weighted avg       0.60      0.60      0.59     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_log, ypred_proba_log)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - Logistic Regression Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_log, ypred_proba_log),4)))
plt.grid(True)
```




```
model_evaluation.loc['Logistic'] = [accuracy_score(ytest_log, ypred_log), accuracy_score(ytrain_log, ypred_log_train),
                                    precision_score(ytest_log, ypred_log), precision_score(ytrain_log, ypred_log_train),
                                    recall_score(ytest_log, ypred_log), recall_score(ytrain_log, ypred_log_train),
                                    cohen_kappa_score(ytest_log, ypred_log), cohen_kappa_score(ytrain_log, ypred_log_train),
                                    f1_score(ytest_log, ypred_log), roc_auc_score(ytest_log, ypred_proba_log)]
model_evaluation
```

	test_accuracy	train_accuracy	test_precision \
Logit_FullModel	0.601513	0.604402	0.558365
DecisionTree	0.665415	1.000000	0.636499
XGBoost	0.776704	0.834015	0.749056
RandomForest Classifier	0.742351	1.000000	0.732189
KNN 2 Cluster	0.610571	0.813040	0.628772
KNN 3 Cluster	0.614879	0.809312	0.577006
Logistic	0.599470	0.604595	0.580764

```
                          train_precision  test_recall  train_recall  \
Logit_FullModel                  0.558812     0.606680      0.606656
DecisionTree                     1.000000     0.622171      1.000000
XGBoost                          0.805924     0.768002      0.835099
RandomForest Classifier          1.000000     0.686555      1.000000
KNN 2 Cluster                    1.000000     0.358102      0.587748
KNN 3 Cluster                    0.788499     0.584897      0.791956
Logistic                         0.585079     0.439913      0.440537

                          test_kappa  train_kappa  f1_score
roc_auc_score
Logit_FullModel             0.202450     0.207675  0.581521
0.636576
DecisionTree                0.324474     1.000000  0.629253
0.661944
XGBoost                     0.550893     0.666162  0.758411
0.776005
RandomForest Classifier     0.478137     1.000000  0.708638
0.737872
KNN 2 Cluster               0.187079     0.609110  0.456319
0.590308
KNN 3 Cluster               0.224699     0.615442  0.580924
0.612473
Logistic                    0.176768     0.185169  0.500620
0.586664
```

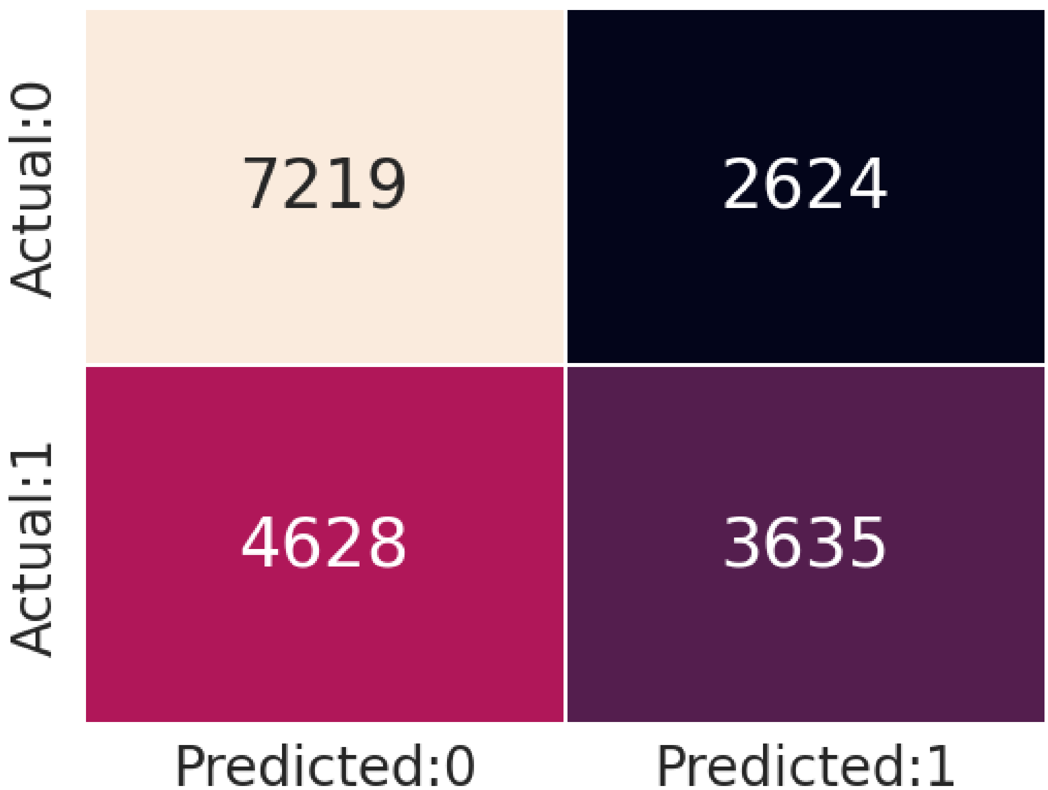
16.9. Navie Bayes

```
xtrain_nav, xtest_nav, ytrain_nav, ytest_nav = train_test_split(X,
df_target, test_size = 0.2, random_state = 500)
print('xtrain: ', xtrain_nav.shape)
print('ytrain: ', ytrain_nav.shape)
print('xtest: ', xtest_nav.shape)
print('ytest: ', ytest_nav.shape)

xtrain:  (72422, 20)
ytrain:  (72422,)
xtest:  (18106, 20)
ytest:  (18106,)

tstats,pvals = stats.ttest_ind(xtrain_nav, xtest_nav)
ref_df =
pd.DataFrame(pvals,index=xtrain_nav.columns,columns=['pvals'])
(ref_df < 0.05).any()

pvals    False
dtype: bool
```

```python
nb = GaussianNB()
nb_model = lr.fit(xtrain_nav,ytrain_nav)

ypred_proba_nav = nb_model.predict(xtest_nav)
ypred_nav = [0 if i < 0.5 else 1 for i in ypred_proba_nav]
ypred_nav[:10]
```

```
[0, 0, 0, 1, 0, 0, 1, 0, 1, 1]
```

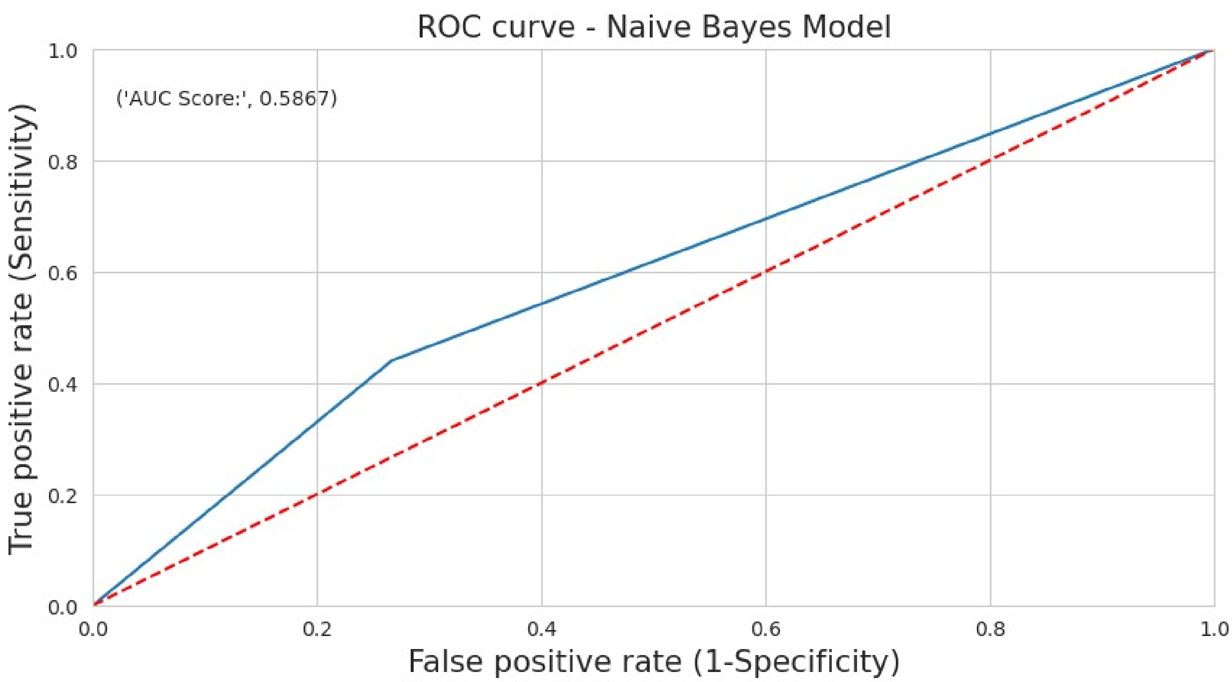
```python
ypred_proba_nav_train = nb_model.predict(xtrain_nav)
ypred_nav_train = [0 if i < 0.5 else 1 for i in ypred_proba_nav_train]

cm = confusion_matrix(ytest_nav, ypred_nav)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```python
print(classification_report(ytest_nav, ypred_nav))
```

```
              precision    recall  f1-score   support
```

```
           0       0.61      0.73      0.67      9843
           1       0.58      0.44      0.50      8263

    accuracy                           0.60     18106
   macro avg       0.60      0.59      0.58     18106
weighted avg       0.60      0.60      0.59     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_nav, ypred_proba_nav)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - Naive Bayes Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_nav, ypred_proba_nav),4)))
plt.grid(True)
```




```
model_evaluation.loc['GaussianNB'] = [accuracy_score(ytest_nav,
ypred_nav), accuracy_score(ytrain_nav, ypred_nav_train),
                                          precision_score(ytest_nav,
ypred_nav), precision_score(ytrain_nav, ypred_nav_train),
                                          recall_score(ytest_nav,
ypred_nav), recall_score(ytrain_nav, ypred_nav_train),
                                          cohen_kappa_score(ytest_nav,
```

```
ypred_nav), cohen_kappa_score(ytrain_nav, ypred_nav_train),
                                          f1_score(ytest_nav,
ypred_nav), roc_auc_score(ytest_nav, ypred_proba_nav)]

model_evaluation
```

```
                         test_accuracy  train_accuracy  test_precision
\
Logit_FullModel               0.601513        0.604402        0.558365

DecisionTree                  0.665415        1.000000        0.636499

XGBoost                       0.776704        0.834015        0.749056

RandomForest Classifier       0.742351        1.000000        0.732189

KNN 2 Cluster                 0.610571        0.813040        0.628772

KNN 3 Cluster                 0.614879        0.809312        0.577006

Logistic                      0.599470        0.604595        0.580764

GaussianNB                    0.599470        0.604595        0.580764


                         train_precision  test_recall  train_recall  \
Logit_FullModel                 0.558812     0.606680      0.606656
DecisionTree                    1.000000     0.622171      1.000000
XGBoost                         0.805924     0.768002      0.835099
RandomForest Classifier         1.000000     0.686555      1.000000
KNN 2 Cluster                   1.000000     0.358102      0.587748
KNN 3 Cluster                   0.788499     0.584897      0.791956
Logistic                        0.585079     0.439913      0.440537
GaussianNB                      0.585079     0.439913      0.440537

                         test_kappa  train_kappa  f1_score
roc_auc_score
Logit_FullModel            0.202450     0.207675  0.581521
0.636576
DecisionTree               0.324474     1.000000  0.629253
0.661944
XGBoost                    0.550893     0.666162  0.758411
0.776005
RandomForest Classifier    0.478137     1.000000  0.708638
0.737872
KNN 2 Cluster              0.187079     0.609110  0.456319
0.590308
KNN 3 Cluster              0.224699     0.615442  0.580924
0.612473
Logistic                   0.176768     0.185169  0.500620
0.586664
```

```
GaussianNB                         0.176768     0.185169  0.500620
0.586664
```

17. Recursive Feature Elimination for top 4 models

```
model_evaluation.sort_values(by='test_recall',ascending=False)
```

```
                         test_accuracy  train_accuracy  test_precision  \
XGBoost                       0.776704        0.834015        0.749056

RandomForest Classifier       0.742351        1.000000        0.732189

DecisionTree                  0.665415        1.000000        0.636499

Logit_FullModel               0.601513        0.604402        0.558365

KNN 3 Cluster                 0.614879        0.809312        0.577006

Logistic                      0.599470        0.604595        0.580764

GaussianNB                    0.599470        0.604595        0.580764

KNN 2 Cluster                 0.610571        0.813040        0.628772


                         train_precision  test_recall  train_recall  \
XGBoost                         0.805924     0.768002      0.835099
RandomForest Classifier         1.000000     0.686555      1.000000
DecisionTree                    1.000000     0.622171      1.000000
Logit_FullModel                 0.558812     0.606680      0.606656
KNN 3 Cluster                   0.788499     0.584897      0.791956
Logistic                        0.585079     0.439913      0.440537
GaussianNB                      0.585079     0.439913      0.440537
KNN 2 Cluster                   1.000000     0.358102      0.587748

                         test_kappa  train_kappa  f1_score
roc_auc_score
XGBoost                    0.550893     0.666162  0.758411
0.776005
RandomForest Classifier    0.478137     1.000000  0.708638
0.737872
DecisionTree               0.324474     1.000000  0.629253
0.661944
Logit_FullModel            0.202450     0.207675  0.581521
```

```
0.636576
KNN 3 Cluster                    0.224699     0.615442   0.580924
0.612473
Logistic                         0.176768     0.185169   0.500620
0.586664
GaussianNB                       0.176768     0.185169   0.500620
0.586664
KNN 2 Cluster                    0.187079     0.609110   0.456319
0.590308
```

17.1. XGBoost Model - RFE

```
X_train_rfe = X_train.iloc[:,1:]
X_test_rfe = X_test.iloc[:,1:]
xg =  XGBClassifier()
xgb_model = RFE(estimator = xg, n_features_to_select = 10)
rfe_model = xgb_model.fit(X_train_rfe, y_train)
feat_index = pd.Series(data = rfe_model.ranking_, index =
X_train_rfe.columns)
signi_feat_rfe_xg = feat_index[feat_index==1].index
print(signi_feat_rfe_xg)
```

```
Index(['purchased_approved', 'delivered_estimated',
'purchased_delivered',
       'price', 'freight_value', 'product_weight_g',
'product_width_cm',
       'payment_installments', 'payment_type_credit_card',
       'payment_type_debit_card'],
      dtype='object')
```

```
xtrain_xg, xtest_xg, ytrain_xg, ytest_xg =
train_test_split(X[signi_feat_rfe_xg], df_target, random_state = 500,
test_size = 0.2)
print('xtrain: ', xtrain_xg.shape)
print('ytrain: ', ytrain_xg.shape)
print('xtest: ', xtest_xg.shape)
print('ytest: ', ytest_xg.shape)
```

```
xtrain:  (72422, 10)
ytrain:  (72422,)
xtest:  (18106, 10)
ytest:  (18106,)
```

```
tstats,pvals = stats.ttest_ind(xtrain_nav, xtest_nav)
ref_df =
pd.DataFrame(pvals,index=xtrain_nav.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

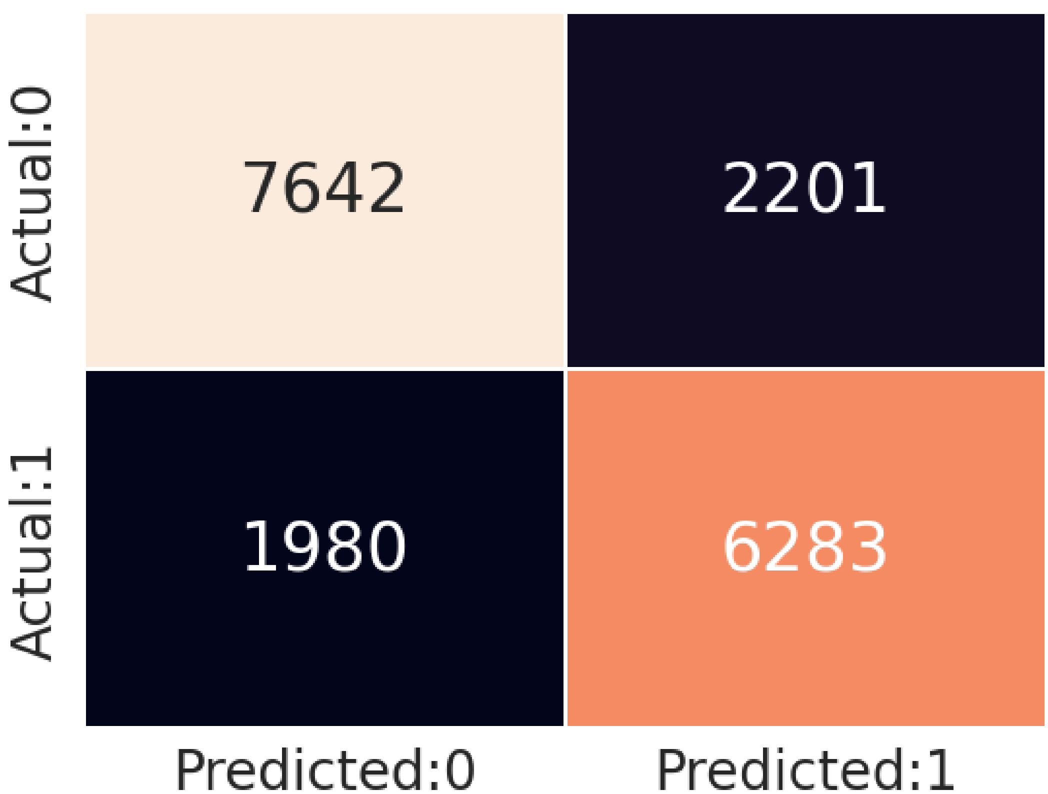
```
gBoost = XGBClassifier()
xbBoost = xgBoost.fit(xtrain_xg, ytrain_xg)
```

```
ypred_proba_xg = xgBoost.predict(xtest_xg)
ypred_xg = [0 if i < 0.5 else 1 for i in ypred_proba_xg]
ypred_xg[:10]
```

```
[0, 0, 0, 1, 1, 0, 1, 0, 1, 1]
```

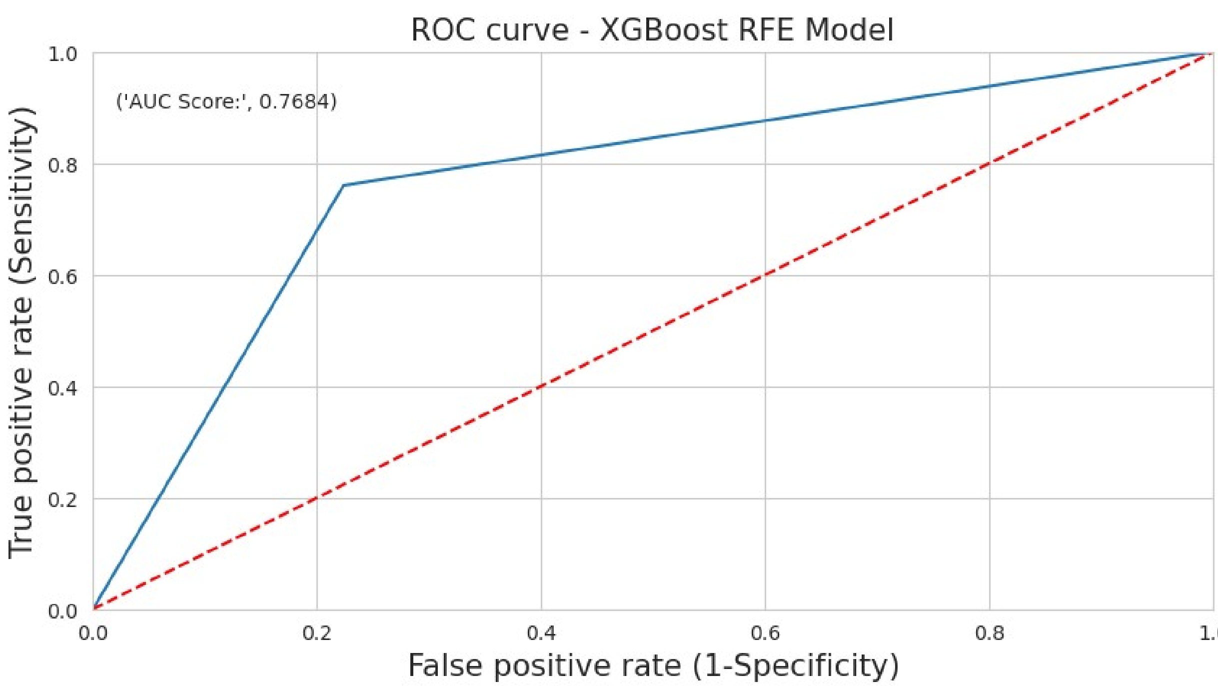
```
ypred_proba_xg_train = xgBoost.predict(xtrain_xg)
ypred_xg_train = [0 if i < 0.5 else 1 for i in ypred_proba_xg_train]
```

```
cm = confusion_matrix(ytest_xg, ypred_xg)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```



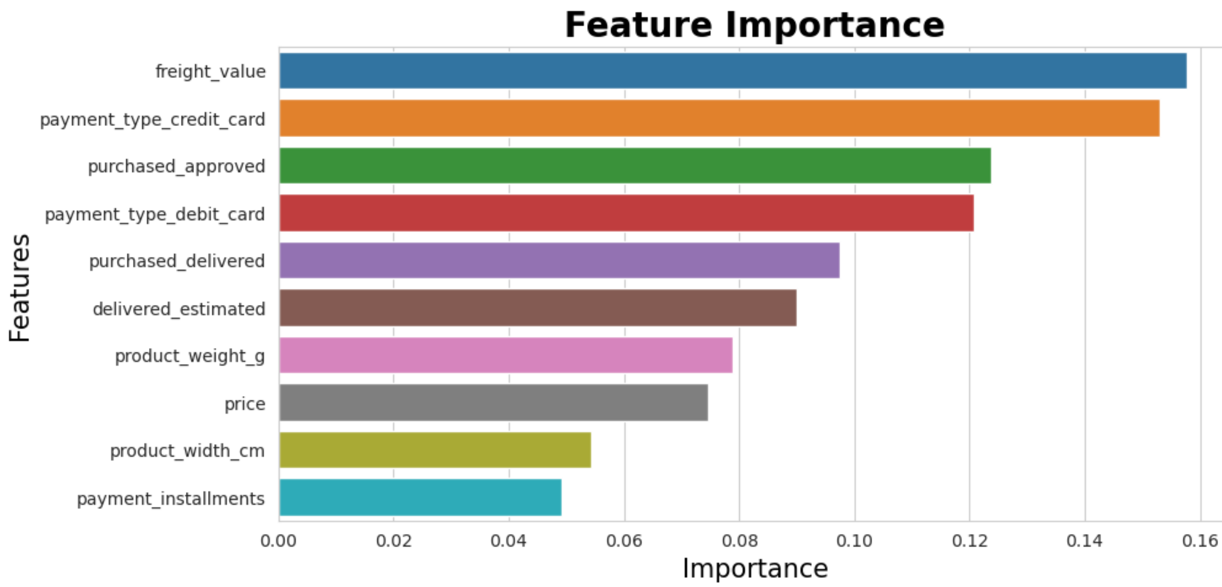

```
print(classification_report(ytest_xg, ypred_xg))
```

```
                precision    recall  f1-score   support

           0       0.79      0.78      0.79      9843
           1       0.74      0.76      0.75      8263

    accuracy                           0.77     18106
   macro avg       0.77      0.77      0.77     18106
weighted avg       0.77      0.77      0.77     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_xg, ypred_proba_xg)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - XGBoost RFE Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_xg, ypred_proba_xg),4)))
plt.grid(True)
```




```
plt.figure(figsize=(10, 5))
important_features = pd.DataFrame({'Features': xtrain_xg.columns,
                                   'Importance':
xbBoost.feature_importances_})
important_features = important_features.sort_values('Importance',
```

```
ascending = False)
sns.barplot(x = 'Importance', y = 'Features', data =
important_features)
plt.title('Feature
Importance',color='black',fontsize=20,fontweight='bold')
plt.xlabel('Importance',color='black',fontsize=15)
plt.ylabel('Features',color='black',fontsize=15)
plt.show()
```




```
cols = ['test_accuracy', 'train_accuracy', 'test_precision',
'train_precision','test_recall','train_recall', 'test_kappa',
'train_kappa', 'f1_score','roc_auc_score']
RFE_model_evaluation = pd.DataFrame(columns=cols)
RFE_model_evaluation.loc['XGBoost RFE'] = [accuracy_score(ytest_xg,
ypred_xg), accuracy_score(ytrain_xg, ypred_xg_train),
                                          precision_score(ytest_xg,
ypred_xg), precision_score(ytrain_xg, ypred_xg_train),
                                          recall_score(ytest_xg,
ypred_xg), recall_score(ytrain_xg, ypred_xg_train),
                                          cohen_kappa_score(ytest_xg,
ypred_xg), cohen_kappa_score(ytrain_xg, ypred_xg_train),
                                          f1_score(ytest_xg,
ypred_xg), roc_auc_score(ytest_xg, ypred_proba_xg)]
RFE_model_evaluation
```

```
             test_accuracy  train_accuracy  test_precision
train_precision  \
XGBoost RFE       0.769082        0.818218         0.74057
0.788084

             test_recall  train_recall  test_kappa  train_kappa
```

```
f1_score  \
XGBoost RFE     0.760378      0.819541    0.535617     0.634507
0.750343

             roc_auc_score
XGBoost RFE       0.768383
```

17.2. Random Forest Classifier - RFE

```
X_train_rfe = X_train.iloc[:,1:]
X_test_rfe = X_test.iloc[:,1:]
rand =  RandomForestClassifier()
rand_model = RFE(estimator = rand, n_features_to_select = 10)
rfe_model = rand_model.fit(X_train_rfe, y_train)
feat_index = pd.Series(data = rfe_model.ranking_, index =
X_train_rfe.columns)
signi_feat_rfe_rf = feat_index[feat_index==1].index
print(signi_feat_rfe_rf)
```

```
Index(['purchased_approved', 'delivered_estimated',
'purchased_delivered',
       'price', 'freight_value', 'product_weight_g',
'product_width_cm',
       'geolocation_lat', 'geolocation_lng', 'Monetary'],
      dtype='object')
```

```
xtrain_random, xtest_random, ytrain_random, ytest_random =
train_test_split(X[signi_feat_rfe_rf], df_target, random_state = 500,
test_size = 0.2)
print('xtrain: ', xtrain_random.shape)
print('ytrain: ', ytrain_random.shape)
print('xtest: ', xtest_random.shape)
print('ytest: ', ytest_random.shape)
```

```
xtrain:  (72422, 10)
ytrain:  (72422,)
xtest:  (18106, 10)
ytest:  (18106,)
```

```
tstats,pvals = stats.ttest_ind(xtrain_nav, xtest_nav)
ref_df =
pd.DataFrame(pvals,index=xtrain_nav.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

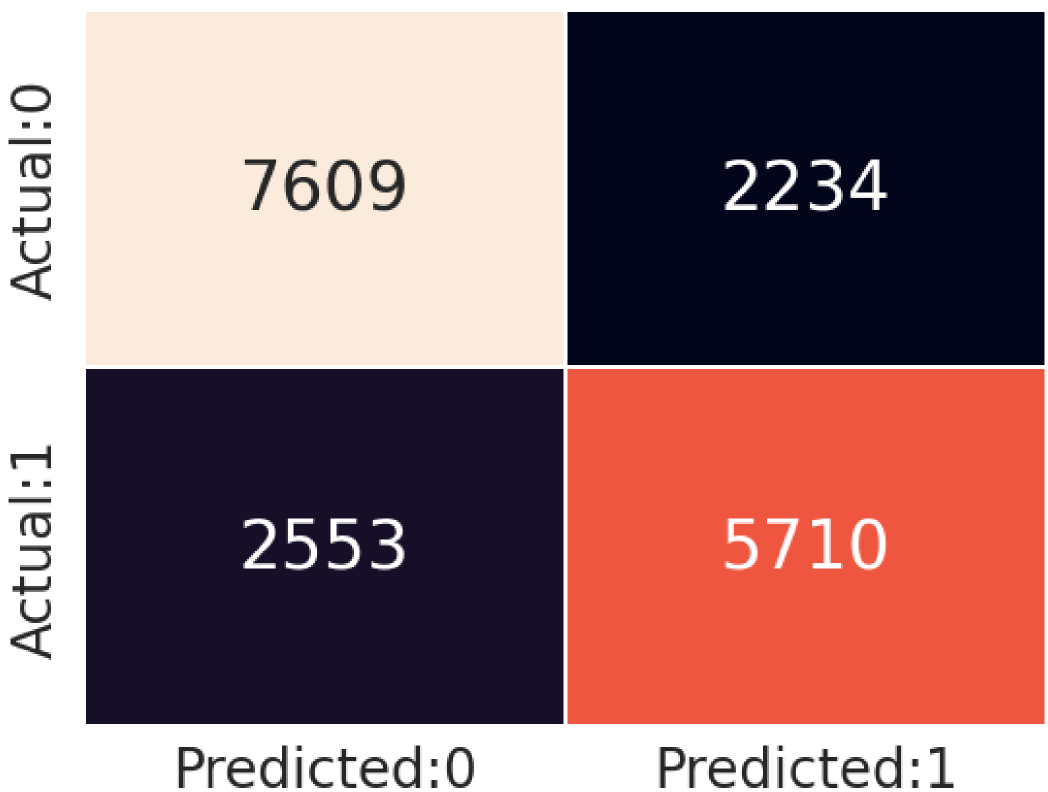
```
rand = RandomForestClassifier()
rand_model = rand.fit(xtrain_random,ytrain_random)
```

```
ypred_proba_random = rand_model.predict(xtest_random)
ypred_random = [0 if i < 0.5 else 1 for i in ypred_proba_random]
ypred_random[:10]
```

```
[0, 0, 0, 1, 1, 0, 1, 0, 1, 1]
```

```
ypred_proba_random_train = rand_model.predict(xtrain_random)
ypred_random_train = [0 if i < 0.5 else 1 for i in
ypred_proba_random_train]
```

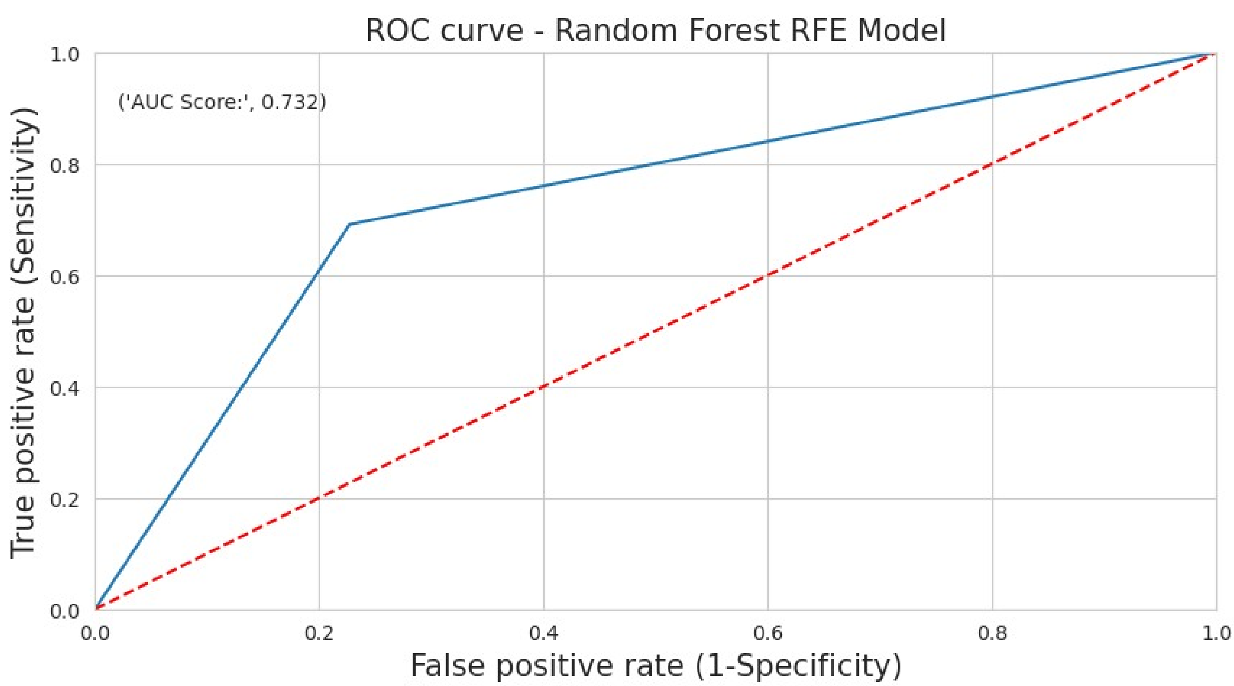
```
cm = confusion_matrix(ytest_random, ypred_random)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_random, ypred_random))
```

```
              precision    recall  f1-score   support

           0       0.75      0.77      0.76      9843
           1       0.72      0.69      0.70      8263
```

```
    accuracy                           0.74     18106
   macro avg       0.73      0.73      0.73     18106
weighted avg       0.74      0.74      0.74     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_random, ypred_proba_random)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - Random Forest RFE Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_random, ypred_proba_random),4)))
plt.grid(True)
```




```
RFE_model_evaluation.loc['RandomForest Classifier'] =
[accuracy_score(ytest_random, ypred_random),
accuracy_score(ytrain_random, ypred_random_train),

precision_score(ytest_random, ypred_random),
precision_score(ytrain_random, ypred_random_train),
                                          recall_score(ytest_random,
ypred_random), recall_score(ytrain_random, ypred_random_train),
```

```
cohen_kappa_score(ytest_random, ypred_random),
cohen_kappa_score(ytrain_random, ypred_random_train),
                                          f1_score(ytest_random,
ypred_random), roc_auc_score(ytest_random, ypred_proba_random)]
RFE_model_evaluation
```

```
                         test_accuracy  train_accuracy  test_precision  \
XGBoost RFE                   0.769082        0.818218        0.740570

RandomForest Classifier       0.735613        1.000000        0.718781


                         train_precision  test_recall  train_recall  \
XGBoost RFE                     0.788084     0.760378      0.819541
RandomForest Classifier         1.000000     0.691032      1.000000

                         test_kappa  train_kappa  f1_score
roc_auc_score
XGBoost RFE                0.535617     0.634507  0.750343
0.768383
RandomForest Classifier    0.465511     1.000000  0.704634
0.732034
```

17.3. Decision Tree Classifier - RFE

```
X_train_rfe = X_train.iloc[:,1:]
X_test_rfe = X_test.iloc[:,1:]
dt =  DecisionTreeClassifier()
dt_model = RFE(estimator = dt, n_features_to_select = 10)
rfe_model = dt_model.fit(X_train_rfe, y_train)
feat_index = pd.Series(data = rfe_model.ranking_, index =
X_train_rfe.columns)
signi_feat_rfe_dt = feat_index[feat_index==1].index
print(signi_feat_rfe_dt)
```

```
Index(['purchased_approved', 'delivered_estimated',
'purchased_delivered',
       'price', 'freight_value', 'product_weight_g',
'product_length_cm',
       'geolocation_lat', 'geolocation_lng', 'Monetary'],
      dtype='object')
```

```
xtrain_dt, xtest_dt, ytrain_dt, ytest_dt =
train_test_split(X[signi_feat_rfe_dt], df_target, test_size = 0.2,
random_state = 500)
print('xtrain: ', xtrain_dt.shape)
print('ytrain: ', ytrain_dt.shape)
```

```
print('xtest: ', xtest_dt.shape)
print('ytest: ', ytest_dt.shape)
```

```
xtrain:  (72422, 10)
ytrain:  (72422,)
xtest:  (18106, 10)
ytest:  (18106,)
```

```
tstats,pvals = stats.ttest_ind(xtrain_dt, xtest_dt)
ref_df = pd.DataFrame(pvals,index=xtrain_dt.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

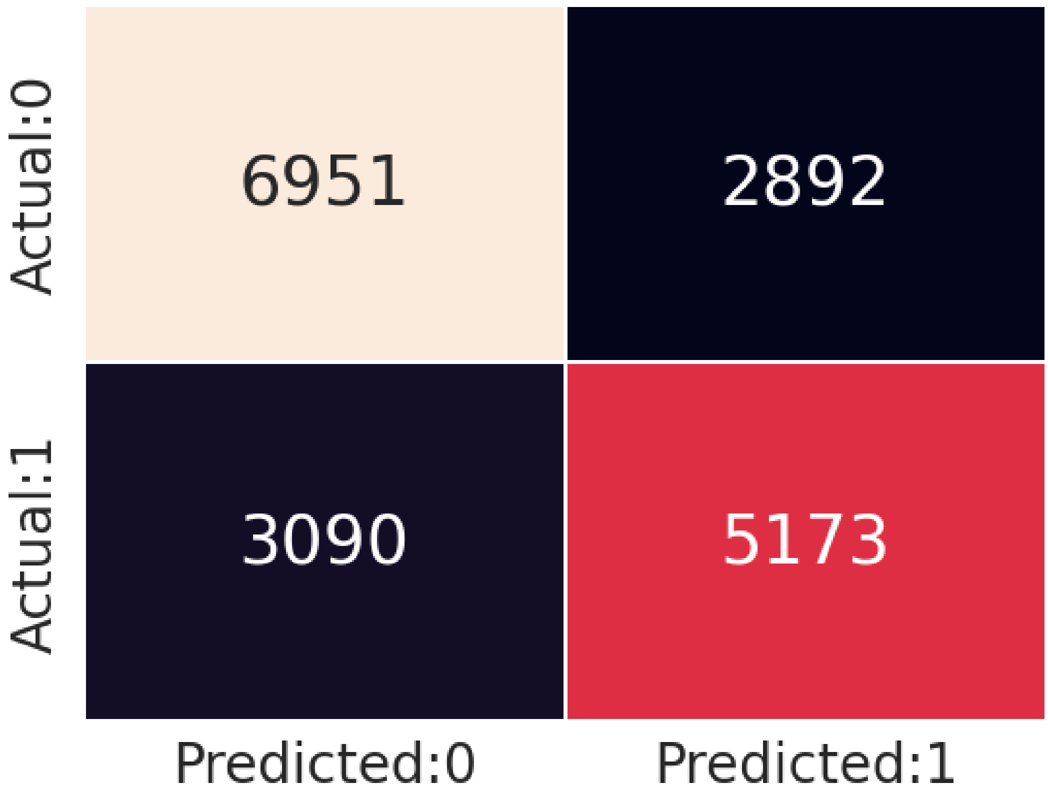
```
decisionTree = DecisionTreeClassifier()
decisionTree = decisionTree.fit(xtrain_dt, ytrain_dt)
```

```
ypred_proba_dt = decisionTree.predict(xtest_dt)
ypred_dt = [0 if i < 0.5 else 1 for i in ypred_proba_dt]
ypred_dt[:10]
```

```
[0, 0, 0, 1, 1, 0, 1, 0, 1, 1]
```

```
ypred_proba_dt_train = decisionTree.predict(xtrain_dt)
ypred_dt_train = [0 if i < 0.5 else 1 for i in ypred_proba_dt_train]
```

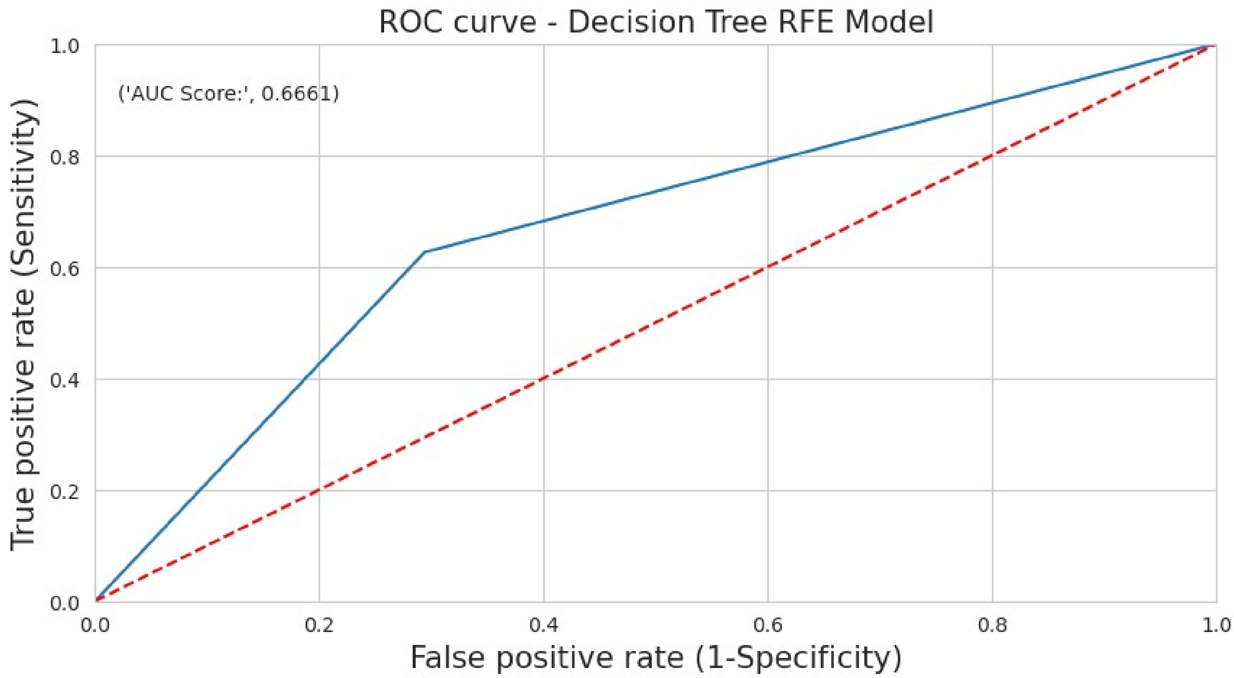
```
cm = confusion_matrix(ytest_dt, ypred_dt)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_dt, ypred_dt))
```

```
              precision    recall  f1-score   support

           0       0.69      0.71      0.70      9843
           1       0.64      0.63      0.63      8263

    accuracy                           0.67     18106
   macro avg       0.67      0.67      0.67     18106
weighted avg       0.67      0.67      0.67     18106
```

```
plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_dt, ypred_proba_dt)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - Decision Tree RFE Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_dt, ypred_proba_dt),4)))
plt.grid(True)
```




```
RFE_model_evaluation.loc['DecisionTree'] = [accuracy_score(ytest_dt, ypred_dt), accuracy_score(ytrain_dt, ypred_dt_train),
                                            precision_score(ytest_dt, ypred_dt), precision_score(ytrain_dt, ypred_dt_train),
                                            recall_score(ytest_dt, ypred_dt), recall_score(ytrain_dt, ypred_dt_train),
                                            cohen_kappa_score(ytest_dt, ypred_dt), cohen_kappa_score(ytrain_dt, ypred_dt_train),
                                            f1_score(ytest_dt, ypred_dt), roc_auc_score(ytest_dt, ypred_proba_dt)]
RFE_model_evaluation
```

	test_accuracy	train_accuracy	test_precision
XGBoost RFE	0.769082	0.818218	0.740570
RandomForest Classifier	0.735613	1.000000	0.718781
DecisionTree	0.669612	1.000000	0.641414

	train_precision	test_recall	train_recall
XGBoost RFE	0.788084	0.760378	0.819541
RandomForest Classifier	1.000000	0.691032	1.000000
DecisionTree	1.000000	0.626044	1.000000

	test_kappa	train_kappa	f1_score	roc_auc_score
XGBoost RFE	0.535617	0.634507	0.750343	

```
0.768383
RandomForest Classifier    0.465511     1.000000  0.704634
0.732034
DecisionTree               0.332871     1.000000  0.633635
0.666115
```

17.4. Logistic Regression - RFE

```
X_train_rfe = X_train.iloc[:,1:]
X_test_rfe = X_test.iloc[:,1:]
logreg =  LogisticRegression()
logreg_model = RFE(estimator = logreg, n_features_to_select = 10)
rfe_model = logreg_model.fit(X_train_rfe, y_train)
feat_index = pd.Series(data = rfe_model.ranking_, index =
X_train_rfe.columns)
signi_feat_rfe_log = feat_index[feat_index==1].index
print(signi_feat_rfe_log)
```

```
Index(['purchased_approved', 'delivered_estimated',
'purchased_delivered',
       'freight_value', 'product_length_cm', 'payment_installments',
       'customer_state_northern', 'payment_type_credit_card',
       'payment_type_debit_card', 'payment_type_voucher'],
      dtype='object')
```

```
xtrain_log, xtest_log, ytrain_log, ytest_log =
train_test_split(X[signi_feat_rfe_log], df_target, test_size = 0.2,
random_state = 500)
print('xtrain: ', xtrain_log.shape)
print('ytrain: ', ytrain_log.shape)
print('xtest: ', xtest_log.shape)
print('ytest: ', ytest_log.shape)
```

```
xtrain:  (72422, 10)
ytrain:  (72422,)
xtest:  (18106, 10)
ytest:  (18106,)
```

```
tstats,pvals = stats.ttest_ind(xtrain_log, xtest_log)
ref_df =
pd.DataFrame(pvals,index=xtrain_log.columns,columns=['pvals'])
(ref_df < 0.05).any()
```

```
pvals    False
dtype: bool
```

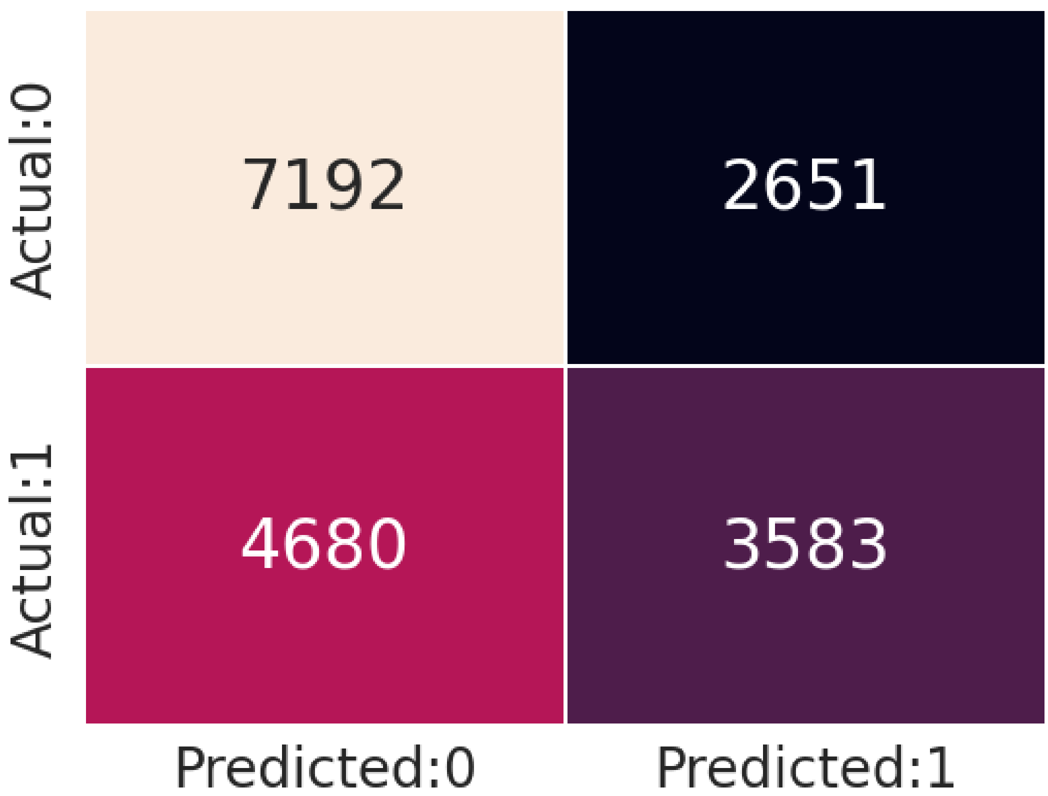
```
logreg = LogisticRegression()
logreg = logreg.fit(xtrain_log, ytrain_log)
```

```
ypred_proba_log = logreg.predict(xtest_log)
ypred_log = [0 if i < 0.5 else 1 for i in ypred_proba_log]
ypred_log[:10]
```

```
[0, 0, 0, 1, 0, 0, 1, 0, 1, 1]
```

```
ypred_proba_log_train = logreg.predict(xtrain_log)
ypred_log_train = [0 if i < 0.5 else 1 for i in ypred_proba_log_train]
```

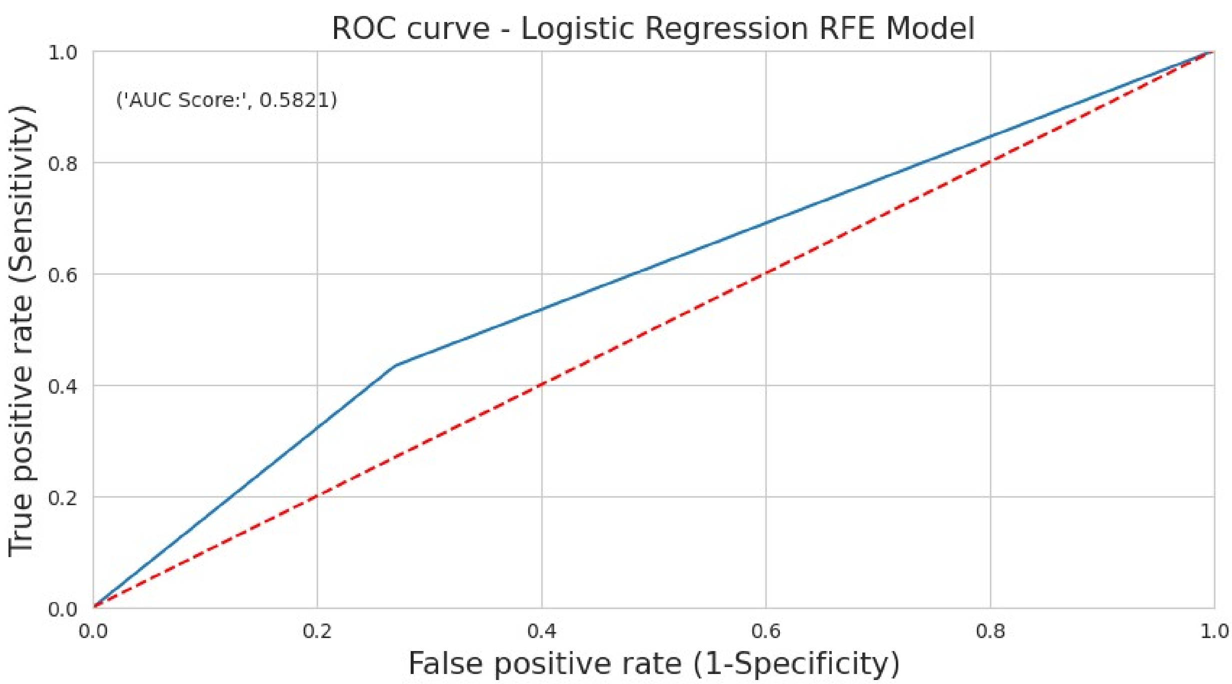
```
cm = confusion_matrix(ytest_log, ypred_log)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_log, ypred_log))
```

```
              precision    recall  f1-score   support

           0       0.61      0.73      0.66      9843
           1       0.57      0.43      0.49      8263
```

```
    accuracy                           0.60     18106
   macro avg       0.59      0.58      0.58     18106
weighted avg       0.59      0.60      0.59     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_log, ypred_proba_log)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - Logistic Regression RFE Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_log, ypred_proba_log),4)))
plt.grid(True)
```




```
RFE_model_evaluation.loc['Logistic Regression'] =
[accuracy_score(ytest_log, ypred_log), accuracy_score(ytrain_log,
ypred_log_train),
                                          precision_score(ytest_log,
ypred_log), precision_score(ytrain_log, ypred_log_train),
                                          recall_score(ytest_log,
ypred_log), recall_score(ytrain_log, ypred_log_train),
                                          cohen_kappa_score(ytest_log,
ypred_log), cohen_kappa_score(ytrain_log, ypred_log_train),
                                          f1_score(ytest_log,
```

```
ypred_log), roc_auc_score(ytest_log, ypred_proba_log)]
RFE_model_evaluation
```

	test_accuracy	train_accuracy	test_precision
XGBoost RFE	0.769082	0.818218	0.740570
RandomForest Classifier	0.735613	1.000000	0.718781
DecisionTree	0.669612	1.000000	0.641414
Logistic Regression	0.595107	0.603090	0.574751

	train_precision	test_recall	train_recall
XGBoost RFE	0.788084	0.760378	0.819541
RandomForest Classifier	1.000000	0.691032	1.000000
DecisionTree	1.000000	0.626044	1.000000
Logistic Regression	0.583609	0.433620	0.435574

	test_kappa	train_kappa	f1_score	roc_auc_score
XGBoost RFE	0.535617	0.634507	0.750343	0.768383
RandomForest Classifier	0.465511	1.000000	0.704634	0.732034
DecisionTree	0.332871	1.000000	0.633635	0.666115
Logistic Regression	0.167594	0.181597	0.494309	0.582146

```
RFE_model_evaluation[['test_recall']].sort_values('test_recall',
ascending = False)
```

	test_recall
XGBoost RFE	0.760378
RandomForest Classifier	0.691032
DecisionTree	0.626044
Logistic Regression	0.433620

Observations:

1. Looking at the **test recall scores**, we conclude that the **2 best performing models** as **XGBoost** and **Random Forest Classifier**.
2. So we tune those two models to get the hyperparameters and thereafter the best model.

18. Hyperparameter Tuning

18.1. Tuned Random Forest Classifier

```
xtrain_random, xtest_random, ytrain_random, ytest_random =
train_test_split(X[signi_feat_rfe_rf], df_target, test_size = 0.2,
random_state = 500)
print('xtrain: ', xtrain_random.shape)
print('ytrain: ', ytrain_random.shape)
print('xtest: ', xtest_random.shape)
print('ytest: ', ytest_random.shape)
```

```
xtrain:  (72422, 10)
ytrain:  (72422,)
xtest:  (18106, 10)
ytest:  (18106,)
```

```
rand = RandomForestClassifier(random_state = 10)
parameters = [{'criterion': ['gini', 'entropy'],
               'max_features': ['sqrt', 'log2'],
               'max_depth': range(2, 7),
               'min_samples_split' : range(2, 7),
               'max_leaf_nodes': range(2, 10)}]
gcv_rf = GridSearchCV(estimator = rand, param_grid = parameters, cv =
5)
gcv_rf.fit(xtrain_random, ytrain_random)
```

```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=10),
             param_grid=[{'criterion': ['gini', 'entropy'],
                          'max_depth': range(2, 7),
                          'max_features': ['sqrt', 'log2'],
                          'max_leaf_nodes': range(2, 10),
                          'min_samples_split': range(2, 7)}])
```

```
gcv_rf.best_params_
```

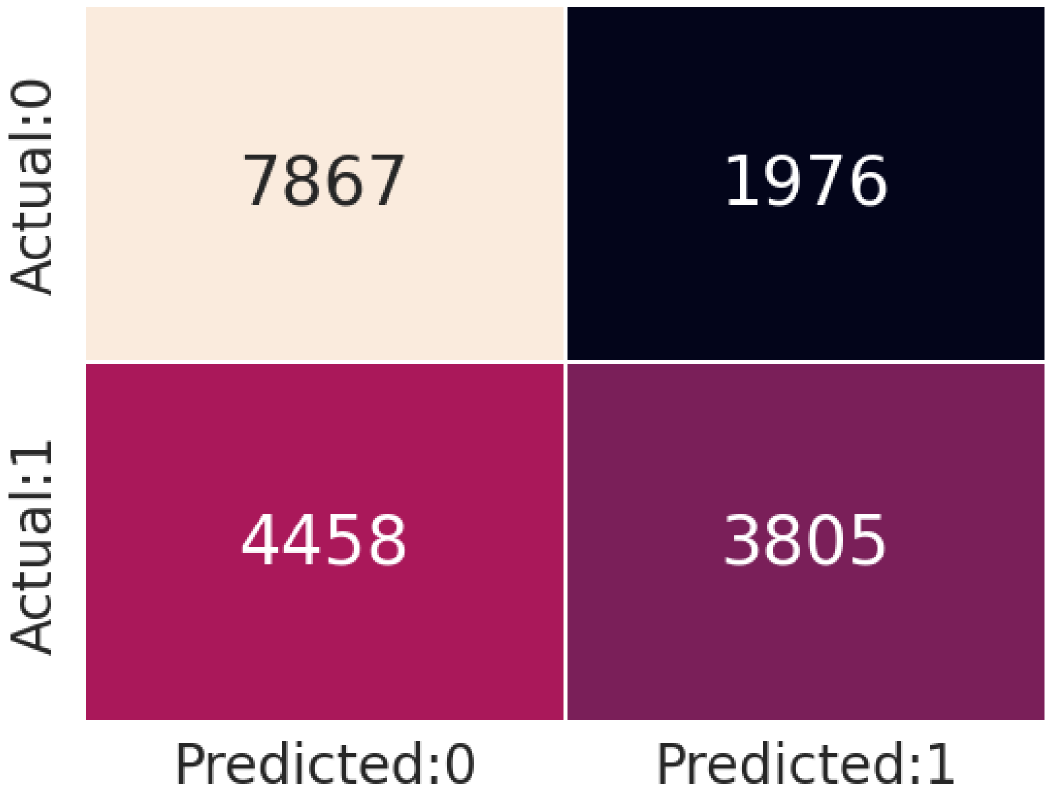
```
{'criterion': 'gini',
 'max_depth': 4,
 'max_features': 'sqrt',
 'max_leaf_nodes': 9,
 'min_samples_split': 2}
```

```
rand = RandomForestClassifier(criterion = 'entropy',max_depth = 6,
max_features = 'sqrt', max_leaf_nodes = 9, min_samples_split = 2)
rand_model = rand.fit(xtrain_random,ytrain_random)
```

```
ypred_proba_random = rand_model.predict(xtest_random)
ypred_random = [0 if i < 0.5 else 1 for i in ypred_proba_random]
ypred_random[:10]
```

```
[0, 1, 1, 1, 0, 0, 0, 0, 1, 0]
```

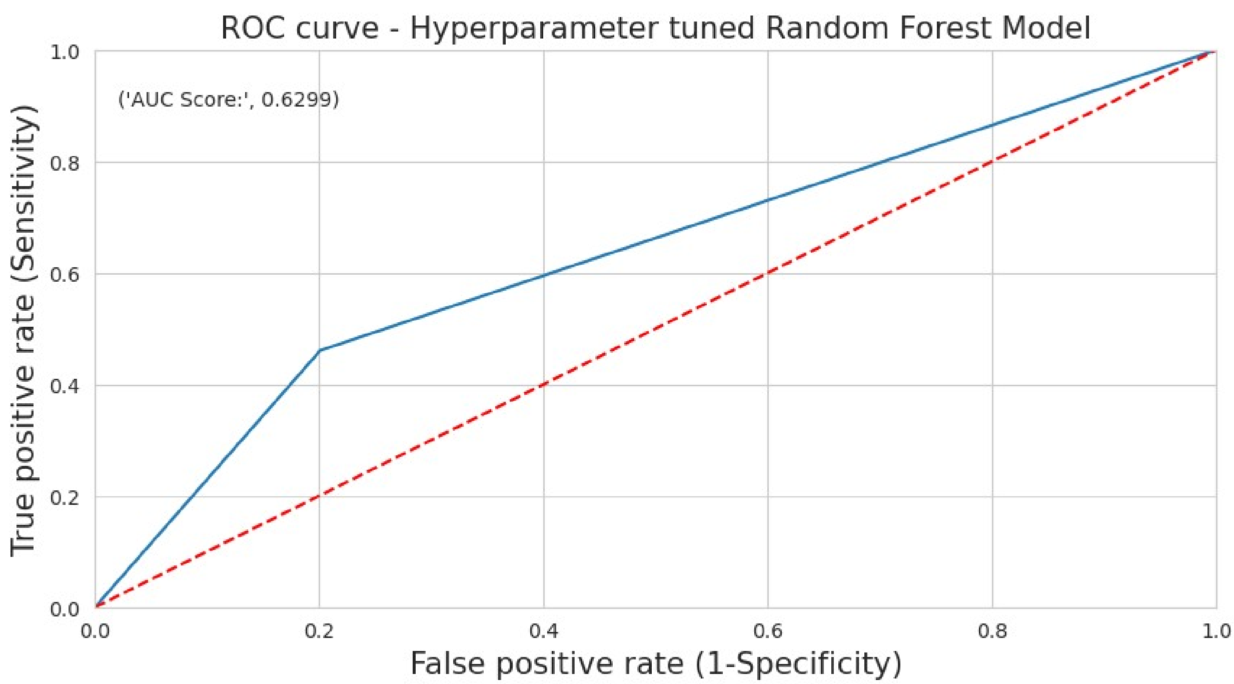
```
ypred_proba_random_train = rand_model.predict(xtrain_random)
ypred_random_train = [0 if i < 0.5 else 1 for i in
ypred_proba_random_train]

cm = confusion_matrix(ytest_random, ypred_random)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_random, ypred_random))
```

```
              precision    recall  f1-score   support

           0       0.64      0.80      0.71      9843
           1       0.66      0.46      0.54      8263

    accuracy                           0.64     18106
   macro avg       0.65      0.63      0.63     18106
```

```
weighted avg       0.65      0.64      0.63     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_random, ypred_proba_random)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - Hyperparameter tuned Random Forest Model',
fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_random, ypred_proba_random),4)))
plt.grid(True)
```




```
cols = ['test_accuracy', 'train_accuracy', 'test_precision',
'train_precision','test_recall','train_recall', 'test_kappa',
'train_kappa', 'f1_score','roc_auc_score']
model_evaluation_tuned = pd.DataFrame(columns=cols)
model_evaluation_tuned.loc['Tuned RandomForest Classifier'] =
[accuracy_score(ytest_random, ypred_random),
accuracy_score(ytrain_random, ypred_random_train),

precision_score(ytest_random, ypred_random),
precision_score(ytrain_random, ypred_random_train),
                                          recall_score(ytest_random,
```

```
ypred_random), recall_score(ytrain_random, ypred_random_train),

cohen_kappa_score(ytest_random, ypred_random),
cohen_kappa_score(ytrain_random, ypred_random_train),
                                          f1_score(ytest_random,
ypred_random), roc_auc_score(ytest_random, ypred_proba_random)]
model_evaluation_tuned
```

```
                               test_accuracy  train_accuracy
test_precision  \
Tuned RandomForest Classifier       0.644648        0.645508
0.658191

                               train_precision  test_recall
train_recall  \
Tuned RandomForest Classifier         0.656388     0.460487
0.458196

                               test_kappa  train_kappa  f1_score  \
Tuned RandomForest Classifier    0.266151     0.265979  0.541868

                               roc_auc_score
Tuned RandomForest Classifier       0.629867
```

18.2. Tuned XGBoost Classifier

```
xtrain_xg, xtest_xg, ytrain_xg, ytest_xg =
train_test_split(X[signi_feat_rfe_xg], df_target, test_size = 0.2,
random_state = 500)
print('xtrain: ', xtrain_xg.shape)
print('ytrain: ', ytrain_xg.shape)
print('xtest: ', xtest_xg.shape)
print('ytest: ', ytest_xg.shape)
```

```
xtrain:  (72422, 10)
ytrain:  (72422,)
xtest:  (18106, 10)
ytest:  (18106,)
```

```
xgb = XGBClassifier(random_state = 10)
parameters = [{'n_estimators': [30, 40, 50, 70, 90],
               'max_depth': range(2, 7),
                'learning_rate': [0.1, 0.2, 0.4, 0.5]}]
gcv_xgb = GridSearchCV(estimator = xgb, param_grid = parameters, cv =
5)
gcv_xgb.fit(xtrain_xg, ytrain_xg)
gcv_xgb.best_params_
```

```
{'learning_rate': 0.4, 'max_depth': 6, 'n_estimators': 90}
```

```
xgBoost = XGBClassifier(learning_rate = 0.5,max_depth = 6,n_estimators
= 90)
xgBoost.fit(xtrain_xg, ytrain_xg)
```

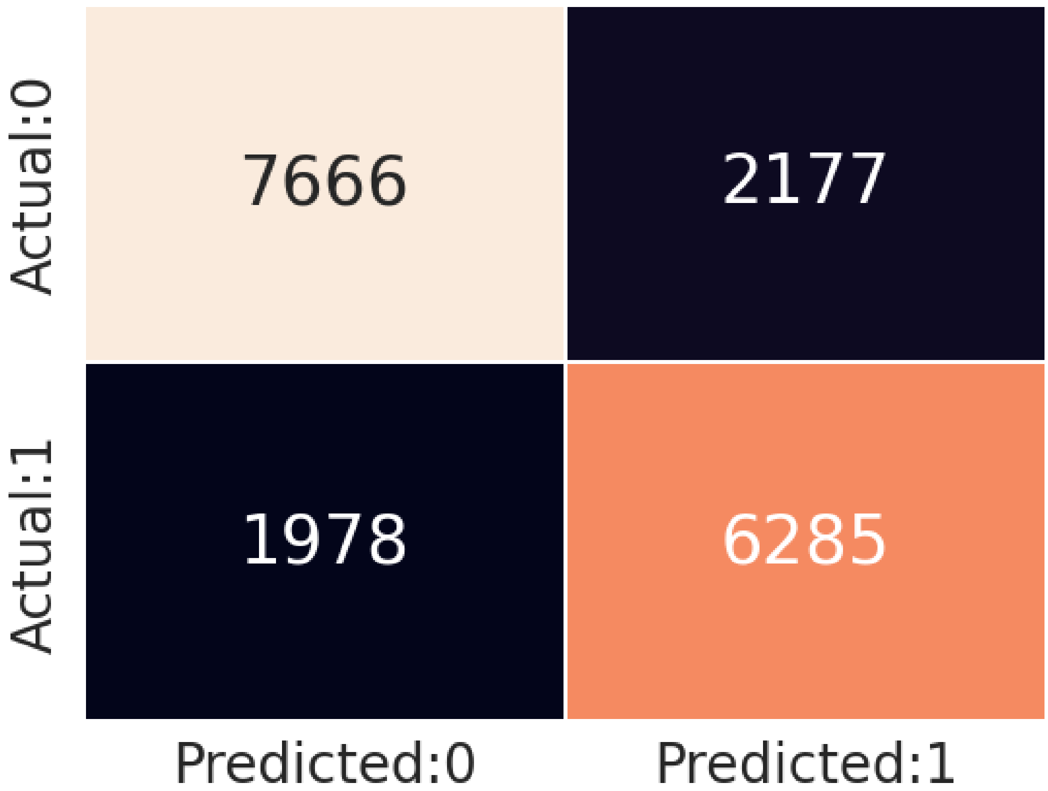
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1,
colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1,
grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.5, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0,
min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=90,
n_jobs=0,
              num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=1, ...)
```

```
ypred_proba_xg = xgBoost.predict(xtest_xg)
ypred_xg = [0 if i < 0.5 else 1 for i in ypred_proba_xg]
ypred_xg[:10]
```

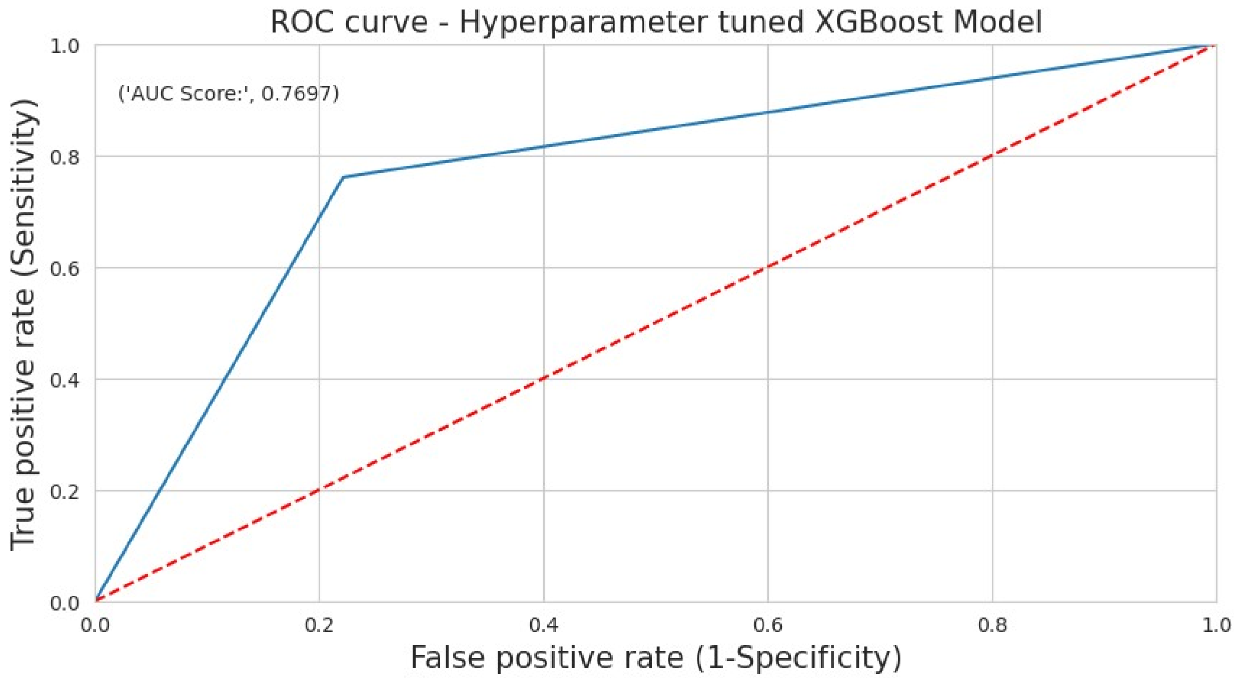
```
[0, 0, 0, 1, 0, 0, 1, 0, 1, 1]
```

```
ypred_proba_xg_train = xgBoost.predict(xtrain_xg)
ypred_xg_train = [0 if i < 0.5 else 1 for i in ypred_proba_xg_train]
```

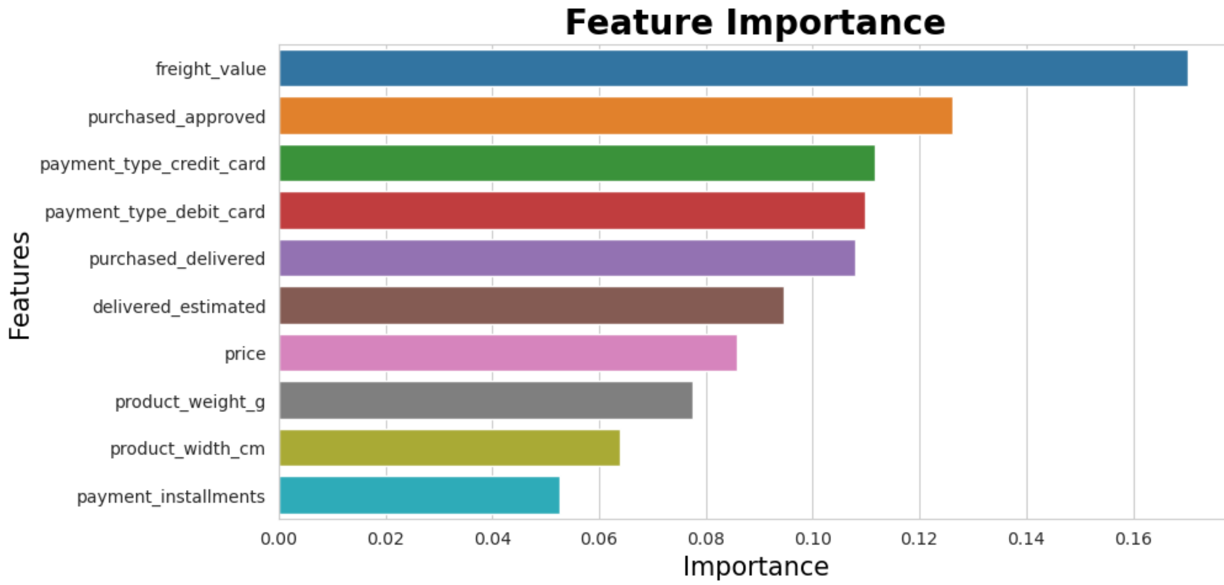
```
cm = confusion_matrix(ytest_xg, ypred_xg)
conf_matrix = pd.DataFrame(data = cm,columns =
['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
print(classification_report(ytest_xg, ypred_xg))

              precision    recall  f1-score   support

           0       0.79      0.78      0.79      9843
           1       0.74      0.76      0.75      8263

    accuracy                           0.77     18106
   macro avg       0.77      0.77      0.77     18106
weighted avg       0.77      0.77      0.77     18106


plt.figure(figsize = (10, 5))
fpr, tpr, thresholds = roc_curve(ytest_xg, ypred_proba_xg)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC curve - Hyperparameter tuned XGBoost Model', fontsize =
15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',
round(metrics.roc_auc_score(ytest_xg, ypred_proba_xg),4)))
plt.grid(True)
```




```
plt.figure(figsize=(10, 5))
important_features = pd.DataFrame({'Features': xtrain_xg.columns,
                                   'Importance':
xgBoost.feature_importances_})
important_features = important_features.sort_values('Importance',
ascending = False)
sns.barplot(x = 'Importance', y = 'Features', data =
important_features)
plt.title('Feature
Importance',color='black',fontsize=20,fontweight='bold')
plt.xlabel('Importance',color='black',fontsize=15)
plt.ylabel('Features',color='black',fontsize=15)
plt.show()
```




```
model_evaluation_tuned.loc['Tuned XGBoost Classifier'] =
[accuracy_score(ytest_xg, ypred_xg), accuracy_score(ytrain_xg,
ypred_xg_train),
                                          precision_score(ytest_xg,
ypred_xg), precision_score(ytrain_xg, ypred_xg_train),
                                          recall_score(ytest_xg,
ypred_xg), recall_score(ytrain_xg, ypred_xg_train),
                                          cohen_kappa_score(ytest_xg,
ypred_xg), cohen_kappa_score(ytrain_xg, ypred_xg_train),
                                          f1_score(ytest_xg,
ypred_xg), roc_auc_score(ytest_xg, ypred_proba_xg)]
model_evaluation_tuned

                               test_accuracy  train_accuracy
test_precision  \
Tuned RandomForest Classifier       0.644648        0.645508
0.658191
Tuned XGBoost Classifier            0.770518        0.839731
0.742732

                               train_precision  test_recall
train_recall  \
Tuned RandomForest Classifier         0.656388     0.460487
0.458196
Tuned XGBoost Classifier              0.811147     0.760620
0.842833

                               test_kappa  train_kappa  f1_score  \
Tuned RandomForest Classifier    0.266151     0.265979  0.541868
Tuned XGBoost Classifier         0.538407     0.677738  0.751570

                               roc_auc_score
```

```
Tuned RandomForest Classifier      0.629867
Tuned XGBoost Classifier           0.769724
```

19. Model Interpretation

Since the **target class is balanced**, we can **any of the metrics** below to measure the **model performance**.

1. **Accuracy**: This metric measures the **proportion of correct predictions** made by the model over all predictions made. It is a simple and intuitive measure, but it may not be the best choice when classes are imbalanced.
2. **Precision**: Precision measures the **proportion of true positives (correctly predicted positives) out of all predicted positives**. It is a useful metric when you want to minimize false positives.
3. **Recall**: Recall measures the **proportion of true positives out of all actual positives in the data**. It is a useful metric when you want to minimize false negatives.
4. **F1 score**: The F1 score is the **harmonic mean of precision and recall**. It balances the tradeoff between precision and recall and provides a single measure of performance.
5. **Area under the ROC curve (AUC-ROC)**: AUC-ROC is a metric that measures the **ability of the model to distinguish between positive and negative classes**. It is a good metric when you want to evaluate the overall performance of the model across different thresholds.

The choice of metric depends on the specific goals of the problem and the tradeoffs we want to make between different types of errors.

Classification report (XG Boost Model)

1. Percision = 0.77 (high - Number of False positives are low)
2. Recall = 0.77 (high - Number of False negatives are low)
3. F1 Score = 0.77 (high - imbalance in recall and percision is low)
4. Accuracy = 0.77

The XG Boost is the best model for predicting Churn classification.

Pipeline