ECOMMERCE SHIPPING PREDICTION USING MACHINE LEARNING

SmartInternz
www.smartinternz.com

Team ID : SWTID1720196555

Team Leader : PATHAKUNTLA NARENDAR REDDY

Team member : MITTA UDAY SRINADH

Team member : Gummadi Jyotshna

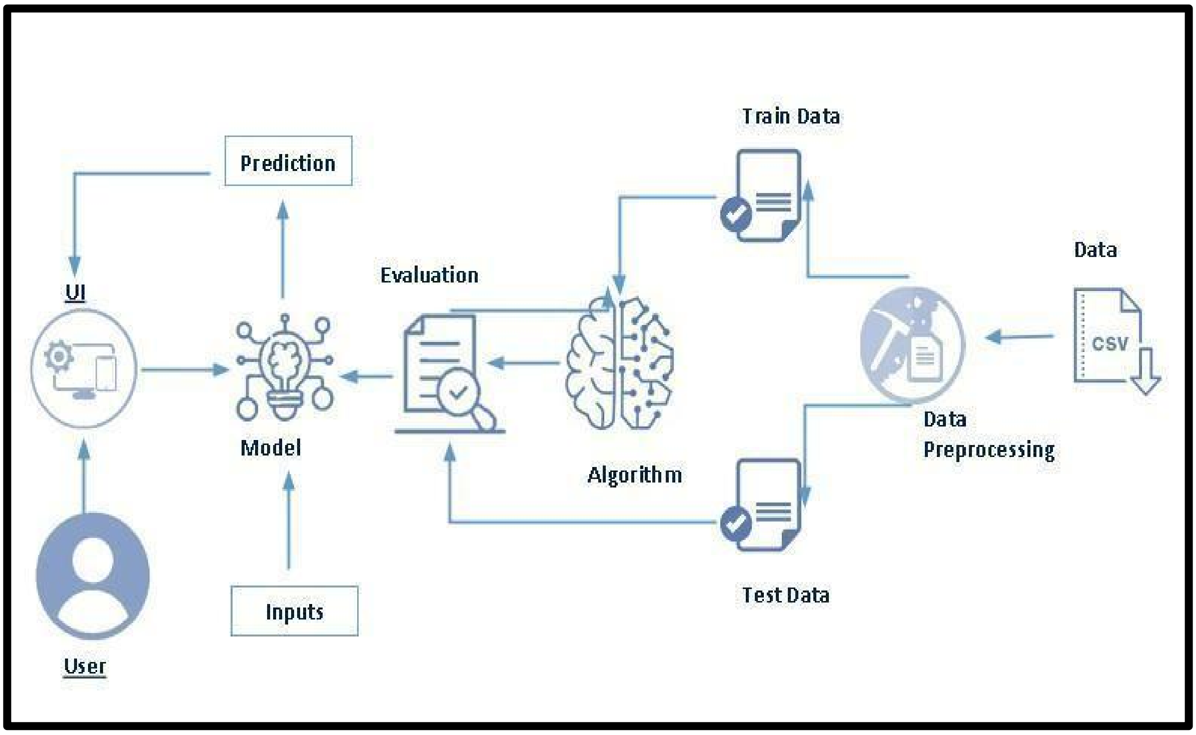
Team member : Mallipeddi Harshitha

Ecommerce Shipping Prediction Using Machine Learning

Category: Machine Learning

Skills Required:
Python,Machine Learning,Numpy,Pandas,Matplotlib,Seaborn,HTML,Python-Flask
Project Description:
Ecommerce shipping prediction is the process of estimating the whether the product reached on time. which is based on various factors such as the origin and destination of the package, the shipping method selected by the customer, the carrier used for shipping, and any potential delays or issues that may arise during the shipping process. Machine learning models can be used to make accurate predictions about shipping times based on historical data and real-time updates from carriers. These models may take into account factors such as weather conditions, traffic, and other external factors that can impact delivery times. Over All Ecommerce shipping prediction is an important tool for ecommerce businesses that want to provide accurate delivery estimates to their customers and improve their overall customer experience.

Technical Architecture:



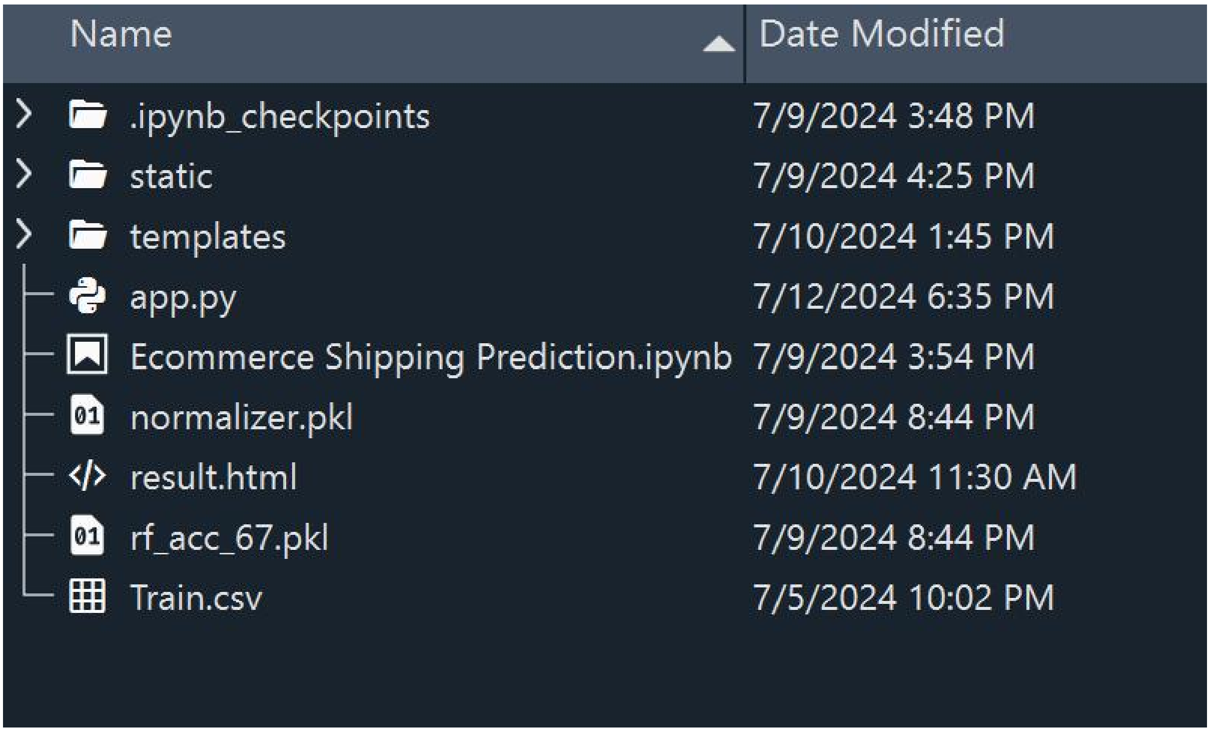
Project Flow:

- User interacts with the UI to enter the input.
- Entered input is analysed by the model which is integrated.
- Once model analyses the input the prediction is showcased on the UI

To accomplish this, we have to complete all the activities listed below,

- Define Problem / Problem Understanding
  - Specify the business problem
  - Business requirements
  - Literature Survey
  - Social or Business Impact.
- Data Collection & Preparation
  - Collect the dataset
  - Data Preparation
- Exploratory Data Analysis
  - Descriptive statistical
  - Visual Analysis
- Model Building
  - Training the model in multiple algorithms
  - Testing the model
- Performance Testing & Hyperparameter Tuning
  - Testing model with multiple evaluation metrics
  - Comparing model accuracy before & after applying hyperparameter tuning
- Model Deployment
  - Save the best model
  - Integrate with Web Framework
- Project Demonstration & Documentation
  - Record explanation Video for project end to end solution
  - Project Documentation-Step by step project development procedure

Project Structure:



Name	Date Modified
.ipynb_checkpoints	7/9/2024 3:48 PM
static	7/9/2024 4:25 PM
templates	7/10/2024 1:45 PM
app.py	7/12/2024 6:35 PM
Ecommerce Shipping Prediction.ipynb	7/9/2024 3:54 PM
normalizer.pkl	7/9/2024 8:44 PM
result.html	7/10/2024 11:30 AM
rf_acc_67.pkl	7/9/2024 8:44 PM
Train.csv	7/5/2024 10:02 PM

We are building a flask application which needs HTML pages stored in the templates folder and a python script app.py for scripting.

Static folder and assets folder contain the CSS and JavaScript files along with images.

rf_acc_67.pkl and normalizer.pkl are our saved models. Further we will use these models for flask integration.

Training folder contains a model training file that are jupyter notebooks

Milestone 1: Define Problem / Problem Understanding

Specify The Business Problem

Skill Tags:

Here are some potential business requirements for an ecommerce product delivery estimation predictor using machine learning:

Accurate Delivery Estimates: The primary goal of the system should be to provide accurate delivery estimates to customers. The estimated delivery time should consider factors such as distance, traffic, weather, and any other relevant variables.

Real-Time Updates: Customers should be able to receive real-time updates on the status of their delivery, including any delays or changes to the estimated delivery time. The system should be able to adjust the estimated delivery time based on the most up-to-date information available.

Integration with Ecommerce Platforms: The system should be able to integrate with popular ecommerce platforms, such as Shopify or Magento, to automatically retrieve order information and provide accurate delivery estimates.

Machine Learning Models: The system should use machine learning models to predict delivery times based on historical delivery data and other relevant variables. The machine learning models should be trained and optimized to improve accuracy over time.

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Activity 3: Literature Survey (Student Will Write).

Activity 4: Social or Business Impact.

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Social Impacts:
Improved Customer Experience: Providing accurate delivery estimates can help improve the overall customer experience by reducing uncertainty and increasing transparency.
Reduced Environmental Impact: By accurately estimating delivery times, businesses can optimize their logistics and reduce the number of unnecessary trips and emissions from delivery vehicles.
Reduced Stress for Delivery Workers: By optimizing delivery routes and times, businesses can reduce the workload and stress on delivery workers, leading to a better work environment and potentially reducing turnover.

Business Impacts:

Increased Sales: Accurate delivery estimates can help increase customer confidence and reduce cart abandonment rates, leading to increased sales and revenue.
Improved Operational Efficiency: By optimizing delivery routes and times, businesses can reduce costs associated with transportation, labor, and inventory management.
Competitive Advantage: Implementing a delivery estimation predictor using machine learning can provide a competitive advantage over other ecommerce businesses that do not offer accurate and transparent delivery estimates.

Milestone 2: Data Collection & Preparation

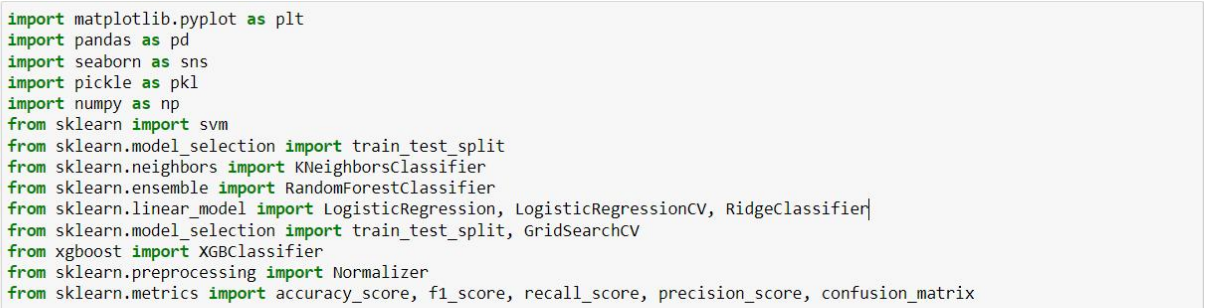
ML depends heavily on data. It is the most crucial aspect that makes algorithm training possible. So, this section allows you to download the required dataset.

Collect The Dataset

There are many popular open sources for collecting the data. Eg: kaggle.com, UCI repository, etc. In this project we have used .csv data. This data is downloaded from kaggle.com. Please refer to the link given below to download the dataset.
Link: https://www.kaggle.com/datasets/prachi13/customer-analytics?select=Train.csv
As the dataset is downloaded. Let us read and understand the data properly with the help of some visualisation techniques and some analysing techniques.
Note:There are a number of techniques for understanding the data. But here we have used some of it. In an additional way, you can use multiple techniques.

Importing the libraries

Import the necessary libraries as shown in the image.

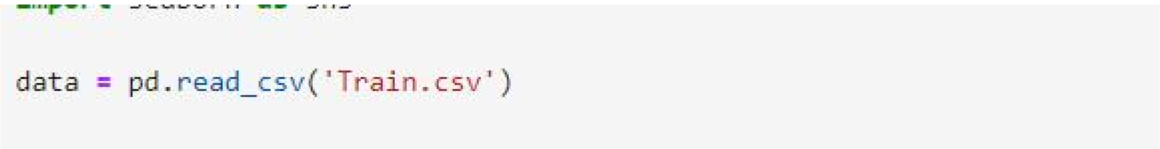


```
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import pickle as pkl
import numpy as np
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV, RidgeClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from xgboost import XGBClassifier
from sklearn.preprocessing import Normalizer
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score, confusion_matrix
```

Read the Dataset

Our dataset format might be in .csv, excel files, .txt, .json, etc. We can read the dataset with the help of pandas.

In pandas we have a function called read_csv() to read the dataset. As a parameter we have to give the directory of the csv file.



```
import seaborn as sns

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

Activity 2: Data Preparation

As we have understood how the data is, let's pre-process the collected data.

The download data set is not suitable for training the machine learning model as it might have so much randomness so we need to clean the dataset properly in order to fetch good results. This activity includes the following steps.

Handling missing values

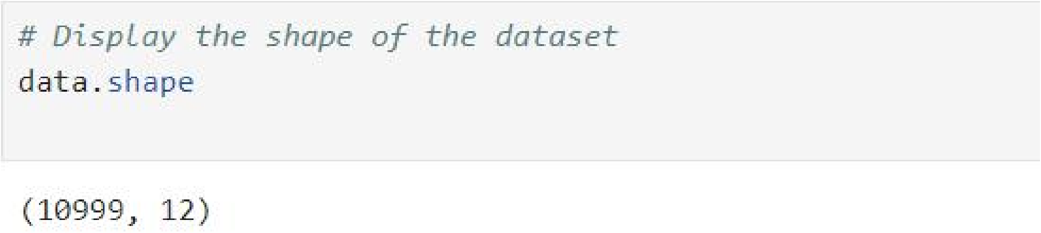
Handling categorical data

Handling Outliers

Note: These are the general steps of pre-processing the data before using it for machine learning. Depending on the condition of your dataset, you may or may not have to go through all these steps.

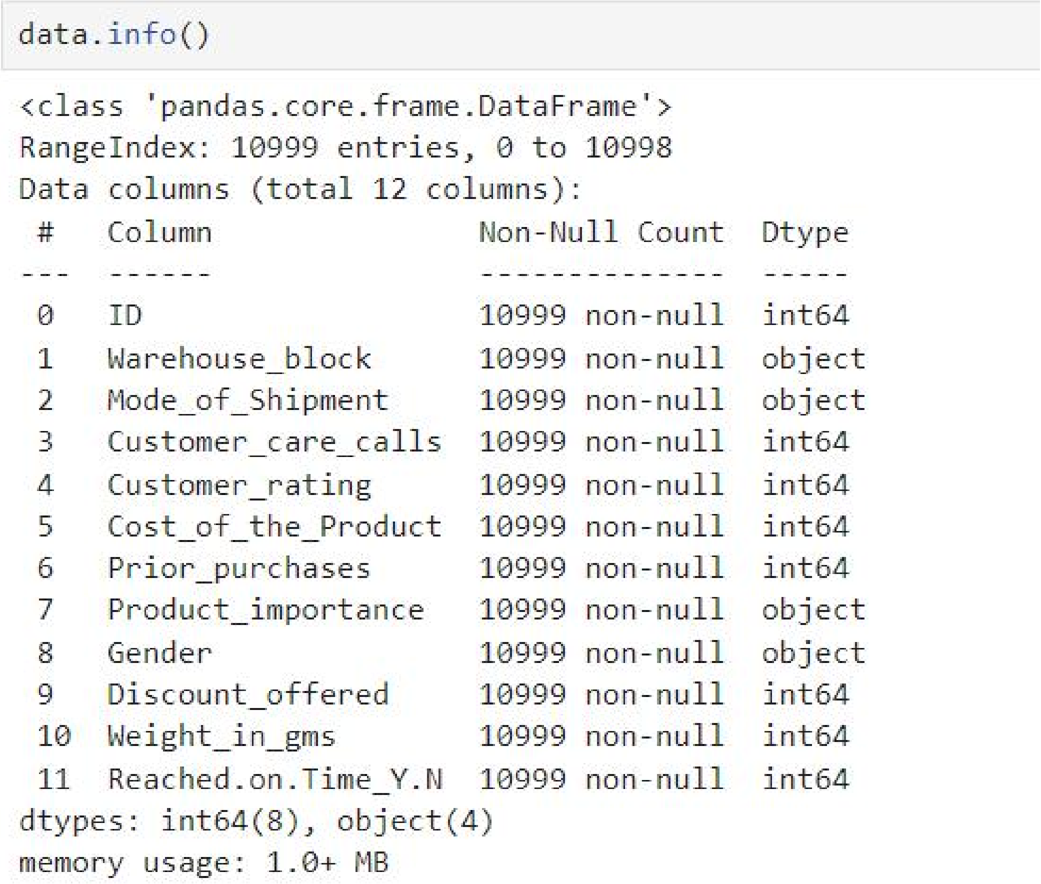
Handling missing values

Let’s find the shape of our dataset first. To find the shape of our data, the df.shape method is used. To find the data type, df.info() function is used



```
# Display the shape of the dataset
data.shape
```

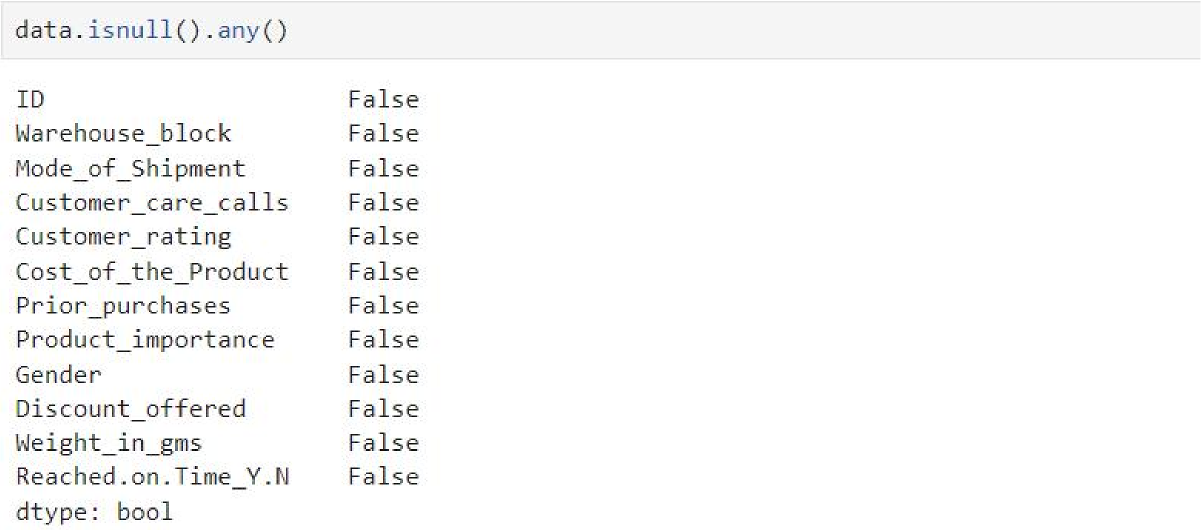
```
(10999, 12)
```



```
data.info()
```

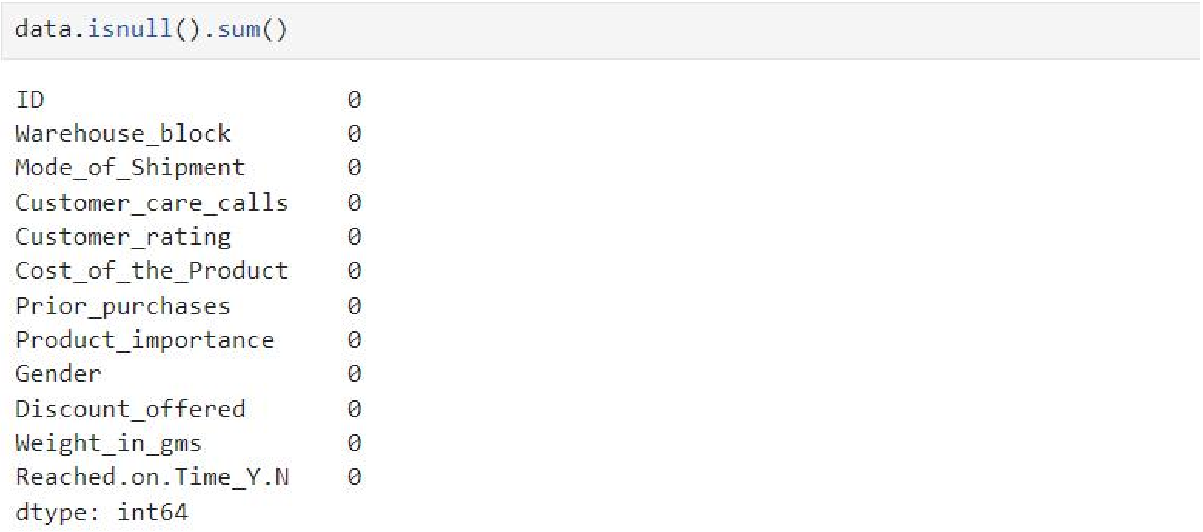
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10999 entries, 0 to 10998
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   ID                   10999 non-null  int64 
 1   Warehouse_block      10999 non-null  object
 2   Mode_of_Shipment     10999 non-null  object
 3   Customer_care_calls  10999 non-null  int64 
 4   Customer_rating      10999 non-null  int64 
 5   Cost_of_the_Product  10999 non-null  int64 
 6   Prior_purchases      10999 non-null  int64 
 7   Product_importance   10999 non-null  object
 8   Gender               10999 non-null  object
 9   Discount_offered     10999 non-null  int64 
 10  Weight_in_gms        10999 non-null  int64 
 11  Reached.on.Time_Y.N  10999 non-null  int64 
dtypes: int64(8), object(4)
memory usage: 1.0+ MB
```

For checking the null values, df.isnull() function is used. To sum those null values we use .sum() function. From the below image we found that there are no null values present in our dataset. So we can skip handling the missing values step.



```
data.isnull().any()
```

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



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

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

Activity 2.2: *Handling Categorical Values*

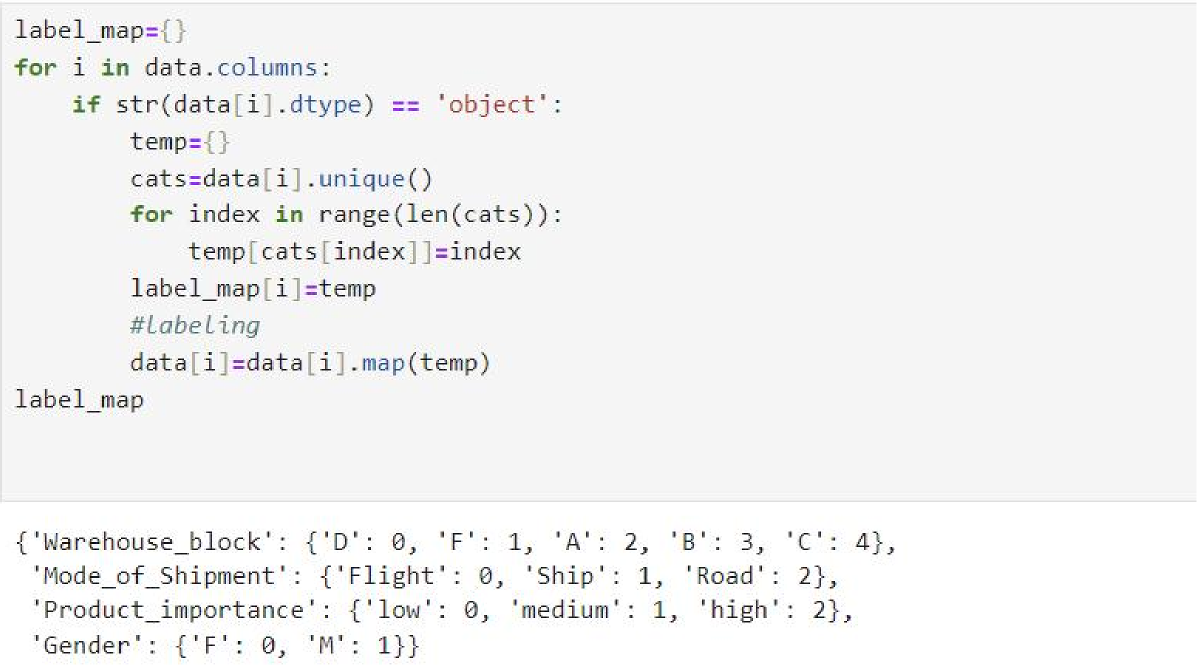
As we can see our dataset has categorical data we must convert the categorical data to integer encoding or binary encoding.

To convert the categorical features into numerical features we use encoding techniques. There are several techniques but in our project we are using manual encoding with the help of list comprehension.

In our project, categorical features are

- Warehouse_block
- Mode_of_shipment
- Product_importance
- Gender.

With list comprehension encoding is done.



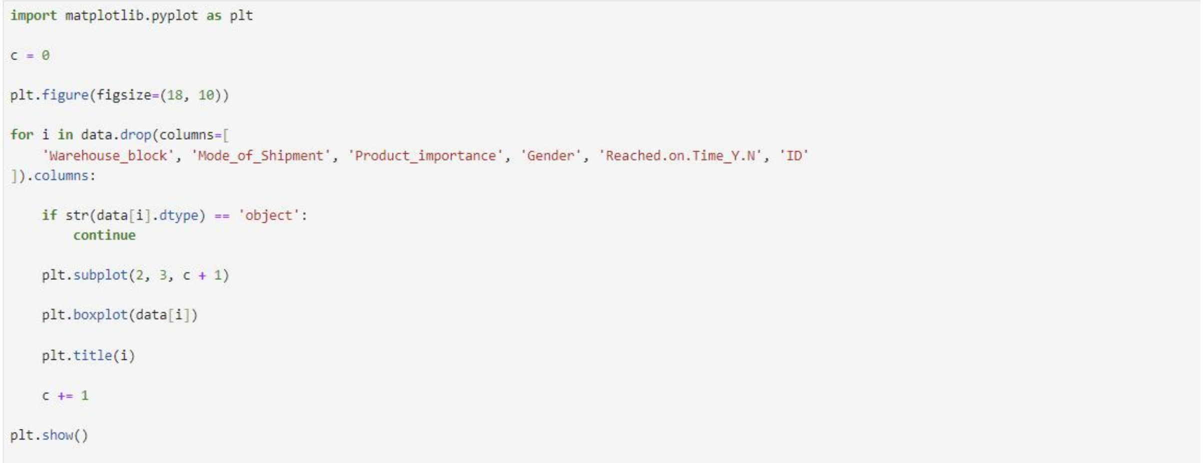
```
label_map={}
for i in data.columns:
    if str(data[i].dtype) == 'object':
        temp={}
        cats=data[i].unique()
        for index in range(len(cats)):
            temp[cats[index]]=index
        label_map[i]=temp
        #labeling
        data[i]=data[i].map(temp)
label_map
```

```
{'Warehouse_block': {'D': 0, 'F': 1, 'A': 2, 'B': 3, 'C': 4},
 'Mode_of_Shipment': {'Flight': 0, 'Ship': 1, 'Road': 2},
 'Product_importance': {'low': 0, 'medium': 1, 'high': 2},
 'Gender': {'F': 0, 'M': 1}}
```

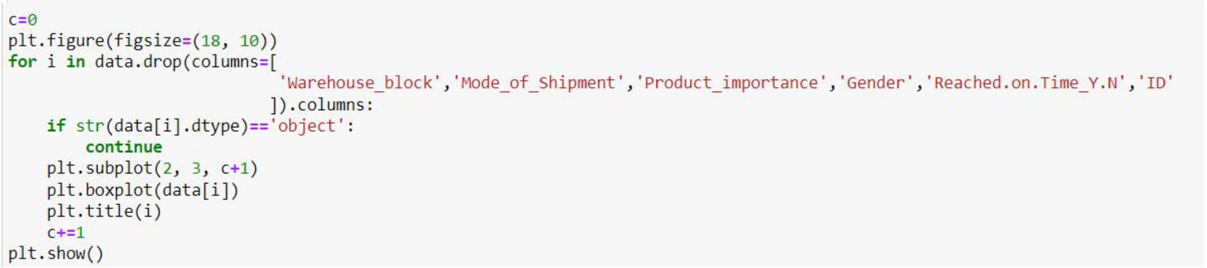
Activity 2.3: Handling Outliers in Data

With the help of boxplot, outliers are visualized. And here we are going to find upper bound and lower bound of numerical features with some mathematical formula.

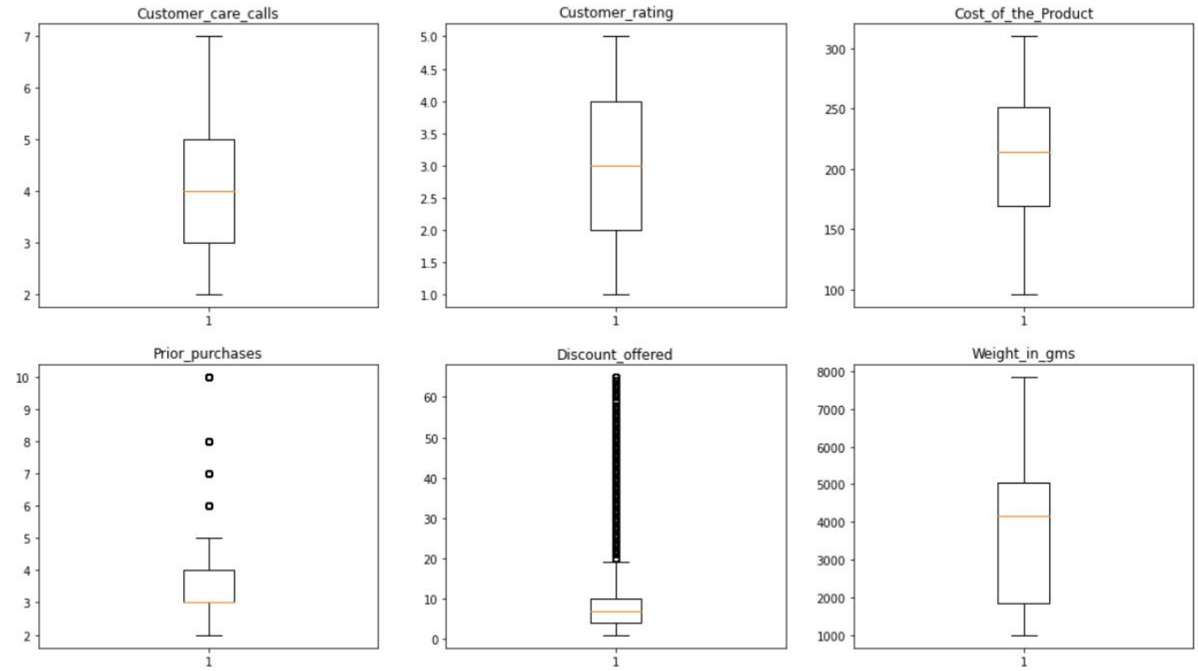
From the below diagram, we could visualize that Discount_offered, Prior_purchases features have outliers. Boxplot from matplotlib library is used here.



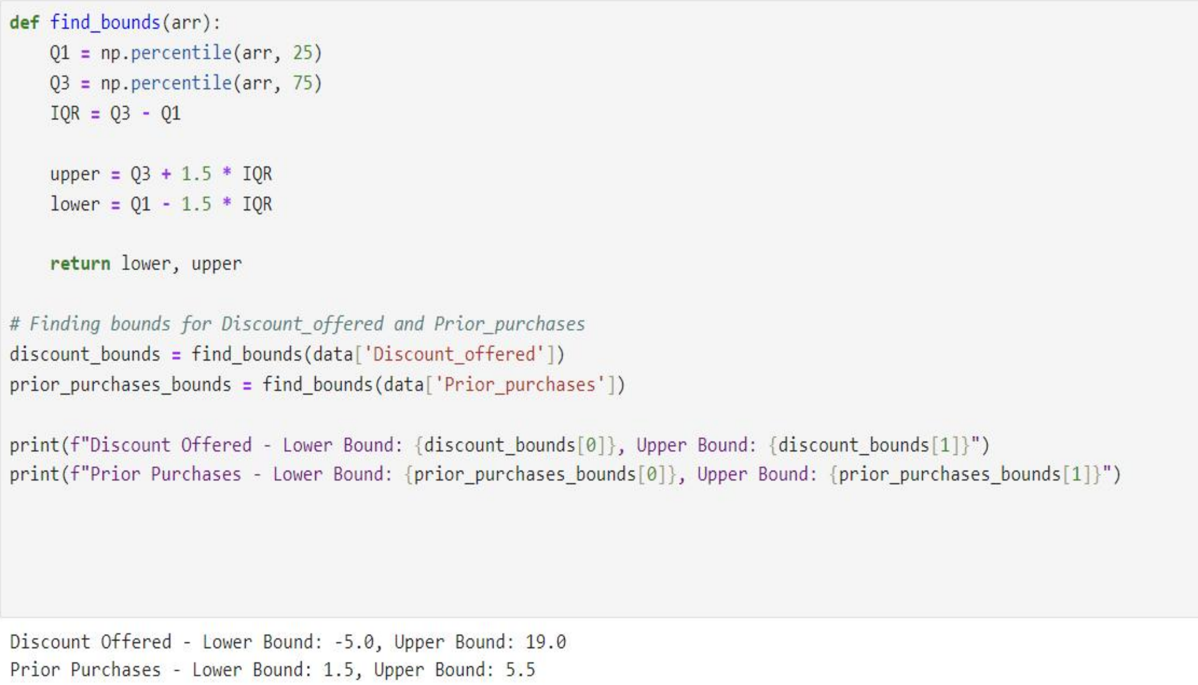
```
import matplotlib.pyplot as plt

c = 0

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

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

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

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

    plt.boxplot(data[i])

    plt.title(i)

    c += 1

plt.show()
```



```
c=0
plt.figure(figsize=(18, 10))
for i in data.drop(columns=[
                            'Warehouse_block','Mode_of_Shipment','Product_importance','Gender','Reached.on.Time_Y.N','ID'
                           ]).columns:
    if str(data[i].dtype)=='object':
        continue
    plt.subplot(2, 3, c+1)
    plt.boxplot(data[i])
    plt.title(i)
    c+=1
plt.show()
```

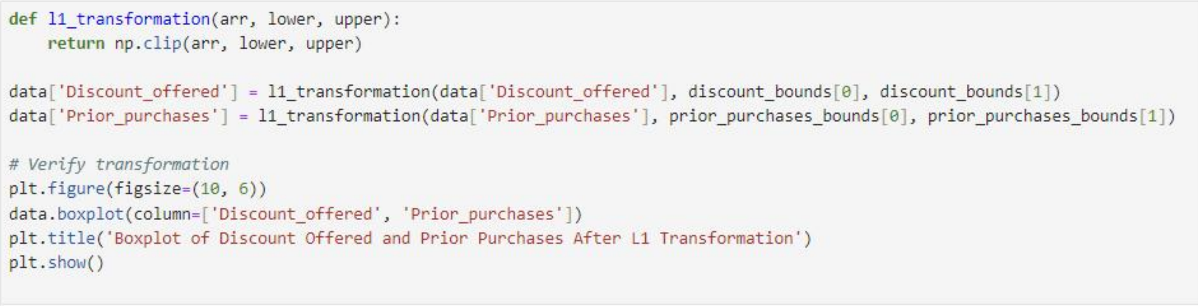


To find upper bound we have to multiply IQR (Interquartile range) with 1.5 and add it with 3rd quantile. To find lower bound instead of adding, subtract it with 1st quantile. Take image attached below as your reference.

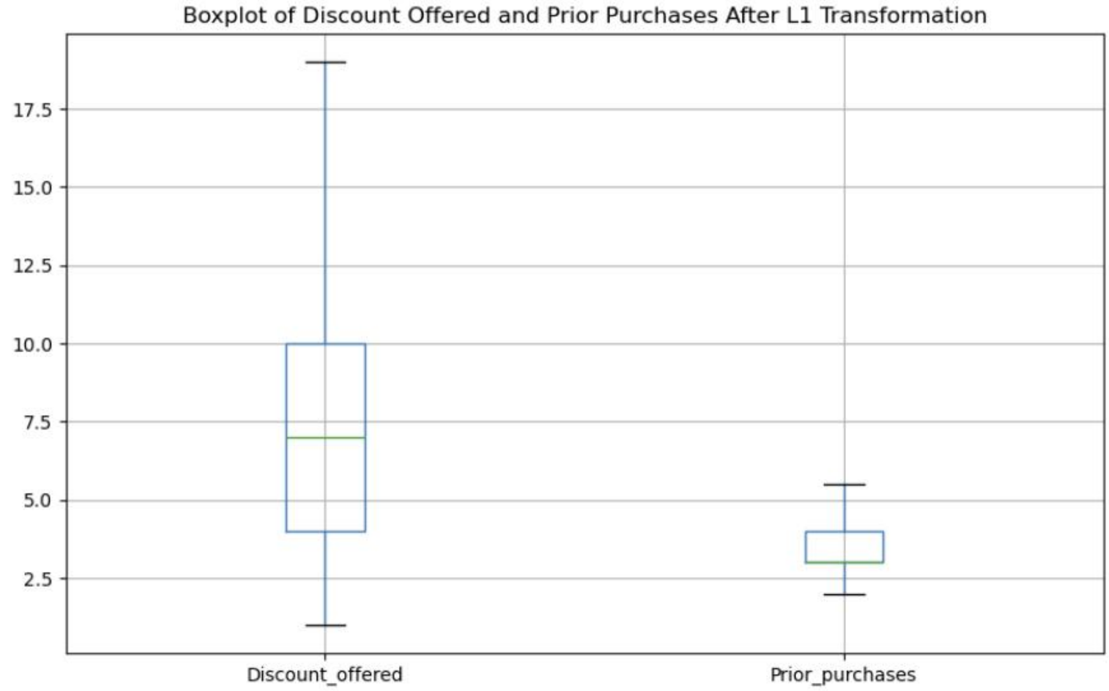


```python
def find_bounds(arr):
    Q1 = np.percentile(arr, 25)
    Q3 = np.percentile(arr, 75)
    IQR = Q3 - Q1

    upper = Q3 + 1.5 * IQR
    lower = Q1 - 1.5 * IQR

    return lower, upper

# Finding bounds for Discount_offered and Prior_purchases
discount_bounds = find_bounds(data['Discount_offered'])
prior_purchases_bounds = find_bounds(data['Prior_purchases'])

print(f"Discount Offered - Lower Bound: {discount_bounds[0]}, Upper Bound: {discount_bounds[1]}")
print(f"Prior Purchases - Lower Bound: {prior_purchases_bounds[0]}, Upper Bound: {prior_purchases_bounds[1]}")
```

```
Discount Offered - Lower Bound: -5.0, Upper Bound: 19.0
Prior Purchases - Lower Bound: 1.5, Upper Bound: 5.5
```

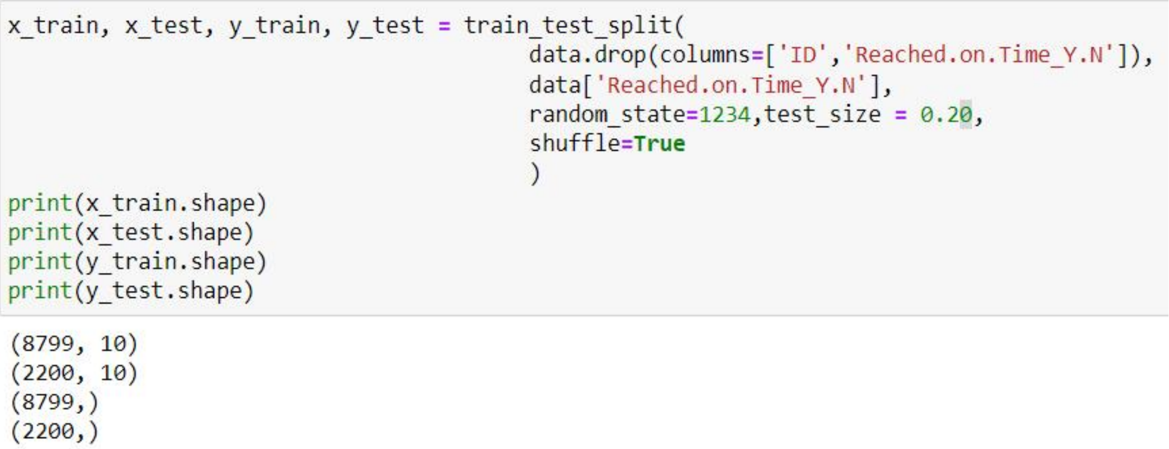


```
def l1_transformation(arr, lower, upper):
    return np.clip(arr, lower, upper)

data['Discount_offered'] = l1_transformation(data['Discount_offered'], discount_bounds[0], discount_bounds[1])
data['Prior_purchases'] = l1_transformation(data['Prior_purchases'], prior_purchases_bounds[0], prior_purchases_bounds[1])

# Verify transformation
plt.figure(figsize=(10, 6))
data.boxplot(column=['Discount_offered', 'Prior_purchases'])
plt.title('Boxplot of Discount Offered and Prior Purchases After L1 Transformation')
plt.show()
```



➔ Data splitting

The data was split into train and test variables as shown below using the train_test_split() method of scikitlearn module with a split_size of 0.20 and a random_state = 1234.



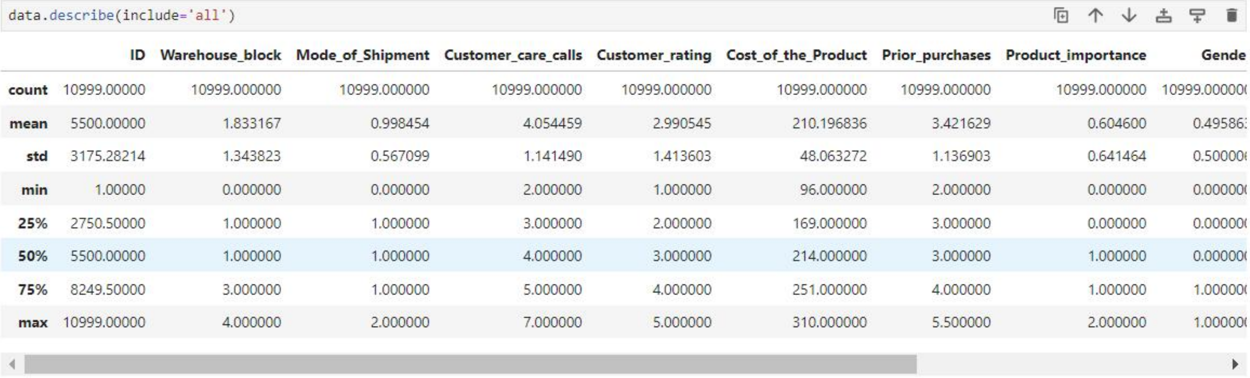
```
x_train, x_test, y_train, y_test = train_test_split(
                                            data.drop(columns=['ID','Reached.on.Time_Y.N']),
                                            data['Reached.on.Time_Y.N'],
                                            random_state=1234,test_size = 0.20,
                                            shuffle=True
                                            )

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(8799, 10)
(2200, 10)
(8799,)
(2200,)
```

Milestone 3: Exploratory Data Analysis

Activity 1: Descriptive statistical

Descriptive analysis is to study the basic features of data with the statistical process. Here pandas has a worthy function called describe. With this describe function we can understand the unique, top and frequent values of categorical features. And we can find mean, std, min, max and percentile values of continuous features.



```
data.describe(include='all')
```

	ID	Warehouse_block	Mode_of_Shipment	Customer_care_calls	Customer_rating	Cost_of_the_Product	Prior_purchases	Product_importance	Gende
count	10999.00000	10999.000000	10999.000000	10999.000000	10999.000000	10999.000000	10999.000000	10999.000000	10999.00000
mean	5500.00000	1.833167	0.998454	4.054459	2.990545	210.196836	3.421629	0.604600	0.49586
std	3175.28214	1.343823	0.567099	1.141490	1.413603	48.063272	1.136903	0.641464	0.50000
min	1.00000	0.000000	0.000000	2.000000	1.000000	96.000000	2.000000	0.000000	0.00000
25%	2750.50000	1.000000	1.000000	3.000000	2.000000	169.000000	3.000000	0.000000	0.00000
50%	5500.00000	1.000000	1.000000	4.000000	3.000000	214.000000	3.000000	1.000000	0.00000
75%	8249.50000	3.000000	1.000000	5.000000	4.000000	251.000000	4.000000	1.000000	1.00000
max	10999.00000	4.000000	2.000000	7.000000	5.000000	310.000000	5.500000	2.000000	1.00000

Activity 2: Visual analysis

Visual analysis is the process of using visual representations, such as charts, plots, and graphs, to explore and understand data. It is a way to quickly identify patterns, trends, and outliers in the data, which can help to gain insights and make informed decisions.

Activity 2.1: Univariate analysis

In simple words, univariate analysis is understanding the data with single feature. Here we have displayed two different graphs such as histplot and countplot.

Seaborn package provides a wonderful function histplot. With the help of histplot, we can find the distribution of the feature. To make multiple graphs in a single plot, we use subplot.

From the plot we came to know,

Customer Care Calls: Slight positive skewed normal distribution with mode at 4.

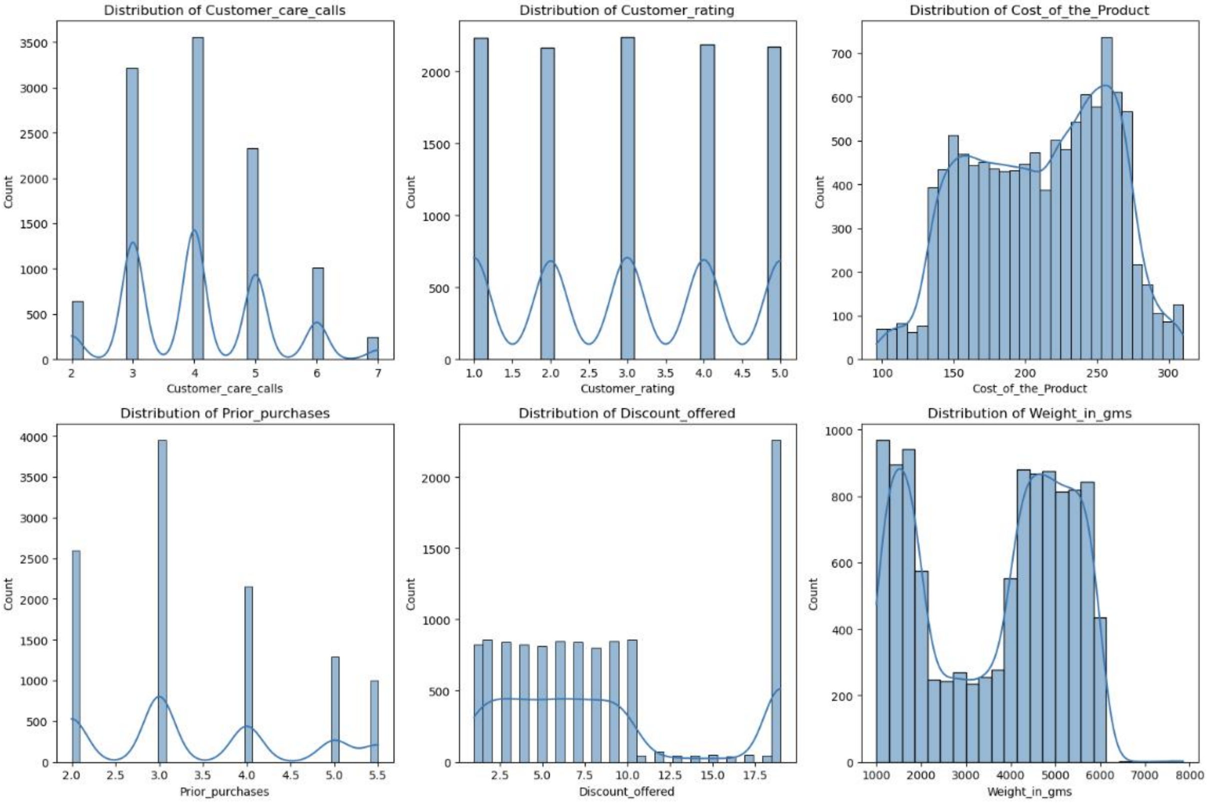
Customer Rating: Uniform distribution.

Cost of the product: 2 picks: smallest around 150, highest around 250.

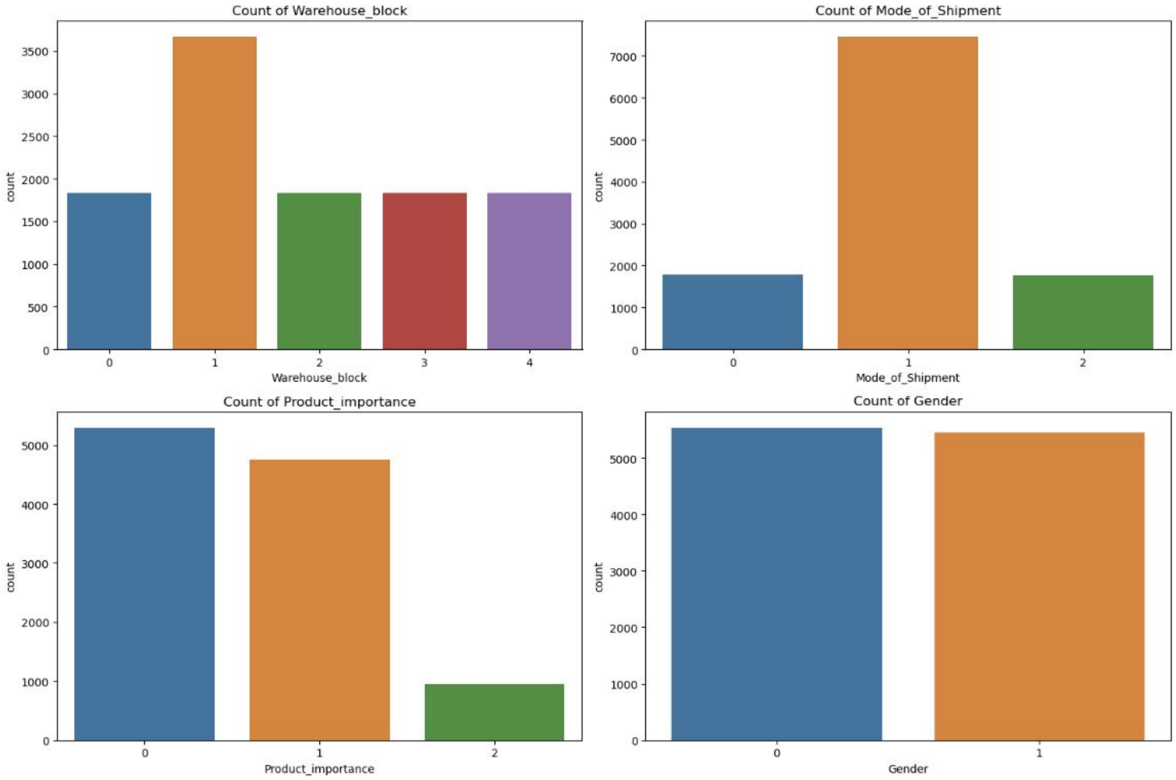
Prior Purchases: Positive skewed normal distribution, mode at 3.

Discount offered: Separated into 2 uniform distributions: 0 to 10 is predominant and then small amount from 10 to 65.

Weight: 3 zones: high from 1000 to 2000 and from 4000 to 6000. Low from 2000 to 4000.



In our dataset we have some categorical features. With the countplot function, we are going to count the unique category in those features. We have created a dummy data frame with categorical features. With for loop and subplot we have plotted this below graph.



Activity 2.2: Bivariate analysis

To find the relation between two features we use bivariate analysis. Here we are visualizing the relationship between drug & BP, drug & sex and drug & cholesterol.

Countplot is used here. As a 1st parameter we are passing x value and as a 2nd parameter we are passing hue value.

From the below plot you can understand that drugA and drugB is not preferred to low and normal BP patients. DrugC is preferred only to low BP patients.

By third graph we can understand, drugC is not preferred to normal cholesterol patients.

Warehouse: Blocks A, B, C, D are equilibrated while block F is predominent (1/2 ratio).

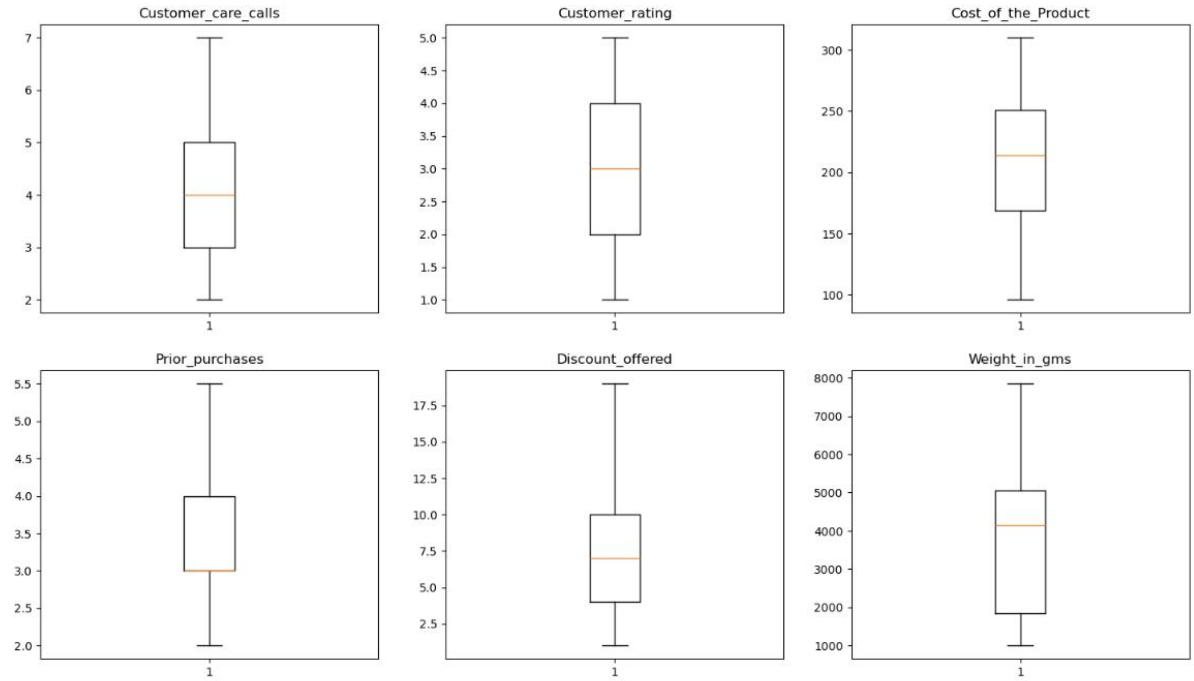
Shipment: Flight and Road have similar observations while Ship is predominent (1/4 ratio).

Importance: There is a majority of low and medium importances and a minority of high importances.

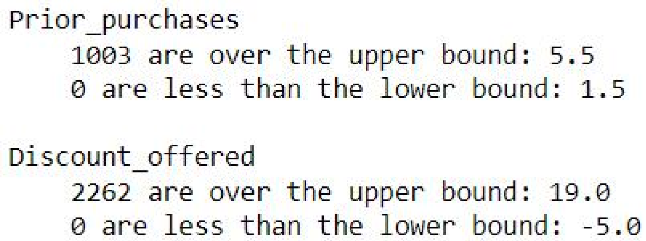
Genders: Both classes are balanced.

From the plots, we observe that very less number of orders are considered as important.

The most common mode of shipment is by Ship and products are packaged from warehouse F. Both genders order the products in a balanced way with orders by Females being slightly higher.



Outliers were found for 2 features (Discount_offered,Weight_in_gms) as visualized above using box plots. To be specific using IQR (inter quartile range) it was observed that,



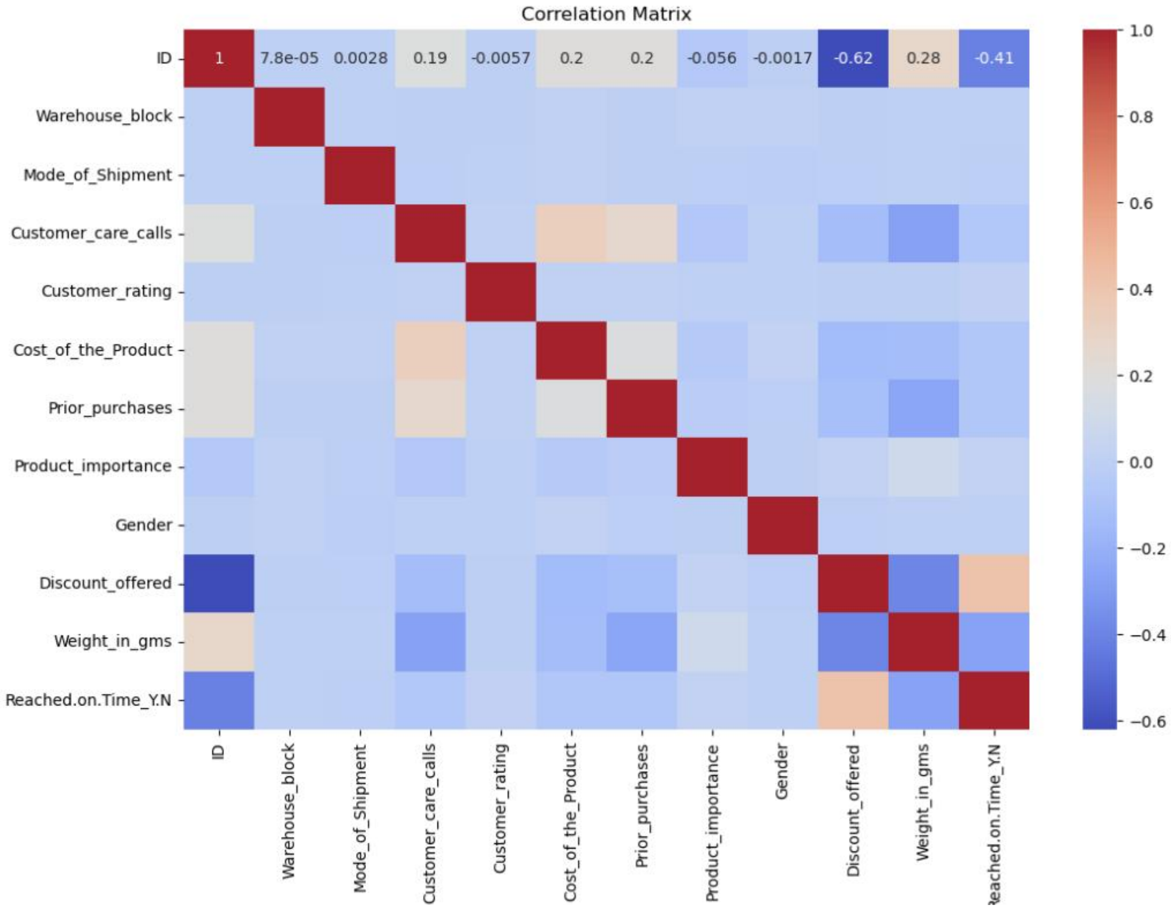
```
Prior_purchases
    1003 are over the upper bound: 5.5
    0 are less than the lower bound: 1.5

Discount_offered
    2262 are over the upper bound: 19.0
    0 are less than the lower bound: -5.0
```

What this means is that there are 1003 and 2263 outliers for Prior_purchases and Discount_offered variables of the dataset.

Activity 2.3: Multivariate analysis

In simple words, multivariate analysis is to find the relation between multiple features. Here we have used heatmap from seaborn package.

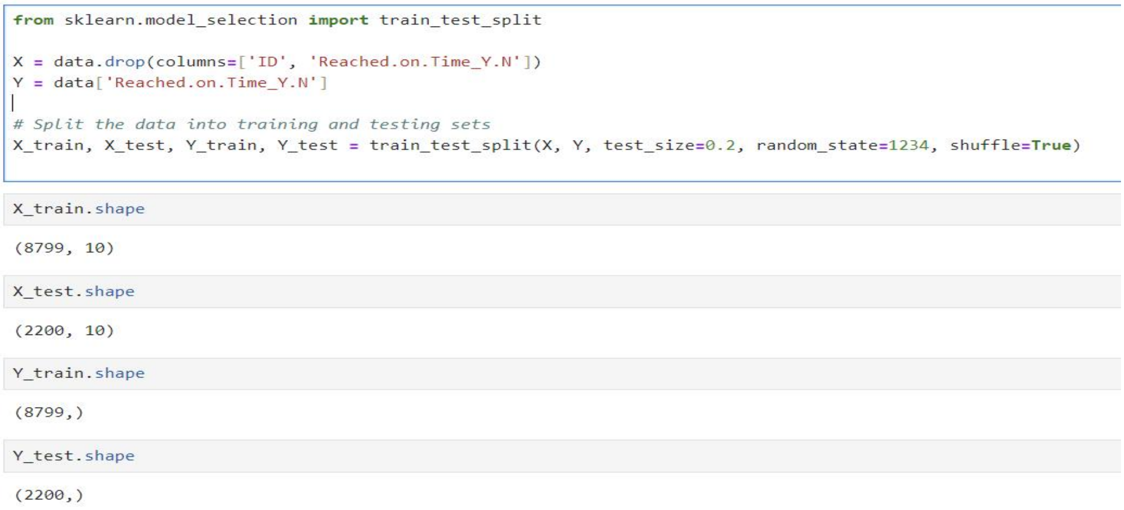
From the below image, we came to a conclusion that the product discount is the feature that most highly correlates to if a product is delivered on time and Number of calls and product cost are also highly correlated among other variables.



Splitting data into train and test

Now let’s split the Dataset into train and test sets. First split the dataset into x and y and then split the data set.

Here x and y variables are created. On x variable, data is passed with dropping the target variable. And on y target variable is passed. For splitting training and testing data we are using train_test_split() function from sklearn. As parameters, we are passing x, y, test_size, random_staten shuffle.



```
from sklearn.model_selection import train_test_split

X = data.drop(columns=['ID', 'Reached.on.Time_Y.N'])
Y = data['Reached.on.Time_Y.N']

# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=1234, shuffle=True)
```

```
X_train.shape
```

```
(8799, 10)
```

```
X_test.shape
```

```
(2200, 10)
```

```
Y_train.shape
```

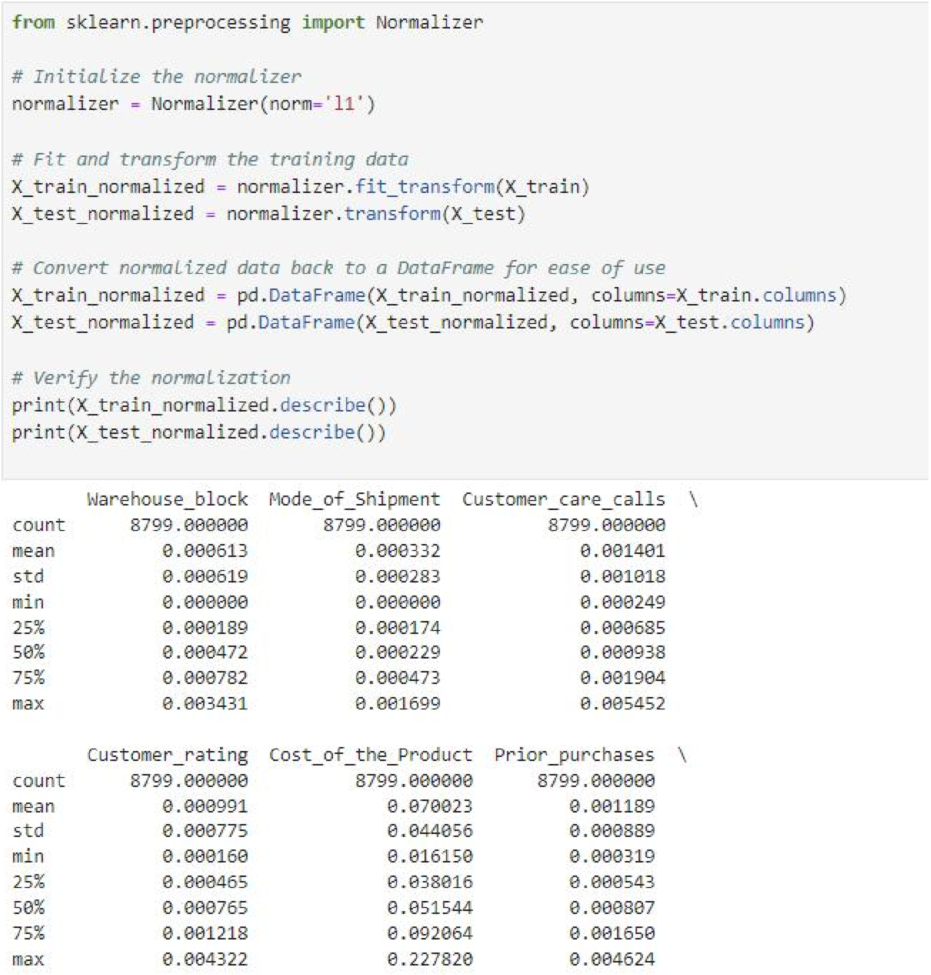
```
(8799,)
```

```
Y_test.shape
```

```
(2200,)
```

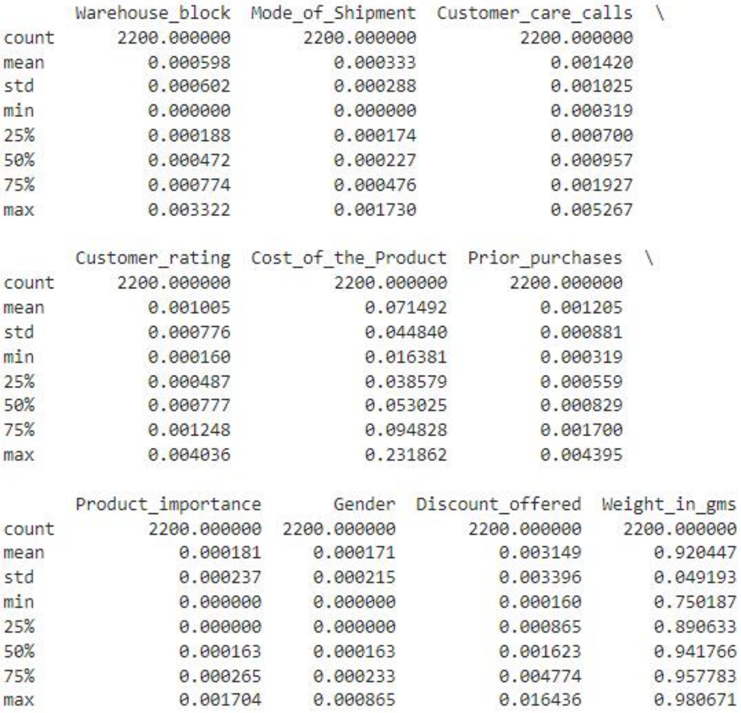
Normalization

The data will be normalized using L1 regularisation that will be applied on x_train and x_test variables separately.



```
from sklearn.preprocessing import Normalizer

# Initialize the normalizer
normalizer = Normalizer(norm='l1')

# Fit and transform the training data
X_train_normalized = normalizer.fit_transform(X_train)
X_test_normalized = normalizer.transform(X_test)

# Convert normalized data back to a DataFrame for ease of use
X_train_normalized = pd.DataFrame(X_train_normalized, columns=X_train.columns)
X_test_normalized = pd.DataFrame(X_test_normalized, columns=X_test.columns)

# Verify the normalization
print(X_train_normalized.describe())
print(X_test_normalized.describe())
```

```
       Warehouse_block  Mode_of_Shipment  Customer_care_calls  \
count      8799.000000       8799.000000          8799.000000
mean          0.000613          0.000332             0.001401
std           0.000619          0.000283             0.001018
min           0.000000          0.000000             0.000249
25%           0.000189          0.000174             0.000685
50%           0.000472          0.000229             0.000938
75%           0.000782          0.000473             0.001904
max           0.003431          0.001699             0.005452

       Customer_rating  Cost_of_the_Product  Prior_purchases  \
count      8799.000000          8799.000000      8799.000000
mean          0.000991             0.070023         0.001189
std           0.000775             0.044056         0.000889
min           0.000160             0.016150         0.000319
25%           0.000465             0.038016         0.000543
50%           0.000765             0.051544         0.000807
75%           0.001218             0.092064         0.001650
max           0.004322             0.227820         0.004624
```



```
       Warehouse_block  Mode_of_Shipment  Customer_care_calls  \
count      2200.000000       2200.000000          2200.000000
mean          0.000598          0.000333             0.001420
std           0.000602          0.000288             0.001025
min           0.000000          0.000000             0.000319
25%           0.000188          0.000174             0.000700
50%           0.000472          0.000227             0.000957
75%           0.000774          0.000476             0.001927
max           0.003322          0.001730             0.005267

       Customer_rating  Cost_of_the_Product  Prior_purchases  \
count      2200.000000          2200.000000      2200.000000
mean          0.001005             0.071492         0.001205
std           0.000776             0.044840         0.000881
min           0.000160             0.016381         0.000319
25%           0.000487             0.038579         0.000559
50%           0.000777             0.053025         0.000829
75%           0.001248             0.094828         0.001700
max           0.004036             0.231862         0.004395

       Product_importance       Gender  Discount_offered  Weight_in_gms
count         2200.000000  2200.000000       2200.000000    2200.000000
mean             0.000181     0.000171          0.003149       0.920447
std              0.000237     0.000215          0.003396       0.049193
min              0.000000     0.000000          0.000160       0.750187
25%              0.000000     0.000000          0.000865       0.890633
50%              0.000163     0.000163          0.001623       0.941766
75%              0.000265     0.000233          0.004774       0.957783
max              0.001704     0.000865          0.016436       0.980671
```

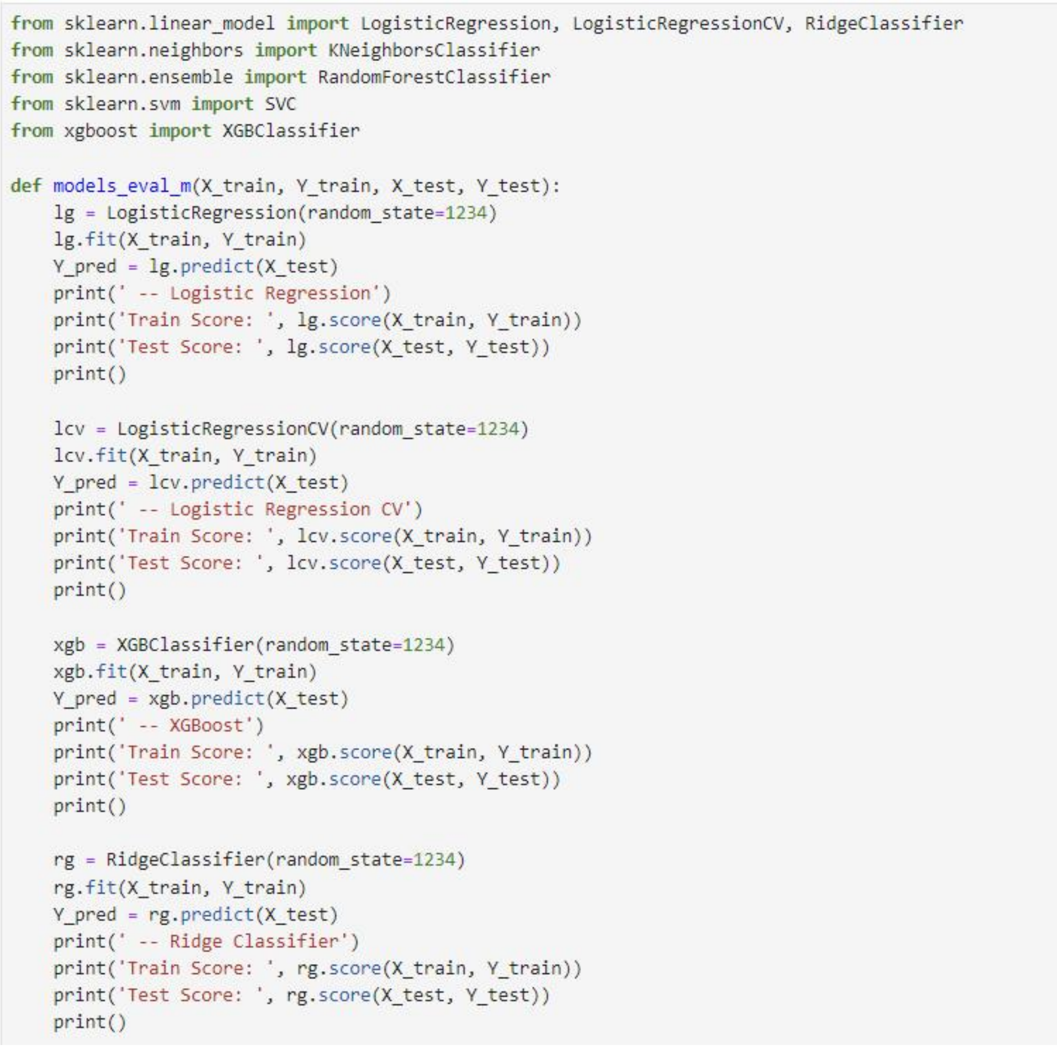
Milestone 4: Model Building

Activity 1: Training the model in multiple algorithms

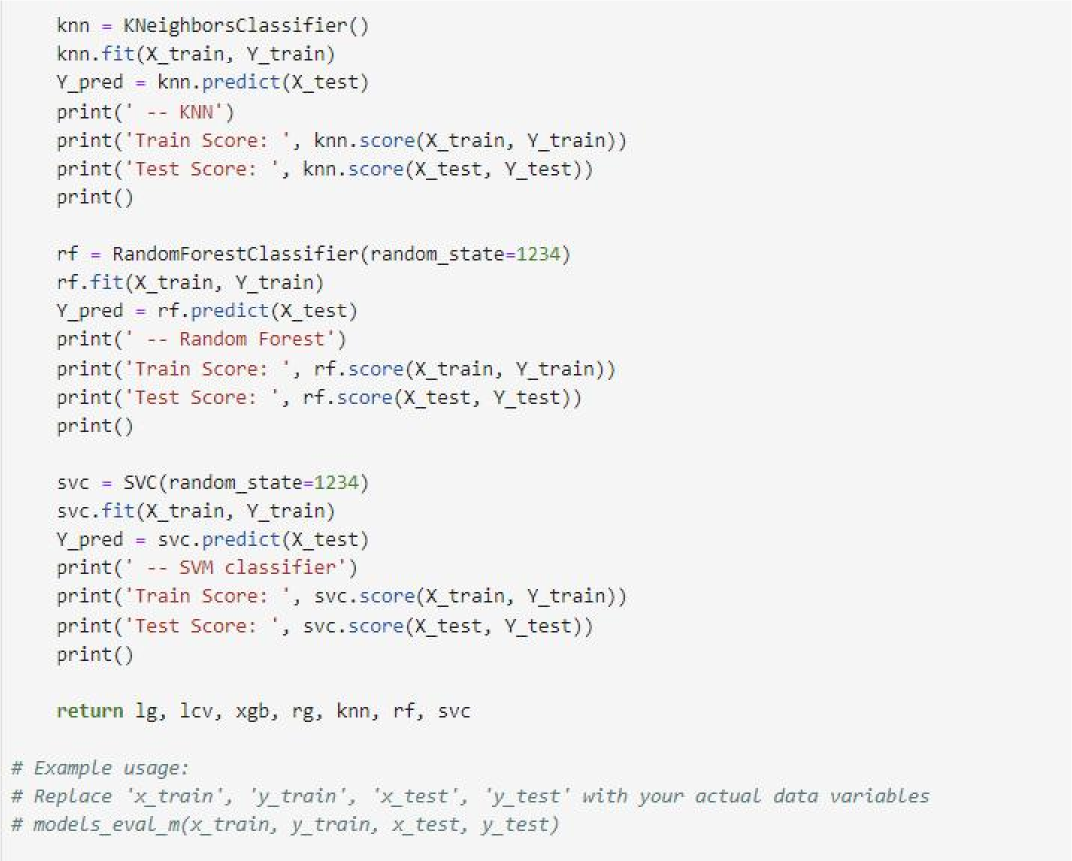
Now our data is cleaned and it’s time to build the model. We can train our data on different algorithms. For this project we are applying seven classification algorithms. The best model is saved based on its performance.

Activity 1.1: Writing function to train the models

A function named models_eval_mm is created and train, test data are passed as parameters. In the function, logistic regression, logistic regression cv, XGBclassifier, RidgeClassifier, KNN classifier, Random forest classifier and SVC algorithms are initialised and training data is passed to the model with.fit() function. Test data is predicted with predict() function and saved in a new variable. For evaluating the model, train and test scores are used.



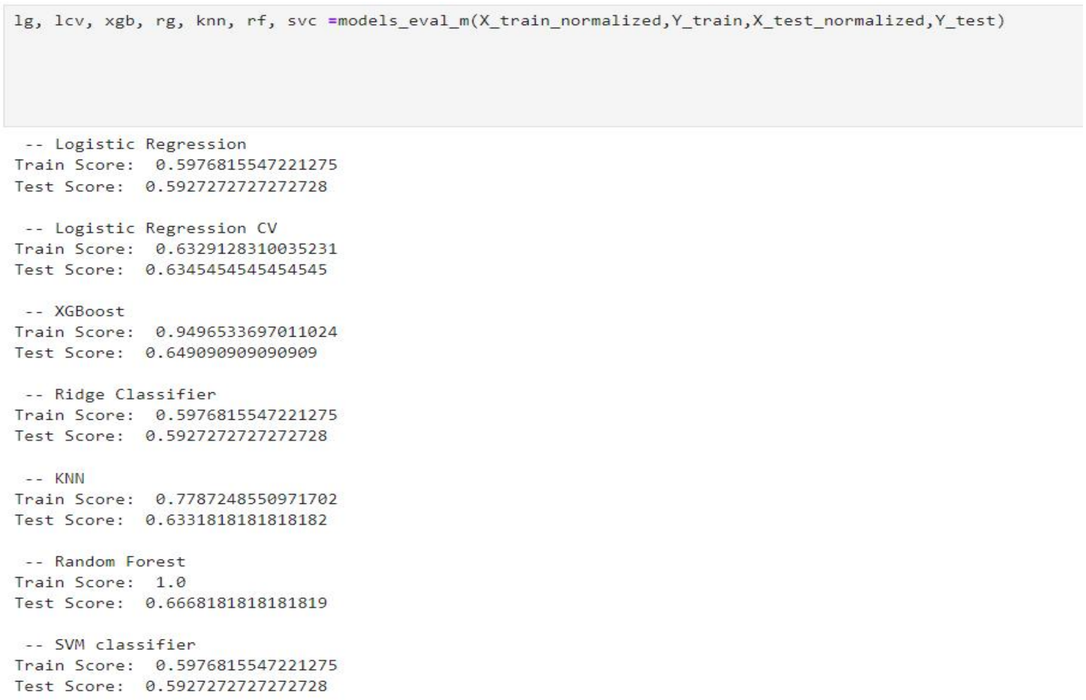
```
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV, RidgeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier

def models_eval_m(X_train, Y_train, X_test, Y_test):
    lg = LogisticRegression(random_state=1234)
    lg.fit(X_train, Y_train)
    Y_pred = lg.predict(X_test)
    print(' -- Logistic Regression')
    print('Train Score: ', lg.score(X_train, Y_train))
    print('Test Score: ', lg.score(X_test, Y_test))
    print()

    lcv = LogisticRegressionCV(random_state=1234)
    lcv.fit(X_train, Y_train)
    Y_pred = lcv.predict(X_test)
    print(' -- Logistic Regression CV')
    print('Train Score: ', lcv.score(X_train, Y_train))
    print('Test Score: ', lcv.score(X_test, Y_test))
    print()

    xgb = XGBClassifier(random_state=1234)
    xgb.fit(X_train, Y_train)
    Y_pred = xgb.predict(X_test)
    print(' -- XGBoost')
    print('Train Score: ', xgb.score(X_train, Y_train))
    print('Test Score: ', xgb.score(X_test, Y_test))
    print()

    rg = RidgeClassifier(random_state=1234)
    rg.fit(X_train, Y_train)
    Y_pred = rg.predict(X_test)
    print(' -- Ridge Classifier')
    print('Train Score: ', rg.score(X_train, Y_train))
    print('Test Score: ', rg.score(X_test, Y_test))
    print()
```



```
    knn = KNeighborsClassifier()
    knn.fit(X_train, Y_train)
    Y_pred = knn.predict(X_test)
    print(' -- KNN')
    print('Train Score: ', knn.score(X_train, Y_train))
    print('Test Score: ', knn.score(X_test, Y_test))
    print()

    rf = RandomForestClassifier(random_state=1234)
    rf.fit(X_train, Y_train)
    Y_pred = rf.predict(X_test)
    print(' -- Random Forest')
    print('Train Score: ', rf.score(X_train, Y_train))
    print('Test Score: ', rf.score(X_test, Y_test))
    print()

    svc = SVC(random_state=1234)
    svc.fit(X_train, Y_train)
    Y_pred = svc.predict(X_test)
    print(' -- SVM classifier')
    print('Train Score: ', svc.score(X_train, Y_train))
    print('Test Score: ', svc.score(X_test, Y_test))
    print()

    return lg, lcv, xgb, rg, knn, rf, svc

# Example usage:
# Replace 'x_train', 'y_train', 'x_test', 'y_test' with your actual data variables
# models_eval_m(x_train, y_train, x_test, y_test)
```

Activity 1.2: Calling the function

The function is called by passing the train, test variables. The models are returned and stored in variables as shown below. Clearly, we can see that the models are not performing well on the data. So, we'll optimise the hyperparameters of models using GridsearchCV.

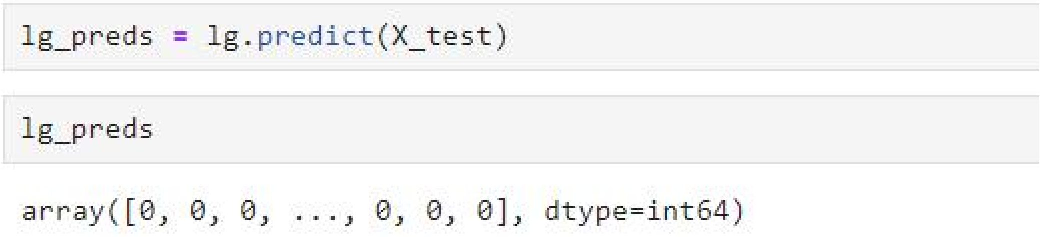


```
lg, lcv, xgb, rg, knn, rf, svc =models_eval_m(X_train_normalized,Y_train,X_test_normalized,Y_test)
```

```
 -- Logistic Regression
Train Score:  0.5976815547221275
Test Score:  0.5927272727272728

 -- Logistic Regression CV
Train Score:  0.6329128310035231
Test Score:  0.6345454545454545

 -- XGBoost
Train Score:  0.9496533697011024
Test Score:  0.649090909090909

 -- Ridge Classifier
Train Score:  0.5976815547221275
Test Score:  0.5927272727272728

 -- KNN
Train Score:  0.7787248550971702
Test Score:  0.6331818181818182

 -- Random Forest
Train Score:  1.0
Test Score:  0.6668181818181819

 -- SVM classifier
Train Score:  0.5976815547221275
Test Score:  0.5927272727272728
```

Activity 2: Testing the model

Here we have tested with Random forest algorithm. You can test with all algorithm. With the help of predict() function.



```
lg_preds = lg.predict(X_test)
```

```
lg_preds
```

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

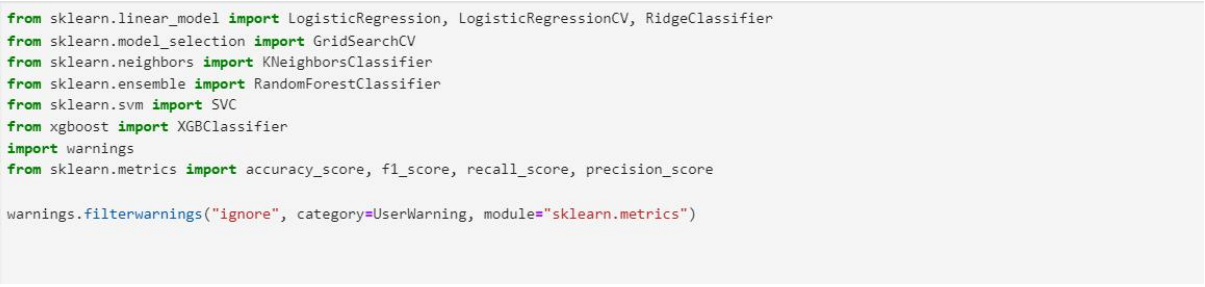
Milestone 5: Performance Testing & Hyperparameter Tuning

Activity 1: Testing model with multiple evaluation metrics

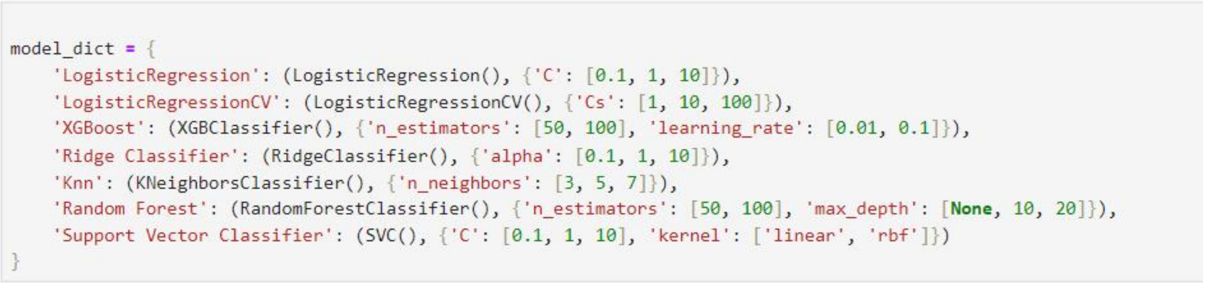
Multiple evaluation metrics means evaluating the model's performance on a test set using different performance measures. This can provide a more comprehensive understanding of the model's strengths and weaknesses. We are using evaluation metrics for classification tasks including accuracy, precision, recall, support and F1-score.

Activity 1.1: Compare the model

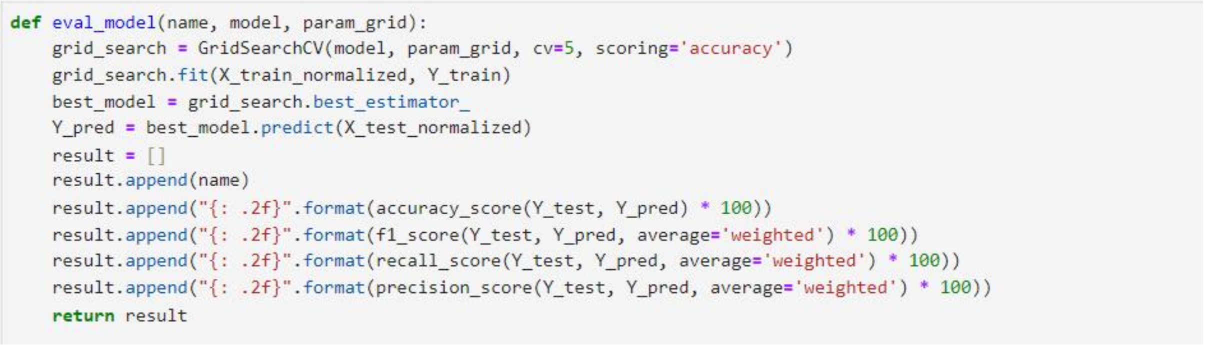
For comparing the above four models, the eval() function is defined. After calling the function, the results of models are displayed as output. From the trained models random forest is performing well



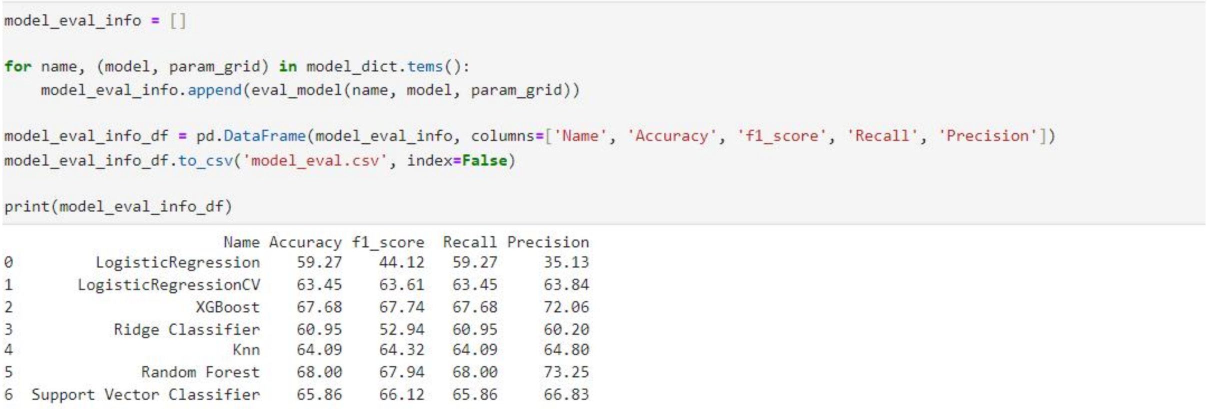
```
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV, RidgeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
import warnings
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score

warnings.filterwarnings("ignore", category=UserWarning, module="sklearn.metrics")
```



```
model_dict = {
    'LogisticRegression': (LogisticRegression(), {'C': [0.1, 1, 10]}),
    'LogisticRegressionCV': (LogisticRegressionCV(), {'Cs': [1, 10, 100]}),
    'XGBoost': (XGBClassifier(), {'n_estimators': [50, 100], 'learning_rate': [0.01, 0.1]}),
    'Ridge Classifier': (RidgeClassifier(), {'alpha': [0.1, 1, 10]}),
    'Knn': (KNeighborsClassifier(), {'n_neighbors': [3, 5, 7]}),
    'Random Forest': (RandomForestClassifier(), {'n_estimators': [50, 100], 'max_depth': [None, 10, 20]}),
    'Support Vector Classifier': (SVC(), {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']})
}
```



```
def eval_model(name, model, param_grid):
    grid_search = GridSearchCV(model, param_grid, cv=5, scoring='accuracy')
    grid_search.fit(X_train_normalized, Y_train)
    best_model = grid_search.best_estimator_
    Y_pred = best_model.predict(X_test_normalized)
    result = []
    result.append(name)
    result.append("{: .2f}".format(accuracy_score(Y_test, Y_pred) * 100))
    result.append("{: .2f}".format(f1_score(Y_test, Y_pred, average='weighted') * 100))
    result.append("{: .2f}".format(recall_score(Y_test, Y_pred, average='weighted') * 100))
    result.append("{: .2f}".format(precision_score(Y_test, Y_pred, average='weighted') * 100))
    return result
```



```
model_eval_info = []

for name, (model, param_grid) in model_dict.tems():
    model_eval_info.append(eval_model(name, model, param_grid))

model_eval_info_df = pd.DataFrame(model_eval_info, columns=['Name', 'Accuracy', 'f1_score', 'Recall', 'Precision'])
model_eval_info_df.to_csv('model_eval.csv', index=False)

print(model_eval_info_df)
```

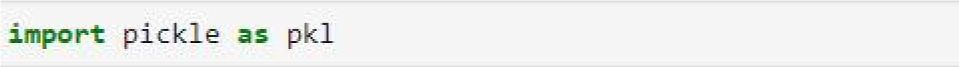
```
                        Name Accuracy f1_score  Recall Precision
0         LogisticRegression    59.27    44.12   59.27     35.13
1       LogisticRegressionCV    63.45    63.61   63.45     63.84
2                    XGBoost    67.68    67.74   67.68     72.06
3           Ridge Classifier    60.95    52.94   60.95     60.20
4                        Knn    64.09    64.32   64.09     64.80
5              Random Forest    68.00    67.94   68.00     73.25
6  Support Vector Classifier    65.86    66.12   65.86     66.83
```

Activity 2: Comparing model accuracy before & after applying hyperparameter tuning (Hyperparameter tuning is optional. For this project it is not required.)

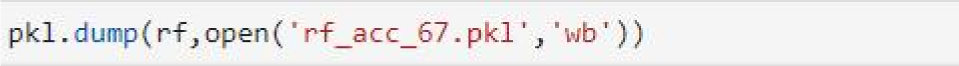
We will perform hyper parameter tuning on models that are better performing which are SVC, Random Forest, XGBoost and Logistic Regression CV. First we'll discover the existing hyperparameters of these models as below.

Save The Best Model

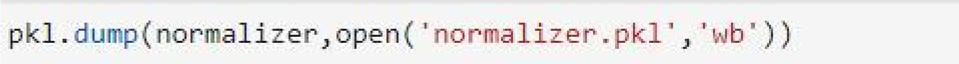
Saving the best model and normalizer after comparing its performance using different evaluation metrics means selecting the model with the highest performance and saving its weightsandconfiguration. This can be useful in avoiding the need to retrain the model every time it is needed and also to be able to use it in the future.



```
import pickle as pkl
```



```
pkl.dump(rf,open('rf_acc_67.pkl','wb'))
```



```
pkl.dump(normalizer,open('normalizer.pkl','wb'))
```

Integrate With Web Framework

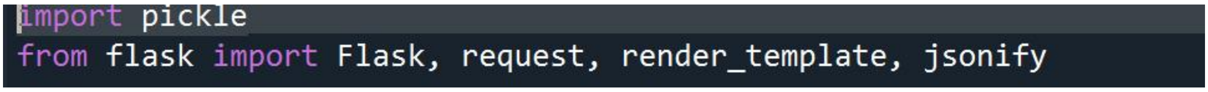
In this section, we will be building a web application that is integrated to the model we built. An UI is provided for the uses where he has to enter the values for predictions. The enter values are given to the saved model and prediction is showcased on the UI.
This section has the following tasks

- Building HTML Pages
- Building server-side script
- Run the web application

Building Html Pages:
For this project create two HTML files namely

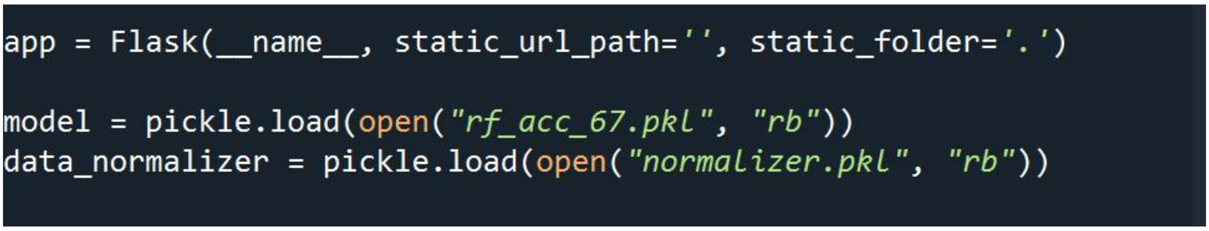
- index.html
- result.html

and save them in the templates folder.
It is not necessary to follow the exact format as above so feel free to use whatever templates or format you like. Be creative!
Build Python code:
Import the libraries



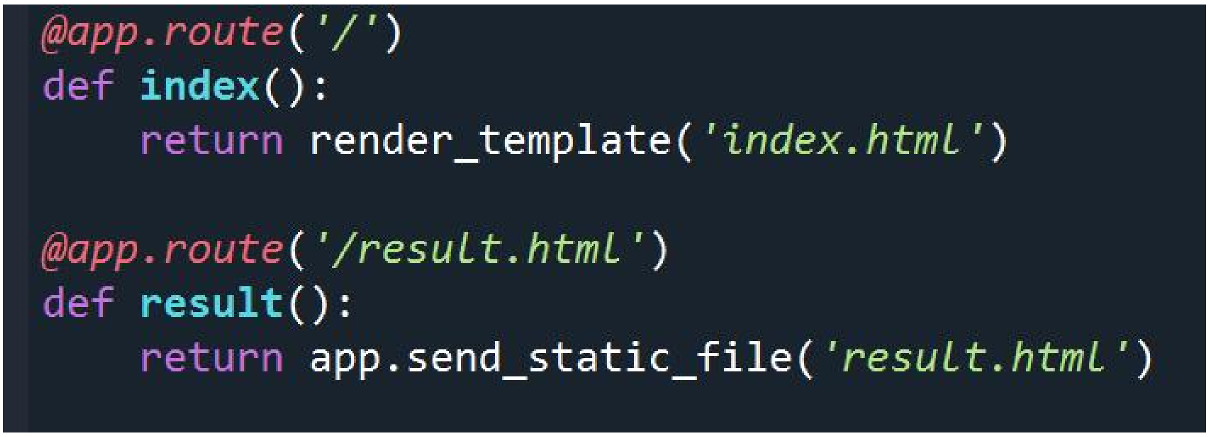
```
import pickle
from flask import Flask, request, render_template, jsonify
```

Load the saved model. Importing the flask module in the project is mandatory. An object of Flask class is our WSGI application. Flask constructor takes the name of the current module (__name__) as argument.

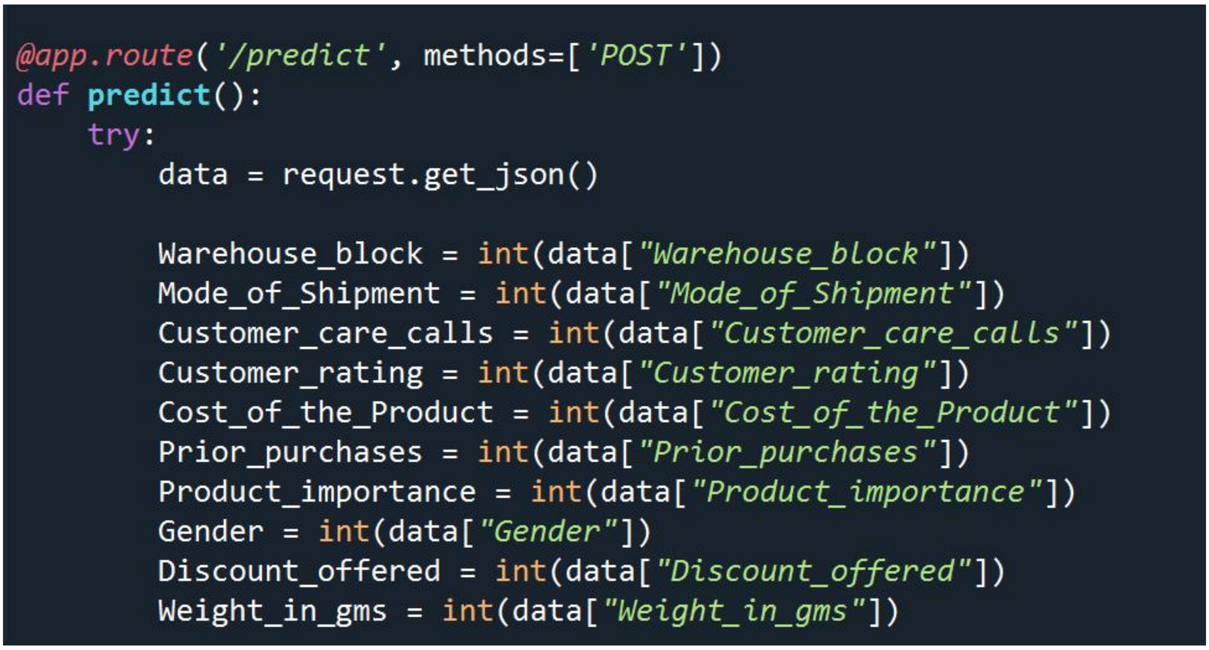


```
app = Flask(__name__, static_url_path='', static_folder='.')

model = pickle.load(open("rf_acc_67.pkl", "rb"))
data_normalizer = pickle.load(open("normalizer.pkl", "rb"))
```

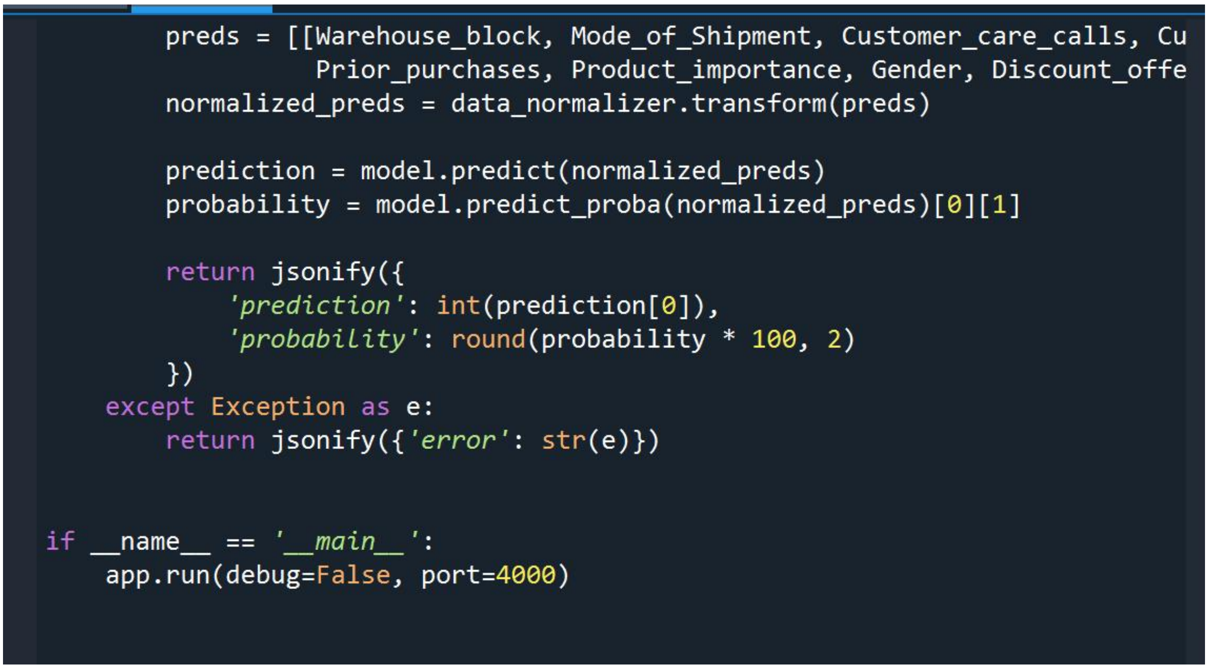
Render HTML page:



```
@app.route('/')
def index():
    return render_template('index.html')

@app.route('/result.html')
def result():
    return app.send_static_file('result.html')
```



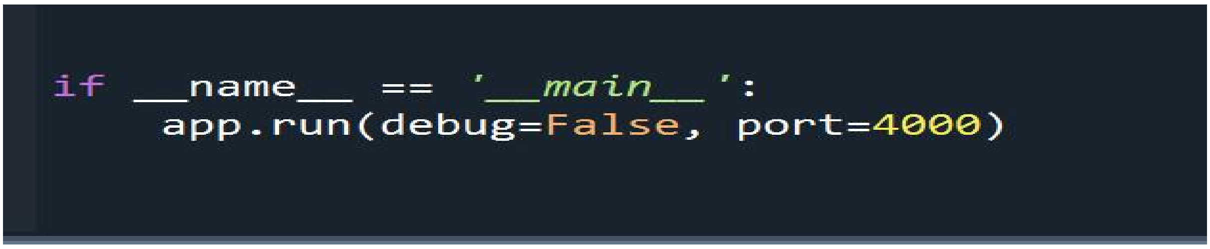
```
@app.route('/predict', methods=['POST'])
def predict():
    try:
        data = request.get_json()

        Warehouse_block = int(data["Warehouse_block"])
        Mode_of_Shipment = int(data["Mode_of_Shipment"])
        Customer_care_calls = int(data["Customer_care_calls"])
        Customer_rating = int(data["Customer_rating"])
        Cost_of_the_Product = int(data["Cost_of_the_Product"])
        Prior_purchases = int(data["Prior_purchases"])
        Product_importance = int(data["Product_importance"])
        Gender = int(data["Gender"])
        Discount_offered = int(data["Discount_offered"])
        Weight_in_gms = int(data["Weight_in_gms"])
```



```
        preds = [[Warehouse_block, Mode_of_Shipment, Customer_care_calls, Cu
                  Prior_purchases, Product_importance, Gender, Discount_offe
        normalized_preds = data_normalizer.transform(preds)

        prediction = model.predict(normalized_preds)
        probability = model.predict_proba(normalized_preds)[0][1]

        return jsonify({
            'prediction': int(prediction[0]),
            'probability': round(probability * 100, 2)
        })
    except Exception as e:
        return jsonify({'error': str(e)})


if __name__ == '__main__':
    app.run(debug=False, port=4000)
```

Here we are routing our app to predict() function. This function retrieves all the values from the HTML page using Post request. That is stored in an array. This array is passed to the model.predict() function. This function returns the prediction. And this prediction value will be rendered to the text that we have mentioned in the submit.html page earlier.

Main Function:



```
if __name__ == '__main__':
    app.run(debug=False, port=4000)
```

Run the web application

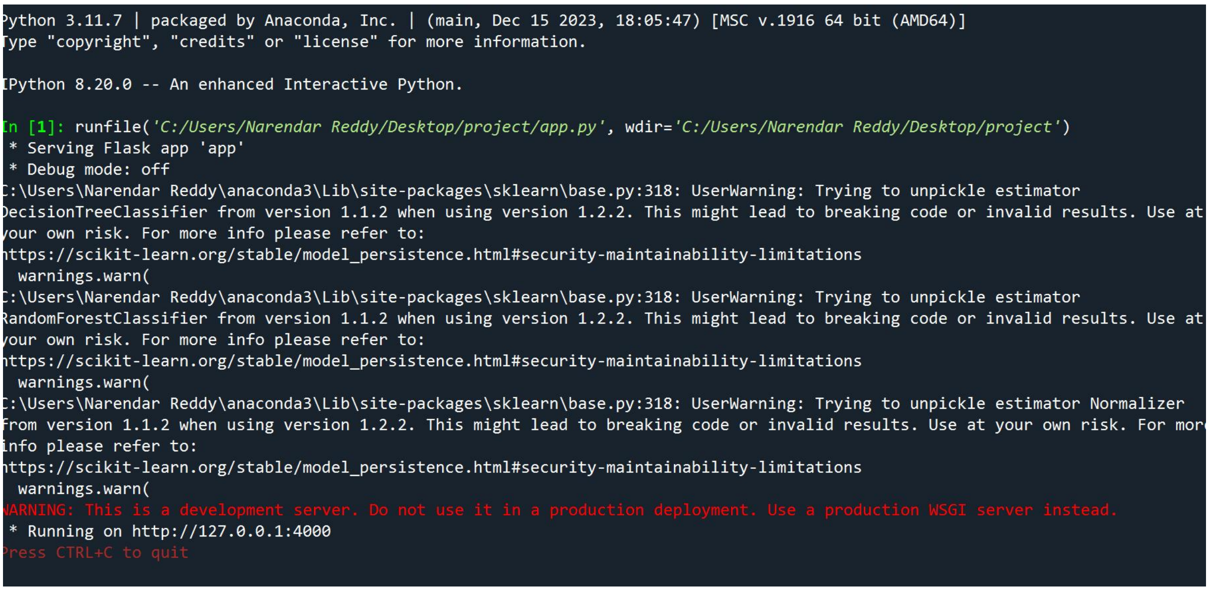
Open anaconda prompt from the start menu

Navigate to the folder where your python script is.

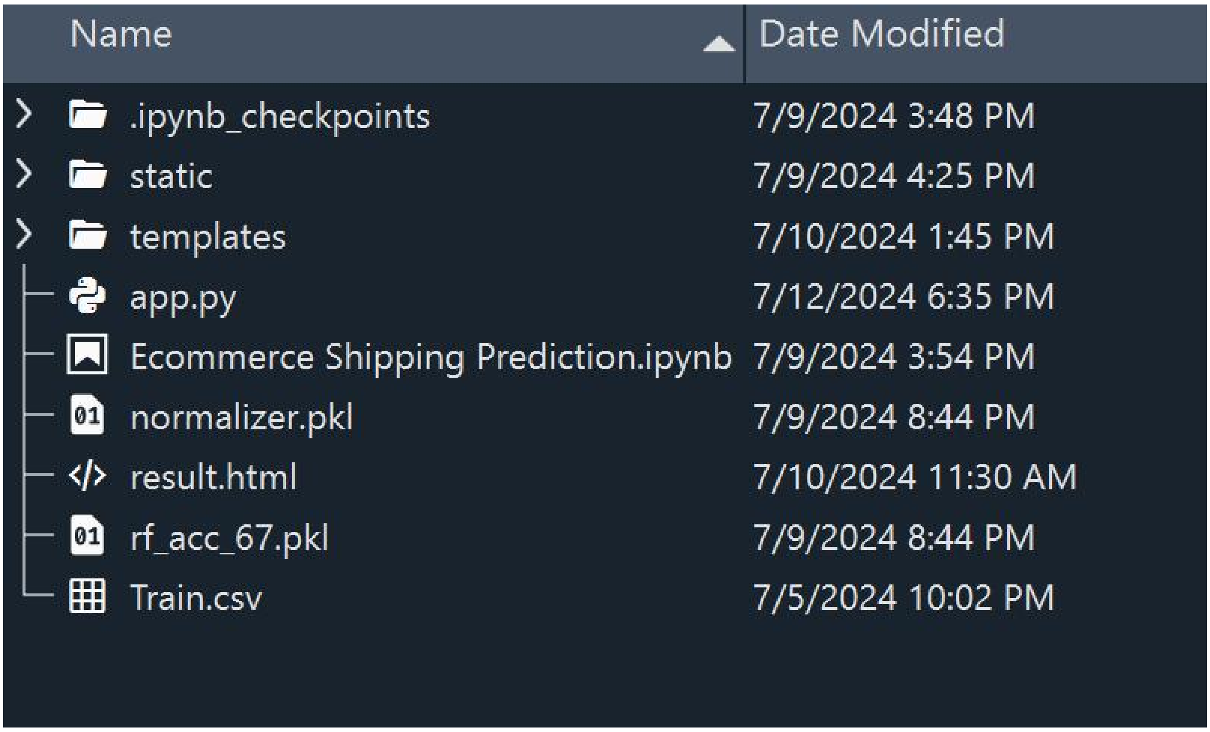
Now type “python app.py” command

Navigate to the localhost where you can view your web page.

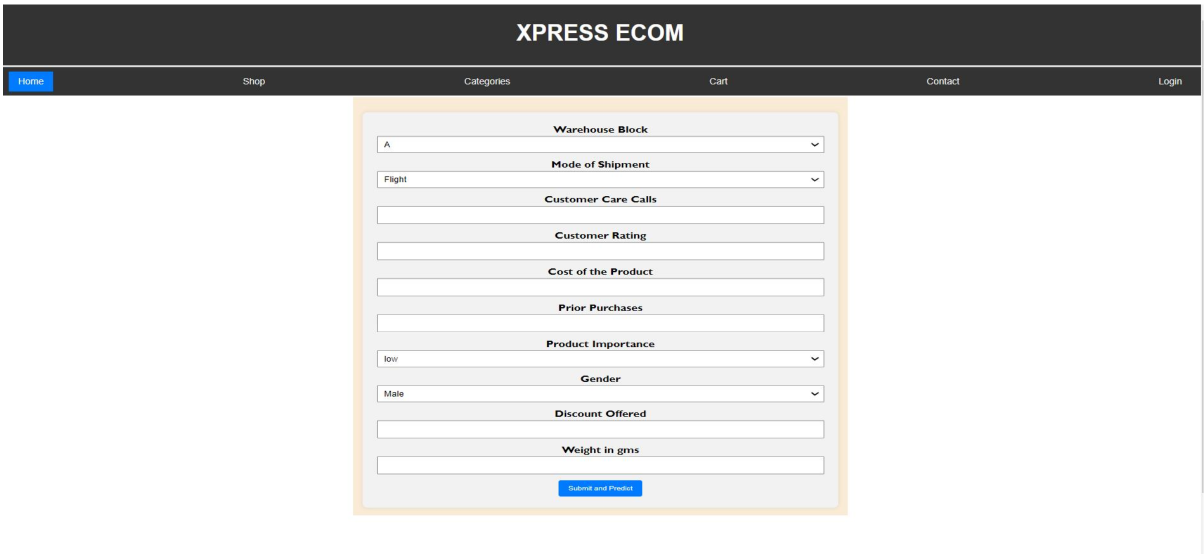
Click on the predict button from the top left corner, enter the inputs, click on the submit button, and see the result/prediction on the web.



```
ython 3.11.7 | packaged by Anaconda, Inc. | (main, Dec 15 2023, 18:05:47) [MSC v.1916 64 bit (AMD64)]
ype "copyright", "credits" or "license" for more information.

Python 8.20.0 -- An enhanced Interactive Python.

n [1]: runfile('C:/Users/Narendar Reddy/Desktop/project/app.py', wdir='C:/Users/Narendar Reddy/Desktop/project')
 * Serving Flask app 'app'
 * Debug mode: off
:\Users\Narendar Reddy\anaconda3\Lib\site-packages\sklearn\base.py:318: UserWarning: Trying to unpickle estimator
ecisionTreeClassifier from version 1.1.2 when using version 1.2.2. This might lead to breaking code or invalid results. Use at
our own risk. For more info please refer to:
ttps://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
  warnings.warn(
:\Users\Narendar Reddy\anaconda3\Lib\site-packages\sklearn\base.py:318: UserWarning: Trying to unpickle estimator
andomForestClassifier from version 1.1.2 when using version 1.2.2. This might lead to breaking code or invalid results. Use at
our own risk. For more info please refer to:
ttps://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
  warnings.warn(
:\Users\Narendar Reddy\anaconda3\Lib\site-packages\sklearn\base.py:318: UserWarning: Trying to unpickle estimator Normalizer
rom version 1.1.2 when using version 1.2.2. This might lead to breaking code or invalid results. Use at your own risk. For mor
nfo please refer to:
ttps://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
  warnings.warn(
ARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:4000
ress CTRL+C to quit
```



Name	Date Modified
.ipynb_checkpoints	7/9/2024 3:48 PM
static	7/9/2024 4:25 PM
templates	7/10/2024 1:45 PM
app.py	7/12/2024 6:35 PM
Ecommerce Shipping Prediction.ipynb	7/9/2024 3:54 PM
normalizer.pkl	7/9/2024 8:44 PM
result.html	7/10/2024 11:30 AM
rf_acc_67.pkl	7/9/2024 8:44 PM
Train.csv	7/5/2024 10:02 PM



Warehouse Block: A

Mode of Shipment: Flight

Customer Care Calls

Customer Rating

Cost of the Product

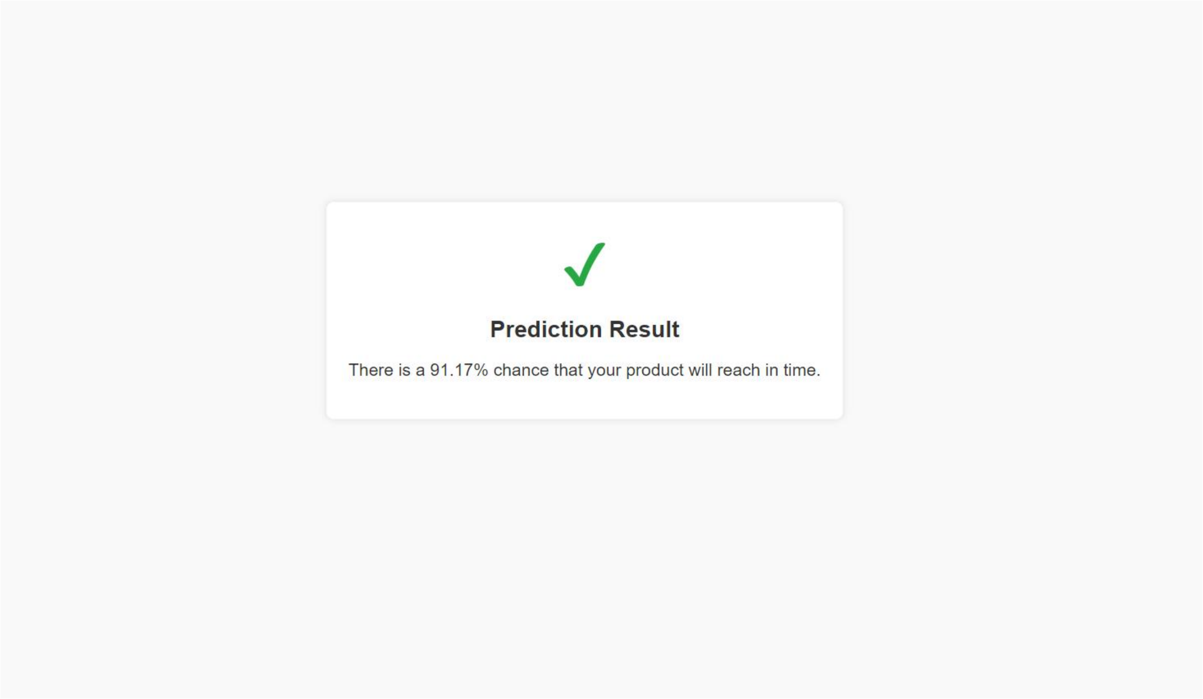
Prior Purchases

Product Importance: low

Gender: Male

Discount Offered

Weight in gms



Prediction Result

There is a 91.17% chance that your product will reach in time.