Do exploratory data analysis on the data. Use linear regression and QDA classification techniques to predict the sales for CH or MM. Compare the methods

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```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression as LR_MODEL
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis as QDA_MODEL
from sklearn.metrics import accuracy_score
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
```

Reading the Data

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

```
data.head()
```

	Purchase	WeekofPurchase	StoreID	PriceCH	PriceMM	DiscCH	DiscMM	SpecialCH	Spe
0	CH	237	1	1.75	1.99	0.00	0.0	0	
1	CH	239	1	1.75	1.99	0.00	0.3	0	
2	CH	245	1	1.86	2.09	0.17	0.0	0	
3	MM	227	1	1.69	1.69	0.00	0.0	0	
4	CH	228	7	1.69	1.69	0.00	0.0	0	

Checking the Shape and Decription of data

```
data.shape
```

```
(1070, 18)
```

```
data.describe()
```

	WeekofPurchase	StoreID	PriceCH	PriceMM	DiscCH	DiscMM
count	1070.000000	1070.000000	1070.000000	1070.000000	1070.000000	1070.000000
mean	254.381308	3.959813	1.867421	2.085411	0.051860	0.123364
std	15.558286	2.308984	0.101970	0.134386	0.117474	0.213834
min	227.000000	1.000000	1.690000	1.690000	0.000000	0.000000
25%	240.000000	2.000000	1.790000	1.990000	0.000000	0.000000
50%	257.000000	3.000000	1.860000	2.090000	0.000000	0.000000
75%	268.000000	7.000000	1.990000	2.180000	0.000000	0.230000
max	278.000000	7.000000	2.090000	2.290000	0.500000	0.800000

Checking the Dataypes of various Parameters/Columns

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1070 entries, 0 to 1069
Data columns (total 18 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Purchase        1070 non-null   object
 1   WeekofPurchase  1070 non-null   int64
 2   StoreID         1070 non-null   int64
```

```
 3   PriceCH         1070 non-null   float64
 4   PriceMM         1070 non-null   float64
 5   DiscCH          1070 non-null   float64
 6   DiscMM          1070 non-null   float64
 7   SpecialCH       1070 non-null   int64
 8   SpecialMM       1070 non-null   int64
 9   LoyalCH         1070 non-null   float64
 10  SalePriceMM     1070 non-null   float64
 11  SalePriceCH     1070 non-null   float64
 12  PriceDiff       1070 non-null   float64
 13  Store7          1070 non-null   object
 14  PctDiscMM       1070 non-null   float64
 15  PctDiscCH       1070 non-null   float64
 16  ListPriceDiff   1070 non-null   float64
 17  STORE           1070 non-null   int64
dtypes: float64(11), int64(5), object(2)
memory usage: 150.6+ KB
```

Checking if Null values are there and if present , removing them

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

```
Purchase          0
WeekofPurchase    0
StoreID           0
PriceCH           0
PriceMM           0
DiscCH            0
DiscMM            0
SpecialCH         0
SpecialMM         0
LoyalCH           0
SalePriceMM       0
SalePriceCH       0
PriceDiff         0
Store7            0
PctDiscMM         0
PctDiscCH         0
ListPriceDiff     0
STORE             0
dtype: int64
```

Checking if Unique Values in each column

```
data.nunique()
```

```
Purchase            2
WeekofPurchase     52
StoreID             5
PriceCH            10
PriceMM             8
DiscCH             12
DiscMM             12
SpecialCH           2
SpecialMM           2
LoyalCH           553
SalePriceMM        18
SalePriceCH        13
PriceDiff          36
Store7              2
PctDiscMM          18
PctDiscCH          13
ListPriceDiff      18
STORE               5
dtype: int64
```

```
category_counts = data['Purchase'].value_counts()

plt.figure(figsize=(8, 6))
category_counts.plot(kind='bar',)
plt.title('Count of Categories in Purchase')
plt.xlabel('Purchase Category')
plt.ylabel('Count')
plt.show()
```

Changing CH =1 and MA = 0 in Purchase & YES=1 and NO=0 in Store7

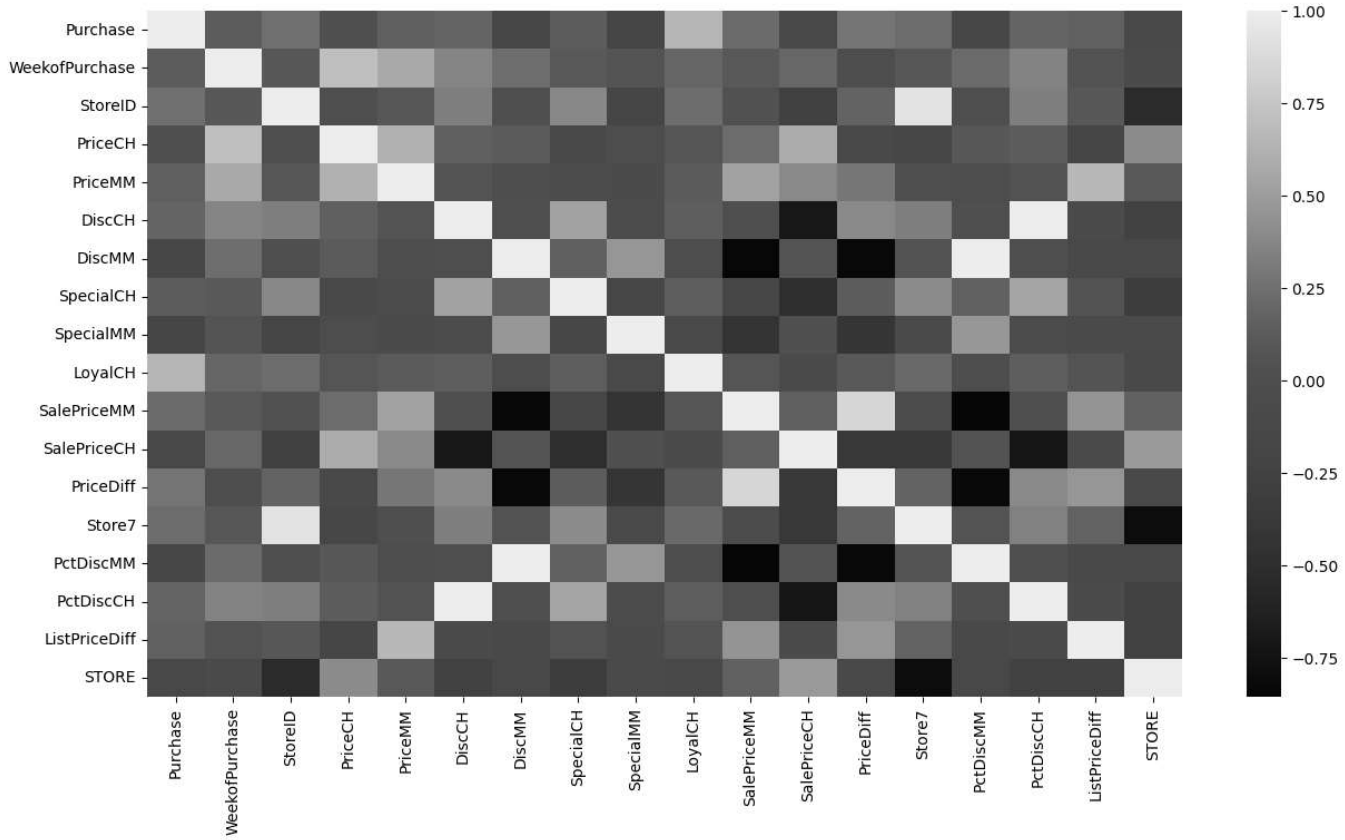
```
data['Purchase'] = data['Purchase'].apply(lambda x: 1 if x == 'CH' else 0)
```

```
data['Store7'] = data['Store7'].apply(lambda x: 1 if x == 'Yes' else 0)
```

Making the HeatMap for Correlation in Data

```
plt.figure(figsize=(15,8))
sns.heatmap(data.corr())
```

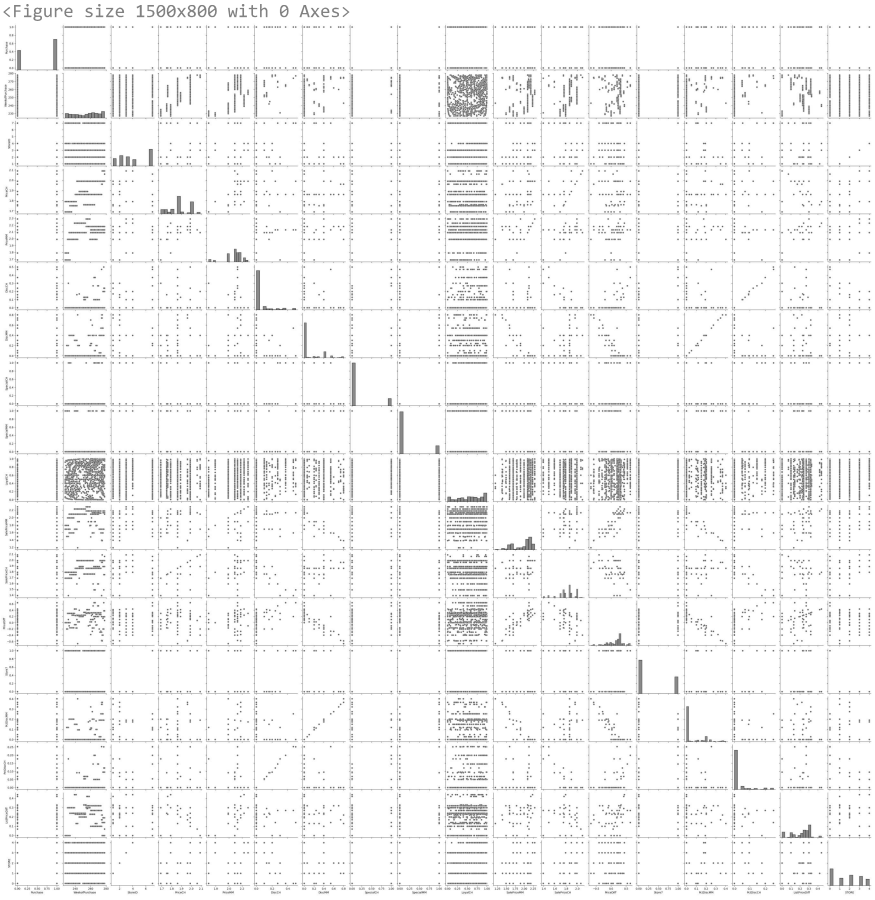
```
<Axes: >
```



Making PairPLot to analyse variable dependency

```
#takes time to execute , comment it or don't run if needed
plt.figure(figsize=(15,8))
sns.pairplot(data)
```

```
<seaborn.axisgrid.PairGrid at 0x7f37c2451cf0>
<Figure size 1500x800 with 0 Axes>
```



Making Results i.e Purchases as Y and Rest of input Variables as X

```
X = data.drop(['Purchase']  , axis =1)
X = X.astype(float)
Y = data['Purchase']
Y
```

```
0       1
1       1
2       1
3       0
4       1
       ..
1065    1
1066    1
1067    0
1068    1
1069    1
Name: Purchase, Length: 1070, dtype: int64
```

As there is multicollinearity as observed in HeatMap Above , I remove those using VIF. Got the Reference from here

```
def calculate_vif_(X, thresh):
    X = X.assign(const=1)  # faster than add_constant from statsmodels
    variables = list(range(X.shape[1]))
    dropped = True
    while dropped:
        dropped = False
        vif = [variance_inflation_factor(X.iloc[:, variables].values, ix)
               for ix in range(X.iloc[:, variables].shape[1])]
        vif = vif[:-1]  # don't let the constant be removed in the loop.
        maxloc = vif.index(max(vif))
        if max(vif) > thresh:
            print('dropping \'' + X.iloc[:, variables].columns[maxloc] +
                  '\' at index: ' + str(maxloc))
            del variables[maxloc]
            dropped = True

    print('Remaining variables:')
    print(X.columns[variables[:-1]])
    return X.iloc[:, variables[:-1]]


X = calculate_vif_(X,7)
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/stats/outliers_influence.py:198: RuntimeWarning: divide by zero encountered in d
  vif = 1. / (1. - r_squared_i)
dropping 'StoreID' at index: 1
dropping 'PriceCH' at index: 1
dropping 'PriceMM' at index: 1
dropping 'DiscCH' at index: 1
dropping 'SalePriceMM' at index: 5
dropping 'PriceDiff' at index: 6
dropping 'DiscMM' at index: 1
dropping 'SalePriceCH' at index: 4
Remaining variables:
Index(['WeekofPurchase', 'SpecialCH', 'SpecialMM', 'LoyalCH', 'Store7',
       'PctDiscMM', 'PctDiscCH', 'ListPriceDiff', 'STORE'],
      dtype='object')
```

The updated Input matrix without multicolinearity

```
X.head()
```

	WeekofPurchase	SpecialCH	SpecialMM	LoyalCH	Store7	PctDiscMM	PctDiscCH	ListP
0	237.0	0.0	0.0	0.500000	0.0	0.000000	0.000000	
1	239.0	0.0	1.0	0.600000	0.0	0.150754	0.000000	
2	245.0	0.0	0.0	0.680000	0.0	0.000000	0.091398	
3	227.0	0.0	0.0	0.400000	0.0	0.000000	0.000000	
4	228.0	0.0	0.0	0.956535	1.0	0.000000	0.000000	

```
X.info()
```

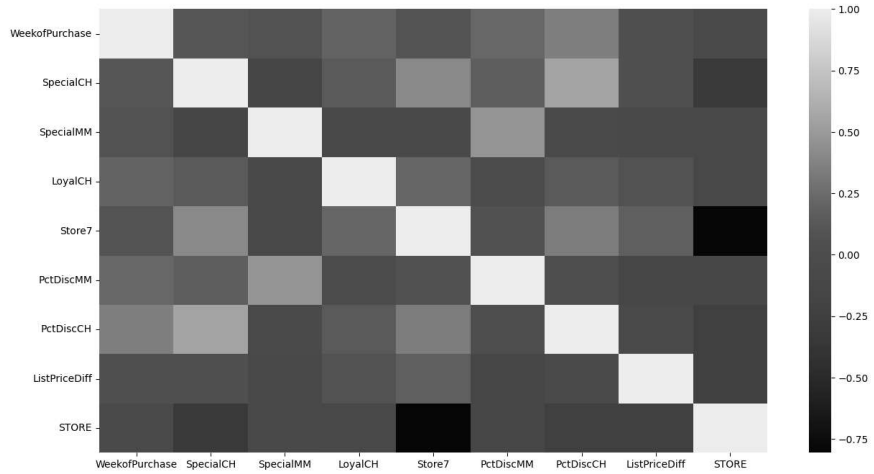
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1070 entries, 0 to 1069
```

```
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   WeekofPurchase  1070 non-null   float64
 1   SpecialCH       1070 non-null   float64
 2   SpecialMM       1070 non-null   float64
 3   LoyalCH         1070 non-null   float64
 4   Store7          1070 non-null   float64
 5   PctDiscMM       1070 non-null   float64
 6   PctDiscCH       1070 non-null   float64
 7   ListPriceDiff   1070 non-null   float64
 8   STORE           1070 non-null   float64
dtypes: float64(9)
memory usage: 75.4 KB
```

Making Heatmap of Correation data of new input Variables

```
plt.figure(figsize=(15,8))
sns.heatmap(X.corr())
```

```
<Axes: >
```



Checking Measures of centeral Tendency on the new Input data

```
print(X.mean())
print(X.var())
print(X.skew())
print(X.kurtosis())
```

```
WeekofPurchase    254.381308
SpecialCH           0.147664
SpecialMM           0.161682
LoyalCH             0.565782
Store7              0.332710
PctDiscMM           0.059298
PctDiscCH           0.027314
ListPriceDiff       0.217991
STORE               1.630841
dtype: float64
WeekofPurchase    242.060268
SpecialCH           0.125977
SpecialMM           0.135668
LoyalCH             0.094767
Store7              0.222222
PctDiscMM           0.010355
PctDiscCH           0.003873
ListPriceDiff       0.011564
```

```
STORE              2.046008
dtype: float64
WeekofPurchase   -0.210990
SpecialCH         1.989092
SpecialMM         1.840470
LoyalCH          -0.278889
Store7            0.711080
PctDiscMM         1.539491
PctDiscCH         2.422300
ListPriceDiff    -0.645208
STORE             0.249493
dtype: float64
WeekofPurchase   -1.274927
SpecialCH         1.960147
SpecialMM         1.389925
LoyalCH          -1.059837
Store7           -1.497167
PctDiscMM         1.272581
PctDiscCH         4.877696
ListPriceDiff    -0.228993
STORE            -1.297145
dtype: float64
```

Converting Pandas dataframe to Numpy Arrays for further process

```
input_X =  np.array(X)
output_Y =  np.array(Y)
```

Splitting the Data into training and Testing Data

```
train_X,test_X,train_Y,test_Y= train_test_split(input_X,output_Y,test_size=0.3)
```

Making Linear Regression and analysis

I tested for various Threshold Limits with a step size of 0.05 and choose the threshold with Maximum Accuracy.

```
def train_linear_regression_model(train_X, train_Y):
    model_lr = LR_MODEL()
    model_lr.fit(train_X, train_Y)
    return model_lr
def predict_with_threshold(model, test_X, threshold):
    predictions = model.predict(test_X)
    temporary = predictions.copy()

    for i in range(len(predictions)):
        temporary[i] = 1 if predictions[i] > threshold else 0

    return temporary.astype(int)
def find_best_threshold(model, test_X, test_Y):
    threshold_values = np.arange(0, 1.05, 0.05)
    best_accuracy = 0
    best_predictions = None
    test_Y = test_Y.astype(int)
    best_threshold  = 0
    for threshold in threshold_values:
        temp_predictions = predict_with_threshold(model, test_X, threshold)
        temp_accuracy = accuracy_score(test_Y, temp_predictions)

        if temp_accuracy > best_accuracy:
            best_threshold = threshold
            best_accuracy = temp_accuracy
            # print(best_accuracy)
            best_predictions = temp_predictions

    return best_predictions.astype(int) , best_threshold


LR_model = train_linear_regression_model(train_X , train_Y)
```

Predicted Values for both Training and Testing Data

```
best_pred_test , threshold_test = find_best_threshold(LR_model , test_X, test_Y)


best_pred_train = predict_with_threshold(LR_model , train_X ,threshold_test )
```

Threshold Value for which it has maximum Acccuracy

```
threshold_test
```

```
0.65
```

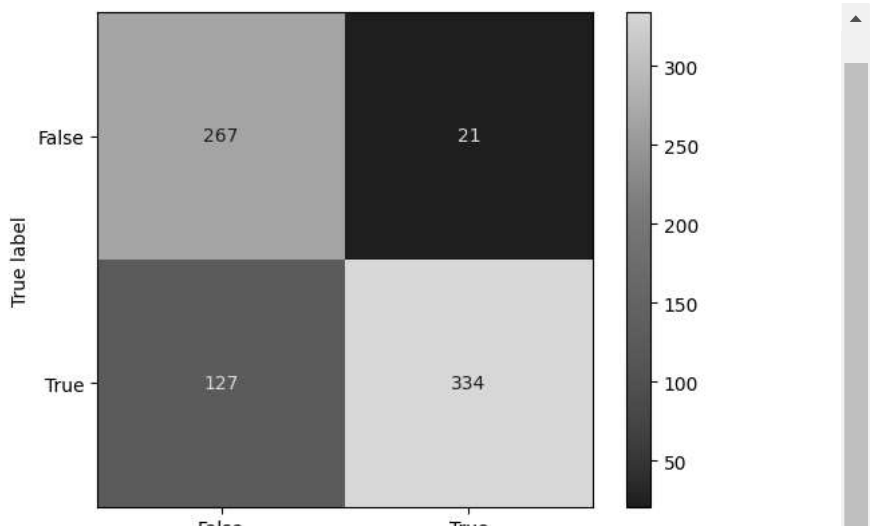
Accuracy Score for Training and testing data

```
print("Accuracy of Linear Regression Model on Testing Data is = ",accuracy_score(test_Y, best_pred_test))
print("Accuracy of Linear Regression Model on Training Data is =" , accuracy_score(train_Y, best_pred_train))
```

```
Accuracy of Linear Regression Model on Testing Data is =  0.8161993769470405
Accuracy of Linear Regression Model on Training Data is = 0.8024032042723631
```

Building Confusion Matrix for the Predicted Values for Both Training and Testng Data

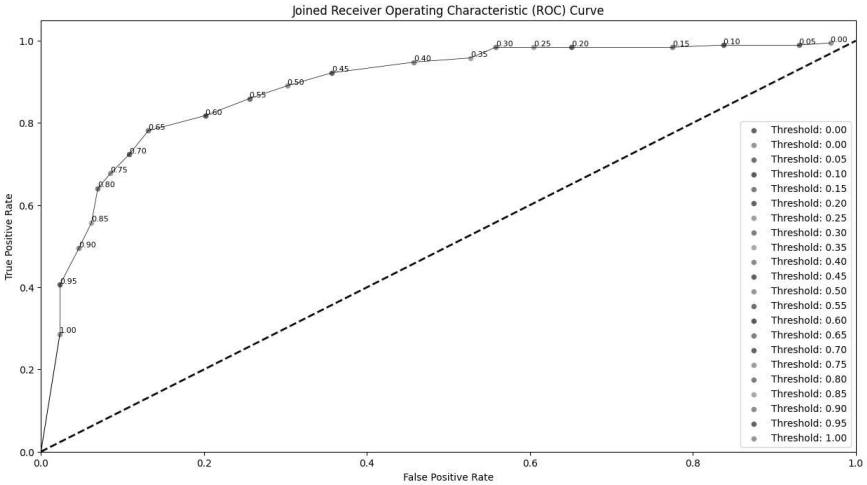
```
def confusion_matrix(Y_actual, Y_predicted,type_of_data ):
    print(f"----------------------------------------{type_of_data}----------------------------------------------------")
    confusion_matrix = metrics.confusion_matrix(Y_actual,Y_predicted)
    cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels = [False, True])
    cm_display.plot()
    plt.show()
    print(f"Accuracy of  Model on {type_of_data} Data is :",accuracy_score(Y_actual,Y_predicted))
    print(f"\n Classification report on {type_of_data} Data is : \n ", metrics.classification_report(Y_actual,Y_predicted))


confusion_matrix(train_Y, best_pred_train,"Training")
confusion_matrix(test_Y, best_pred_test,"Testing")
```



Making Receiver Operating Characteristic for Various Thresholld Values

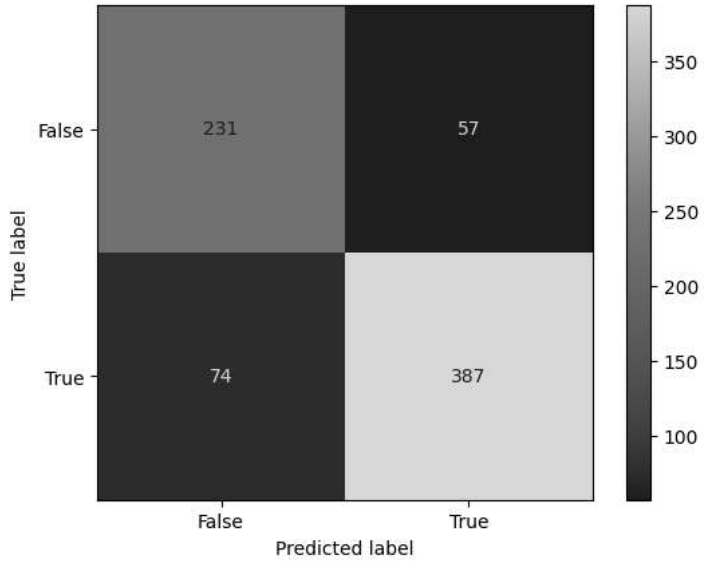
```
def get_roc_points(model, x_test, y_test):
    threshold_values = np.arange(0, 1.05, 0.05)
    roc_points = []

    for threshold in threshold_values:
        predictions = predict_with_threshold(model, x_test, threshold)
        fpr, tpr, _ = roc_curve(y_test, predictions)
        roc_points.append((fpr, tpr, threshold))

    return roc_points

def plot_roc_curve(roc_points):
    roc_points.sort(key=lambda x: x[2])  # Sort by threshold
    plt.figure(figsize=(15,8))
    plt.scatter(0, 0, label='Threshold: 0.00', s=20)
    for i in range(len(roc_points) - 1):
        fpr1, tpr1, threshold1 = roc_points[i]
        fpr2, tpr2, threshold2 = roc_points[i + 1]
        plt.plot([fpr1[1], fpr2[1]], [tpr1[1], tpr2[1]], color='black', lw=0.5)
    fpr2, tpr2, threshold2 = roc_points[len(roc_points)-1]
    plt.plot([0, fpr2[1]], [0, tpr2[1]], color='black', lw=0.75)
    for fpr, tpr, threshold in roc_points:
        plt.scatter(fpr[1], tpr[1], label=f'Threshold: {threshold:.2f}', s=20)
        plt.text(fpr[1], tpr[1], f'{threshold:.2f}', fontsize=8, ha='left', va='bottom', color='black')

    # auc_values = [auc(fpr, tpr) for fpr, tpr, _ in roc_points]
    # mean_auc = np.mean(auc_values)
    # plt.text(0.5, 0.05, f'Mean AUC = {mean_auc:.2f}', ha='center', va='center', fontsize=12, color='black')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Joined Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc="lower right")
    plt.show()
```

```
p = get_roc_points(LR_model , test_X, test_Y )
plot_roc_curve(p)
```



Training QDA

```
def train_qda_model(train_X, train_Y):
    model_qda = QDA_MODEL()
    train_X = train_X.astype(float)
    train_Y = train_Y.astype(int)
    model_qda.fit(train_X, train_Y)
    return model_qda

def evaluate_qda_model(model, test_X, test_Y):
    predictions_qda_test = model.predict(test_X)
    predictions_qda_train = model.predict(train_X)

    confusion_matrix(train_Y , predictions_qda_train, "Training")
    confusion_matrix(test_Y , predictions_qda_test, "Testing")
    return predictions_qda_test ,  predictions_qda_train

model_qda = train_qda_model(train_X, train_Y)
predicted_qda_test ,predictions_qda_train =  evaluate_qda_model(model_qda, test_X, test_Y)
```




```
Accuracy of  Model on Training Data is : 0.8251001335113485

 Classification report on Training Data is :
               precision    recall  f1-score   support

           0       0.76      0.80      0.78       288
           1       0.87      0.84      0.86       461

    weighted avg       0.83      0.83      0.83       749
```

Plotting ROC curve for Both QDA and for best Threshold in Linear Regression:

```
def plot_roc_curve(true_Values, predicted_prob_qda, predicted_prob_linear):
    fpr1, tpr1, thresholds1 = roc_curve(true_Values, predicted_prob_qda)
    roc_auc_qda = auc(fpr1, tpr1)
    fpr2, tpr2, thresholds2 = roc_curve(true_Values, predicted_prob_linear)
    roc_auc_linear = auc(fpr2, tpr2)

    # Plot ROC curve
    plt.figure()
    plt.plot(fpr1, tpr1, color='darkorange', lw=2, label='ROC curve for QDA (area = {:.4f})'.format(roc_auc_qda))
    plt.plot(fpr2, tpr2, color='Green', lw=2, label='ROC curve for Linear (area = {:.4f})'.format(roc_auc_linear))

    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc="lower right")
    plt.show()
plot_roc_curve(test_Y, predicted_qda_test,best_pred_test)
```