Task 3

- Part A - Fitting Simple Linear Regression Model

In [1]:
```
# Importing package and classes needed
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

%matplotlib inline
```

In [2]:
```
# Importing and reading csv file
df=pd.read_csv("E:HIGGS_6M.csv")
```

In [3]:
```
# Displaying top 5 row
df.head()
```

Out[3]:

	1.000000000000000000e+00	8.692932128906250000e-01	-6.350818276405334473e-01	2.256902605295181
0	1.0	0.907542	0.329147	0.35
1	1.0	0.798835	1.470639	-1.63
2	0.0	1.344385	-0.876626	0.93
3	1.0	1.105009	0.321356	1.52
4	0.0	1.595839	-0.607811	0.00

5 rows × 29 columns

In [4]:
```
# Getting Information about the data types used and also for checking for null va
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5999999 entries, 0 to 5999998
Data columns (total 29 columns):
 #   Column                       Dtype  
---  ------                       -----  
 0   1.000000000000000000e+00    float64
 1   8.692932128906250000e-01    float64
 2   -6.350818276405334473e-01   float64
 3   2.256902605295181274e-01    float64
 4   3.274700641632080078e-01    float64
 5   -6.899932026863098145e-01   float64
 6   7.542022466659545898e-01    float64
 7   -2.485731393098831177e-01   float64
 8   -1.092063903808593750e+00   float64
 9   0.000000000000000000e+00    float64
 10  1.374992132186889648e+00    float64
 11  -6.536741852760314941e-01   float64
 12  9.303491115570068359e-01    float64
 13  1.107436060905456543e+00    float64
 14  1.138904333114624023e+00    float64
 15  -1.578198313713073730e+00   float64
 16  -1.046985387802124023e+00   float64
 17  0.000000000000000000e+00.1  float64
 18  6.579295396804809570e-01    float64
 19  -1.045456994324922562e-02   float64
 20  -4.576716944575309753e-02   float64
 21  3.101961374282836914e+00    float64
 22  1.353760004043579102e+00    float64
 23  9.795631170272827148e-01    float64
 24  9.780761599540710449e-01    float64
 25  9.200048446655273438e-01    float64
 26  7.216574549674987793e-01    float64
 27  9.887509346008300781e-01    float64
 28  8.766783475875854492e-01    float64
dtypes: float64(29)
memory usage: 1.3 GB
```

In [5]:
```
# Anaylsing the distribution of classes
# data["column_name"].value_counts(), returns unique values in that column

print(df['1.000000000000000000e+00'].value_counts())
print('Zeros', round(df['1.000000000000000000e+00'].value_counts()[0]/len(df) * 1
print('Ones', round(df['1.000000000000000000e+00'].value_counts()[1]/len(df) * 10
```

```
1.0    3178344
0.0    2821655
Name: 1.000000000000000000e+00, dtype: int64
Zeros 47.03 % of the dataset
Ones 52.97 % of the dataset
```

In [6]:
```
Ones_df = df.loc[df['1.000000000000000000e+00'] == 1][0:1000] # smaples which hav
Zeros_df = df.loc[df['1.000000000000000000e+00'] == 0][0:1000] #

normal_distributed_df = pd.concat([Ones_df, Zeros_df])

# Shuffle dataframe rows
df_new= normal_distributed_df.sample(frac=1, random_state=100)

print(df_new['1.000000000000000000e+00'].value_counts()/len(df))
```

```
1.0    0.000167
0.0    0.000167
Name: 1.000000000000000000e+00, dtype: float64
```

In [7]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2000 entries, 58 to 1180
Data columns (total 29 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   1.000000000000000000e+00    2000 non-null   float64
 1   8.692932128906250000e-01    2000 non-null   float64
 2   -6.350818276405334473e-01   2000 non-null   float64
 3   2.256902605295181274e-01    2000 non-null   float64
 4   3.274700641632080078e-01    2000 non-null   float64
 5   -6.899932026863098145e-01   2000 non-null   float64
 6   7.542022466659545898e-01    2000 non-null   float64
 7   -2.485731393098831177e-01   2000 non-null   float64
 8   -1.092063903808593750e+00   2000 non-null   float64
 9   0.000000000000000000e+00    2000 non-null   float64
 10  1.374992132186889648e+00    2000 non-null   float64
 11  -6.536741852760314941e-01   2000 non-null   float64
 12  9.303491115570068359e-01    2000 non-null   float64
 13  1.107436060905456543e+00    2000 non-null   float64
 14  1.138904333114624023e+00    2000 non-null   float64
 15  -1.578198313713073730e+00   2000 non-null   float64
 16  -1.046985387802124023e+00   2000 non-null   float64
 17  0.000000000000000000e+00.1  2000 non-null   float64
 18  6.579295396804809570e-01    2000 non-null   float64
 19  -1.045456994324922562e-02   2000 non-null   float64
 20  -4.576716944575309753e-02   2000 non-null   float64
 21  3.101961374282836914e+00    2000 non-null   float64
 22  1.353760004043579102e+00    2000 non-null   float64
 23  9.795631170272827148e-01    2000 non-null   float64
 24  9.780761599540710449e-01    2000 non-null   float64
 25  9.200048446655273438e-01    2000 non-null   float64
 26  7.216574549674987793e-01    2000 non-null   float64
 27  9.887509346008300781e-01    2000 non-null   float64
 28  8.766783475875854492e-01    2000 non-null   float64
dtypes: float64(29)
memory usage: 468.8 KB
```

In [8]:
```
# Importing package for train-test split of datasets to avoid overfitting

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import roc_curve
```

In [9]:
```
# separating dependent and independent feature

X = df_new.drop("1.000000000000000000e+00",axis=1)
y = df_new["1.000000000000000000e+00"]
```

In [10]:
```
#Feature matrix

#Train-Test split
# Following an 60-40 split on data.
# The dataset is shuffled with 100 as the random seed for reproducible results.

X_train,X_test,y_train,y_test = train_test_split(X,y,shuffle=True,test_size=0.4,r
print("Shape of training dataset:",X_train.shape)
print("Shape of test dataset:",X_test.shape)
```

```
Shape of training dataset: (1200, 28)
Shape of test dataset: (800, 28)
```

In [11]:
```
#Feature Normalization
# standardization-or-mean-removal-and-variance-scaling

scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

#Adding x0 = 1 to each instance for the bias term

X_train = np.concatenate((np.ones((X_train.shape[0],1)),X_train),axis=1)
X_test = np.concatenate((np.ones((X_test.shape[0],1)),X_test),axis=1)
```

In [12]:
```
# Importing Package for Logistic Regression model and to show some metric

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, classification_report, conf
```

In [13]:
```
# Calling LogisticRegression function and using fit method on training datasets

logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
```

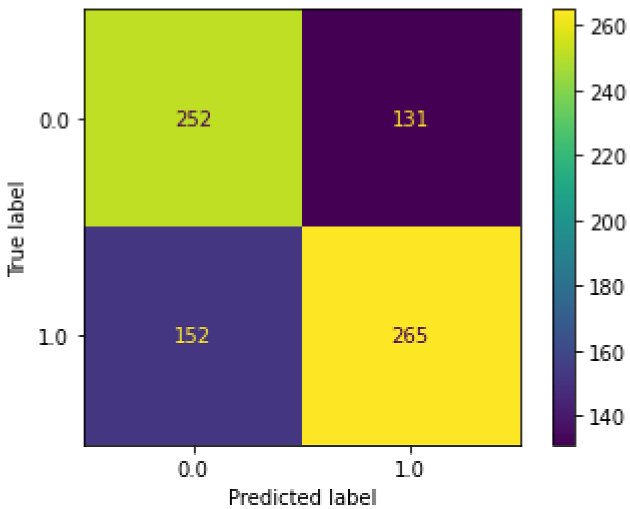
Out[13]:
```
LogisticRegression()
```

In [14]:
```
# predicting output using predict method of logistic Regression function

y_pred = logmodel.predict(X_test)
```

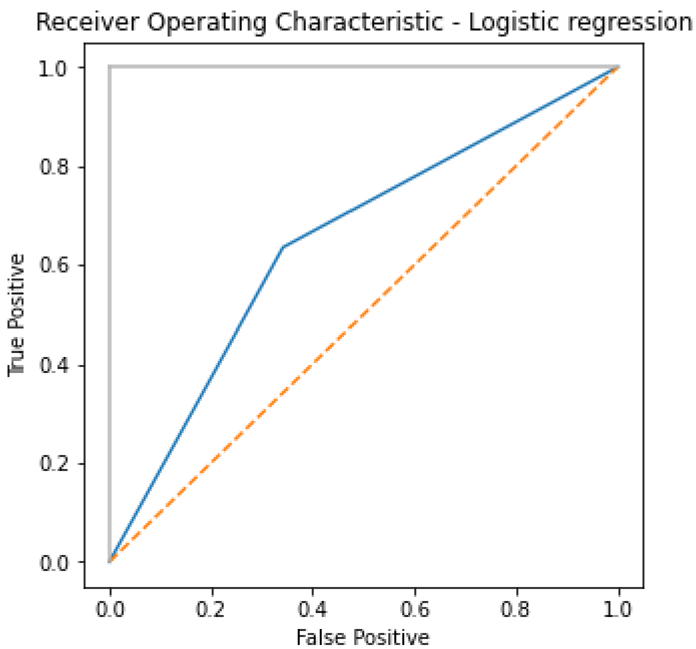
In [15]:
```
false_positive, true_positive, threshold1 = roc_curve(y_test, y_pred)
```

In [16]:
```
# Plotting
# Confusion Matrix

class_labels = df_new['1.000000000000000000e+00'].unique()
cm = confusion_matrix(y_test, y_pred, labels=class_labels)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_labels)
disp.plot()
```

Out[16]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1b1a6c0ee80
>
```



In [17]:
```
plt.subplots(1, figsize=(5,5))
plt.title('Receiver Operating Characteristic - Logistic regression')
plt.plot(false_positive, true_positive)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
plt.ylabel('True Positive')
plt.xlabel('False Positive')
plt.show()
```



In [18]:
```
# Calculating model accuarcy
accuracy=accuracy_score(y_test,y_pred)
accuracy
```

Out[18]: 0.64625

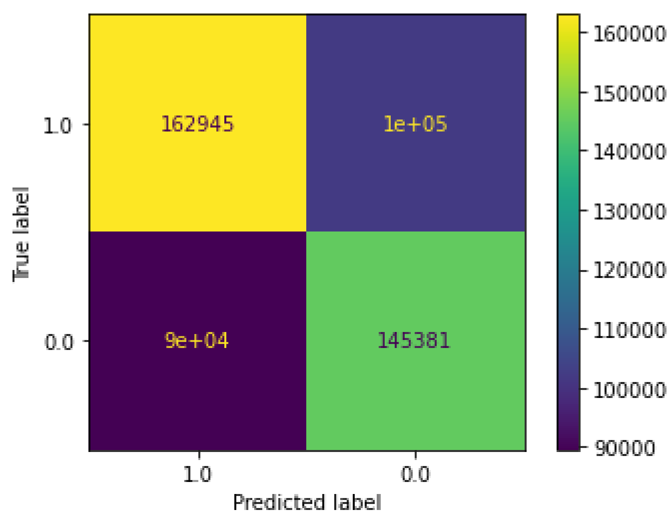
Final Testing

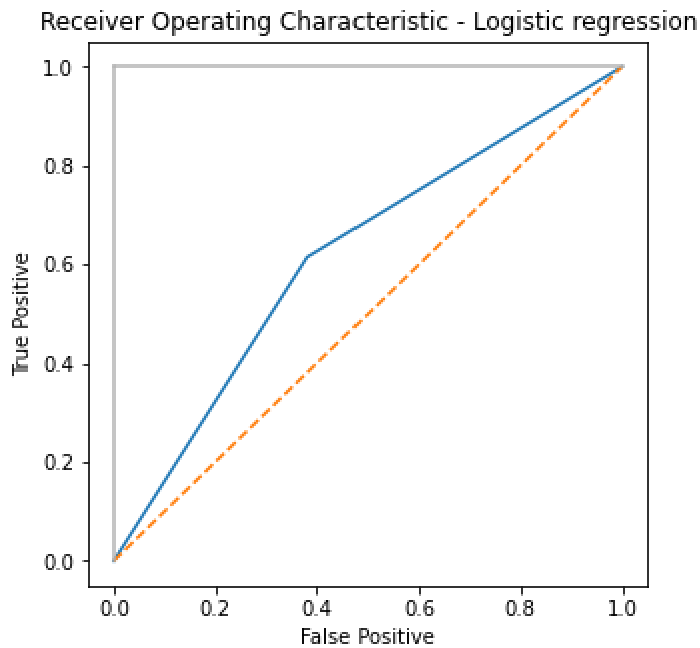
In [19]:
```
df_test=df[5499999:]
```

In [20]:
```
# separating dependent and independent feature

X_final_test= df_test.drop("1.000000000000000000e+00",axis=1)
y_final_test = df_test["1.000000000000000000e+00"]
```

In [21]:
```
#Feature Normalization
# standardization-or-mean-removal-and-variance-scaling
X_final_test = scaler.transform(X_final_test)

#Adding x0 = 1 to each instance for the bias term
X_final_test = np.concatenate((np.ones((X_final_test.shape[0],1)),X_final_test),a
```

In [22]:
```
# predicting output using predict method of logistic Regression function
y_final_pred = logmodel.predict(X_final_test)
false_positive_test, true_positive_test, threshold1 = roc_curve(y_final_test, y_f
# Plotting
# Confusion Matrix
class_labels = df_test['1.000000000000000000e+00'].unique()
cm_new= confusion_matrix(y_final_test, y_final_pred, labels=class_labels)
disp_new= ConfusionMatrixDisplay(confusion_matrix=cm_new, display_labels=class_la
disp_new.plot()

#ROC Plotting
plt.subplots(1, figsize=(5,5))
plt.title('Receiver Operating Characteristic - Logistic regression')
plt.plot(false_positive_test, true_positive_test)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
plt.ylabel('True Positive')
plt.xlabel('False Positive')
plt.show()

# Calculating model accuarcy
accuracy_test=accuracy_score(y_final_test,y_final_pred)
accuracy_test
```





Out[22]: 0.616652

In [ ]: