```
import datetime
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from math import sin,cos,pi
from sklearn import metrics
from sklearn.preprocessing import LabelEncoder, OneHotEncoder,
StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.model_selection import GridSearchCV
from sklearn import svm
from imblearn.ensemble import BalancedBaggingClassifier
from matplotlib.colors import LinearSegmentedColormap
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from xgboost.sklearn import XGBClassifier
from sklearn.tree import DecisionTreeClassifier
plt.style.use('seaborn')
```

```
<ipython-input-1-03f97543ffc2>:19: MatplotlibDeprecationWarning: The
seaborn styles shipped by Matplotlib are deprecated since 3.6, as they
no longer correspond to the styles shipped by seaborn. However, they
will remain available as 'seaborn-v0_8-<style>'. Alternatively,
directly use the seaborn API instead.
  plt.style.use('seaborn')
```

```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

```
import datetime
def Time_Formatx(x):
    # Formatting Time

    if x == 2400:
        x = 0
    try: #Try to perform the conversion, except if there is an error.
        x = "{0:04d}".format(int(x))
        T = datetime.time(int(x[0:2]), int(x[2:4]))
    except ValueError: #Handle the ValueError
        print(f"Invalid time format: {x}") #Print the problematic
value
        T = datetime.time(0, 0) # Or handle it in another way, perhaps
return None.
    return T

def stats(g):
```

```
    # Statistical Information for a Group

    return {'mean':g.mean(), 'variance':g.var(), 'count':g.count(),
'min':g.min(), 'max':g.max()}


def dataOverview(Airlines, Airports, Flights):

    # Dataset descriptions
    print(Flights.info(verbose = True, show_counts=True))
    print(Airlines.info(verbose = True, show_counts=True))
    print(Airports.info(verbose = True, show_counts=True))

     # Cancellation Reasons

    cancelled = Flights['CANCELLATION_REASON']
    cancelled.dropna(inplace=True)
    cancelledCount = dict(cancelled.value_counts())
    labels = ['Weather','Airline','National Air System','Security']
    sizes = cancelledCount.values()

    fig, ax = plt.subplots(figsize=(8,8))
    ax.pie(sizes, labels=labels, pctdistance=1.25, labeldistance=1.45,
autopct='%1.2f%%', startangle=90, textprops={'fontsize': 20})
    ax.axis('equal')  # Equal aspect ratio ensures that pie is drawn
as a circle.
    plt.show()


    # Cancellation Reasons

    cancelled = Flights['CANCELLATION_REASON']
    cancelled.dropna(inplace=True)
    cancelledCount = dict(cancelled.value_counts())
    sizes = [Flights[Flights['CANCELLED'] == 0].shape[0],
Flights[Flights['CANCELLED'] == 1].shape[0]]
    labels = ['Not Cancelled', 'Cancelled']

    fig, ax = plt.subplots(figsize=(8,8))
    ax.pie(sizes, labels=labels, pctdistance=1.25, labeldistance=1.45,
autopct='%1.2f%%', startangle=90, textprops={'fontsize': 20})
    ax.axis('equal')  # Equal aspect ratio ensures that pie is drawn
as a circle.
    plt.show()


    # Flights on Different Days of Week

    daysOfWeek = Flights['DAY_OF_WEEK']
    dayCounts = dict(daysOfWeek.value_counts())
    dayFreq = {}
```

```
    for day in sorted(dayCounts):
        dayFreq[day] = dayCounts[day]

    plt.figure(figsize=(12,8))
    flightFreq = list(dayFreq.values())
    flightFreq.append(dayFreq[1]) # add monday
    flightFreq.append(dayFreq[2]) # add tuesday
    days = ['Mon','Tue','Wed','Thu','Fri','Sat','Sun','Mon.','Tue...']
    plt.plot(days,flightFreq)
    plt.xlabel("Days of week", fontsize=16)
    plt.ylabel("No of flights", fontsize=16)
    plt.title("No of flights on days of week", fontsize=16)
    plt.tick_params(labelsize=16)
    plt.show()


    # Flights in Different Months

    months = Flights['MONTH']
    monthCounts = dict(months.value_counts())
    monthFreq = {}
    for month in sorted(monthCounts):
        monthFreq[month] = monthCounts[month]

    plt.figure(figsize=(12,8))
    flightFreq = list(monthFreq.values())
    monthsArr = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul',
'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
    plt.plot(monthsArr, flightFreq)
    plt.xlabel("Months", fontsize=16)
    plt.ylabel("No of flights", fontsize=16)
    plt.title("No of flights on different months", fontsize=16)
    plt.tick_params(labelsize=16)
    plt.show()


    # Delay Threshold

    ttl = Flights.shape[0]
    threshold = 3
    delayLessThanThreshold = Flights[Flights['ARRIVAL_DELAY'] <=
threshold].shape[0] / ttl
    print(delayLessThanThreshold)


def exploratoryDataAnalysis(df):

    # # Overall analysis

    # report = sv.analyze(df)
```

```
    # report.show_html("EDA.html")


    # Air Traffic Share of Airlines

    plt.subplots(figsize=(15,20))

plt.pie(df['AIRLINE'].value_counts(),labels=df['AIRLINE_NAME'].unique(
),autopct='%1.0f%%',textprops={'fontsize': 20})
    plt.show()


    # Calculating Data Statistics

    Origin_Stats =
df['ARRIVAL_DELAY'].groupby(df['ORIGIN']).apply(stats).unstack().sort_
values('count',ascending=False)
    Destination_Stats =
df['ARRIVAL_DELAY'].groupby(df['DESTINATION']).apply(stats).unstack().
sort_values('count',ascending=False)
    Airline_Stats =
df['ARRIVAL_DELAY'].groupby(df['AIRLINE']).apply(stats).unstack().sort
_values('mean')
    print(Airline_Stats)


    # Airline Delays on Different Days of Week

    Days = ["Monday",
"Tuesday","Wednesday","Thursday","Friday","Saturday","Sunday"]
    Airline_Day_Stats = pd.DataFrame()
    for a in df['AIRLINE'].unique():
        x = df[df['AIRLINE']==a]
        t = x['ARRIVAL_DELAY'].groupby(df['DAY']).mean()
        Airline_Day_Stats[a]=t
    Airline_Day_Stats.dropna(inplace=True)
    print(Airline_Day_Stats)

    sns.set(context="paper")
    plt.subplots(figsize=(10,8))
    plt.title("Mean Delay for Airline Vs. Day of Week")
    sns.heatmap(Airline_Day_Stats, linewidths=0.01,
cmap=LinearSegmentedColormap.from_list('rg',["g", "w", "r"],
N=256),robust=True,yticklabels=Days)
    plt.show()


    # Busiest airports and Airlines

    Airports =
df['DESTINATION_CITY'].groupby(df["DESTINATION_CITY"]).count().sort_va
```

```
lues(ascending=False).iloc[:11].keys().tolist()
    map = df[['AIRLINE_NAME','DESTINATION_CITY','ARRIVAL_DELAY']]

    frames = list()
    for x in Airports:
        frames.append(map.loc[map["DESTINATION_CITY"] == x])
    map = pd.concat(frames)

    airline_city_delay = pd.DataFrame()
    for airlines in map["AIRLINE_NAME"].unique():
        t = map.loc[map["AIRLINE_NAME"] == airlines]
        temp =
t["ARRIVAL_DELAY"].groupby(t["DESTINATION_CITY"]).mean()
        airline_city_delay[airlines] = temp

    sns.set(context="paper")
    plt.subplots(figsize=(10,8))
    plt.title("Mean Delay for Airline Vs. Destination Airports")
    sns.heatmap(airline_city_delay, linewidths=0.01,
cmap=LinearSegmentedColormap.from_list('rg',["g", "w", "r"],
N=256),robust=True,yticklabels=Airports)
    plt.show()


    # Distance and Delay

    map = df[["DISTANCE","ARRIVAL_DELAY","AIRLINE_NAME"]].copy()
    interval = list()
    for i in range(0,5000,100):
        interval.append(i)

    map["DISTANCE_INTERVAL"] = pd.cut(x = map["DISTANCE"], bins =
interval)
    map["DISTANCE_MID"] = map["DISTANCE_INTERVAL"].apply(lambda x :
x.mid)
    newMap =
map["ARRIVAL_DELAY"].groupby(map["DISTANCE_MID"]).mean().to_frame()
    newMap.dropna(inplace=True)
    newMap.plot.line(title = "Distance vs Delay graph (Bucket
Size:100)")
    plt.show()


    # Distribution of Arrival Delay

    sns.displot(df['ARRIVAL_DELAY'], bins = [i for i in range(-
50,100)])
    plt.show()
```

```
def preprocess(analysis = False):

    Airlines =
pd.read_csv('/content/gdrive/MyDrive/FlightDelayDataset/airlines.csv')
    Airports =
pd.read_csv('/content/gdrive/MyDrive/FlightDelayDataset/airports.csv')
    Flights  =
pd.read_csv('/content/gdrive/MyDrive/FlightDelayDataset/flights.csv',
on_bad_lines='skip')

    if analysis:
        dataOverview(Airlines, Airports, Flights)


    # Dropping rows with NaN values and selecting data for January

    Flights = Flights.iloc[:,:23]
    Flights.dropna(inplace=True)
    Flights = Flights[Flights["MONTH"]==1]
    Flights.reset_index(inplace=True)


    # Collecting Names of Airlines and Airports

    Airline_Names = {}
    for i in range(len(Airlines)):
        Airline_Names[Airlines["IATA_CODE"][i]] = Airlines["AIRLINE"]
[i]

    Airport_Names = {}
    for i in range(len(Airports)):
        Airport_Names[Airports["IATA_CODE"][i]] = Airports["AIRPORT"]
[i]

    City_Names = {}
    for i in range(len(Airports)):
        City_Names[Airports["IATA_CODE"][i]] = Airports["CITY"][i]


    # Merging Datasets & Selecting relevant columns

    df = pd.DataFrame()
    df['DATE'] = pd.to_datetime(Flights[['YEAR','MONTH', 'DAY']])
    df['DAY'] = Flights["DAY_OF_WEEK"]
    df['AIRLINE'] = Flights["AIRLINE"]
    df['AIRLINE_NAME'] = [Airline_Names[Flights["AIRLINE"][x]] for x
in range(len(Flights))]
    df['FLIGHT_NUMBER'] = Flights['FLIGHT_NUMBER']
    df['TAIL_NUMBER'] = Flights['TAIL_NUMBER']
    df['ORIGIN'] = Flights['ORIGIN_AIRPORT']
```

```
    df['ORIGIN_AIRPORT_NAME'] =
[Airport_Names[Flights["ORIGIN_AIRPORT"][x]] for x in
range(len(Flights))]
    df['ORIGIN_CITY'] = [City_Names[Flights["ORIGIN_AIRPORT"][x]] for
x in range(len(Flights))]
    df['DESTINATION'] = Flights['DESTINATION_AIRPORT']
    df['DESTINATION_AIRPORT_NAME'] =
[Airport_Names[Flights["DESTINATION_AIRPORT"][x]] for x in
range(len(Flights))]
    df['DESTINATION_CITY'] =
[City_Names[Flights["DESTINATION_AIRPORT"][x]] for x in
range(len(Flights))]
    df['DISTANCE'] = Flights['DISTANCE']
    df['SCHEDULED_DEPARTURE'] =
Flights['SCHEDULED_DEPARTURE'].apply(Time_Formatx)
    df['SCHEDULED_ARRIVAL'] =
Flights['SCHEDULED_ARRIVAL'].apply(Time_Formatx)
    df['TAXI_OUT'] = Flights['TAXI_OUT']
    df['DEPARTURE_DELAY'] = Flights['DEPARTURE_DELAY']
    df['ARRIVAL_DELAY'] = Flights['ARRIVAL_DELAY']
    df = df[df.ARRIVAL_DELAY < 500]

    if analysis:
        print(df)

    if analysis:
        exploratoryDataAnalysis(df)

    # Selecting Features
    Data =
df[['ARRIVAL_DELAY','ORIGIN','DESTINATION','DISTANCE','TAXI_OUT','DEPA
RTURE_DELAY','DATE','DAY','AIRLINE','SCHEDULED_DEPARTURE','SCHEDULED_A
RRIVAL']].copy()


    # Handling Date and Time Data

    SD = Data['SCHEDULED_DEPARTURE']
    SA = Data['SCHEDULED_ARRIVAL']
    DA = Data['DATE']

    Data['SDH_Sin'] = [sin(2*pi*d.hour/24) for d in SD]
    Data['SDH_Cos'] = [cos(2*pi*d.hour/24) for d in SD]
    Data['SDM_Sin'] = [sin(2*pi*d.minute/60) for d in SD]
    Data['SDM_Cos'] = [cos(2*pi*d.minute/60) for d in SD]

    Data['SAH_Sin'] = [sin(2*pi*d.hour/24) for d in SA]
    Data['SAH_Cos'] = [cos(2*pi*d.hour/24) for d in SA]
    Data['SAM_Sin'] = [sin(2*pi*d.minute/60) for d in SA]
    Data['SAM_Cos'] = [cos(2*pi*d.minute/60) for d in SA]
```

```
    Data['DAM_Sin'] = [sin(2*pi*d.month/12) for d in DA]
    Data['DAM_Cos'] = [cos(2*pi*d.month/12) for d in DA]
    Data['DAD_Sin'] = [sin(2*pi*d.day/31) for d in DA]
    Data['DAD_Cos'] = [cos(2*pi*d.day/31) for d in DA]

    Data =
Data.drop(['SCHEDULED_DEPARTURE','SCHEDULED_ARRIVAL','DATE'],axis=1)
    Data.dropna(inplace=True)
    Data.reset_index(inplace=True,drop=True)

    if analysis:
        print(Data)


    # Handling Categorical Variables

    L = LabelEncoder()


Data['AIRLINE']=L.fit_transform(np.array(Data['AIRLINE']).reshape(-
1,1))
    Data['ORIGIN']=L.fit_transform(np.array(Data['ORIGIN']).reshape(-
1,1))

Data['DESTINATION']=L.fit_transform(np.array(Data['DESTINATION']).resh
ape(-1,1))

    H = OneHotEncoder()

    a =
pd.DataFrame(H.fit_transform(np.array(Data['AIRLINE']).reshape(-
1,1)).toarray())
    a.columns = [str(i) for i in range(len(a.columns))]
    b =
pd.DataFrame(H.fit_transform(np.array(Data['ORIGIN']).reshape(-
1,1)).toarray())
    b.columns = [str(i+len(a.columns)) for i in range(len(b.columns))]
    c =
pd.DataFrame(H.fit_transform(np.array(Data['DESTINATION']).reshape(-
1,1)).toarray())
    c.columns = [str(i+len(a.columns)+len(b.columns)) for i in
range(len(c.columns))]

    Data = Data.drop(['AIRLINE'],axis=1)
    Data = Data.join(a)
    #Data = Data.drop(['ORIGIN'],axis=1)
    #Data = Data.join(b)
    #Data = Data.drop(['DESTINATION'],axis=1)
    #Data = Data.join(c)
```

```
    Data.dropna(inplace=True)

    if analysis:
        print(Data)


    # Splitting into X and Y

    X = Data.copy()
    X.drop(['ARRIVAL_DELAY'],axis=1, inplace = True)
    Y = Data['ARRIVAL_DELAY'].copy()

    for i in range(len(Y)):
        if Y[i]<3: Y[i]=0
        else: Y[i]=1

    X = X.to_numpy()
    Y = Y.to_numpy()

    if analysis:
        print("X shape: ", X.shape)
        print("Y shape: ", Y.shape)


    # Splitting into Train, Val, Test

    X_train, X_test, y_train, y_test = train_test_split( X, Y,
test_size=0.3, random_state=0, stratify = Y)
    X_val, X_test, y_val, y_test = train_test_split( X_test, y_test,
test_size=0.66, random_state=0, stratify = y_test)

    if analysis:
        print(f"X_train: {X_train.shape}, X_val: {X_val.shape},
X_test: {X_test.shape}")
        print(f"y_train: {y_train.shape}, y_val: {y_val.shape},
y_test: {y_test.shape}")


    # Standard Scaling

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

    return X_train, y_train, X_val, y_val, X_test, y_test


def train(model, X_train, y_train, X_val, y_val, X_test, y_test,
params):
```

```
    # Decision Tree
    if model == "dt":
        dt = DecisionTreeClassifier(**params)
        dt.fit(X_train,y_train)
        y_pred = dt.predict(X_test)

        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        score = dt.score(X_test,y_test)
        print("Test Score:", score)

        sns.set(context="paper")
        plt.subplots(figsize=(6,6))
        sns.heatmap(confusionMatrix, annot=True, fmt=".0f",
linewidths=1.5, square = True)
        plt.ylabel('Actual label')
        plt.xlabel('Predicted label')
        plt.title("Confusion Matrix", size = 15)
        plt.show()

        return dt

    # Logistic Regression
    if model == "logistic":

        logistic = LogisticRegression(**params)
        logistic.fit(X_train,y_train)
        y_pred = logistic.predict(X_test)

        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        score = logistic.score(X_test,y_test)
        print("Test Score:", score)

        sns.set(context="paper")
        plt.subplots(figsize=(6,6))
        sns.heatmap(confusionMatrix, annot=True, fmt=".0f",
linewidths=1.5, square = True)
        plt.ylabel('Actual label')
        plt.xlabel('Predicted label')
        plt.title("Confusion Matrix", size = 15)
        plt.show()

        return logistic

    # SGD Classifier
    if model == "sgd classifier":

        sgd = SGDClassifier(**params)
        sgd.fit(X_train,y_train)
        y_pred = sgd.predict(X_test)
```

```
        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        score = sgd.score(X_test,y_test)
        print("Test Score:", score)

        sns.set(context="paper")
        plt.subplots(figsize=(6,6))
        sns.heatmap(confusionMatrix, annot=True, fmt=".0f",
linewidths=1.5, square = True)
        plt.ylabel('Actual label')
        plt.xlabel('Predicted label')
        plt.title("Confusion Matrix", size = 15)
        plt.show()

        return sgd

    # Random Forests
    if model == "rf":

        rf = RandomForestClassifier(**params)
        rf.fit(X_train,y_train)
        y_pred = rf.predict(X_test)

        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        score = rf.score(X_test,y_test)
        print("Test Score:", score)

        sns.set(context="paper")
        plt.subplots(figsize=(6,6))
        sns.heatmap(confusionMatrix, annot=True, fmt=".0f",
linewidths=1.5, square = True)
        plt.ylabel('Actual label')
        plt.xlabel('Predicted label')
        plt.title("Confusion Matrix", size = 15)
        plt.show()

        return rf

    # Gaussian Naive Bayes
    if model == "gnb":

        gnb = GaussianNB(**params)
        gnb.fit(X_train,y_train)
        y_pred = gnb.predict(X_test)

        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        score = gnb.score(X_test,y_test)
        print("Test Score:", score)

        sns.set(context="paper")
        plt.subplots(figsize=(6,6))
```

```
        sns.heatmap(confusionMatrix, annot=True, fmt=".0f",
linewidths=1.5, square = True)
        plt.ylabel('Actual label')
        plt.xlabel('Predicted label')
        plt.title("Confusion Matrix", size = 15)
        plt.show()

        return gnb

    # XGBoost Classifier
    if model == "xgb":

        xgb = XGBClassifier(**params)
        xgb.fit(X_train,y_train)
        y_pred = xgb.predict(X_test)

        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        score = xgb.score(X_test,y_test)
        print("Test Score:", score)

        sns.set(context="paper")
        plt.subplots(figsize=(6,6))
        sns.heatmap(confusionMatrix, annot=True, fmt=".0f",
linewidths=1.5, square = True)
        plt.ylabel('Actual label')
        plt.xlabel('Predicted label')
        plt.title("Confusion Matrix", size = 15)
        plt.show()

        importance = xgb.feature_importances_

        for i in range(len(importance)):
            print("Feature: {:d}, Score:
{:.3f}".format(i,importance[i]))

        plt.bar([x for x in range(len(importance))], importance)
        plt.show()

        return xgb


def optimalParams(model, X_train, y_train, X_val, y_val, X_test,
y_test):
    '''
    Enter the parameter and it's possible types here
    If max_depth = 10,100,1000 and loss = L1,L2
    The code will run 3*2 times.
    For plotting the graph, please keep only 2 sets of parameters as
it's a 2D graph.
    Otherwise one would have to split the array and it will lead to
```

```
confusion.
    '''

    # # Logistic Regression
    if model == "logistic":

        parameters = {
            'penalty': ['l2'],
            'fit_intercept': [True, False],
            'max_iter': [2,4,6,8,10],
            'n_jobs': [-1]}

        clf = GridSearchCV(LogisticRegression(), parameters, n_jobs=-
1, cv=3)
        clf.fit(X_train,y_train)
        print("Best Score:", clf.best_score_)
        print("Best Parameters:", clf.best_params_)

        bestEstimator = clf.best_estimator_
        y_pred = bestEstimator.predict(X_test)
        score = bestEstimator.score(X_test,y_test)
        print("Test Score:", score)


        # Plotting the parameters

        param_xAxis_name = 'max_iter' # parameter that you want in the
x axis. (max_iter, n_estimators etc. are preferred)
        param_color_name = 'fit_intercept' # parameter that you want
as the different colored curves

        param_xAxis = parameters[param_xAxis_name]
        param_color = parameters[param_color_name]

        mean_test_score = clf.cv_results_['mean_test_score']
        mean_test_score =
np.array(mean_test_score).reshape(len(param_color), len(param_xAxis))

        _, ax = plt.subplots(1,1, figsize=(9,6))

        for i in range(len(param_color)):
            ax.plot(param_xAxis, mean_test_score[i,:],
label=param_color_name+': ' + str(param_color[i]))

        ax.set_title("Grid Search CV Scores for Logistic Regression",
fontsize=18, fontweight='bold')
        ax.set_xlabel(param_xAxis_name, fontsize=14)
        ax.set_ylabel('CV Avg Score', fontsize=14)
        ax.legend(fontsize=14)
        # plt.show()
```

```
    # Random Forests
    if model == "rf":

        parametersrf = {
            'criterion': ["gini", "entropy"],
            'class_weight': [None, "balanced"],
            'n_estimators': [200,400,600]
            }

        clf = GridSearchCV(RandomForestClassifier(), parametersrf,
n_jobs=-1, cv=3)
        clf.fit(X_train,y_train)
        print("Best Score:", clf.best_score_)
        print("Best Parameters:", clf.best_params_)
        bestEstimatorrf = clf.best_estimator_

        y_pred = bestEstimatorrf.predict(X_test)

        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        score = bestEstimatorrf.score(X_test,y_test)
        print("Test Score:", score)

        param_xAxis_name = 'n_estimators' # parameter that you want in
the x axis. (max_iter, n_estimators etc. are preferred)
        param_color_name = 'criterion' # parameter that you want as
the different colored curves

        param_xAxis = parametersrf[param_xAxis_name]
        param_color = parametersrf[param_color_name]
        param_label = parameters["class_weight"]
        mean_test_score = clf.cv_results_['mean_test_score']
        mean_test_score_none =
mean_test_score[:len(mean_test_score)//2]
        mean_test_score_bal =
mean_test_score[len(mean_test_score)//2:]
        mean_test_score_none =
np.array(mean_test_score_none).reshape(len(param_color),
len(param_xAxis))
        mean_test_score_bal =
np.array(mean_test_score_bal).reshape(len(param_color),
len(param_xAxis))


        _, ax = plt.subplots(1,1, figsize=(9,6))

        for i in range(len(param_color)):
            ax.plot(param_xAxis, mean_test_score_none[i,:],
label=param_color_name+': ' + str(param_color[i]) + ", class weight:"
+ str(param_label[i]))
```

```
            ax.plot(param_xAxis, mean_test_score_bal[i,:],
label=param_color_name+': ' + str(param_color[i]) + ", class weight:"
+ str(param_label[i]))

        ax.set_title("Grid Search CV Scores for Random Forest
Classifier", fontsize=18, fontweight='bold')
        ax.set_xlabel(param_xAxis_name, fontsize=14)
        ax.set_ylabel('CV Avg Score', fontsize=14)
        ax.legend(fontsize=14, bbox_to_anchor=(1.05, 1), title =
"Criterion, class weight")
        plt.setp(legend.get_title(),fontsize='x-large')
        # plt.show()


    # Gaussian Naive Bayes
    if model == "gnb":

        parametersnb = {
            "var_smoothing": [10**-20,10**-11,10**-9, 10**-7, 10**-5,
10**-2]
            }

        clf = GridSearchCV(GaussianNB(), parametersnb, n_jobs=-1,
cv=3)
        clf.fit(X_train,y_train)
        print("Best Score:", clf.best_score_)
        print("Best Parameters:", clf.best_params_)
        bestEstimatornb = clf.best_estimator_
        y_pred = bestEstimatornb.predict(X_test)

        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        print(confusionMatrix)
        scorenb = bestEstimatornb.score(X_test,y_test)
        print("Test Score:", scorenb)

        param_xAxis_name = 'var_smoothing' # parameter that you want
in the x axis. (max_iter, n_estimators etc. are preferred)
        param_xAxis = parameters[param_xAxis_name]
        param_label = parameters[param_xAxis_name]
        print(clf.cv_results_["params"])
        mean_test_score = clf.cv_results_['mean_test_score']

        _, ax = plt.subplots(1,1, figsize=(9,6))

        ax.plot(param_xAxis, mean_test_score)
        ax.set_title("Grid Search CV Scores for Gaussian naive bayes",
fontsize=18, fontweight='bold')
        ax.set_xlabel(param_xAxis_name, fontsize=14)
        ax.set_ylabel('CV Avg Score', fontsize=14)
        # plt.show()
```

```
    # XGBoost Classifier
    if model == "xgb":

        parameters = {
            'max_depth':[5,7,15],
            'learning_rate': [0.01,0.001,0.1],
            'class_weight': [None, "balanced"],
            'n_estimators': [100,200,300]
            }

        clf = GridSearchCV(XGBClassifier(), parameters, n_jobs=-1,
cv=3)
        clf.fit(X_train,y_train)
        print("Best Score:", clf.best_score_)
        print("Best Parameters:", clf.best_params_)
        bestEstimator = clf.best_estimator_
        y_pred = bestEstimator.predict(X_test)

        confusionMatrix = metrics.confusion_matrix(y_test, y_pred)
        score = bestEstimator.score(X_test,y_test)
        print("Test Score:", score)

        # Plotting the parameters

        param_xAxis_name = 'n_estimators' # parameter that you want in
the x axis. (max_iter, n_estimators etc. are preferred)
        param_color_name = 'max_depth' # parameter that you want as
the different colored curves

        param_xAxis = parameters[param_xAxis_name]
        param_color = parameters[param_color_name]
        param_breaks = clf.cv_results_["params"]
        mean_score = clf.cv_results_["mean_test_score"]
        scores_list = [[] for i in range(6)]
        j, k = len(param_xAxis)*len(param_color), 0
        labels = dict()
        for i in param_breaks:
            scores_list[k//j].append(mean_score[k])
            labels["learning_rate:"+str(clf.cv_results_["params"][k]
["learning_rate"]) + ", class_weight:"+str(clf.cv_results_["params"]
[k]["class_weight"])] = k//j
            k += 1

        labels = {v: k for k, v in labels.items()}
        mean_test_score =
np.array(scores_list).reshape(len(scores_list), len(param_color),
len(param_xAxis))
```

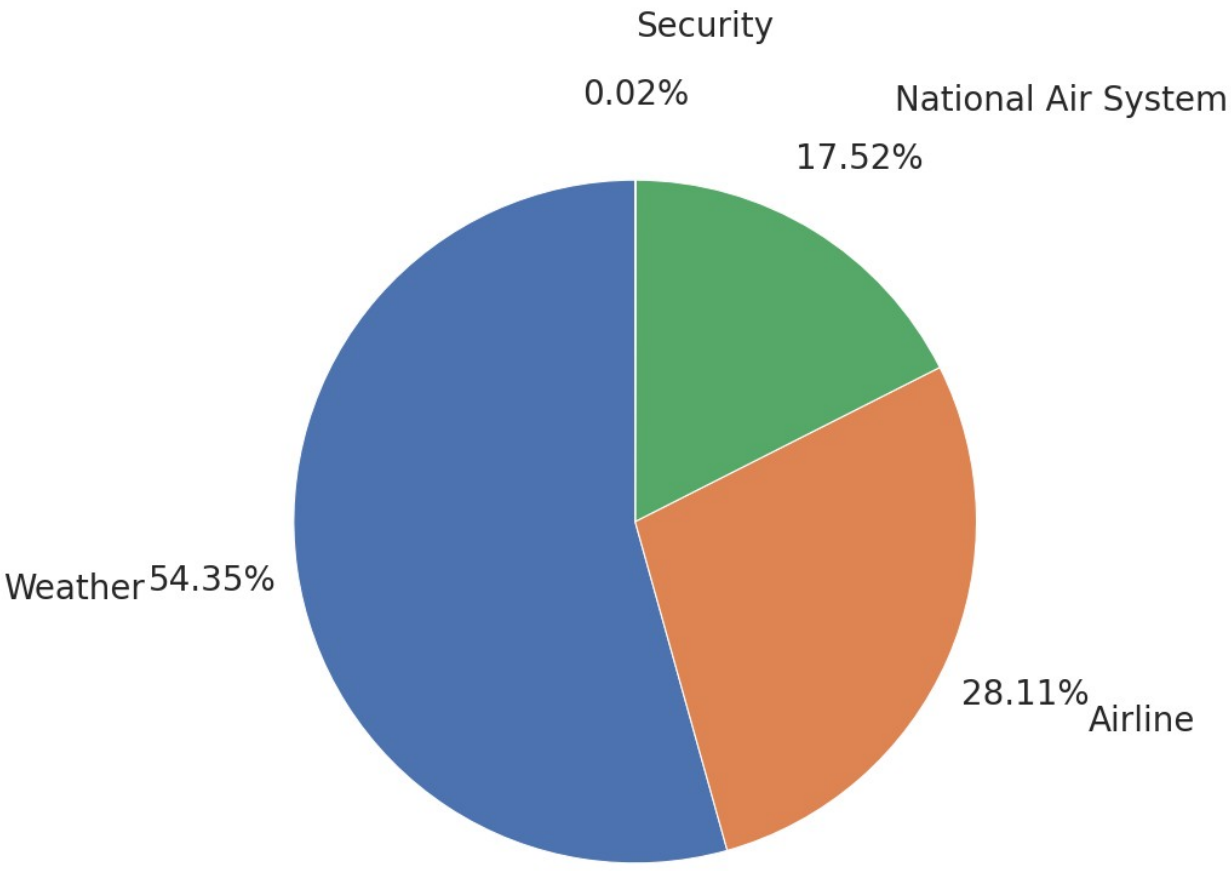
```
        _, ax = plt.subplots(1,1, figsize=(9,6))

        for i in range(len(param_color)):
            for j in range(len(mean_test_score)):
                ax.plot(param_xAxis, mean_test_score[j,i,:],
label=param_color_name+': ' + str(param_color[i]) + "," + labels[j])


        ax.set_title("Grid Search CV Scores for XGB Classifier",
fontsize=18, fontweight='bold')
        ax.set_xlabel(param_xAxis_name, fontsize=14)
        ax.set_ylabel('CV Avg Score', fontsize=14)
        ax.legend(fontsize=14,  bbox_to_anchor=(1, 1.1), title = "max
depth, learning rate, class weight")
        plt.setp(legend.get_title(),fontsize='x-large')
        # plt.show()

    return clf

def plotRocAuc(model, X_test, y_test, labels):

    y_pred = model.predict_proba(X_test)

    fpr, tpr, threshold= metrics.roc_curve(y_test, y_pred[:, 1])
    roc_auc = metrics.auc(fpr, tpr)

    plt.subplots(figsize=(9,7))
    plt.title("Receiver Operating Characteristic", fontsize=14)
    plt.plot(fpr, tpr, label = labels + " AUC = %0.2f"%roc_auc)
    plt.plot([0,1], [0,1], "--", label="No skill")
    plt.legend(loc = "lower right", prop={'size': 12})
    plt.ylabel("True Positive Rate")
    plt.xlabel("False Positive Rate")

    plt.show()

def process(analysis = False):
    '''
      Calls preprocess on the train and test set - Link to the dataset
:
https://drive.google.com/drive/folders/1HRDxih_6xN0uU2Js3xGF8zp5r_XPSE
Jc?usp=sharing

      Parameters
      ----------
      analysis : Default False, If set to true, displays all the
analytical & statistical graphs for the dataset provided.

      Returns
      -------
```

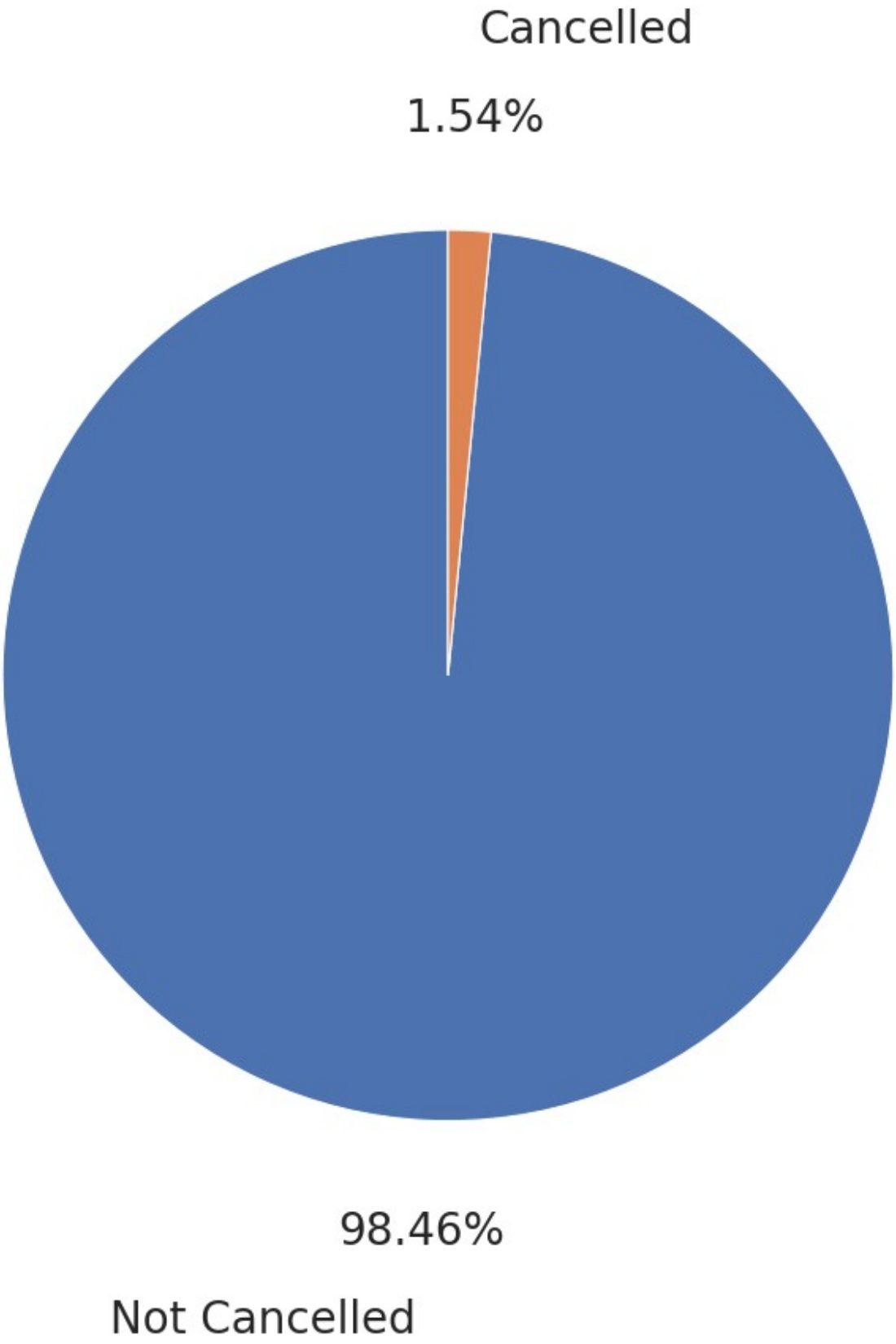
```
      A stratified 70-10-20 split of the dataset
    '''
    X_train, y_train, X_val, y_val, X_test, y_test =
preprocess(analysis)
    return X_train, y_train, X_val, y_val, X_test, y_test

def plotAllROC(data):
    X_train, y_train, X_val, y_val, X_test, y_test = data
    models = ['logistic',
              'gnb',
              'xgb',
              'dt',
              'rf']
    params = [{},
              {},
              {'class_weight': None, 'learning_rate': 0.1,
'max_depth': 7, 'n_estimators': 300, "random_state": 42},
              {"random_state": 42},
              {'class_weight': None, 'criterion': 'entropy',
'n_estimators': 400, "random_state": 42}]
    labels = ["Logistic Regression",
              "GNB",
              "XGB Classifier",
              "Decision Tree",
              "Random Forest"]

    tpr, fpr, roc_auc = [], [], []

    for i in range(len(models)):
        print(i)
        trainedModel = train(models[i], X_train, y_train, X_val,
y_val, X_test, y_test, params[i])

        y_pred = trainedModel.predict_proba(X_test)
        fpr_, tpr_, threshold= metrics.roc_curve(y_test, y_pred[:, 1])
        fpr.append(fpr_)
        tpr.append(tpr_)
        roc_auc_ = metrics.auc(fpr_, tpr_)
        roc_auc.append(roc_auc_)

    plt.clf()
    plt.subplots(figsize=(9,6))

    for i in range(len(models)):
      plt.plot(fpr[i], tpr[i], label = labels[i] + " AUC =
%0.2f"%roc_auc[i])
    plt.plot([0,1], [0,1], "--", label="No skill")

    plt.title("Receiver Operating Characteristic", fontsize=14,
fontweight = "bold")
```

```
    plt.legend(loc = "lower right", prop={'size': 12})
    plt.ylabel("True Positive Rate")
    plt.xlabel("False Positive Rate")

    plt.show()

def runner(model, data, optimal = False, params = {}):
    '''
      Trains the models, Plots confusion matrix and roc-auc curve.

      Parameters
      ----------
      model : {
        'logistic' : logistic regression model
        'rf' : Random forest
        'gnb' : Gaussian naive bayes
        'xgb' : XGB boost
        'dt' : Decision tree
      }
      optimal : Default False, If set to true, performs a grid search
on predetermined hyperparameters and trains the model based on those
parameters
      params : parameters that you want to pass to the model - Default
is an empty dictionary. If optimal set to true, there is no need to
pass params

    Returns
    ------
    None, but accuracy is printed
    '''
    modelDict = {
        'logistic' : "Logistic Regression",
        'rf' : "Random Forest",
        'gnb' : "GNB",
        'xgb' : "XGB Classifier",
        'dt' : "Decision Tree"
      }
    X_train, y_train, X_val, y_val, X_test, y_test = data
    if optimal:
        trainedModel = optimalParams(model, X_train, y_train, X_val,
y_val, X_test, y_test)
    else:
        trainedModel = train(model, X_train, y_train, X_val, y_val,
X_test, y_test, params)

    plotRocAuc(trainedModel, X_test, y_test, modelDict[model])

data = process(analysis = True)
```

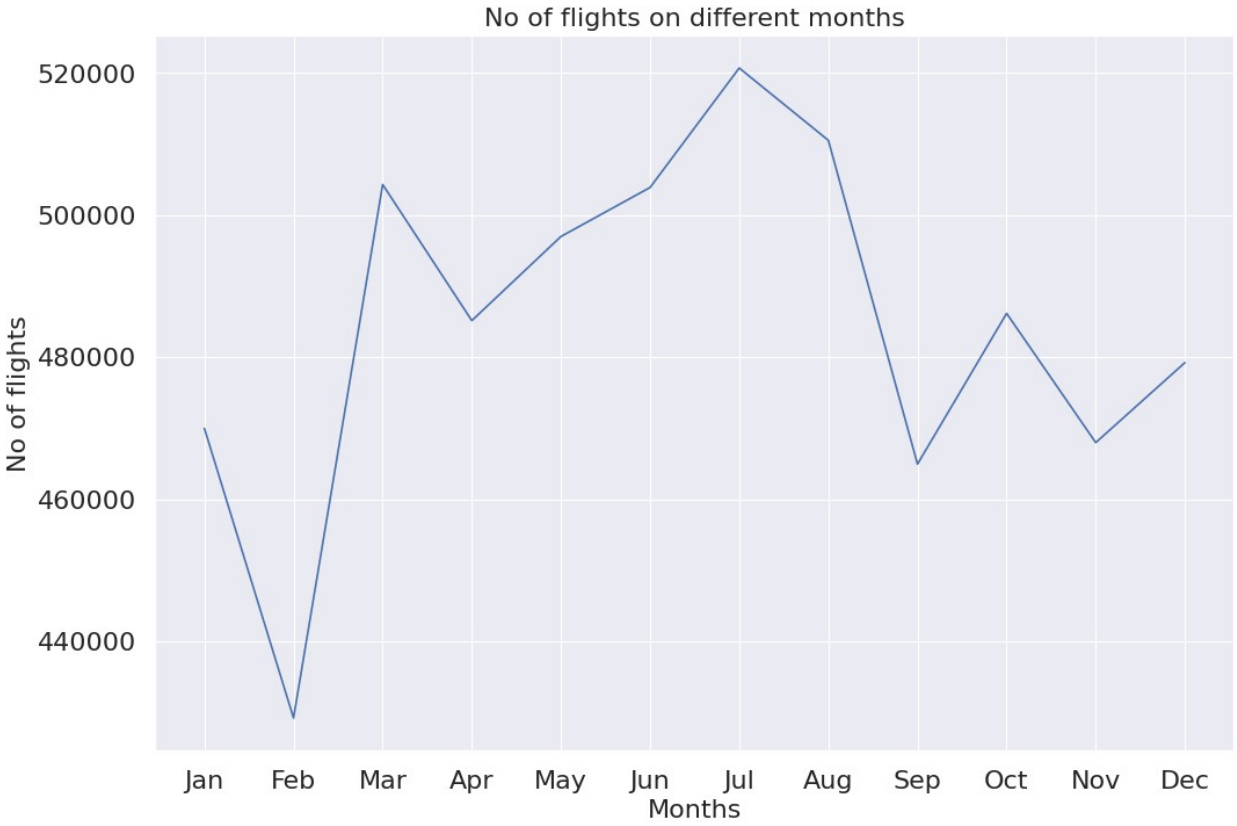
```
<ipython-input-14-0b05dbc0d8be>:193: DtypeWarning: Columns (7,8) have mixed types. Specify dtype option on import or set low_memory=False.
  Flights  = pd.read_csv('/content/gdrive/MyDrive/FlightDelayDataset/flights.csv', on_bad_lines='skip')

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5819079 entries, 0 to 5819078
Data columns (total 31 columns):
 #   Column               Non-Null Count    Dtype  
---  ------               --------------    -----  
 0   YEAR                 5819079 non-null  int64  
 1   MONTH                5819079 non-null  int64  
 2   DAY                  5819079 non-null  int64  
 3   DAY_OF_WEEK          5819079 non-null  int64  
 4   AIRLINE              5819079 non-null  object 
 5   FLIGHT_NUMBER        5819079 non-null  int64  
 6   TAIL_NUMBER          5804358 non-null  object 
 7   ORIGIN_AIRPORT       5819079 non-null  object 
 8   DESTINATION_AIRPORT  5819079 non-null  object 
 9   SCHEDULED_DEPARTURE  5819079 non-null  int64  
 10  DEPARTURE_TIME       5732926 non-null  float64
 11  DEPARTURE_DELAY      5732926 non-null  float64
 12  TAXI_OUT             5730032 non-null  float64
 13  WHEELS_OFF           5730032 non-null  float64
 14  SCHEDULED_TIME       5819073 non-null  float64
 15  ELAPSED_TIME         5714008 non-null  float64
 16  AIR_TIME             5714008 non-null  float64
 17  DISTANCE             5819079 non-null  int64  
 18  WHEELS_ON            5726566 non-null  float64
 19  TAXI_IN              5726566 non-null  float64
 20  SCHEDULED_ARRIVAL    5819079 non-null  int64  
 21  ARRIVAL_TIME         5726566 non-null  float64
 22  ARRIVAL_DELAY        5714008 non-null  float64
 23  DIVERTED             5819079 non-null  int64  
 24  CANCELLED            5819079 non-null  int64  
 25  CANCELLATION_REASON  89884 non-null    object 
 26  AIR_SYSTEM_DELAY     1063439 non-null  float64
 27  SECURITY_DELAY       1063439 non-null  float64
 28  AIRLINE_DELAY        1063439 non-null  float64
 29  LATE_AIRCRAFT_DELAY  1063439 non-null  float64
 30  WEATHER_DELAY        1063439 non-null  float64
dtypes: float64(16), int64(10), object(5)
memory usage: 1.3+ GB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14 entries, 0 to 13
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
```

```
 0   IATA_CODE  14 non-null     object
 1   AIRLINE    14 non-null     object
dtypes: object(2)
memory usage: 352.0+ bytes
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 322 entries, 0 to 321
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   IATA_CODE  322 non-null    object
 1   AIRPORT    322 non-null    object
 2   CITY       322 non-null    object
 3   STATE      322 non-null    object
 4   COUNTRY    322 non-null    object
 5   LATITUDE   319 non-null    float64
 6   LONGITUDE  319 non-null    float64
dtypes: float64(2), object(5)
memory usage: 17.7+ KB
None
```




Cancelled
1.54%
98.46%
Not Cancelled


No of flights on days of week
875000
850000
825000
800000
775000
750000
725000
700000
No of flights
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Mon.
Tue...
Days of week

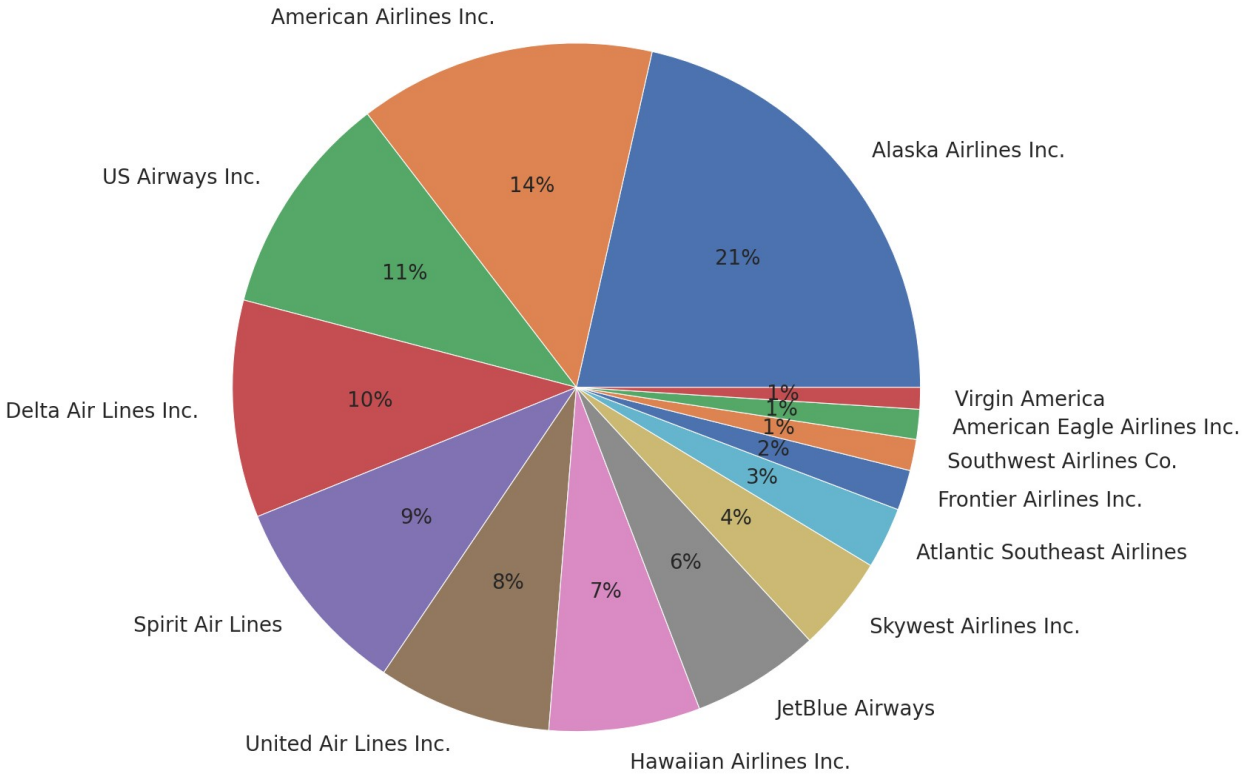

No of flights on different months
520000
500000
480000
460000
440000
No of flights
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Months

```
0.6780059181186576
             DATE  DAY AIRLINE            AIRLINE_NAME  FLIGHT_NUMBER
\
0      2015-01-01    4      AS    Alaska Airlines Inc.             98

1      2015-01-01    4      AA  American Airlines Inc.           2336

2      2015-01-01    4      US         US Airways Inc.            840

3      2015-01-01    4      AA  American Airlines Inc.            258

4      2015-01-01    4      AS    Alaska Airlines Inc.            135

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

457008 2015-01-31    6      B6         JetBlue Airways            839

457009 2015-01-31    6      DL    Delta Air Lines Inc.           1887

457010 2015-01-31    6      F9  Frontier Airlines Inc.            300

457011 2015-01-31    6      F9  Frontier Airlines Inc.            422

457012 2015-01-31    6      UA   United Air Lines Inc.           1104


       TAIL_NUMBER ORIGIN
ORIGIN_AIRPORT_NAME  \
0           N407AS    ANC        Ted Stevens Anchorage International
Airport
1           N3KUAA    LAX                Los Angeles International
Airport
2           N171US    SFO              San Francisco International
Airport
3           N3HYAA    LAX                Los Angeles International
Airport
4           N527AS    SEA              Seattle-Tacoma International
Airport
...            ...    ...
...
457008      N658JB    JFK  John F. Kennedy International Airport (New
Yor...
457009      N855NW    SEA              Seattle-Tacoma International
Airport
457010      N218FR    DEN                   Denver International
Airport
457011      N954FR    DEN                   Denver International
Airport
457012      N73251    ANC        Ted Stevens Anchorage International
Airport
```

```
          ORIGIN_CITY DESTINATION  \
0           Anchorage         SEA
1         Los Angeles         PBI
2       San Francisco         CLT
3         Los Angeles         MIA
4             Seattle         ANC
...               ...         ...
457008       New York         BQN
457009        Seattle         DTW
457010         Denver         TPA
457011         Denver         ATL
457012      Anchorage         DEN

                                  DESTINATION_AIRPORT_NAME
DESTINATION_CITY  \
0                   Seattle-Tacoma International Airport
Seattle
1                       Palm Beach International Airport  West Palm
Beach
2                Charlotte Douglas International Airport
Charlotte
3                            Miami International Airport
Miami
4             Ted Stevens Anchorage International Airport
Anchorage
...                                                   ...
...
457008                          Rafael Hernández Airport
Aguadilla
457009                       Detroit Metropolitan Airport
Detroit
457010                        Tampa International Airport
Tampa
457011  Hartsfield-Jackson Atlanta International Airport
Atlanta
457012                       Denver International Airport
Denver

        DISTANCE SCHEDULED_DEPARTURE SCHEDULED_ARRIVAL  TAXI_OUT  \
0           1448            00:05:00          04:30:00      21.0
1           2330            00:10:00          07:50:00      12.0
2           2296            00:20:00          08:06:00      16.0
3           2342            00:20:00          08:05:00      15.0
4           1448            00:25:00          03:20:00      11.0
...          ...                 ...               ...       ...
457008      1576            23:59:00          04:40:00      18.0
457009      1927            23:59:00          07:11:00      16.0
457010      1506            23:59:00          05:11:00      35.0
457011      1199            23:59:00          04:41:00      40.0
```

```
457012      2405             23:59:00           07:08:00       23.0
```

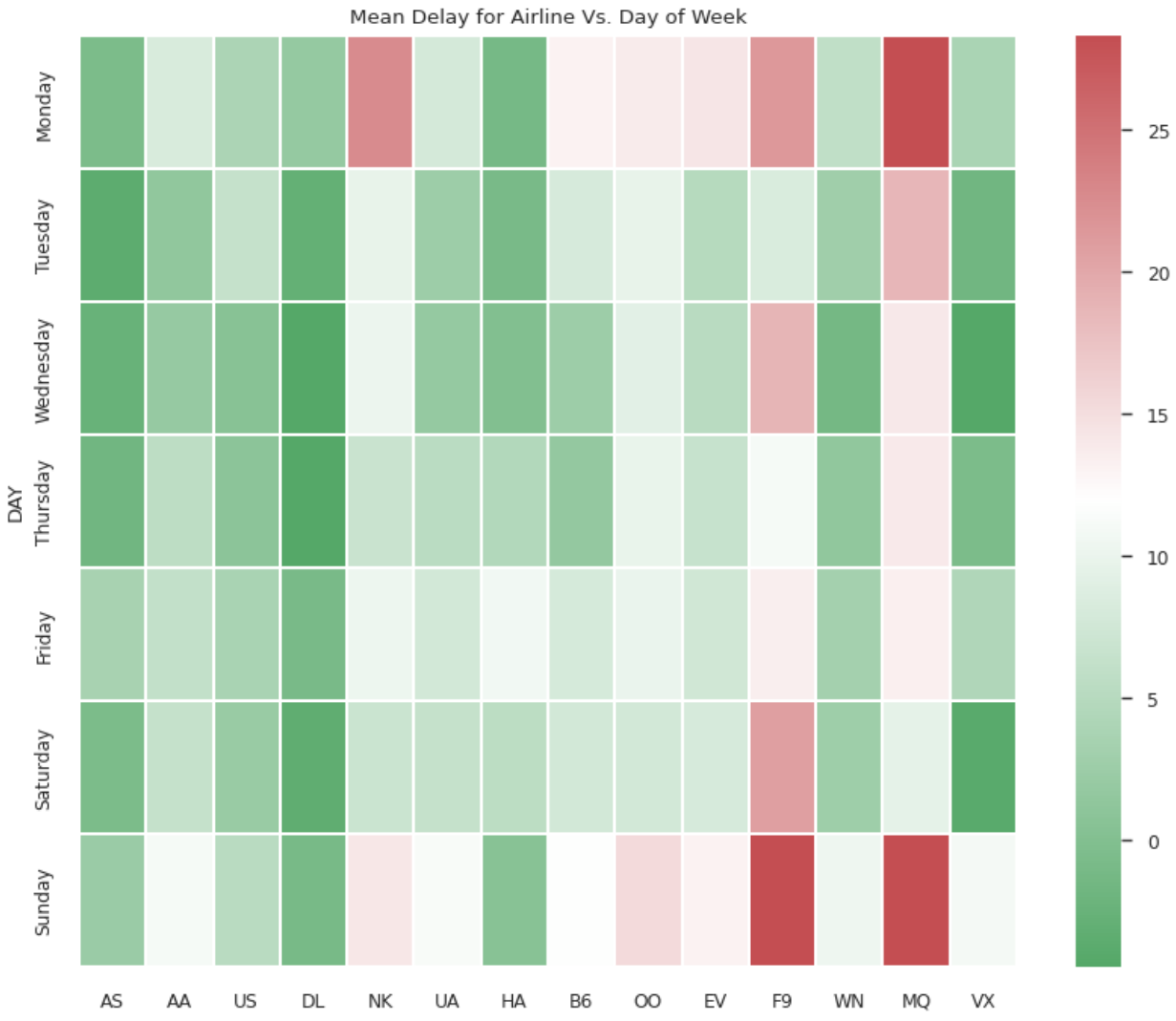
```
        DEPARTURE_DELAY  ARRIVAL_DELAY
0                 -11.0          -22.0
1                  -8.0           -9.0
2                  -2.0            5.0
3                  -5.0           -9.0
4                  -1.0          -21.0
...                 ...            ...
457008              0.0          -21.0
457009              0.0          -13.0
457010              3.0           23.0
457011              0.0           29.0
457012             -1.0            2.0

[456855 rows x 18 columns]
```



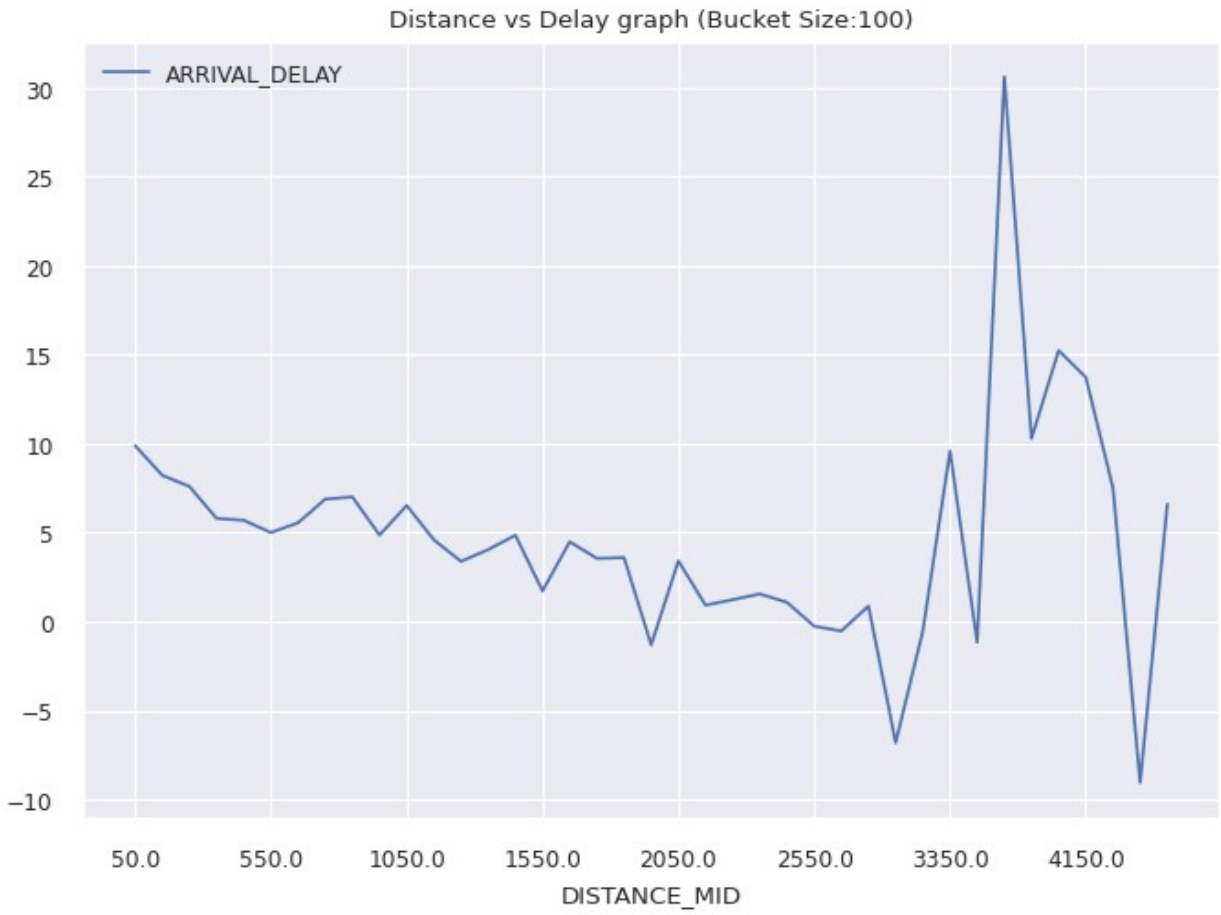
AIRLINE	mean	variance	count	min	max
DL	-2.447386	947.445375	63643.0	-72.0	491.0
AS	-0.320888	972.458088	13151.0	-82.0	451.0
VX	1.420702	1093.283368	4647.0	-70.0	384.0
US	3.055889	892.031643	32475.0	-67.0	391.0

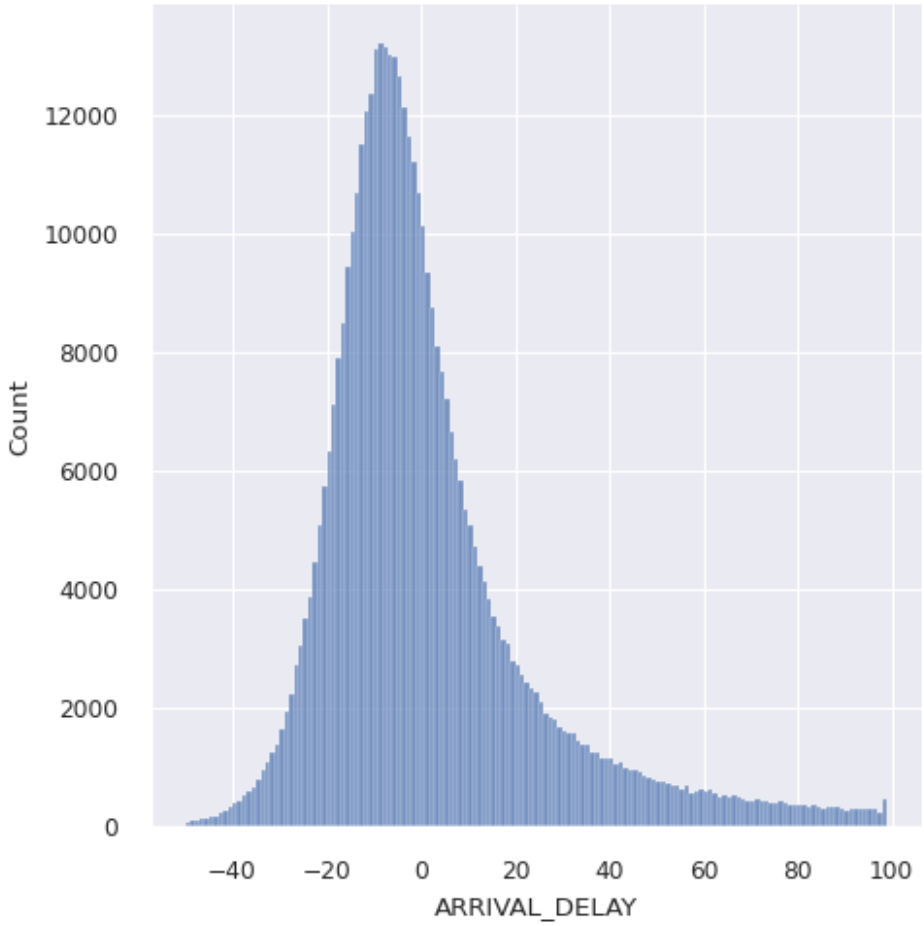
```
HA         3.224009   407.472841   6406.0 -52.0  288.0
WN         3.378031   904.806508  98058.0 -63.0  495.0
AA         5.850545  1319.580982  43023.0 -69.0  498.0
UA         6.152637  1578.022298  37350.0 -69.0  474.0
B6         7.323129  1373.844020  20481.0 -76.0  419.0
EV         8.408129  1654.781630  48073.0 -60.0  499.0
OO        10.691552  1845.370756  46640.0 -57.0  491.0
NK        11.154613  1713.248609   8628.0 -59.0  484.0
F9        17.132589  2535.237813   6720.0 -47.0  477.0
MQ        17.999601  2200.488153  27560.0 -60.0  493.0
           AS          AA         US         DL          NK          UA
HA  \
DAY

1   -0.669213   8.128536  3.971244  1.813559  22.681777   7.726204  -
1.218335
2   -3.576303   1.335855  6.324079 -2.974732   9.708295   2.539216  -
0.944374
3   -2.532967   1.862974  0.440235 -5.980217  10.125225   1.748618
0.020757
4   -1.661771   5.570502  0.865514 -4.860832   6.800429   5.294171
4.531731
5    3.530099   6.179608  3.704043 -0.926373  10.220971   7.706485
10.549550
6   -0.708596   6.355490  2.116998 -3.319775   6.862044   6.428691
5.519000
7    2.337176  11.021388  5.225352 -0.985548  14.178826  11.280266
0.552020

             B6          OO          EV          F9          WN          MQ
\
DAY

1    13.179350  13.869401  14.257760  21.547872   5.886859  29.782941

2     8.013188   9.670826   5.026897   8.342074   2.759279  18.667411

3     2.519346   9.169206   5.285780  18.758119  -1.354079  14.000792

4     1.663891   9.781780   6.557175  11.003466   1.400615  13.961879

5     7.919722  10.011841   7.355466  13.501290   3.144844  13.426827

6     7.597444   7.600246   8.092070  20.873357   2.647851   9.517314

7    11.778564  15.297936  13.195975  28.249441  10.334727  29.847709


             VX
DAY
```

```
1     3.802528
2    -1.667283
3    -4.412458
4    -0.672050
5     4.392645
6    -3.944631
7    10.877165
```




```
<ipython-input-14-0b05dbc0d8be>:177: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
  newMap =
map["ARRIVAL_DELAY"].groupby(map["DISTANCE_MID"]).mean().to_frame()
```


Distance vs Delay graph (Bucket Size:100)
ARRIVAL_DELAY
30
25
20
15
10
5
0
−5
−10
50.0
550.0
1050.0
1550.0
2050.0
2550.0
3350.0
4150.0
DISTANCE_MID




```
        ARRIVAL_DELAY ORIGIN DESTINATION  DISTANCE  TAXI_OUT
DEPARTURE_DELAY  \
0               -22.0    ANC         SEA      1448      21.0
-11.0
1                -9.0    LAX         PBI      2330      12.0
-8.0
2                 5.0    SFO         CLT      2296      16.0
-2.0
3                -9.0    LAX         MIA      2342      15.0
-5.0
4               -21.0    SEA         ANC      1448      11.0
-1.0
...               ...    ...         ...       ...       ...
...
456850          -21.0    JFK         BQN      1576      18.0
0.0
456851          -13.0    SEA         DTW      1927      16.0
0.0
456852           23.0    DEN         TPA      1506      35.0
3.0
456853           29.0    DEN         ATL      1199      40.0
```

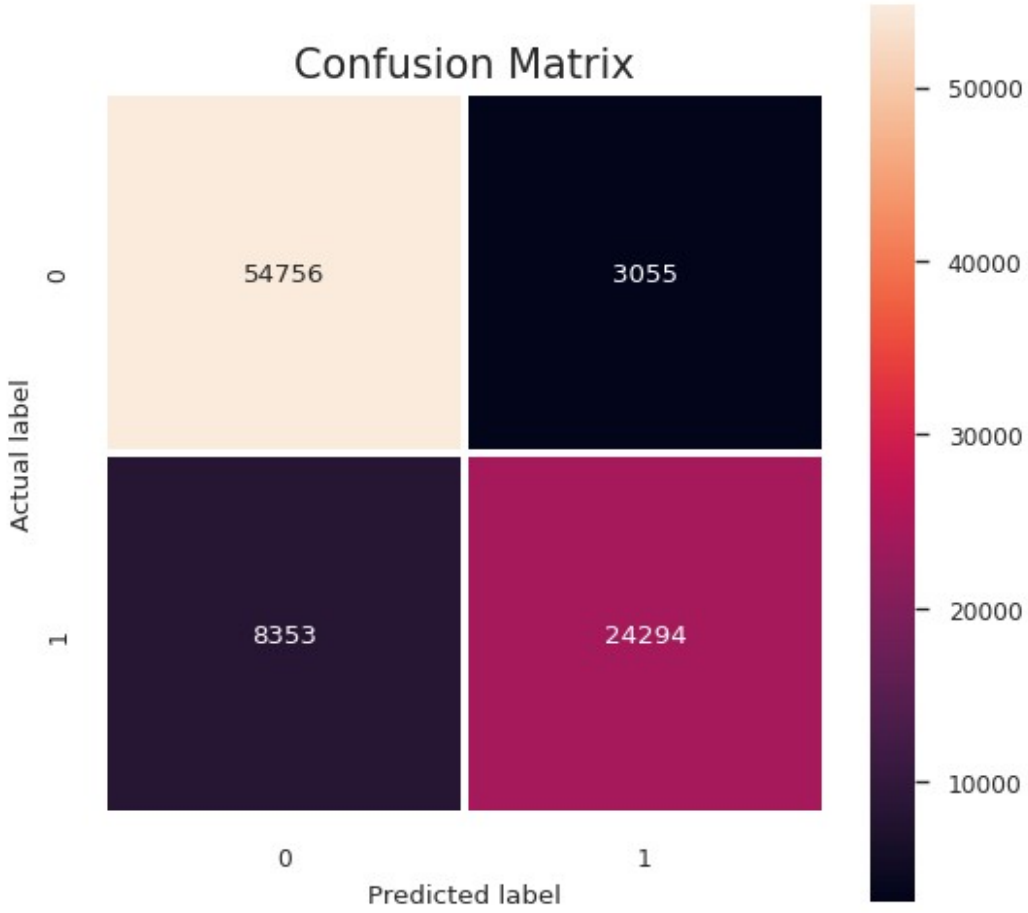
```
0.0
456854            2.0    ANC         DEN      2405      23.0
-1.0

        DAY AIRLINE   SDH_Sin   SDH_Cos   SDM_Sin   SDM_Cos   SAH_Sin
\
0         4      AS  0.000000  1.000000  0.500000  0.866025  0.866025

1         4      AA  0.000000  1.000000  0.866025  0.500000  0.965926

2         4      US  0.000000  1.000000  0.866025 -0.500000  0.866025

3         4      AA  0.000000  1.000000  0.866025 -0.500000  0.866025

4         4      AS  0.000000  1.000000  0.500000 -0.866025  0.707107

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

456850    6      B6 -0.258819  0.965926 -0.104528  0.994522  0.866025

456851    6      DL -0.258819  0.965926 -0.104528  0.994522  0.965926

456852    6      F9 -0.258819  0.965926 -0.104528  0.994522  0.965926

456853    6      F9 -0.258819  0.965926 -0.104528  0.994522  0.866025

456854    6      UA -0.258819  0.965926 -0.104528  0.994522  0.965926


         SAH_Cos       SAM_Sin   SAM_Cos  DAM_Sin   DAM_Cos
DAD_Sin  \
0       0.500000  5.665539e-16 -1.000000      0.5  0.866025
2.012985e-01
1      -0.258819 -8.660254e-01  0.500000      0.5  0.866025
2.012985e-01
2      -0.500000  5.877853e-01  0.809017      0.5  0.866025
2.012985e-01
3      -0.500000  5.000000e-01  0.866025      0.5  0.866025
2.012985e-01
4       0.707107  8.660254e-01 -0.500000      0.5  0.866025
2.012985e-01
...          ...           ...       ...       ...       ...
...
456850  0.500000 -8.660254e-01 -0.500000      0.5  0.866025 -
2.449294e-16
456851 -0.258819  9.135455e-01  0.406737      0.5  0.866025 -
2.449294e-16
456852  0.258819  9.135455e-01  0.406737      0.5  0.866025 -
2.449294e-16
456853  0.500000 -9.135455e-01 -0.406737      0.5  0.866025 -
```

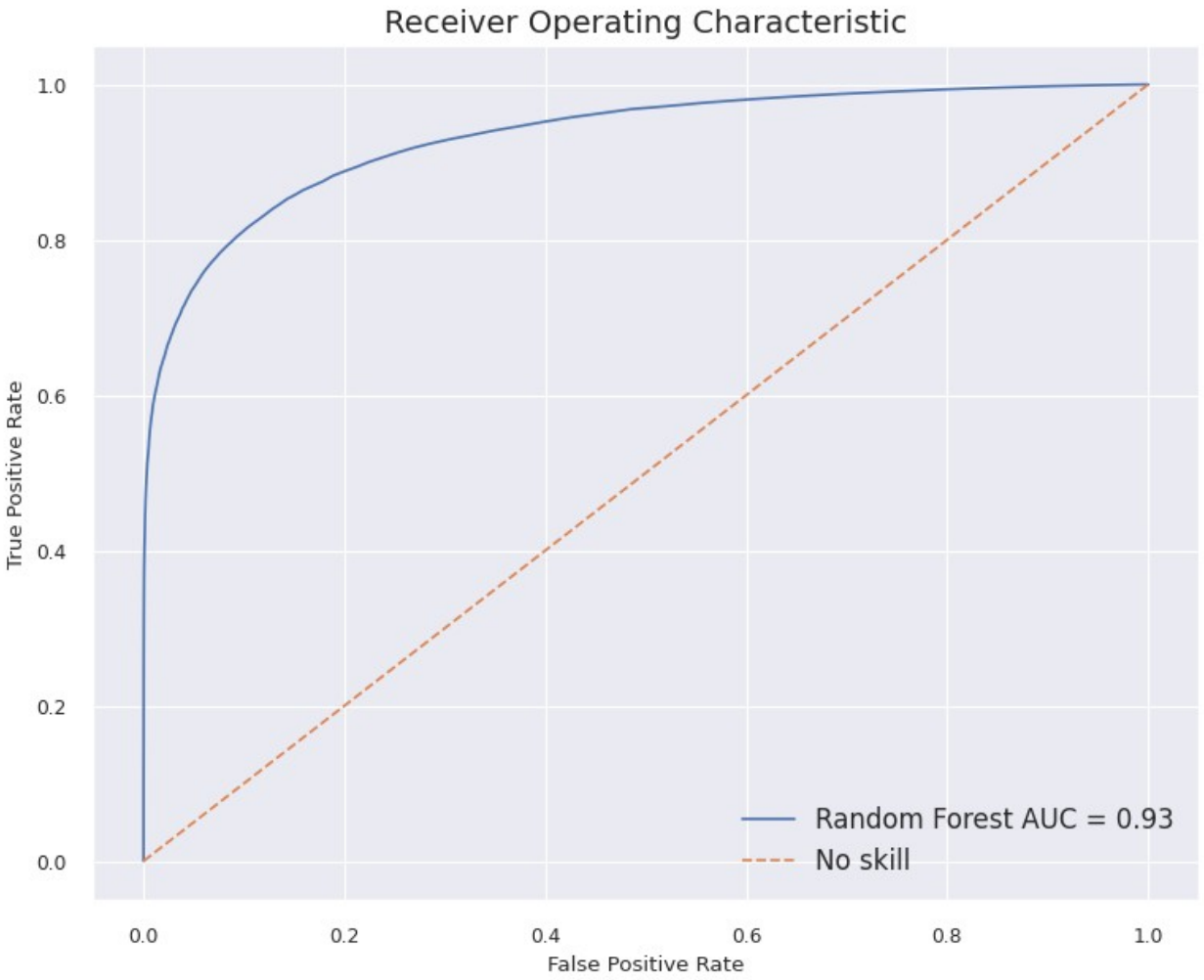
```
2.449294e-16
456854 -0.258819  7.431448e-01  0.669131      0.5  0.866025 -
2.449294e-16

        DAD_Cos
0       0.97953
1       0.97953
2       0.97953
3       0.97953
4       0.97953
...         ...
456850  1.00000
456851  1.00000
456852  1.00000
456853  1.00000
456854  1.00000

[456855 rows x 20 columns]

/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/
_label.py:114: DataConversionWarning: A column-vector y was passed
when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_label.p
y:114: DataConversionWarning: A column-vector y was passed when a 1d
array was expected. Please change the shape of y to (n_samples, ), for
example using ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_label.p
y:114: DataConversionWarning: A column-vector y was passed when a 1d
array was expected. Please change the shape of y to (n_samples, ), for
example using ravel().
  y = column_or_1d(y, warn=True)

        ARRIVAL_DELAY  ORIGIN  DESTINATION  DISTANCE  TAXI_OUT  \
0               -22.0      15          268      1448      21.0
1                -9.0     168          226      2330      12.0
2                 5.0     269           62      2296      16.0
3                -9.0     168          195      2342      15.0
4               -21.0     268           15      1448      11.0
...               ...     ...          ...       ...       ...
456850          -21.0     158           38      1576      18.0
456851          -13.0     268           88      1927      16.0
456852           23.0      81          294      1506      35.0
456853           29.0      81           18      1199      40.0
456854            2.0      15           81      2405      23.0

        DEPARTURE_DELAY  DAY   SDH_Sin   SDH_Cos   SDM_Sin  ...    4
5  \
```

```
0                  -11.0    4  0.000000  1.000000  0.500000  ...  0.0
0.0
1                   -8.0    4  0.000000  1.000000  0.866025  ...  0.0
0.0
2                   -2.0    4  0.000000  1.000000  0.866025  ...  0.0
0.0
3                   -5.0    4  0.000000  1.000000  0.866025  ...  0.0
0.0
4                   -1.0    4  0.000000  1.000000  0.500000  ...  0.0
0.0
...                  ...  ...       ...       ...       ...  ...  ...
...
456850               0.0    6 -0.258819  0.965926 -0.104528  ...  0.0
0.0
456851               0.0    6 -0.258819  0.965926 -0.104528  ...  0.0
0.0
456852               3.0    6 -0.258819  0.965926 -0.104528  ...  0.0
1.0
456853               0.0    6 -0.258819  0.965926 -0.104528  ...  0.0
1.0
456854              -1.0    6 -0.258819  0.965926 -0.104528  ...  0.0
0.0

          6    7    8    9   10   11   12   13
0       0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
1       0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
2       0.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0
3       0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
4       0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
...     ...  ...  ...  ...  ...  ...  ...  ...
456850  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
456851  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
456852  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
456853  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
456854  0.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0

[456855 rows x 33 columns]
X shape:  (456855, 32)
Y shape:  (456855,)
X_train: (319798, 32), X_val: (46599, 32), X_test: (90458, 32)
y_train: (319798,), y_val: (46599,), y_test: (90458,)
```

```
paramsrf = {'class_weight': None, 'criterion': 'entropy',
'n_estimators': 400, "random_state":42}
runner(model = "rf", data = data, optimal = False)
```

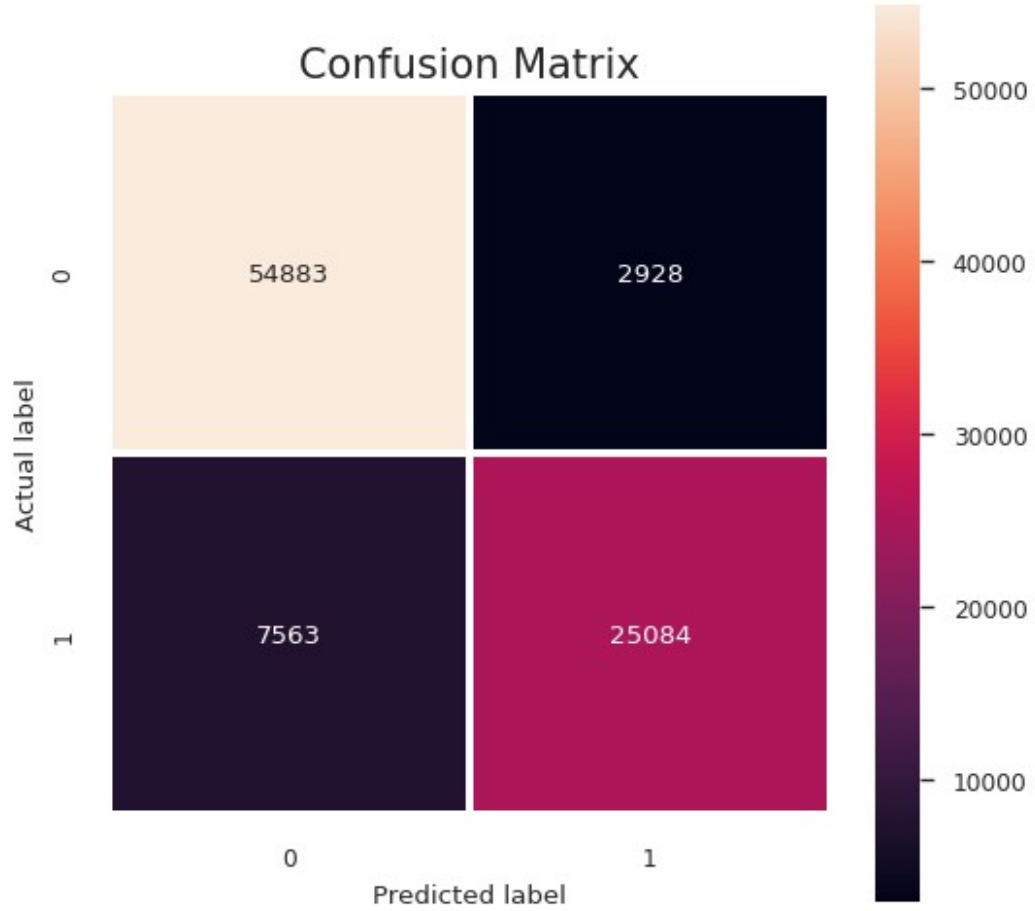
```
Test Score: 0.8738862234407128
```


Confusion Matrix
54756
3055
8353
24294
0
1
Actual label
0
1
Predicted label
50000
40000
30000
20000
10000



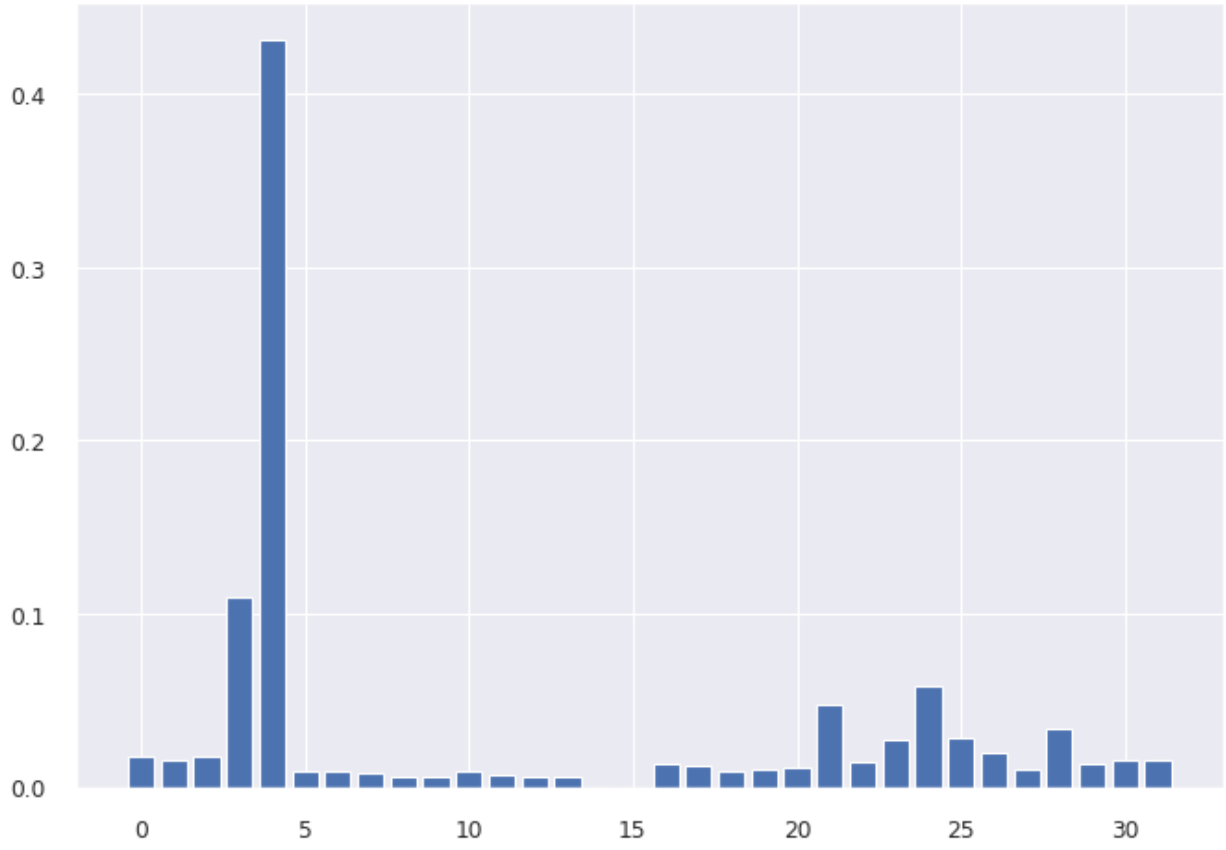

```
paramsxgb = {'class_weight': None, 'learning_rate': 0.1, 'max_depth':
7, 'n_estimators': 300, "random_state":42}
runner(model = "xgb", data = data, optimal = False, params =
paramsxgb)
```

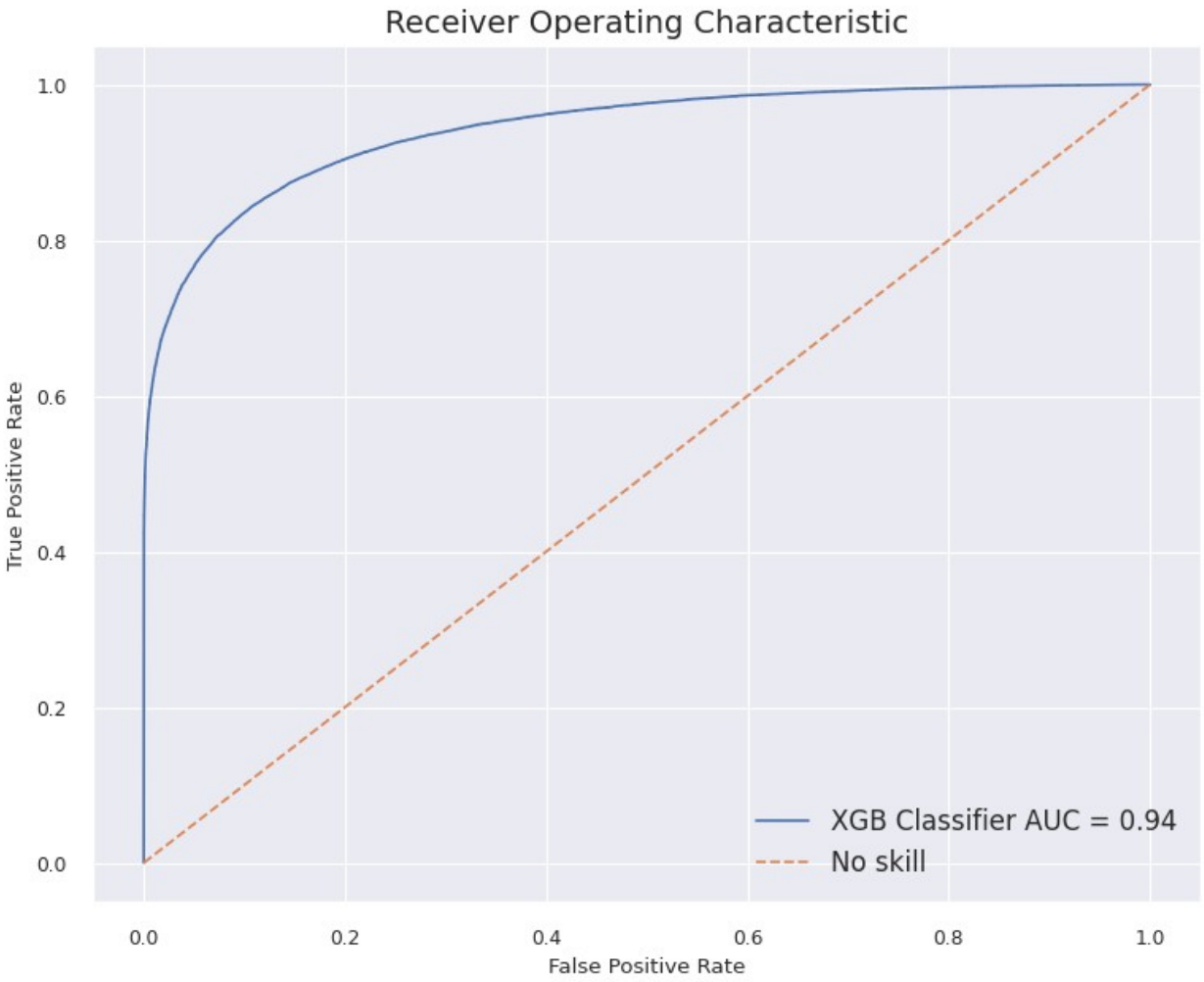
```
Test Score: 0.8840235247297088
```




```
Feature: 0, Score: 0.018
Feature: 1, Score: 0.015
Feature: 2, Score: 0.018
Feature: 3, Score: 0.109
Feature: 4, Score: 0.431
Feature: 5, Score: 0.009
Feature: 6, Score: 0.010
Feature: 7, Score: 0.008
Feature: 8, Score: 0.006
Feature: 9, Score: 0.006
Feature: 10, Score: 0.010
Feature: 11, Score: 0.007
Feature: 12, Score: 0.006
Feature: 13, Score: 0.006
Feature: 14, Score: 0.000
Feature: 15, Score: 0.000
Feature: 16, Score: 0.013
Feature: 17, Score: 0.012
Feature: 18, Score: 0.009
Feature: 19, Score: 0.010
Feature: 20, Score: 0.011
```

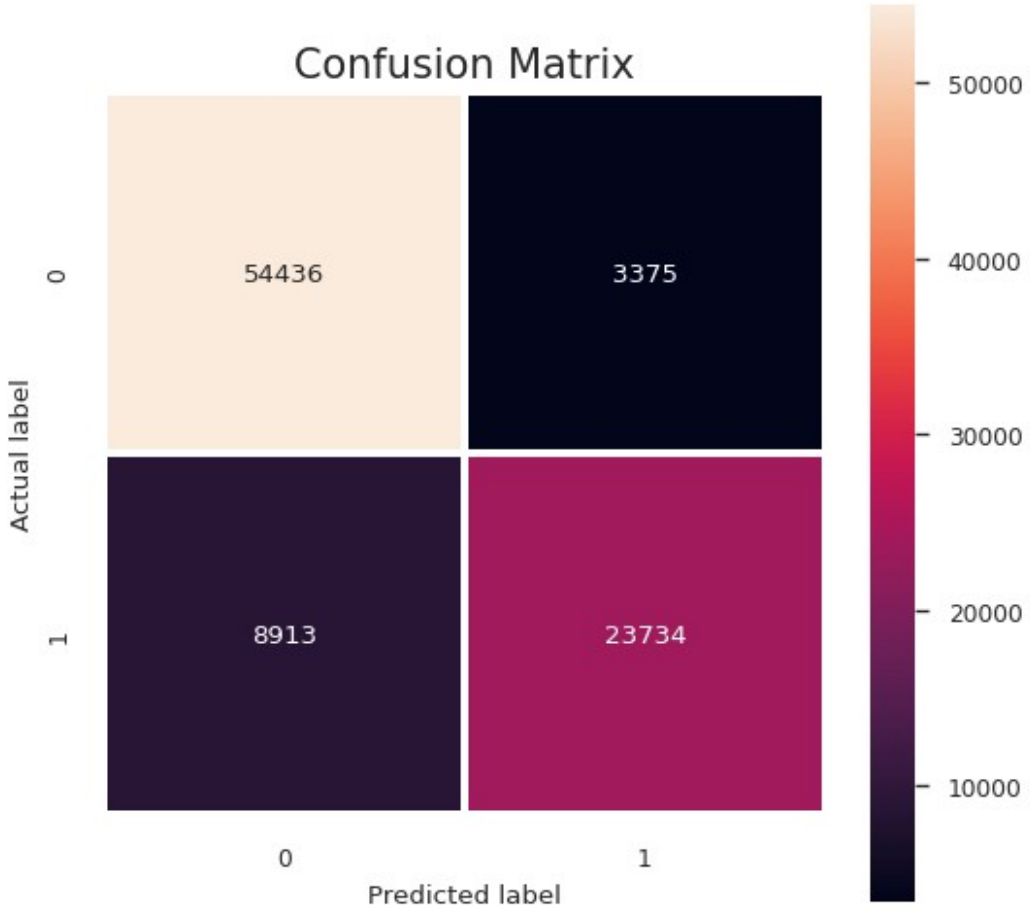
```
Feature: 21, Score: 0.048
Feature: 22, Score: 0.014
Feature: 23, Score: 0.027
Feature: 24, Score: 0.058
Feature: 25, Score: 0.028
Feature: 26, Score: 0.020
Feature: 27, Score: 0.010
Feature: 28, Score: 0.034
Feature: 29, Score: 0.014
Feature: 30, Score: 0.016
Feature: 31, Score: 0.015
```

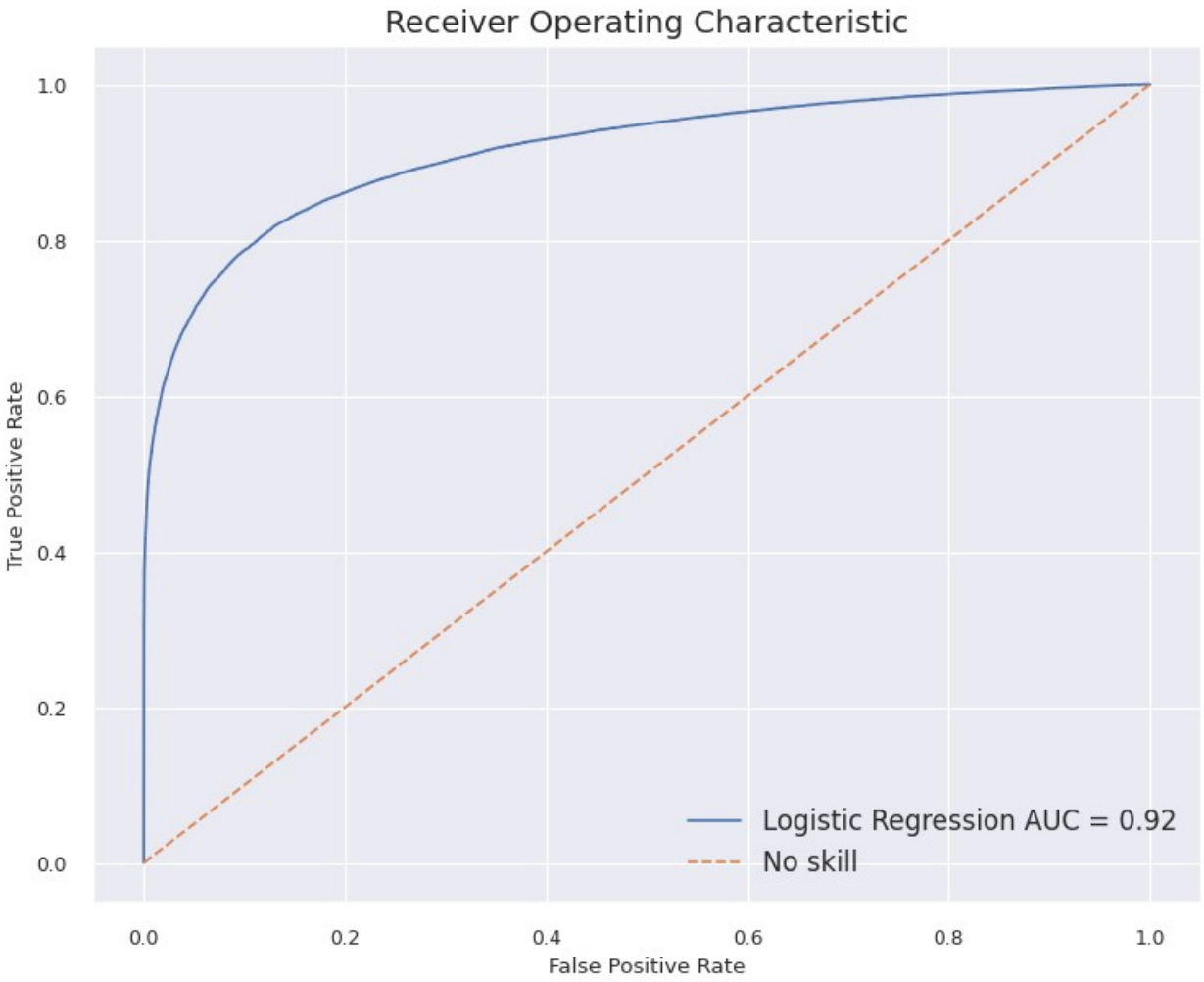





```
runner(model = "logistic", data = data, optimal = False)
```

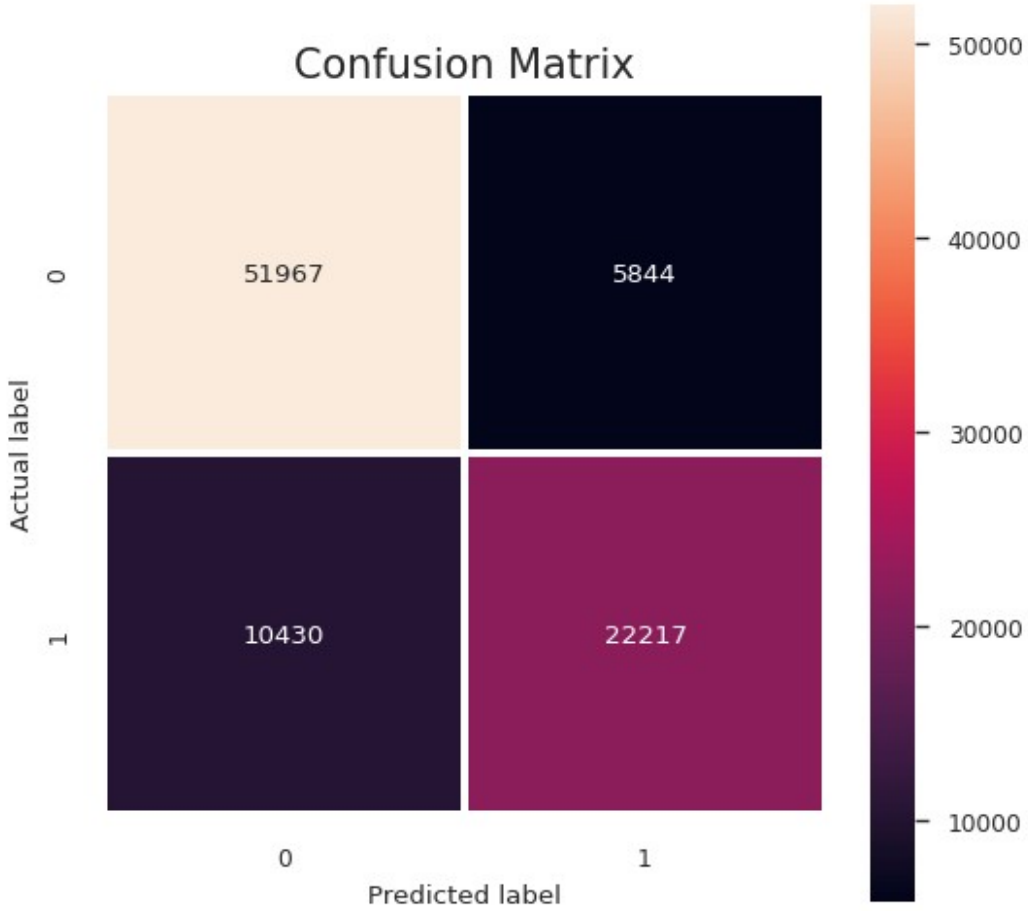
```
Test Score: 0.8641579517566164
```

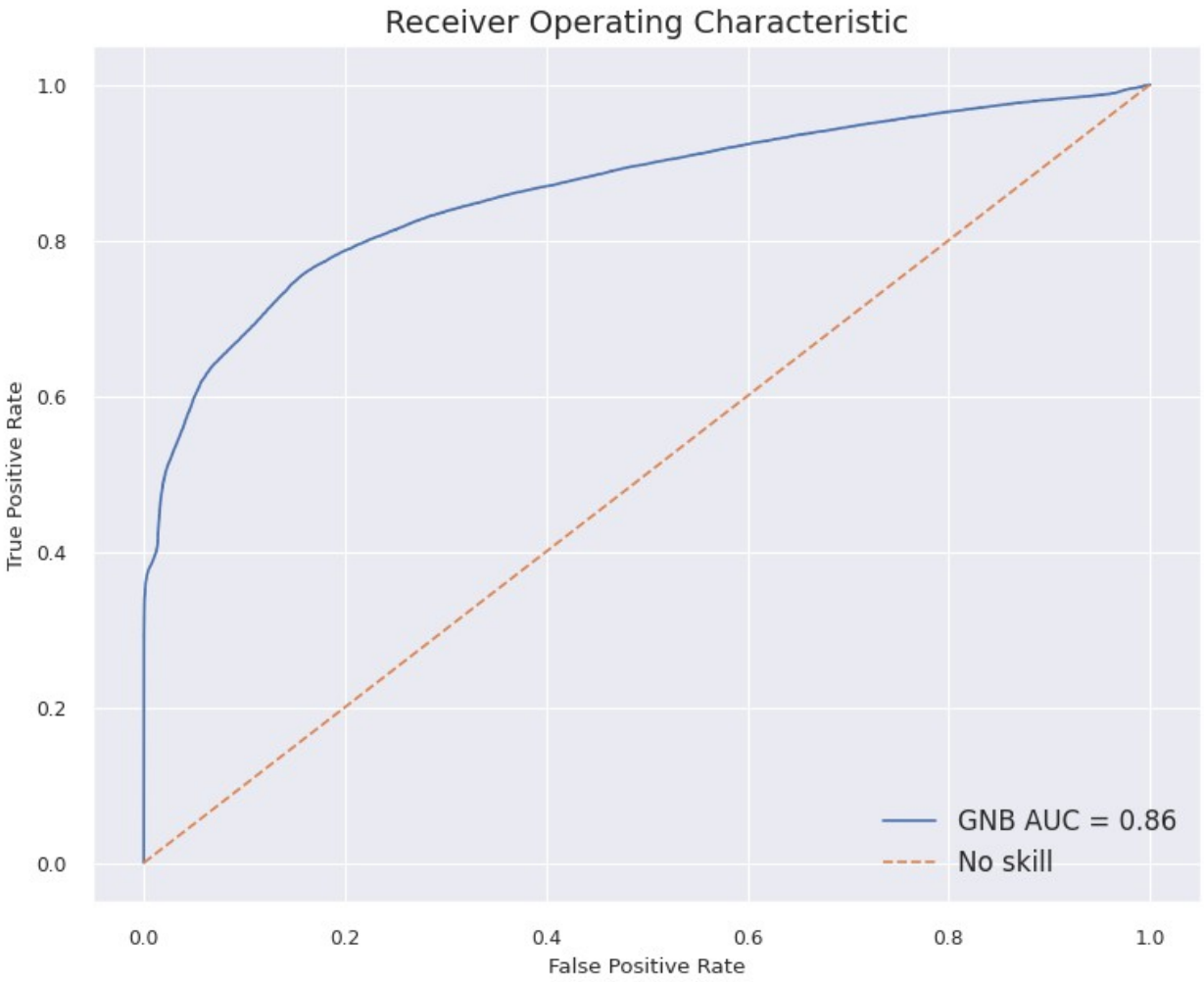

Confusion Matrix
54436
3375
8913
23734
0
1
Actual label
0
1
Predicted label
50000
40000
30000
20000
10000



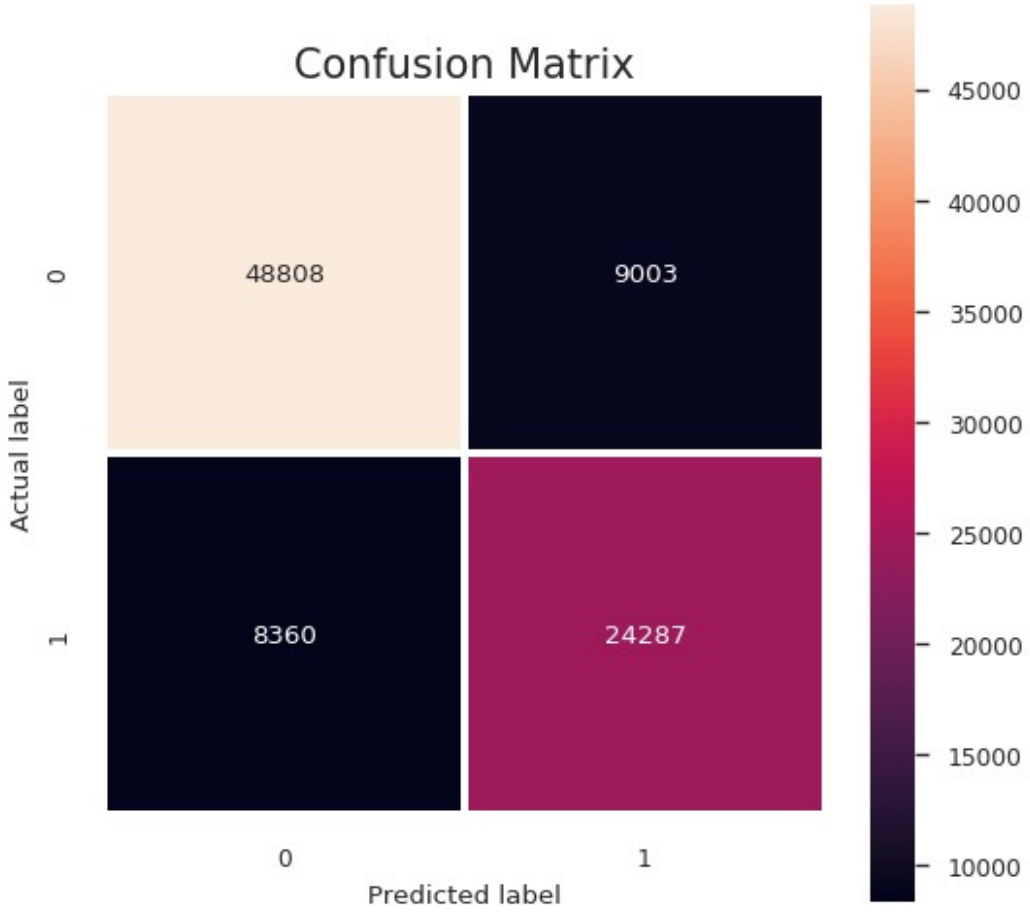

```
runner(model = "gnb", data = data, optimal = False)
```

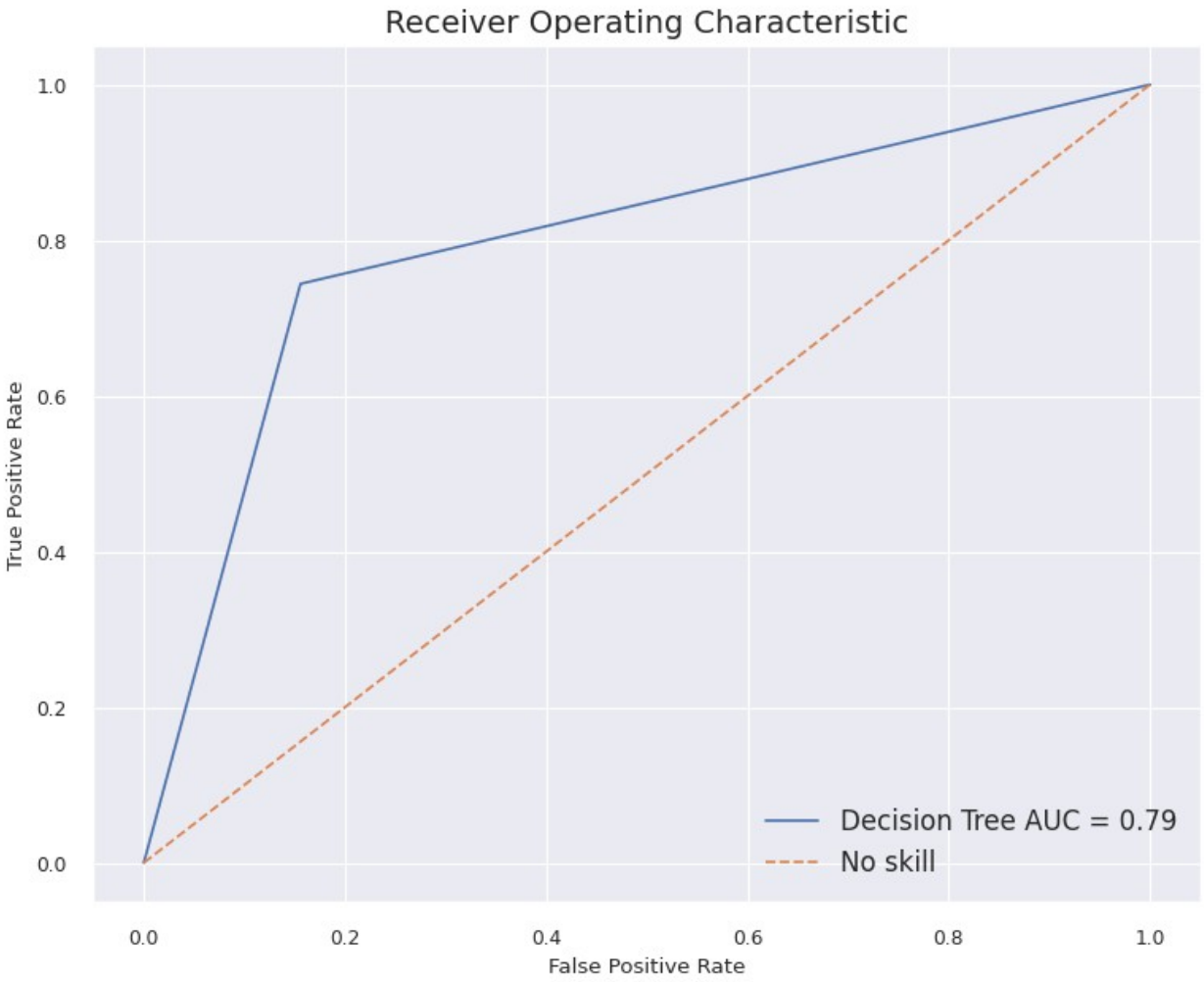
```
Test Score: 0.8200933029693338
```


Confusion Matrix
51967
5844
10430
22217
0
1
Actual label
0
1
Predicted label
50000
40000
30000
20000
10000

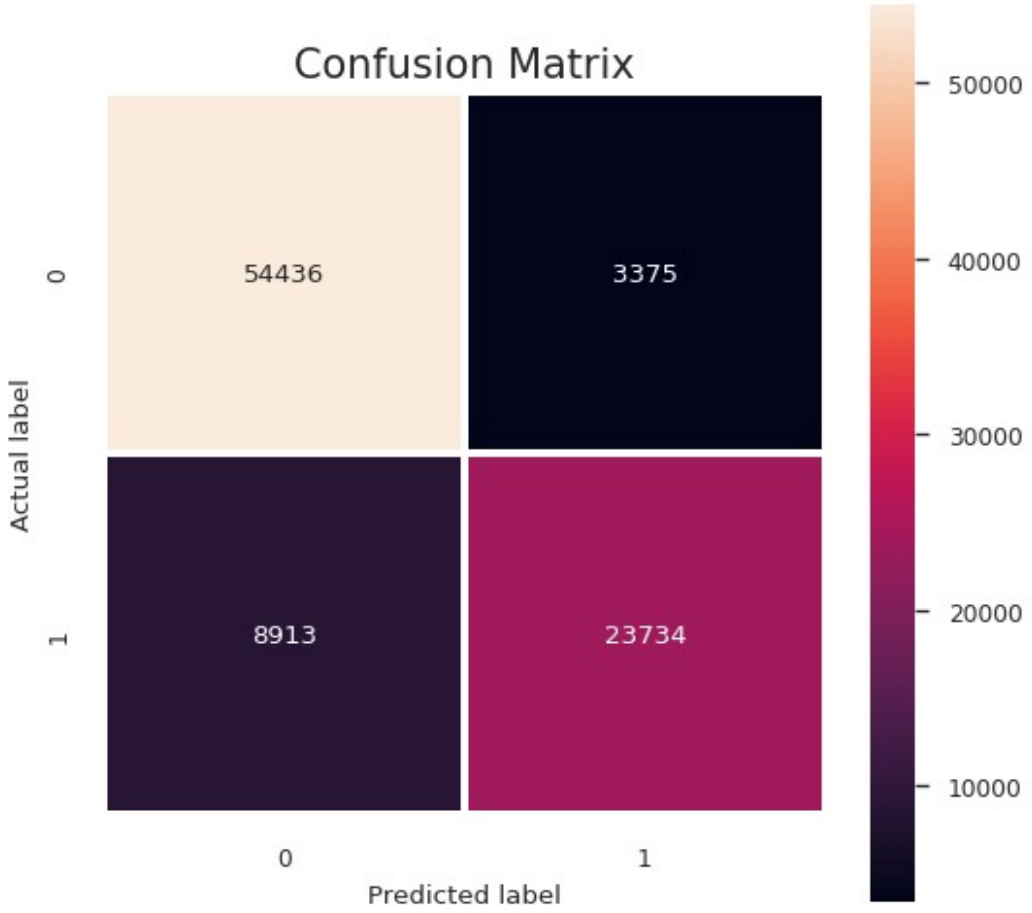



```
paramsDt = {"random_state" : 42}
runner(model = "dt", data = data, optimal = False, params = paramsDt)

Test Score: 0.8080545667602644
```

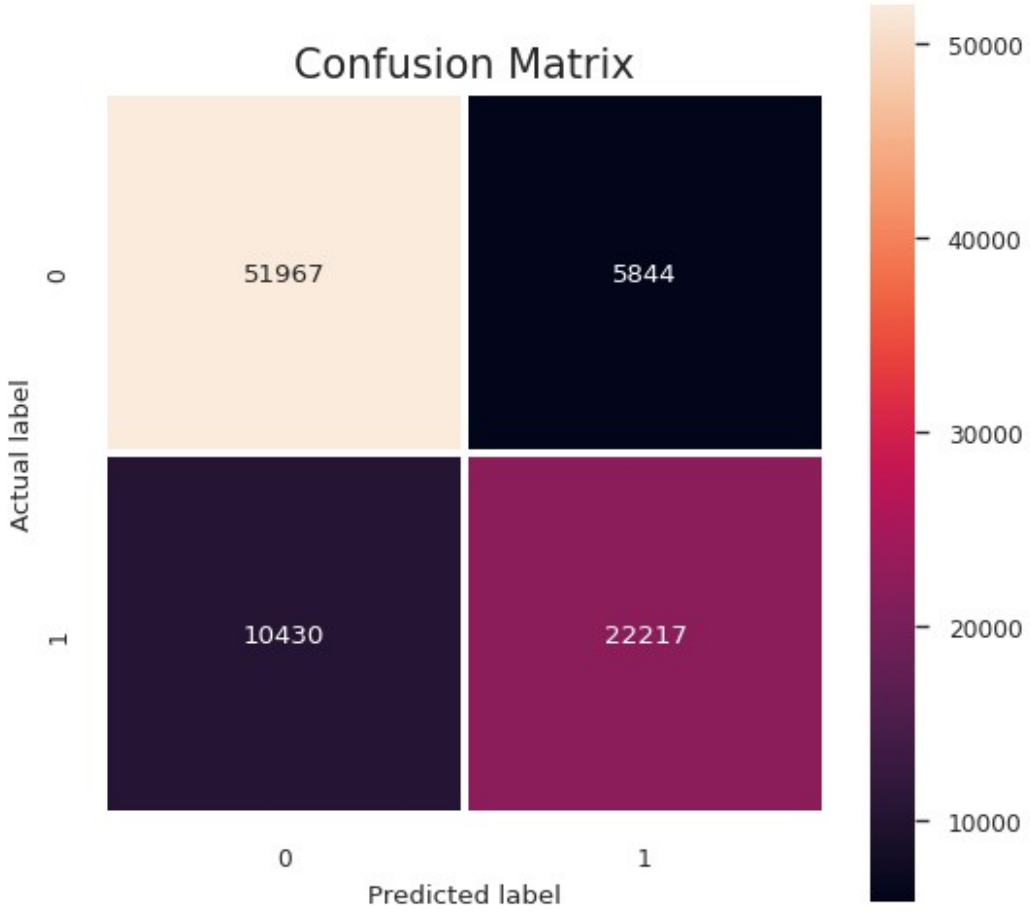

Confusion Matrix
48808
9003
8360
24287
0
1
Actual label
0
1
Predicted label
45000
40000
35000
30000
25000
20000
15000
10000



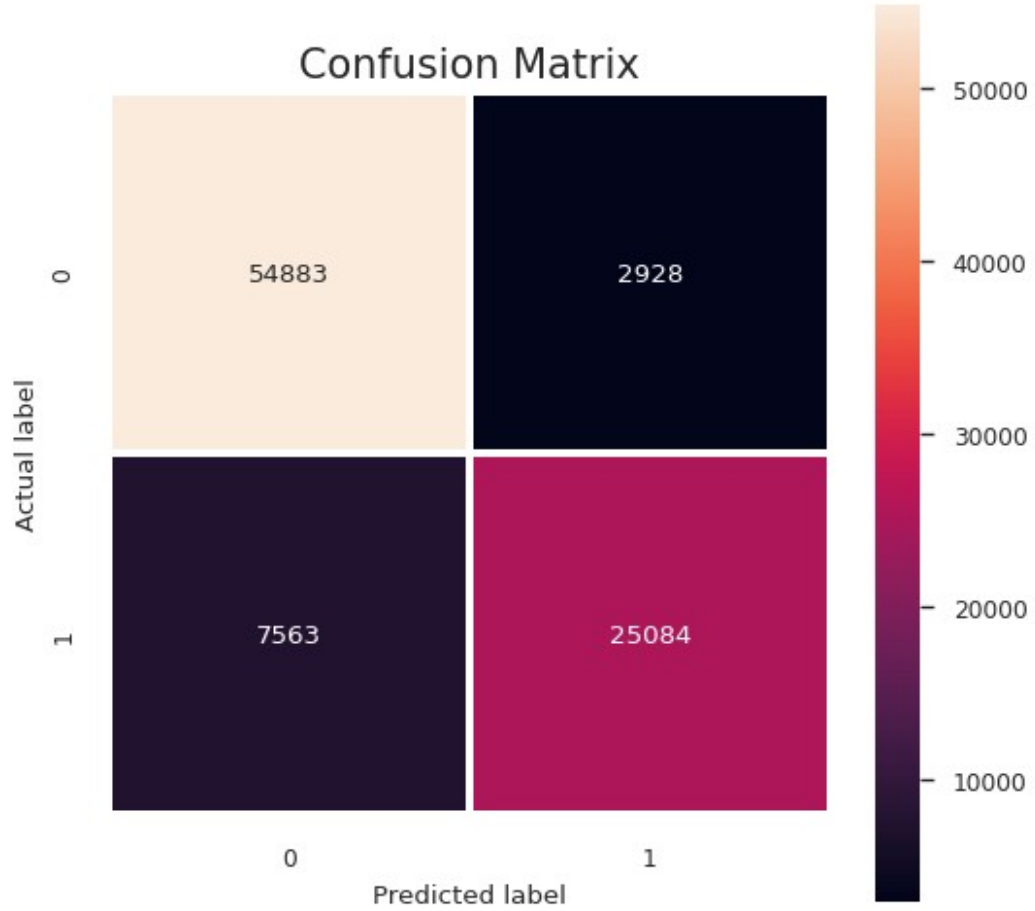

```
plotAllROC(data)

0
Test Score: 0.8641579517566164
```




```
1
Test Score: 0.8200933029693338
```

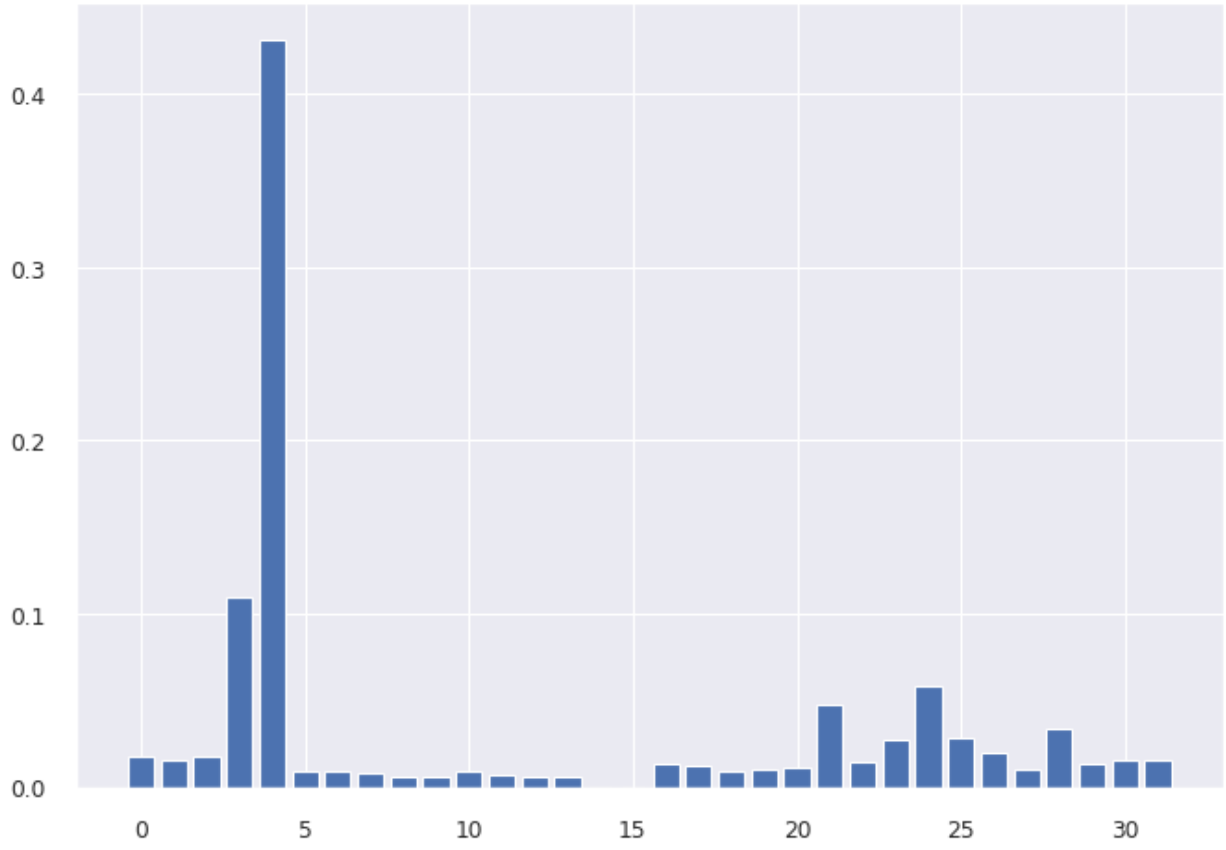



```
2
Test Score: 0.8840235247297088
```

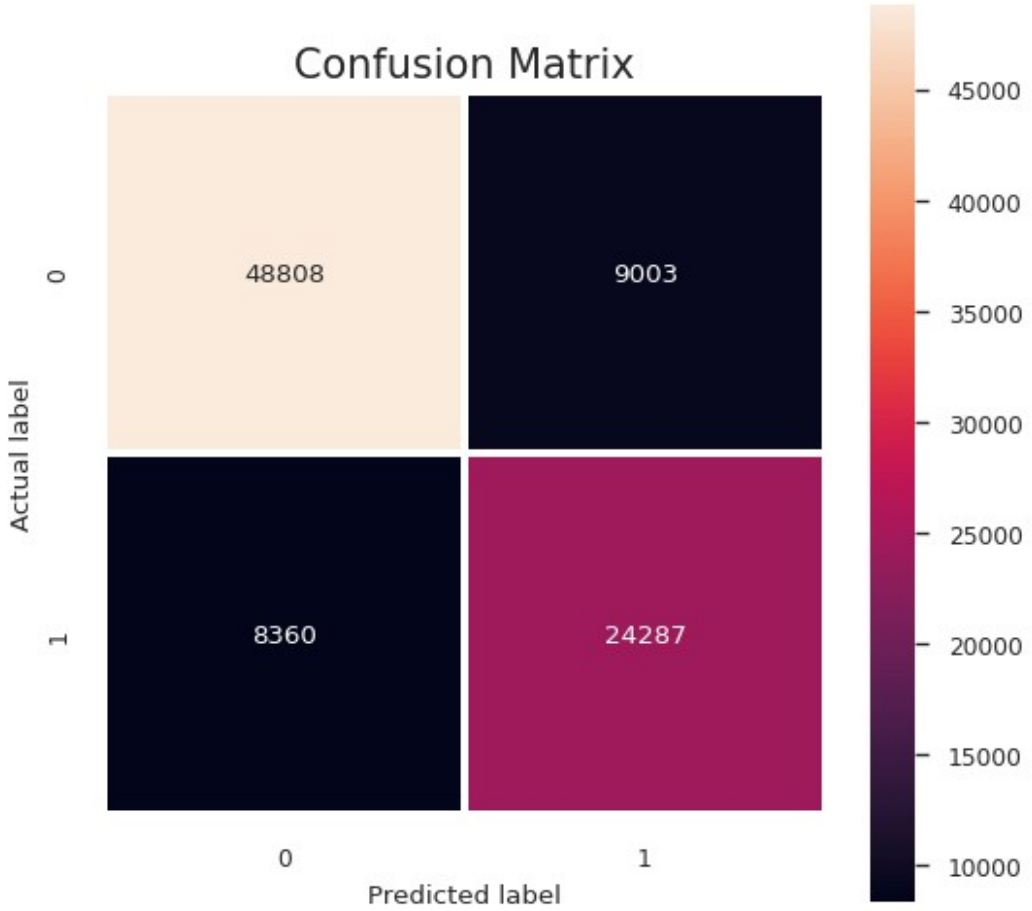



```
Feature: 0, Score: 0.018
Feature: 1, Score: 0.015
Feature: 2, Score: 0.018
Feature: 3, Score: 0.109
Feature: 4, Score: 0.431
Feature: 5, Score: 0.009
Feature: 6, Score: 0.010
Feature: 7, Score: 0.008
Feature: 8, Score: 0.006
Feature: 9, Score: 0.006
Feature: 10, Score: 0.010
Feature: 11, Score: 0.007
Feature: 12, Score: 0.006
Feature: 13, Score: 0.006
Feature: 14, Score: 0.000
Feature: 15, Score: 0.000
Feature: 16, Score: 0.013
Feature: 17, Score: 0.012
Feature: 18, Score: 0.009
Feature: 19, Score: 0.010
Feature: 20, Score: 0.011
```

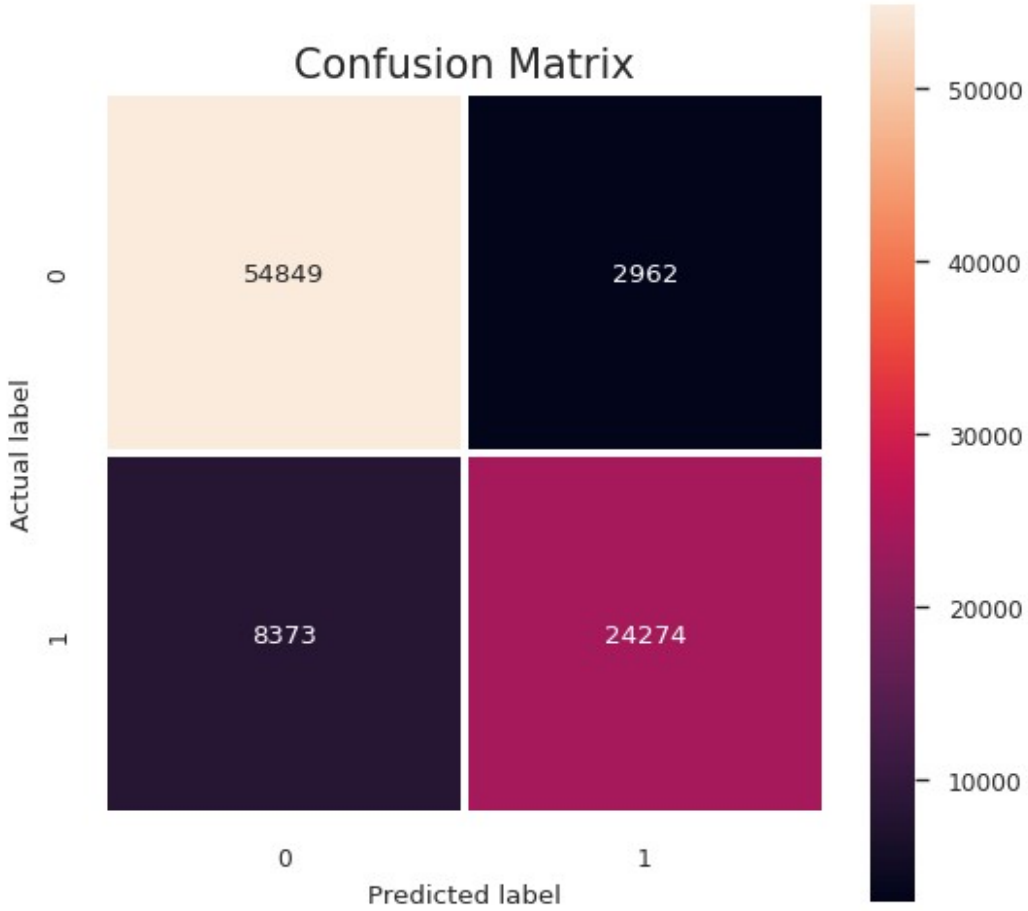
```
Feature: 21, Score: 0.048
Feature: 22, Score: 0.014
Feature: 23, Score: 0.027
Feature: 24, Score: 0.058
Feature: 25, Score: 0.028
Feature: 26, Score: 0.020
Feature: 27, Score: 0.010
Feature: 28, Score: 0.034
Feature: 29, Score: 0.014
Feature: 30, Score: 0.016
Feature: 31, Score: 0.015
```



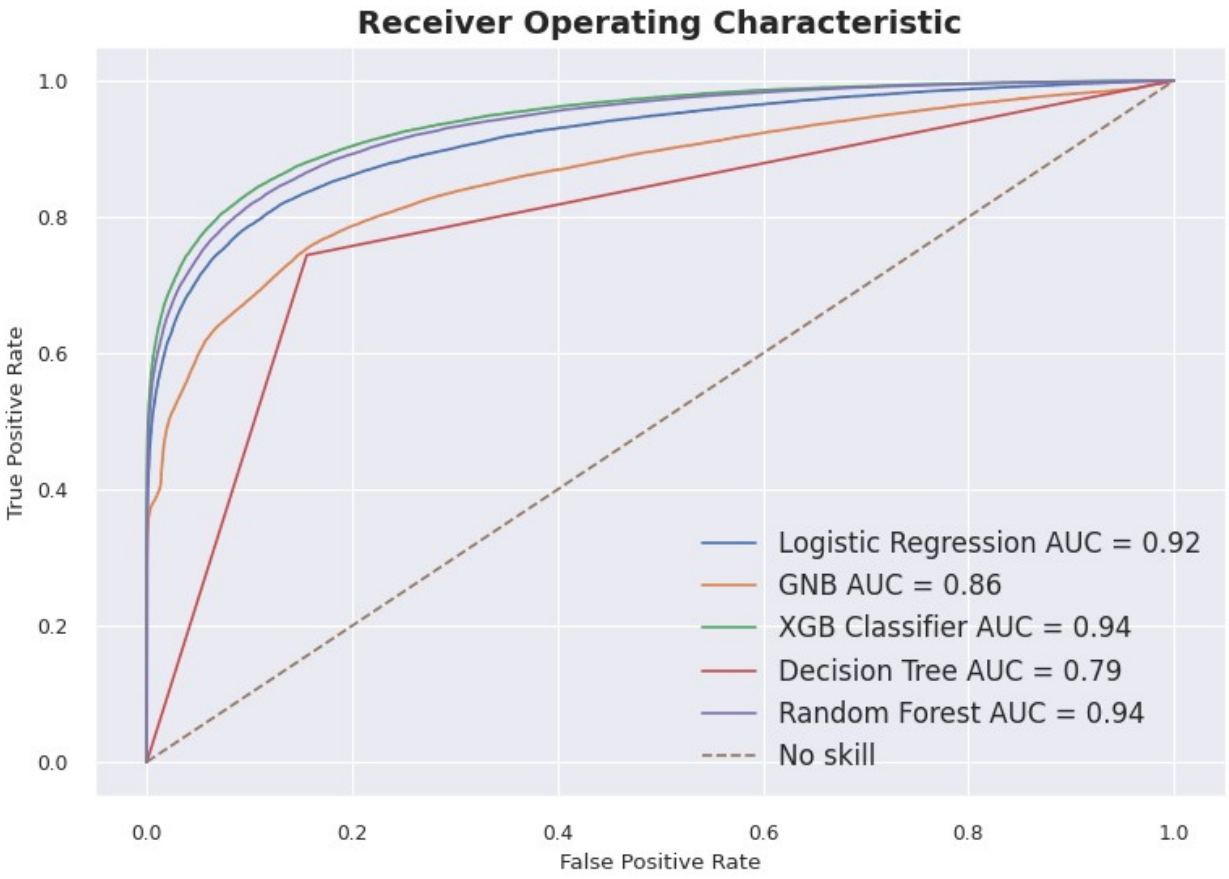

```
3
Test Score: 0.8080545667602644
```




```
4
Test Score: 0.8746932277963254
```




```
<Figure size 800x550 with 0 Axes>
```


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression AUC = 0.92
GNB AUC = 0.86
XGB Classifier AUC = 0.94
Decision Tree AUC = 0.79
Random Forest AUC = 0.94
No skill