In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
c:\Users\bkhan\AppData\Local\Programs\Python\Python39\lib\site-packages\scipy\__init__.py:155: UserWarning: A N
umPy version >=1.18.5 and <1.25.0 is required for this version of SciPy (detected version 1.26.1
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

In [3]:
```
df = pd.read_csv("Employees Promotion.csv")    # loading employee promotion.csv data from day09-project s3 bucke
df.head()
```

Out[3]:

	EmployeeID	Department	Region_Employment	Education Level	Gender	Recruitment Channel	NO_Trainings_LstYear	Age	previous_year_rating
0	65438	Sales & Marketing	7	Master's & above	f	sourcing	1	35.0	5.0
1	65141	Operations	22	Bachelor's	m	other	1	30.0	5.0
2	7513	Sales & Marketing	19	Bachelor's	m	sourcing	1	34.0	3.0
3	2542	Sales & Marketing	23	Bachelor's	m	other	2	39.0	1.0
4	48945	Technology	26	Bachelor's	m	other	1	45.0	3.0

Analysing Data

In [4]:
```
df.info()   # checking data types, dimensions of df
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54808 entries, 0 to 54807
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   EmployeeID            54808 non-null  int64  
 1   Department            54808 non-null  object 
 2   Region_Employment     54808 non-null  int64  
 3   Education Level       52399 non-null  object 
 4   Gender                54808 non-null  object 
 5   Recruitment Channel   44404 non-null  object 
 6   NO_Trainings_LstYear  54808 non-null  int64  
 7   Age                   54268 non-null  float64
 8   previous_year_rating  50684 non-null  float64
 9   Service Length        54808 non-null  int64  
 10  Awards                54808 non-null  object 
 11  Avg_Training_Score    52248 non-null  float64
 12  Is Promoted           54808 non-null  object 
dtypes: float64(3), int64(4), object(6)
memory usage: 5.4+ MB
```

In [5]:
```
df.describe()    # stats of the df
```

Out[5]:

	EmployeeID	Region_Employment	NO_Trainings_LstYear	Age	previous_year_rating	Service Length	Avg_Training_Score
count	54808.000000	54808.000000	54808.000000	54268.000000	50684.000000	54808.000000	52248.00000
mean	39195.830627	14.195045	1.253011	34.586644	3.329256	5.865512	63.71223
std	22586.581449	10.086273	0.609264	8.114136	1.259993	4.265094	13.52191
min	1.000000	1.000000	1.000000	0.000000	1.000000	1.000000	39.00000
25%	19669.750000	4.000000	1.000000	29.000000	3.000000	3.000000	51.00000
50%	39225.500000	13.000000	1.000000	33.000000	3.000000	5.000000	60.00000
75%	58730.500000	22.000000	1.000000	39.000000	4.000000	7.000000	77.00000
max	78298.000000	34.000000	10.000000	60.000000	5.000000	37.000000	99.00000

In [6]:
```
df.shape    # dimesnsions of the df
```
Out[6]:
```
(54808, 13)
```

In [7]:
```
df.duplicated().sum()    # checking any duplicated values in the df
```
Out[7]:
```
0
```

In [8]:
```
df.isnull().sum()    # checking total null values in each column
```
Out[8]:
```
EmployeeID                0
Department                0
Region_Employment         0
Education Level        2409
Gender                    0
Recruitment Channel   10404
NO_Trainings_LstYear      0
Age                     540
previous_year_rating   4124
Service Length            0
Awards                    0
Avg_Training_Score     2560
Is Promoted               0
dtype: int64
```

In [9]:
```
df['Is Promoted'].value_counts()    # target column value counts
```
Out[9]:
```
NO     50140
YES     4668
Name: Is Promoted, dtype: int64
```

Cleaning and Engineering data

In [10]:
```
df['Is Promoted'] = df['Is Promoted'].map({'YES': 1, 'NO': 0})    # mapping the target column values i.e. Yes ar
```

In [11]:
```
df['Education Level'].unique()    # unique values of Education Level column
```
Out[11]:
```
array(["Master's & above", "Bachelor's", nan, 'Below Secondary'],
      dtype=object)
```

In [12]:
```
df['Education Level'].value_counts()    # Value counts of each values in the Education Level column.
```
Out[12]:
```
Bachelor's          36669
Master's & above    14925
Below Secondary       805
Name: Education Level, dtype: int64
```

In [13]:
```
df['Education Level'].isnull().sum()    # total null values in Education Level column
```
Out[13]:
```
2409
```

In [14]:
```
df['Education Level'].fillna(method='ffill', inplace=True)    # using forward fill to fill null values
```

In [15]:
```
df['Education Level'].value_counts()    # now checking the count
```

Out[15]:
```
Bachelor's          38390
Master's & above    15579
Below Secondary       839
Name: Education Level, dtype: int64
```

In [16]:
```
df['Education Level'].isnull().sum()    # checking null values
```

Out[16]:
```
0
```

In [17]:
```
df.Age.unique()    # unique values of age column
```

Out[17]:
```
array([35., 30., 34., 39., 45., 31., 33., 28., 32., 49., 37., 38., 41.,
       27., 29., 26., 24., 57., 40., 42., 23., 59., nan, 50., 56., 20.,
       25., 47., 36., 46., 44., 60.,  0., 43., 22., 54., 58., 48., 53.,
       55., 51., 52., 21.])
```

In [18]:
```
df.Age.value_counts()    # value counts of age column
```

Out[18]:
```
30.0    3597
32.0    3479
31.0    3474
29.0    3352
33.0    3157
28.0    3103
34.0    3017
27.0    2784
35.0    2673
36.0    2482
37.0    2134
26.0    2019
38.0    1894
39.0    1660
40.0    1634
25.0    1283
41.0    1265
42.0    1133
43.0     978
44.0     834
24.0     832
45.0     749
46.0     686
48.0     554
47.0     550
50.0     516
49.0     435
23.0     419
51.0     386
53.0     354
52.0     345
0.0      340
54.0     306
55.0     285
56.0     262
57.0     234
22.0     228
60.0     214
58.0     211
59.0     202
20.0     110
21.0      98
Name: Age, dtype: int64
```

In [19]:
```
df.Age.fillna(df['Age'].median())    # filling the null values of age column using median of age column
```

Out[19]:
```
0        35.0
1        30.0
2        34.0
3        39.0
4        45.0
         ...
54803    48.0
54804    37.0
54805     0.0
54806    29.0
54807    27.0
Name: Age, Length: 54808, dtype: float64
```

In [20]:
```
df.previous_year_rating.unique()    # unique values of previous_year_rating column
```

Out[20]:
```
array([ 5.,  3.,  1.,  4., nan,  2.])
```

In [21]:
```
df.previous_year_rating.value_counts()    # value counts of previous_year_rating col
```

Out[21]:
```
3.0    18618
5.0    11741
4.0     9877
1.0     6223
2.0     4225
Name: previous_year_rating, dtype: int64
```

In [22]:
```
df.previous_year_rating.fillna(df.previous_year_rating.median())    # filling previous_year_rating col using its
```

Out[22]:
```
0        5.0
1        5.0
2        3.0
3        1.0
4        3.0
        ...
54803    3.0
54804    2.0
54805    5.0
54806    1.0
54807    1.0
Name: previous_year_rating, Length: 54808, dtype: float64
```

In [23]:
```
df.Avg_Training_Score.unique()   # unique values of Avg_Training_Score col
```

Out[23]:
```
array([49., 60., 50., 73., 85., 59., 63., 83., 54., 77., 80., 84., 51.,
       46., 75., 57., 70., 68., 79., 44., 72., nan, 48., 58., 87., 47.,
       52., 88., 71., 65., 62., 53., 78., 91., 82., 69., 55., 74., 86.,
       90., 92., 67., 89., 56., 76., 81., 64., 39., 94., 93., 66., 95.,
       42., 96., 40., 99., 43., 97., 41., 98.])
```

In [24]:
```
df.Avg_Training_Score.value_counts()   # value counts of Avg_Training_Score col
```

Out[24]:
```
50.0    2716
49.0    2681
48.0    2437
51.0    2347
60.0    2155
59.0    2064
58.0    1898
52.0    1856
47.0    1746
62.0    1450
82.0    1447
57.0    1437
81.0    1357
53.0    1324
80.0    1206
83.0    1198
84.0    1168
79.0    1160
46.0    1136
85.0    1072
56.0    1070
70.0    1055
63.0    1021
69.0    1018
54.0     997
68.0     935
78.0     933
86.0     912
71.0     898
55.0     872
67.0     728
72.0     725
64.0     708
77.0     697
87.0     655
65.0     599
66.0     580
73.0     523
76.0     516
88.0     444
74.0     433
75.0     403
44.0     335
89.0     301
90.0     185
43.0     176
91.0     117
92.0      99
93.0      84
94.0      65
42.0      62
97.0      49
96.0      48
95.0      45
98.0      37
99.0      35
41.0      26
40.0       5
39.0       2
Name: Avg_Training_Score, dtype: int64
```

In [25]:
```
df.Avg_Training_Score.fillna(df.Avg_Training_Score.median())    # filling null values using Avg_Training_Score r
```

Out[25]:
```
0        49.0
1        60.0
2        50.0
3        50.0
4        73.0
         ...
54803    78.0
54804    56.0
54805    79.0
54806    60.0
54807    49.0
Name: Avg_Training_Score, Length: 54808, dtype: float64
```

In [26]:
```
df = df.drop(['EmployeeID', 'Gender', 'Service Length', 'Recruitment Channel'], axis=1)    # dropping these four
```

In [27]:
```
df.head()
```

Out[27]:

	Department	Region_Employment	Education Level	NO_Trainings_LstYear	Age	previous_year_rating	Awards	Avg_Training_Score	Prom
0	Sales & Marketing	7	Master's & above	1	35.0	5.0	NO	49.0	
1	Operations	22	Bachelor's	1	30.0	5.0	NO	60.0	
2	Sales & Marketing	19	Bachelor's	1	34.0	3.0	NO	50.0	
3	Sales & Marketing	23	Bachelor's	2	39.0	1.0	NO	50.0	
4	Technology	26	Bachelor's	1	45.0	3.0	NO	73.0	

In [28]:
```
df.duplicated().sum()    # checking total duolicate values
```

Out[28]: 5013

In [29]:
```
df.drop_duplicates(keep='first', inplace=True)    # dropping duplicates whuile keeping its first value
```

In [30]:
```
df.duplicated().sum()
```

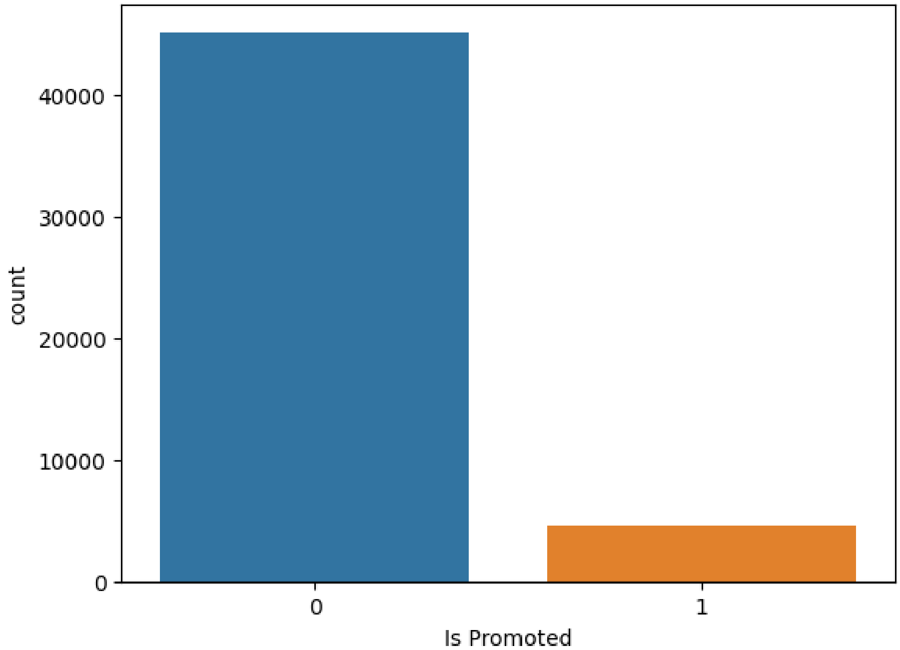
Out[30]: 0

In [31]:
```
df['Is Promoted'].value_counts()
```

Out[31]:
```
0    45175
1     4620
Name: Is Promoted, dtype: int64
```

In [32]:
```
sns.countplot(x=df['Is Promoted'], data=df)    # countplot of target variable
```

Out[32]: <AxesSubplot:xlabel='Is Promoted', ylabel='count'>



In [33]:
```
df = pd.get_dummies(df, columns=['Department', 'Education Level', 'Awards'])    # getting dummies data of these
```

In [34]:
```
df.head()
```

Out[34]:

	Region_Employment	NO_Trainings_LstYear	Age	previous_year_rating	Avg_Training_Score	Is Promoted	Department_-	Department_
0	7	1	35.0	5.0	49.0	0	0	
1	22	1	30.0	5.0	60.0	0	0	
2	19	1	34.0	3.0	50.0	0	0	
3	23	2	39.0	1.0	50.0	0	0	
4	26	1	45.0	3.0	73.0	0	0	

5 rows × 21 columns

In [34]:
```
import os
import boto3
import re
import sagemaker

role = sagemaker.get_execution_role()   # execution role
region = boto3.Session().region_name    # region name
smclient = boto3.Session().client("sagemaker")    # setting sagemaker session
bucket = "day09-project1"
prefix = ("sagemaker/Employess-Promotion") # place to upload training files within the bucket
print (region)
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/sagemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-user/.config/sagemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/sagemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-user/.config/sagemaker/config.yaml
us-east-1
```

Training

In [38]:
```
# splitting df into train, validation and test data in 70%, 20% and 10% respectively.
train_data, validation_data, test_data = np.split(df.sample(frac=1, random_state=1729),[int(0.7 * len(df)), int

pd.concat([train_data["Is Promoted"], train_data.drop("Is Promoted", axis=1)], axis=1).to_csv("train.csv", inde
```

```
pd.concat([validation_data["Is Promoted"], validation_data.drop("Is Promoted", axis=1)], axis=1).to_csv("validat
pd.concat([test_data["Is Promoted"], test_data.drop("Is Promoted", axis=1)], axis=1).to_csv("test.csv", index=Fa
```

In [36]:
```
# storing test and train data
train_y = train_data["Is Promoted"]
train_X = train_data.drop("Is Promoted", axis=1)
test_y = test_data["Is Promoted"]
test_X = test_data.drop("Is Promoted", axis=1)
```

In [37]:
```
# uploading train and validation in s3 bucket
boto3.Session().resource("s3").Bucket(bucket).Object(
 os.path.join(prefix, "train/train.csv")
).upload_file("train.csv")
boto3.Session().resource("s3").Bucket(bucket).Object(
 os.path.join(prefix, "validation/validation.csv")
).upload_file("validation.csv")
```

HP Tuning

ParameterRanges: Specifies the search space for hyperparameters.

- CategoricalParameterRanges: Categorical hyperparameters are those whose values come from a discrete set of categories or options.(none in this example).
- ContinuousParameterRanges: Continuous hyperparameters are those that can take any real value within a specified range:
- eta: Learning rate with a range between 0 and 1.
- min_child_weight: Minimum sum of instance weight (hessian) needed in a child.
- alpha: L1 regularization term with a range between 0 and 2.
- IntegerParameterRanges: For integer-valued hyperparameters.
- max_depth: Maximum depth of a tree with a range between 1 and 10.

ResourceLimits: Specifies resource limits for the tuning job.

- MaxNumberOfTrainingJobs: Maximum number of training jobs to run during the tuning job.
- MaxParallelTrainingJobs: Maximum number of training jobs to run in parallel.

Strategy: Specifies the tuning strategy. In this case, it's set to "Bayesian".

HyperParameterTuningJobObjective: Specifies the objective metric to optimize and whether to minimize or maximize it.

MetricName: Name of the metric to optimize, set to "validation:accuracy" (The ratio of correctly predicted instances to the total instances). Type: Set to "Maximize" since we want to maximize the accuracy.

In [38]:
```
from time import gmtime, strftime, sleep

tuning_job_name = "xgboost-tuningjob-" + strftime("%d-%H-%M-%S", gmtime())   # generating unique hyperaparameter
print(tuning_job_name)

# configuration for the hyperparameter tuning job
tuning_job_config = {
    "ParameterRanges": {
        "CategoricalParameterRanges": [],
        "ContinuousParameterRanges": [
            {
                "MaxValue": "1",
                "MinValue": "0",
                "Name": "eta",      # Learning rate parameter
            },
            {
                "MaxValue": "10",
                "MinValue": "1",
                "Name": "min_child_weight",    # Minimum sum of instance weight in a child
            },
            {
                "MaxValue": "2",
                "MinValue": "0",
```

```
                "Name": "alpha",    # # L1 regularization term
            },
        ],
        "IntegerParameterRanges": [
            {
                "MaxValue": "10",
                "MinValue": "1",
                "Name": "max_depth",    # Maximum depth of a tree
            }
        ],
    },
    "ResourceLimits": {"MaxNumberOfTrainingJobs": 10, "MaxParallelTrainingJobs": 3},
    "Strategy": "Bayesian",
    "HyperParameterTuningJobObjective": {"MetricName": "validation:accuracy", "Type": "Maximize"},
}
```

```
xgboost-tuningjob-26-21-56-00
```

The following block includes details about the algorithm, input data configuration, output data configuration, resource configuration, role ARN, hyperparameters, and stopping conditions.

- The AlgorithmSpecification section specifies the training image and input mode.
- The InputDataConfig section specifies details about the training and validation datasets, including S3 paths.
- The OutputDataConfig section specifies the S3 path where the output model artifacts will be stored.
- The ResourceConfig section specifies the instance count, instance type, and volume size.
- The StaticHyperParameters section specifies static hyperparameters for the XGBoost algorithm.
- The StoppingCondition section specifies the maximum runtime for the training job.

Static hyperparamters:

- eval_metric: Specifies the evaluation metric to be used for model performance assessment during training. In this case, the chosen evaluation metric is Area Under the Curve (AUC) for the Receiver Operating Characteristic (ROC) curve. Since it is a common metric for binary classification problems and represents the area under the ROC curve, which measures the model's ability to distinguish between positive and negative examples.
- num_round: Specifies the number of boosting rounds (iterations) for the XGBoost algorithm. This parameter determines the number of boosting rounds (iterations) during the training process. A higher number of rounds can potentially lead to a more accurate model, but it's important to monitor for overfitting.
- objective: Specifies the learning task and corresponding objective function. This parameter indicates that the training task is binary classification, and the objective function to be optimized is the logistic loss. Since the logistic loss is suitable for binary classification problems, and optimizing it leads to the logistic regression model.
- rate_drop: Specifies the rate at which the algorithm drops trees during the dropout process. Dropout is a regularization technique used to prevent overfitting. This parameter controls the fraction of previously dropped trees to be dropped during a training iteration. A value of 0.3 means that 30% of the trees are dropped during each iteration.
- tweedie_variance_power: Specifies the power for the variance function in the Tweedie distribution. This parameter is relevant when the objective function is set to Tweedie, which is used for modeling non-negative continuous target variables with a variance function. The specified value of 1.4 determines the power parameter for the Tweedie distribution's variance function.

In [39]:
```
from sagemaker.image_uris import retrieve

training_image = retrieve(framework="xgboost", region=region, version="1.5-1")    # Retrieving the URI of the pr

# S3 input paths for training and validation data
s3_input_train = "s3://{}/{}/train".format(bucket, prefix)
s3_input_validation = "s3://{}/{}/validation/".format(bucket, prefix)

# configuration for the SageMaker training job
training_job_definition = {
    "AlgorithmSpecification": {"TrainingImage": training_image, "TrainingInputMode": "File"},    # algorithm and
    "InputDataConfig": [    # input data configuration for training and validation
        {
            "ChannelName": "train",    # Channel name for training data
            "CompressionType": "None",
            "ContentType": "csv",
```

```
            "DataSource": {
                "S3DataSource": {
                    "S3DataDistributionType": "FullyReplicated",
                    "S3DataType": "S3Prefix",
                    "S3Uri": s3_input_train,    # S3 path for training data
                }
            },
        },
        {
            "ChannelName": "validation",    # Channel name for validation data
            "CompressionType": "None",
            "ContentType": "csv",
            "DataSource": {
                "S3DataSource": {
                    "S3DataDistributionType": "FullyReplicated",
                    "S3DataType": "S3Prefix",
                    "S3Uri": s3_input_validation,   # S3 path for validation data
                }
            },
        },
    ],
    "OutputDataConfig": {"S3OutputPath": "s3://{}/{}/output".format(bucket, prefix)},    # output data configur
    "ResourceConfig": {"InstanceCount": 1, "InstanceType": "ml.m4.xlarge", "VolumeSizeInGB": 10},    # resource
    "RoleArn": role,   # IAM role
    "StaticHyperParameters": {    # static hyperparameters for the XGBoost algorithm
        "eval_metric": "auc",
        "num_round": "100",
        "objective": "binary:logistic",
        "rate_drop": "0.3",
        "tweedie_variance_power": "1.4",
    },
    "StoppingCondition": {"MaxRuntimeInSeconds": 43200},    #  stopping conditions for the training job
}
```

In [40]:

```
# creating the hyperparameter tuning job
smclient.create_hyper_parameter_tuning_job(
    HyperParameterTuningJobName=tuning_job_name,
    HyperParameterTuningJobConfig=tuning_job_config,
    TrainingJobDefinition=training_job_definition,
)
```

Out[40]:

```
{'HyperParameterTuningJobArn': 'arn:aws:sagemaker:us-east-1:585522057818:hyper-parameter-tuning-job/xgboost-tun
ingjob-26-21-56-00',
 'ResponseMetadata': {'RequestId': '4764dc56-9e64-411d-b17d-851601b8cfa7',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '4764dc56-9e64-411d-b17d-851601b8cfa7',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '130',
   'date': 'Sun, 26 Nov 2023 21:56:04 GMT'},
  'RetryAttempts': 0}}
```

In [41]:

```
# status of hp
smclient.describe_hyper_parameter_tuning_job(HyperParameterTuningJobName=tuning_job_name)["HyperParameterTuning
```

Out[41]: 'InProgress'

In [42]:

```
# Job name of hp
smclient.describe_hyper_parameter_tuning_job(HyperParameterTuningJobName=tuning_job_name)['HyperParameterTuning
```

Out[42]: 'xgboost-tuningjob-26-21-56-00'

In [50]:

```
# run this cell to check current status of hyperparameter tuning job
tuning_job_result = smclient.describe_hyper_parameter_tuning_job(
    HyperParameterTuningJobName=tuning_job_name
)

status = tuning_job_result["HyperParameterTuningJobStatus"]
if status != "Completed":
    print("Reminder: the tuning job has not been completed.")

job_count = tuning_job_result["TrainingJobStatusCounters"]["Completed"]
```

```
print("%d training jobs have completed" % job_count)

objective = tuning_job_result["HyperParameterTuningJobConfig"]["HyperParameterTuningJobObjective"]
is_minimize = objective["Type"] != "Maximize"
objective_name = objective["MetricName"]
```

```
10 training jobs have completed
```

In [51]:

```
from pprint import pprint
# extracting best training job from the rest
if tuning_job_result.get("BestTrainingJob", None):
    print("Best model found so far:")
    pprint(tuning_job_result["BestTrainingJob"])
else:
    print("No training jobs have reported results yet.")
```

```
Best model found so far:
{'CreationTime': datetime.datetime(2023, 11, 26, 22, 2, 1, tzinfo=tzlocal()),
 'FinalHyperParameterTuningJobObjectiveMetric': {'MetricName': 'validation:accuracy',
                                                 'Value': 0.9371399879455566},
 'ObjectiveStatus': 'Succeeded',
 'TrainingEndTime': datetime.datetime(2023, 11, 26, 22, 2, 52, tzinfo=tzlocal()),
 'TrainingJobArn': 'arn:aws:sagemaker:us-east-1:585522057818:training-job/xgboost-tuningjob-26-21-56-00-010-62a
4af05',
 'TrainingJobName': 'xgboost-tuningjob-26-21-56-00-010-62a4af05',
 'TrainingJobStatus': 'Completed',
 'TrainingStartTime': datetime.datetime(2023, 11, 26, 22, 2, 5, tzinfo=tzlocal()),
 'TunedHyperParameters': {'alpha': '1.524352266875594',
                          'eta': '0.5504740010557349',
                          'max_depth': '6',
                          'min_child_weight': '5.804222989525692'}}
```

In [52]:

```
# Now training the model with the best hp values
xgboost_job = "xgboost-" + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print("Job name is:", xgboost_job)

s3_input_train = "s3://{}/{}/train".format(bucket, prefix)
s3_input_validation = "s3://{}/{}/validation/".format(bucket, prefix)

training_job_definition = {
    "RoleArn": role,
    "TrainingJobName": xgboost_job,
    "AlgorithmSpecification": {"TrainingImage": training_image, "TrainingInputMode": "File"},
    "InputDataConfig": [
        {
            "ChannelName": "train",
            "CompressionType": "None",
            "ContentType": "csv",
            "DataSource": {
                "S3DataSource": {
                    "S3DataDistributionType": "FullyReplicated",
                    "S3DataType": "S3Prefix",
                    "S3Uri": s3_input_train,
                }
            },
        },
        {
            "ChannelName": "validation",
            "CompressionType": "None",
            "ContentType": "csv",
            "DataSource": {
                "S3DataSource": {
                    "S3DataDistributionType": "FullyReplicated",
                    "S3DataType": "S3Prefix",
                    "S3Uri": s3_input_validation,
                }
            },
        },
    ],
    "OutputDataConfig": {"S3OutputPath": "s3://{}/{}/output".format(bucket, prefix)},
    "ResourceConfig": {"InstanceCount": 1, "InstanceType": "ml.m4.xlarge", "VolumeSizeInGB": 10},
    "RoleArn": role,
    "HyperParameters": {
```

```
        "eval_metric": "auc",
        "num_round": "100",
        "objective": "binary:logistic",
        "rate_drop": "0.3",
        "tweedie_variance_power": "1.4",
        "alpha": '1.524352266875594',
        'eta': '0.5504740010557349',
        'max_depth': '6',
        'min_child_weight': '5.804222989525692'
    },
    "StoppingCondition": {"MaxRuntimeInSeconds": 43200},
}
```

```
Job name is: xgboost-2023-11-26-22-05-31
```

In [53]:

```
sm = boto3.client("sagemaker")
sm.create_training_job(**training_job_definition)
# checking the status of training
status = sm.describe_training_job(TrainingJobName=xgboost_job)["TrainingJobStatus"]
print(status)
sm.get_waiter("training_job_completed_or_stopped").wait(TrainingJobName=xgboost_job)
if status == "Failed":
    message = sm.describe_training_job(TrainingJobName=xgboost_job)["FailureReason"]
    print("Training failed with the following error: {}".format(message))
    raise Exception("Training job failed")
```

```
InProgress
```

Hosting

In [54]:

```
# creating a model using the specified configuration.
xgboost_hosting_container = {
    "Image": training_image,
    "ModelDataUrl": sm.describe_training_job(TrainingJobName=xgboost_job)["ModelArtifacts"][
        "S3ModelArtifacts"
    ],
}

create_model_response = sm.create_model(
    ModelName=xgboost_job, ExecutionRoleArn=role, PrimaryContainer=xgboost_hosting_container
)

print(create_model_response["ModelArn"])
```

```
arn:aws:sagemaker:us-east-1:585522057818:model/xgboost-2023-11-26-22-05-31
```

In [55]:

```
# configuring endpoint with unique name based on current time
xgboost_endpoint_config = "xgboost-endpoint-config-" + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print(xgboost_endpoint_config)
create_endpoint_config_response = sm.create_endpoint_config(
    EndpointConfigName=xgboost_endpoint_config,
    ProductionVariants=[
        {
            "InstanceType": "ml.m4.xlarge",
            "InitialInstanceCount": 1,
            "ModelName": xgboost_job,
            "VariantName": "AllTraffic",
        }
    ],
)

print("Endpoint Config Arn: " + create_endpoint_config_response["EndpointConfigArn"])
```

```
xgboost-endpoint-config-2023-11-26-22-10-27
Endpoint Config Arn: arn:aws:sagemaker:us-east-1:585522057818:endpoint-config/xgboost-endpoint-config-2023-11-2
6-22-10-27
```

In [56]:

```
%%time

# configuring, creating, waiting and then checking the status again of an endpoint
xgboost_endpoint = "xgboost-endpoint-" + strftime("%Y%m%d%H%M", gmtime())
print(xgboost_endpoint)
create_endpoint_response = sm.create_endpoint(
```

```
    EndpointName=xgboost_endpoint, EndpointConfigName=xgboost_endpoint_config
)
print(create_endpoint_response["EndpointArn"])

resp = sm.describe_endpoint(EndpointName=xgboost_endpoint)
status = resp["EndpointStatus"]
print("Status: " + status)

sm.get_waiter("endpoint_in_service").wait(EndpointName=xgboost_endpoint)

resp = sm.describe_endpoint(EndpointName=xgboost_endpoint)
status = resp["EndpointStatus"]
print("Arn: " + resp["EndpointArn"])
print("Status: " + status)

if status != "InService":
    raise Exception("Endpoint creation did not succeed")
```

```
xgboost-endpoint-202311262210
arn:aws:sagemaker:us-east-1:585522057818:endpoint/xgboost-endpoint-202311262210
Status: Creating
Arn: arn:aws:sagemaker:us-east-1:585522057818:endpoint/xgboost-endpoint-202311262210
Status: InService
CPU times: user 44.2 ms, sys: 3.02 ms, total: 47.2 ms
Wall time: 3min 31s
```

Inferencing

In [57]:
```
def np2csv(arr):
    csv = io.BytesIO() #the function gets an array (Numpy array) and creates an in-memory binary buffer named cs
    np.savetxt(csv, arr, delimiter=",", fmt="%g") # write the array 'arr' to csv object, columns should be seper
    # In the following line:
    # csv.getvalue() retrieves the entire contents of the buffer csv as a byte string.
    # .decode() converts the byte string into a normal Python string by decoding it using the default UTF-8 enco
    #.rstrip() removes any trailing whitespace or newlines from the end of the string.
    return csv.getvalue().decode().rstrip()
```

In [58]:
```
import io, json
runtime = boto3.client("runtime.sagemaker")

payload = np2csv(test_X)

# invoking endpoint which is used to make a prediction request to the SageMaker endpoint.
response = runtime.invoke_endpoint(
    EndpointName=xgboost_endpoint, ContentType="text/csv", Body=payload
)
result = response["Body"].read().decode()
test_pred = np.array(result.split(), dtype=float)
#The following line:
# extracts the prediction results from the result dictionary, from the "predictions" key.
# It is a list of dictionaries where each dictionary has a key "score" representing the model's prediction.
```

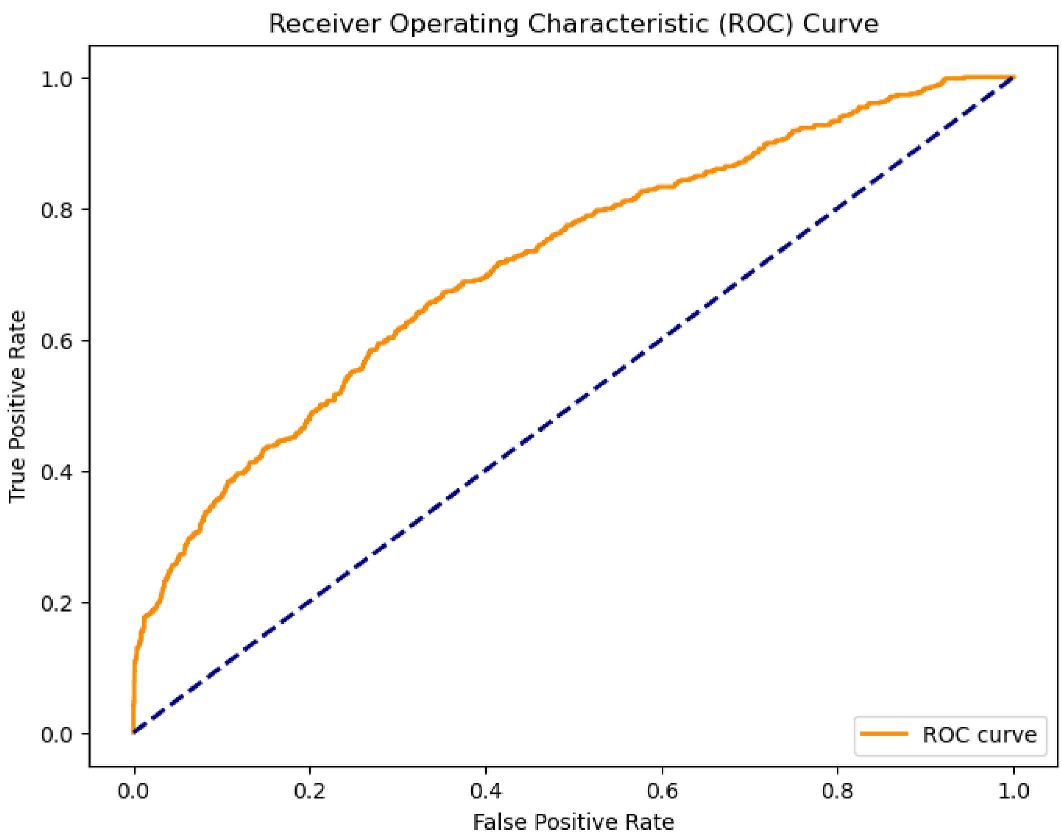
In [59]:
```
print(test_pred)
```

```
[0.98641372 0.00207751 0.03878499 ... 0.18620981 0.92541814 0.20467584]
```

In [60]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, roc_curve, c
import matplotlib.pyplot as plt

# Assuming test_y and test_pred are your true labels and predicted probabilities

# Convert probabilities to binary predictions (0 or 1)
test_pred_class = (test_pred > 0.5).astype(int)

# Calculate and print accuracy
accuracy = accuracy_score(test_y, test_pred_class)
print(f'Accuracy: {accuracy:.4f}')

# Calculate and print precision, recall, and F1 score
precision = precision_score(test_y, test_pred_class)
recall = recall_score(test_y, test_pred_class)
```

```
f1 = f1_score(test_y, test_pred_class)

print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')

# Calculate and print ROC AUC
roc_auc = roc_auc_score(test_y, test_pred)
print(f'ROC AUC: {roc_auc:.4f}')

# Plot ROC curve
fpr, tpr, thresholds = roc_curve(test_y, test_pred)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()

# Print confusion matrix
conf_matrix = confusion_matrix(test_y, test_pred_class)
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 0.8046
Precision: 0.2289
Recall: 0.4372
F1 Score: 0.3005
ROC AUC: 0.7152
```




```
Confusion Matrix:
[[3798  704]
 [ 269  209]]
```

In [61]:
```
#If the predicted probability (test_pred) is greater than 0.5, it is considered a prediction for the positive cl
#The + 0 part is used to convert the resulting boolean values (True for values above 0.5 and False for values be
test_pred_class = (test_pred > 0.5) + 0   # converts the predicted probabilities to binary predictions based on

# We sort the train_y values and select the mdedian (if is 0, then we select 0 otherwise 1). Then we generate th
```

```
test_pred_baseline = np.repeat(np.median(train_y), len(test_y))   # This line creates a baseline prediction by r

#compare the binary prediction (test_pred_class) with actual outcomes (test_y)
prediction_accuracy = np.mean((test_y == test_pred_class)) * 100    # calculates the accuracy of your model by c
baseline_accuracy = np.mean((test_y == test_pred_baseline)) * 100   # calculates the accuracy of the baseline by

print("Prediction Accuracy:", round(prediction_accuracy, 1), "%")
print("Baseline Accuracy:", round(baseline_accuracy, 1), "%")
```

```
Prediction Accuracy: 80.5 %
Baseline Accuracy: 90.4 %
```

In [62]:

```
sm.delete_endpoint(EndpointName=xgboost_endpoint)
```

Out[62]:


```
{'ResponseMetadata': {'RequestId': '2a85b420-c5c6-4fbb-b9b0-23f16d3516a9',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '2a85b420-c5c6-4fbb-b9b0-23f16d3516a9',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '0',
   'date': 'Sun, 26 Nov 2023 22:14:34 GMT',
   'connection': 'close'},
  'RetryAttempts': 0}}
```


In [ ]: