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ML pipeline

In [280]:
```
! pip install sagemaker botocore boto3 awscli --upgrade
```

```
Requirement already satisfied: rpds-py>=0.7.1 in /home/ec2-user/anaconda3/
envs/python3/lib/python3.10/site-packages (from jsonschema->sagemaker) (0.
10.6)
Requirement already satisfied: pytz>=2020.1 in /home/ec2-user/anaconda3/en
vs/python3/lib/python3.10/site-packages (from pandas->sagemaker) (2023.3.p
ost1)
Requirement already satisfied: tzdata>=2022.1 in /home/ec2-user/anaconda3/
envs/python3/lib/python3.10/site-packages (from pandas->sagemaker) (2023.
3)
Requirement already satisfied: ppft>=1.7.6.7 in /home/ec2-user/anaconda3/e
nvs/python3/lib/python3.10/site-packages (from pathos->sagemaker) (1.7.6.
7)
Requirement already satisfied: dill>=0.3.7 in /home/ec2-user/anaconda3/env
s/python3/lib/python3.10/site-packages (from pathos->sagemaker) (0.3.7)
Requirement already satisfied: pox>=0.3.3 in /home/ec2-user/anaconda3/env
s/python3/lib/python3.10/site-packages (from pathos->sagemaker) (0.3.3)
Requirement already satisfied: multiprocess>=0.70.15 in /home/ec2-user/ana
conda3/envs/python3/lib/python3.10/site-packages (from pathos->sagemaker)
(0.70.15)
```

Importing necessary libraries

In [98]:
```
import boto3
import sagemaker
from sagemaker.estimator import Estimator
import pandas as pd

boto_session = boto3.session.Session()
region = boto_session.region_name
print(region)

sagemaker_session = sagemaker.Session()
client = boto3.client(service_name="sagemaker")
runtime = boto3.client(service_name="sagemaker-runtime")
role = sagemaker.get_execution_role()
print(role)

default_bucket = 'mlpipeline-sid1'
s3_prefix = 'mlpipeline-sid'

training_instance_type = "ml.m4.xlarge"
```

```
us-east-1
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/sag
emaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-us
er/.config/sagemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/sag
emaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-us
er/.config/sagemaker/config.yaml
arn:aws:iam::457756105170:role/fast-ai-academic-60-Student-Azure
```

Data Preprocessing

Reading data from the csv

In [99]:
```
df = pd.read_csv('complete_dataset.csv')
```

In [100]:
```
df.head()
```

Out[100]:

	date	demand	RRP	demand_pos_RRP	RRP_positive	demand_neg_RRP	RRP_negative	frac_a
0	2015-01-01	99635.030	25.633696	97319.240	26.415953	2315.790	-7.240000	
1	2015-01-02	129606.010	33.138988	121082.015	38.837661	8523.995	-47.809777	
2	2015-01-03	142300.540	34.564855	142300.540	34.564855	0.000	0.000000	
3	2015-01-04	104330.715	25.005560	104330.715	25.005560	0.000	0.000000	
4	2015-01-05	118132.200	26.724176	118132.200	26.724176	0.000	0.000000	

In [101]:
```
df.count()
```

Out[101]:
```
date                2106
demand              2106
RRP                 2106
demand_pos_RRP      2106
RRP_positive        2106
demand_neg_RRP      2106
RRP_negative        2106
frac_at_neg_RRP     2106
min_temperature     2106
max_temperature     2106
solar_exposure      2105
rainfall            2103
school_day          2106
holiday             2106
dtype: int64
```

Listing the null values for each column

In [102]:
```
df.isnull().sum()
```

Out[102]:
```
date                0
demand              0
RRP                 0
demand_pos_RRP      0
RRP_positive        0
demand_neg_RRP      0
RRP_negative        0
frac_at_neg_RRP     0
min_temperature     0
max_temperature     0
solar_exposure      1
rainfall            3
school_day          0
holiday             0
dtype: int64
```

Dropping null values for rainfall attribute

In [103]:
```
df = df.dropna(subset=['rainfall'])
```

Replacing null values for column solar_exposure with that of the mean value of the column

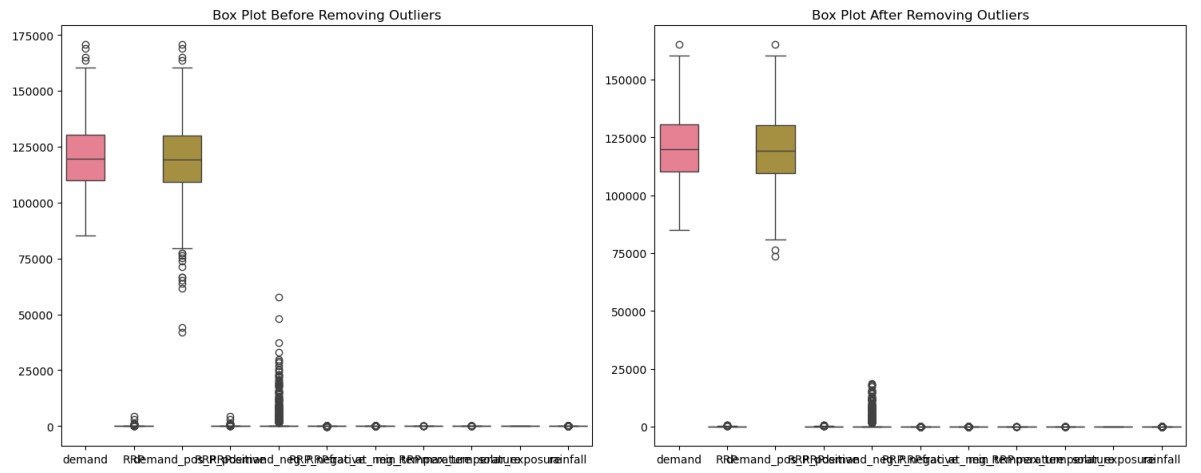
In [104]:
```
mean_solar_exposure = df['solar_exposure'].mean()
df['solar_exposure'].fillna(mean_solar_exposure, inplace=True)
```

In [105]:
```
df.isnull().sum()
```

Out[105]:
```
date                0
demand              0
RRP                 0
demand_pos_RRP      0
RRP_positive        0
demand_neg_RRP      0
RRP_negative        0
frac_at_neg_RRP     0
min_temperature     0
max_temperature     0
solar_exposure      0
rainfall            0
school_day          0
holiday             0
dtype: int64
```

Detecting outliers and removing rows with z score value more than 5 and plotting before and after removing outliers

In [106]:
```
import matplotlib.pyplot as plt
import seaborn as sns

numerical_cols = df.select_dtypes(include=[np.number]).columns.tolist()

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15, 6))

sns.boxplot(data=df[numerical_cols], ax=axes[0])
axes[0].set_title('Box Plot Before Removing Outliers')

z_scores = np.abs(stats.zscore(df[numerical_cols]))

threshold = 5

outliers = np.where(z_scores > threshold)

df_no_outliers = df[(z_scores <= threshold).all(axis=1)]

sns.boxplot(data=df_no_outliers[numerical_cols], ax=axes[1])
axes[1].set_title('Box Plot After Removing Outliers')
plt.tight_layout()
plt.show()
```



Label encoding school_day and holiday

In [107]:
```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()

df['school_day'] = label_encoder.fit_transform(df['school_day'])

df['holiday'] = label_encoder.fit_transform(df['holiday'])
```

In [108]:
```
df.tail()
```

Out[108]:

	date	demand	RRP	demand_pos_RRP	RRP_positive	demand_neg_RRP	RRP_negative	fra
2101	2020-10-02	99585.835	-6.076028	41988.240	26.980251	57597.595	-30.173823	
2102	2020-10-03	92277.025	-1.983471	44133.510	32.438156	48143.515	-33.538025	
2103	2020-10-04	94081.565	25.008614	88580.995	26.571687	5500.570	-0.163066	
2104	2020-10-05	113610.030	36.764701	106587.375	39.616015	7022.655	-6.511550	
2105	2020-10-06	122607.560	75.771059	122607.560	75.771059	0.000	0.000000	

Scaling the data using min max scalar

In [109]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0, 5))

columns_to_scale = df.columns.difference(['date'])

df[columns_to_scale] = scaler.fit_transform(df[columns_to_scale])
```

Converting date column to year, month and day attributes and dropping date column

In [110]:
```
df['date'] = pd.to_datetime(df['date'])

# Extracting year month and day from the date column
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month
df['day'] = df['date'].dt.day

df = df.drop('date', axis=1)
```

In [114]:
```
## Rearranging dataframe columns for RRP to be the first column

df = df[['RRP', 'demand', 'demand_pos_RRP', 'RRP_positive', 'demand_neg_RRP',
         'frac_at_neg_RRP', 'min_temperature', 'max_temperature', 'solar_exposu
         'rainfall', 'school_day', 'holiday', 'year', 'month', 'day']]
```

In [147]:
```
df.head()
```

Out[147]:

	RRP	demand	demand_pos_RRP	RRP_positive	demand_neg_RRP	RRP_negative	frac_at_neg_RRP
0	0.034802	0.849740	2.150186	0.014161	0.201032	4.894220	0.166667
1	0.043039	2.601210	3.073618	0.027853	0.739961	4.301476	0.500000
2	0.044604	3.343065	3.898179	0.023143	0.000000	5.000000	0.000000
3	0.034113	1.124150	2.422655	0.012606	0.000000	5.000000	0.000000
4	0.035999	1.930694	2.958987	0.014501	0.000000	5.000000	0.000000

Data organizing in S3 buckets

Splitting train and test split with 80% train data, 10% as test and 10% as validationn and saving them to S3 buckets

In [117]:
```
import numpy as np
rand_split = np.random.rand(len(df))
train_list = rand_split < 0.8
val_list = (rand_split >= 0.8) & (rand_split < 0.9)
test_list = rand_split >= 0.9

s3 = boto3.resource('s3')
data_train = df[train_list]
data_train_csv = data_train.to_csv(index=False)
s3.Object(default_bucket, "train/train.csv").put(Body=data_train_csv)


data_val = df[val_list]
data_valid_csv = data_val.to_csv(index=False)
s3.Object(default_bucket, "validation/validation.csv").put(Body=data_valid_csv)


data_test = df[test_list]
data_test_csv = data_test.to_csv(index=False)
s3.Object(default_bucket, "test/test.csv").put(Body=data_test_csv)
```

Out[117]:
```
{'ResponseMetadata': {'RequestId': 'G8CYF6ABM9SA7YJ0',
  'HostId': 'Ej8DZtEOLYdXuNuL8VLgVq/cOjGxYIHr/co9iMy6BL8Qjdj9bl5El6BLeCf2mRbY
uNL2kIAm+bU=',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amz-id-2': 'Ej8DZtEOLYdXuNuL8VLgVq/cOjGxYIHr/co9iMy6BL8Q
jdj9bl5El6BLeCf2mRbYuNL2kIAm+bU=',
   'x-amz-request-id': 'G8CYF6ABM9SA7YJ0',
   'date': 'Thu, 23 Nov 2023 06:36:24 GMT',
   'x-amz-server-side-encryption': 'AES256',
   'etag': '"2c5b2b3087eb3d2da8ed1b259a8fd185"',
   'server': 'AmazonS3',
   'content-length': '0'},
  'RetryAttempts': 0},
 'ETag': '"2c5b2b3087eb3d2da8ed1b259a8fd185"',
 'ServerSideEncryption': 'AES256'}
```

Training

defining xgboost container

In [294]:
```
from sagemaker import image_uris, model_uris, script_uris

container = "683313688378.dkr.ecr.us-east-1.amazonaws.com/sagemaker-xgboost:1.7
```

In [119]:
```
import time
xgboost_job = "xgboost-" + time.strftime("%Y-%m-%d-%H-%M-%S", time.gmtime())

print("Job name is:", xgboost_job)
```

```
Job name is: xgboost-2023-11-23-06-38-49
```

In [120]:
```
train_data = "s3://mlpipeline-sid1/train/train.csv"
validation_data = "s3://mlpipeline-sid1/validation/validation.csv"
```

Defining training params with train and validation data

In [121]:
```
xgboost_training_params = {
    "TrainingJobName": xgboost_job,
    "AlgorithmSpecification": {
        "TrainingImage": container,
        "TrainingInputMode": "File",
    },
    "RoleArn": role,
    "OutputDataConfig": {
        "S3OutputPath": "s3://week7-output/output/",
    },
    "ResourceConfig": {
        "InstanceType": "ml.m4.xlarge",
        "InstanceCount": 1,
        "VolumeSizeInGB": 30,
    },
    "StoppingCondition": {
        "MaxRuntimeInSeconds": 86400,
    },
    "InputDataConfig": [
        {
            "ChannelName": "train",
            "DataSource": {
                "S3DataSource": {
                    "S3DataType": "S3Prefix",
                    "S3Uri": train_data,
                    "S3DataDistributionType": "FullyReplicated",
                }
            },
            "ContentType": "csv",
        },
        {
            "ChannelName": "validation",
            "DataSource": {
                "S3DataSource": {
                    "S3DataType": "S3Prefix",
                    "S3Uri": validation_data,
                    "S3DataDistributionType": "FullyReplicated",
                }
            },
            "ContentType": "csv",
        },
    ],
    "HyperParameters": {
        "objective": "reg:squarederror",
        "num_round": "100",
        "max_depth": "5"
    },
}
```

Creating a training job for the xgboost model with the train data.

In [122]:
```
%%time

region = boto3.Session().region_name
sm = boto3.client("sagemaker")

sm.create_training_job(**xgboost_training_params)

status = sm.describe_training_job(TrainingJobName=xgboost_job)["TrainingJobSta
print(status)
sm.get_waiter("training_job_completed_or_stopped").wait(TrainingJobName=xgboos
if status == "Failed":
    message = sm.describe_training_job(TrainingJobName=xgboost_job)["FailureRea
    print("Training failed with the following error: {}".format(message))
    raise Exception("Training job failed")
```

```
InProgress
CPU times: user 138 ms, sys: 14.3 ms, total: 152 ms
Wall time: 4min
```

Hosting

Creating model for the above trained xgboost algorithm

In [123]:
```
xgboost_hosting_container = {
    "Image": container,
    "ModelDataUrl": sm.describe_training_job(TrainingJobName=xgboost_job)["Mode
        "S3ModelArtifacts"
    ],
}

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

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

```
arn:aws:sagemaker:us-east-1:457756105170:model/xgboost-2023-11-23-06-38-49
```

Defining endpoint configurations for the model to be deployed along with instance type

In [124]:
```
xgboost_endpoint_config = "DEMO-xgboost-endpoint-config-" + time.strftime(
    "%Y-%m-%d-%H-%M-%S", time.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["EndpointConfig
```

```
DEMO-xgboost-endpoint-config-2023-11-23-06-44-58
Endpoint Config Arn: arn:aws:sagemaker:us-east-1:457756105170:endpoint-confi
g/demo-xgboost-endpoint-config-2023-11-23-06-44-58
```

Deploying the endopoint for the trained xgboost model

In [125]:
```
xgboost_endpoint = "xgboost-endpoint-" + time.strftime("%Y%m%d%H%M", time.gmtim
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")
```

```
DEMO-xgboost-endpoint-202311230645
arn:aws:sagemaker:us-east-1:457756105170:endpoint/demo-xgboost-endpoint-20231
1230645
Status: Creating
Arn: arn:aws:sagemaker:us-east-1:457756105170:endpoint/demo-xgboost-endpoint-
202311230645
Status: InService
```

Predicting

In [153]:
```
test_X = data_test.iloc[:,1:].to_csv(index=False, header=False)
test_y = data_test.iloc[:,0].to_csv(index=False, header=False)
```

Invoking the created point to make predictions on the test dataset

In [154]:
```
%%time

runtime = boto3.client("sagemaker-runtime")

response = runtime.invoke_endpoint(
    EndpointName=xgboost_endpoint,
    ContentType="text/csv",
    Body=test_X.encode('utf-8')
)

response_body = response["Body"].read()
```

```
CPU times: user 33.8 ms, sys: 0 ns, total: 33.8 ms
Wall time: 107 ms
```

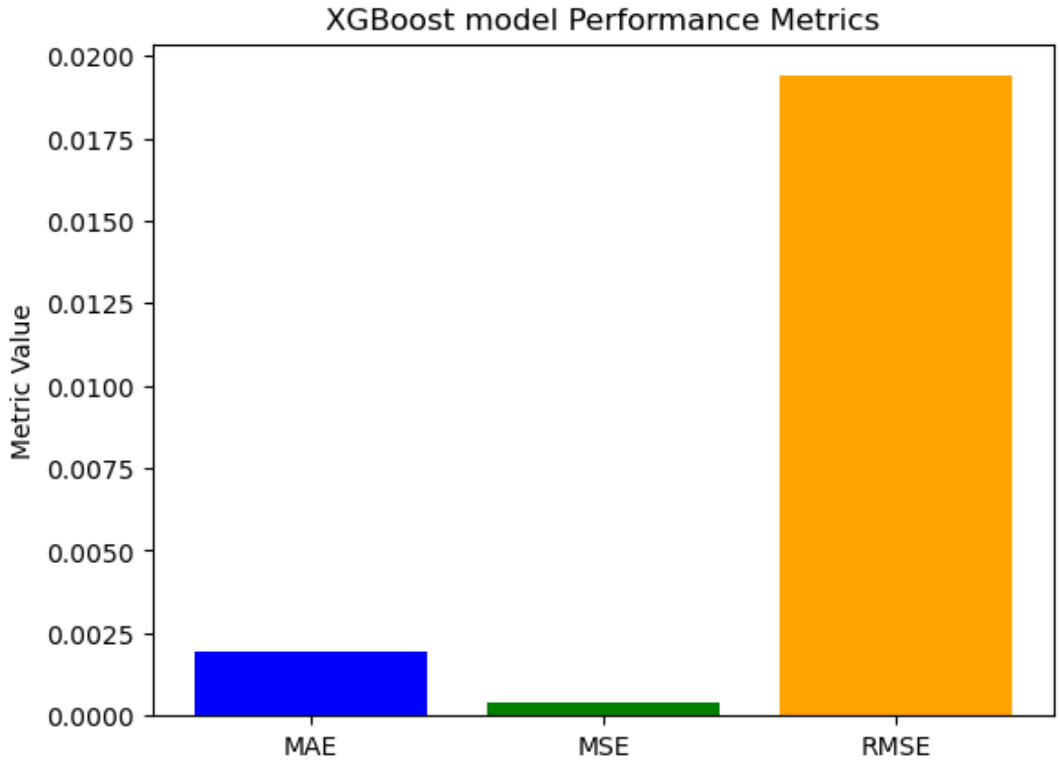
Calculating accuracy metrics using the test set

In [159]:
```
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error

# Actual data
actual_data = data_test.iloc[:, 0].values

# Predicted data from the response
predicted_data_str = response_body.decode('utf-8')
predicted_data = np.array([float(val) for val in predicted_data_str.split('\n'

# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(actual_data, predicted_data)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(actual_data, predicted_data)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)

print(f'MAE: {mae}')
print(f'MSE: {mse}')
print(f'RMSE: {rmse}')
```

```
MAE: 0.001970258560460822
MSE: 0.00037584436325163945
RMSE: 0.01938670583806438
```

Plotting MAE, MSE and RMSE

In [161]:
```
import matplotlib.pyplot as plt

# Plotting
metrics_names = ['MAE', 'MSE', 'RMSE']
metrics_values = [mae, mse, rmse]

plt.bar(metrics_names, metrics_values, color=['blue', 'green', 'orange'])
plt.ylabel('Metric Value')
plt.title('XGBoost model Performance Metrics')
plt.show()
```



Optimization

Hyperparameter Optimization

In [318]:
```
from time import gmtime, strftime, sleep

tun_job_name = "xgb-tun" + time.strftime("%Y-%m-%d-%H-%M-%S", time.gmtime())
print(tun_job_name)
```

```
xgb-tun2023-11-23-09-10-07
```

Defining tuning job parameters and hyperparameters to be considered

In [319]:
```
tuning_job_config = {
    "ParameterRanges": {
        "CategoricalParameterRanges": [
        ],
        "ContinuousParameterRanges": [
            {
                "MaxValue": "1",
                "MinValue": "0",
                "Name": "eta",
            },
            {
                "MaxValue": "53",
                "MinValue": "1",
                "Name": "min_child_weight",
            },
            {
                "MaxValue": "250",
                "MinValue": "0",
                "Name": "alpha",
            },
            {
                "MaxValue": "1",
                "MinValue": "0.6",
                "Name": "subsample",
            },
        ],
        "IntegerParameterRanges": [
            {
                "MaxValue": "10",
                "MinValue": "2",
                "Name": "max_depth",
            },
            {
                "MaxValue": "1000",
                "MinValue": "25",
                "Name": "num_round",
            }
        ],
    },
    "ResourceLimits": {"MaxNumberOfTrainingJobs": 10, "MaxParallelTrainingJobs"
    "Strategy": "Bayesian",
    "HyperParameterTuningJobObjective": {"MetricName": "validation:mse", "Type"
}
```

Defining training job for the tuning job with eval metric as auc

In [320]:
```
from sagemaker.image_uris import retrieve

training_image = retrieve(framework="xgboost", region=region, version="1.7-1")

s3_input_train = "s3://{}/train/train.csv".format(default_bucket)
s3_input_validation = "s3://{}/validation/validation.csv".format(default_bucke

training_job_definition = {
    "AlgorithmSpecification": {"TrainingImage": training_image, "TrainingInputM
    "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(default_bucke
    "ResourceConfig": {"InstanceCount": 1, "InstanceType": "ml.m4.xlarge", "Vo
    "RoleArn": role,
    "StaticHyperParameters": {
        "objective": "reg:squarederror",
    },
    "StoppingCondition": {"MaxRuntimeInSeconds": 43200},
}
```

Starting the HPO job

In [321]:
```
client.create_hyper_parameter_tuning_job(
    HyperParameterTuningJobName=tun_job_name,
    HyperParameterTuningJobConfig=tuning_job_config,
    TrainingJobDefinition=training_job_definition,
)
```

Out[321]:
```
{'HyperParameterTuningJobArn': 'arn:aws:sagemaker:us-east-1:457756105170:hype
r-parameter-tuning-job/xgb-tun2023-11-23-09-10-07',
 'ResponseMetadata': {'RequestId': 'c5f66756-ebfa-49cd-9aa2-9a96ef5a2442',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': 'c5f66756-ebfa-49cd-9aa2-9a96ef5a2442',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '127',
   'date': 'Thu, 23 Nov 2023 09:10:40 GMT'},
  'RetryAttempts': 0}}
```

Checking the status of HPO job

In [323]:
```
client.describe_hyper_parameter_tuning_job(HyperParameterTuningJobName=tun_job_
    "HyperParameterTuningJobStatus"
]
```

Out[323]:
```
'Completed'
```

Printing the list of all models with their parmeters

In [324]:
```
from sagemaker.analytics import HyperparameterTuningJobAnalytics
```

In [325]:
```
import pandas as pd

tuner = HyperparameterTuningJobAnalytics(tun_job_name)

full_df = tuner.dataframe()

if len(full_df) > 0:
    df = full_df[full_df["FinalObjectiveValue"] > -float("inf")]
    if len(df) > 0:
        df = df.sort_values("FinalObjectiveValue", ascending=is_minimize)
        print("Number of training jobs with valid objective: %d" % len(df))
        print({"lowest": min(df["FinalObjectiveValue"]), "highest": max(df["Fi
        pd.set_option("display.max_colwidth", None)  # Don't truncate TrainingJ
    else:
        print("No training jobs have reported valid results yet.")

full_df
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/sag
emaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-us
er/.config/sagemaker/config.yaml
Number of training jobs with valid objective: 10
{'lowest': 0.00215000007301569, 'highest': 0.034699998795986176}
```

Out[325]:

	alpha	eta	max_depth	min_child_weight	num_round	subsample	TrainingJobName	TrainingJ
0	19.279175	0.113070	6.0	22.789492	613.0	0.773005	xgb-tun2023-11-23-09-10-07-010-73b6b1d6	C
1	0.000000	0.605104	5.0	53.000000	194.0	1.000000	xgb-tun2023-11-23-09-10-07-009-909d19eb	C
2	82.044614	0.990737	3.0	21.653845	311.0	0.765038	xgb-tun2023-11-23-09-10-07-008-56c7a30d	C
3	26.177276	0.524912	7.0	22.346308	564.0	0.744045	xgb-tun2023-11-23-09-10-07-007-89f5b867	C
4	174.356153	0.376643	5.0	22.811113	477.0	0.704446	xgb-tun2023-11-23-09-10-07-006-e473f1d2	C
5	128.748294	0.627166	9.0	29.895597	65.0	0.605507	xgb-tun2023-11-23-09-10-07-005-adce4436	C
6	89.071695	0.083588	8.0	22.215055	423.0	0.714692	xgb-tun2023-11-23-09-10-07-004-826ff805	C
7	188.442196	0.302182	8.0	43.681616	531.0	0.630335	xgb-tun2023-11-23-09-10-07-003-d145a9be	C
8	140.316306	0.684837	7.0	26.185962	52.0	0.827705	xgb-tun2023-11-23-09-10-07-002-a943d28f	C
9	139.801250	0.864528	9.0	12.687480	763.0	0.702473	xgb-tun2023-11-23-09-10-07-001-803ece45	C

Selecting the best model from the HPO job and printing its details

In [326]:
```
from pprint import pprint

tuning_job_result = client.describe_hyper_parameter_tuning_job(
    HyperParameterTuningJobName=tun_job_name
)

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, 23, 9, 16, 27, tzinfo=tzlocal
()),
 'FinalHyperParameterTuningJobObjectiveMetric': {'MetricName': 'validation:ms
e',
                                                 'Value': 0.0021500000730156
9},
 'ObjectiveStatus': 'Succeeded',
 'TrainingEndTime': datetime.datetime(2023, 11, 23, 9, 17, 8, tzinfo=tzlocal
()),
 'TrainingJobArn': 'arn:aws:sagemaker:us-east-1:457756105170:training-job/xgb
-tun2023-11-23-09-10-07-010-73b6b1d6',
 'TrainingJobName': 'xgb-tun2023-11-23-09-10-07-010-73b6b1d6',
 'TrainingJobStatus': 'Completed',
 'TrainingStartTime': datetime.datetime(2023, 11, 23, 9, 16, 31, tzinfo=tzloc
al()),
 'TunedHyperParameters': {'alpha': '19.27917461236256',
                          'eta': '0.11307039788259454',
                          'max_depth': '6',
                          'min_child_weight': '22.789492011548198',
                          'num_round': '613',
                          'subsample': '0.7730052668427267'}}
```

Deploying the best model chosen from the HPO job

In [327]:
```
xgb_best_model = tuning_job_result.get("BestTrainingJob", None)
model_name = 'xgb-best-model1'

xgboost_hosting_container = {
    "Image": container,
    "ModelDataUrl": sm.describe_training_job(TrainingJobName=xgb_best_model['T
        "S3ModelArtifacts"
    ],
}

create_model_response = sm.create_model(
    ModelName=model_name, ExecutionRoleArn=role, PrimaryContainer=xgboost_host
)

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

```
arn:aws:sagemaker:us-east-1:457756105170:model/xgb-best-model1
```

In [328]:
```
xgboost_endpoint_config = "xgboost-best-endpoint-" + time.strftime(
    "%Y-%m-%d-%H-%M-%S", time.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": model_name,
            "VariantName": "AllTraffic",
        }
    ],
)

print("Endpoint Config Arn: " + create_endpoint_config_response["EndpointConfig
```

```
xgboost-best-endpoint-2023-11-23-09-18-37
Endpoint Config Arn: arn:aws:sagemaker:us-east-1:457756105170:endpoint-confi
g/xgboost-best-endpoint-2023-11-23-09-18-37
```

In [329]:
```
xgboost_endpoint = "xgboost-best-endpt-" + time.strftime("%Y%m%d%H%M", time.gm
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-best-endpt-202311230918
arn:aws:sagemaker:us-east-1:457756105170:endpoint/xgboost-best-endpt-20231123
0918
Status: Creating
Arn: arn:aws:sagemaker:us-east-1:457756105170:endpoint/xgboost-best-endpt-202
311230918
Status: InService
```

Using the best deployed model to make prediction

In [330]:
```
test_X = data_test.iloc[:,1:].to_csv(index=False, header=False)
test_y = data_test.iloc[:,0].to_csv(index=False, header=False)
```

In [331]:
```
%%time

runtime = boto3.client("sagemaker-runtime")

response = runtime.invoke_endpoint(
    EndpointName=xgboost_endpoint,
    ContentType="text/csv",
    Body=test_X.encode('utf-8')
)

response_body = response["Body"].read()
```

```
CPU times: user 35.4 ms, sys: 101 µs, total: 35.5 ms
Wall time: 155 ms
```

Measuring the performance metrics of the best deployed Xgboost model

In [332]:
```
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error

# Actual data
actual_data = data_test.iloc[:, 0].values

# Predicted data from the response
predicted_data_str = response_body.decode('utf-8')
predicted_data = np.array([float(val) for val in predicted_data_str.split('\n'

# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(actual_data, predicted_data)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(actual_data, predicted_data)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)

print(f'MAE: {mae}')
print(f'MSE: {mse}')
print(f'RMSE: {rmse}')
```

```
MAE: 0.02279733735755633
MSE: 0.004205050165484049
RMSE: 0.06484635815127977
```

In [ ]:
```
```