Starbucks Offer Acceptance Forecast Model With AWS

1. Introduction

This article describes my capstone project developed in for the Machine Learning Engineer nanodegree program from Udacity. I developed this Starbucks offer acceptance forecast model in the context of the Machine Learning Engineer nanodegree program from Udacity, using a dataset that is also utilized in the Data Scientist nanodegree program but with a different approach. My main goal was to apply and demonstrate my understanding of machine learning engineering concepts, using multiple AWS services such as S3, Lambda, Cloud Watch, IAM and, of curse, Sagemaker.

2. Project Overview

As a marketing strategy, Starbucks constantly sends offers for the users of the mobile app. The type of offer can vary significantly from a simply informational advertise to a ‘buy one, get one” (BOGO) offer. Since not all customers receive different offers, in different quantities at different times, it's not elementary to indicate its effectiveness o indicate for each customers are prone to accept the offer. Our task focus on deploying a machine learning model in aws that indicates if a customer is prone to accept the offer given some data that is available.

The data provided for this project is composed by 3 json files. It’s general meaning and fields are indicated above:

- portfolio.joson: Information about 10 different offer strategies.
  - id (string) — offer id
  - offer_type (string) — a type of offer ie BOGO, discount, informational
  - difficulty (int) — the minimum required to spend to complete an offer
  - reward (int) — the reward is given for completing an offer
  - duration (int) — time for the offer to be open, in days
  - channels (list of strings)
- profile.json: Demographic data for each customer.
  - age (int) — age of the customer
  - became_member_on (int) — the date when customer created an app account

- gender (str) — gender of the customer ('M','F' and 'O' for any other)
- id (str) — customer-id
- income (float) — customer's income

- transcript.json: Event registries for offer interaction or transaction.
  - event (str) — record description (ie transaction, offer received, offer viewed, etc.)
  - person (str) — customer-id
  - time (int) — time in hours since the start of the test. The data begins at time t=0
  - value — (dictionary of strings) — either an offer id or transaction amount depending on the record

3. Data Preparation and Analysis

3.1. Portfolio

	reward	channels	difficulty	duration	offer_type	id
0	10	[email, mobile, social]	10	7	bogo	ae264e3637204a6fb9bb56bc8210ddfd
1	10	[web, email, mobile, social]	10	5	bogo	4d5c57ea9a6940dd891ad53e9dbe8da0
2	0	[web, email, mobile]	0	4	informational	3f207df678b143eea3cee63160fa8bed
3	5	[web, email, mobile]	5	7	bogo	9b98b8c7a33c4b65b9aebfe6a799e6d9
4	5	[web, email]	20	10	discount	0b1e1539f2cc45b7b9fa7c272da2e1d7

Changes:

- No integrity issues found;
- 'channels' and 'offer_type' were encoded for better compatibility with ML algorithims;
- Email information as droped because is present in all offers;
- Some columns were renamed for clarity.

```
# one-hot encoding channels column
portfolio = portfolio_.copy()
portfolio['channels'] = portfolio['channels'].apply(lambda x: ','.join(map(str, x)))
portfolio = portfolio.join(portfolio['channels'].str.get_dummies(','))
portfolio.drop('channels', axis=1, inplace=True)

# one-hot encoding offer_type column
portfolio = portfolio.join(pd.get_dummies(portfolio['offer_type']))
portfolio.drop('offer_type', axis=1, inplace=True)

#drop email column since it it contains no useful information
portfolio.drop('email', axis=1, inplace=True)

#rename id column to offer_id, reward to offer_reward and duration to offer_duration
portfolio.rename(columns={'id':'offer_id', 'reward':'offer_reward', 'duration':'offer_duration'}, inplace=True)
portfolio
```

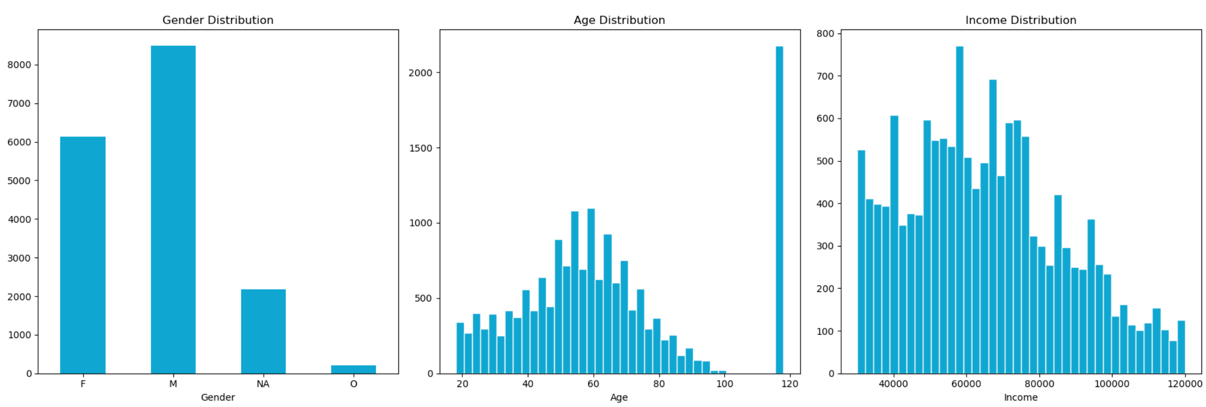
Final portfolio dataset:

	offer_reward	difficulty	offer_duration	offer_id	mobile	social	web	bogo	discount	informational
0	10	10	7	ae264e3637204a6fb9bb56bc8210ddfd	1	1	0	1	0	0
1	10	10	5	4d5c57ea9a6940dd891ad53e9dbe8da0	1	1	1	1	0	0
2	0	0	4	3f207df678b143eea3cee63160fa8bed	1	0	1	0	0	1
3	5	5	7	9b98b8c7a33c4b65b9aebfe6a799e6d9	1	0	1	1	0	0
4	5	20	10	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	1	0	1	0
5	3	7	7	2298d6c36e964ae4a3e7e9706d1fb8c2	1	1	1	0	1	0
6	2	10	10	fafdcd668e3743c1bb461111dcafc2a4	1	1	1	0	1	0
7	0	0	3	5a8bc65990b245e5a138643cd4eb9837	1	1	0	0	0	1
8	5	5	5	f19421c1d4aa40978ebb69ca19b0e20d	1	1	1	1	0	0
9	2	10	7	2906b810c7d4411798c6938adc9daaa5	1	0	1	0	1	0

3.2. Profile

	gender	age	id	became_member_on	income
0	None	118	68be06ca386d4c31939f3a4f0e3dd783	20170212	NaN
1	F	55	0610b486422d4921ae7d2bf64640c50b	20170715	112000.0
2	None	118	38fe809add3b4fcf9315a9694bb96ff5	20180712	NaN
3	F	75	78afa995795e4d85b5d9ceeca43f5fef	20170509	100000.0
4	None	118	a03223e636434f42ac4c3df47e8bac43	20170804	NaN

Some profile data is missing both on income and gender information. Histograms were used to verify the presence of outliers.



Since the number of outliers in the 'Age' field and the registers with missing data were approximately 2 thousand, I suspected they were the same, what turned out to be the case.

Changes:

- Records with missing data/outliers identified;

- Some columns were renamed for clarity;
- ‘member days’ column calculated.
- Gender encoded.

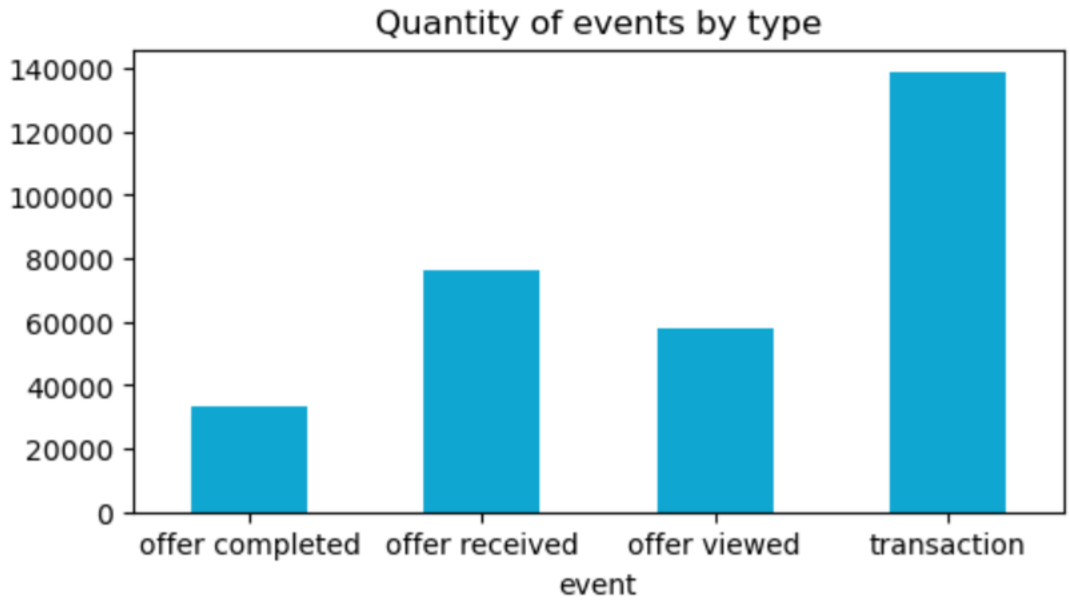
```
profile = profile_.copy()
# Since the age outliers and missing age values are the same customers, we lets identify them

# identify the age outliers
profile['incomplete_data'] = profile['gender'].isnull()

#rename id column to customer_id, became_member_on to became_member_date and income to customer_income
profile.rename(columns={'id':'customer_id', 'became_member_on':'became_member_date', 'income':'customer_income'}, inplace=True)

# adjust became_member_date from string in format YYYYMMDD to datetime
profile['became_member_date'] = pd.to_datetime(profile['became_member_date'], format='%Y%m%d')

# create a new column with the number of days since the customer became a member
profile['memberdays'] = (datetime.datetime.today() - profile['became_member_date']).dt.days

# one hot encoding gender column
profile['gender_M'] = profile['gender'].apply(lambda x: 1 if x == 'M' else 0)
profile['gender_F'] = profile['gender'].apply(lambda x: 1 if x == 'F' else 0)
profile['gender_0'] = profile['gender'].apply(lambda x: 1 if x == '0' else 0)
```

	gender	age	customer_id	became_member_date	customer_income	incomplete_data	memberdays	gender_M	gender_F	gender_0
0	None	118	68be06ca386d4c31939f3a4f0e3dd783	2017-02-12	NaN	True	2293	0	0	0
1	F	55	0610b486422d4921ae7d2bf64640c50b	2017-07-15	112000.0	False	2140	0	1	0
2	None	118	38fe809add3b4fcf9315a9694bb96ff5	2018-07-12	NaN	True	1778	0	0	0
3	F	75	78afa995795e4d85b5d9ceeca43f5fef	2017-05-09	100000.0	False	2207	0	1	0
4	None	118	a03223e636434f42ac4c3df47e8bac43	2017-08-04	NaN	True	2120	0	0	0

3.3 Transcript

	person	event	value	time
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	0
1	a03223e636434f42ac4c3df47e8bac43	offer received	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	0
2	e2127556f4f64592b11af22de27a7932	offer received	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	0
3	8ec6ce2a7e7949b1bf142def7d0e0586	offer received	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	0
4	68617ca6246f4fbc85e91a2a49552598	offer received	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	0

The main point of attention in this dataset is that the column values contain different information depending on whether the event is an offer or a transaction. There are 4 types of event not equali distibuted as shown in the follwing image.



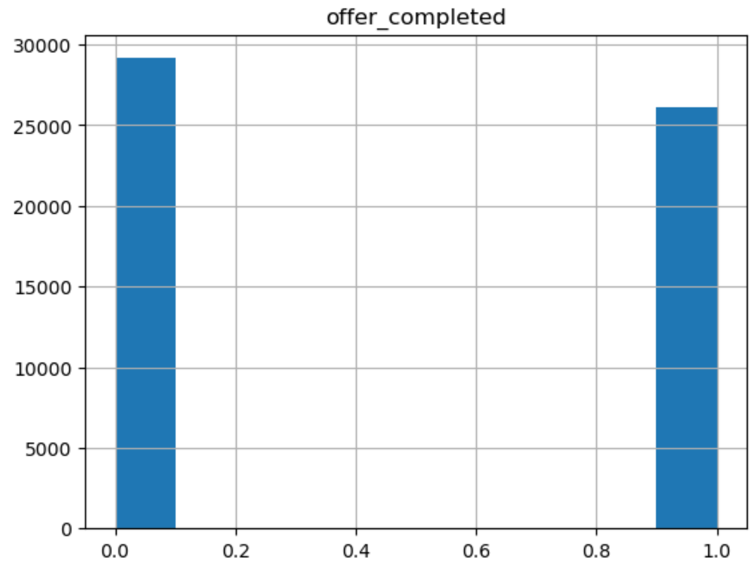
Changes:

- The transcript dataset was modified by renaming the 'person' column to 'customer_id' for clarity.
- The 'value' column was split into 'offer_id' and 'amount' columns for better compatibility with ML algorithms.
- The 'event' column was one-hot encoded using a for loop to create new columns for each unique event.

```
transcript = transcript_.copy()
#rename person column to customer_id
transcript.rename(columns={'person':'customer_id'}, inplace=True)

transcript['offer_id'] = transcript['value'].apply(lambda x: x.get('offer id')  if x.get('offer id') != None else x.get('offer_id'))
transcript['amount'] = transcript['value'].apply(lambda x: x.get('amount'))
# transcript.drop('value', axis=1, inplace=True)

# one-hot encoding event column with a for loop
for event in transcript['event'].drop_duplicates().reset_index(drop=True):
    try:
        transcript[event.split(' ')[1]] = transcript['event'].apply(lambda x: 1 if x == event else 0)
    except:
        transcript[event.split(' ')[0]] = transcript['event'].apply(lambda x: 1 if x == event else 0)
```

	customer_id	event	value	time	offer_id	amount	received	viewed	transaction	completed
12658	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	offer completed	{'offer_id': '2906b810c7d4411798c6938adc9daaa5...	0	2906b810c7d4411798c6938adc9daaa5	NaN	0	0	0	1
12672	fe97aa22dd3e48c8b143116a8403dd52	offer completed	{'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...	0	fafdcd668e3743c1bb461111dcafc2a4	NaN	0	0	0	1
12679	629fc02d56414d91bca360decdfa9288	offer completed	{'offer_id': '9b98b8c7a33c4b65b9aebfe6a799e6d9...	0	9b98b8c7a33c4b65b9aebfe6a799e6d9	NaN	0	0	0	1

It should be noted that the ratio between completed and not completed offers is similar, so was not nedded to take any effort related do ballancing the dataset.



3.4 Final dataset

After treating each data source separately, I grouped the transcripts events by customer and offer for it to make sense from a analysis point of view, since its crucial to know what happed to every offer after being received. In a model building perspective, the offer_completed id the target value for every offer received records.

I merged them into a single dataset. I then created three new columns to identify whether the offer was completed, received, or if a transaction was made. We filtered the dataset to only include records where the offer was received, and dropped any records with incomplete data. Finally, we dropped unnecessary columns to create our final dataset that can now be used as an input to train our desired model.

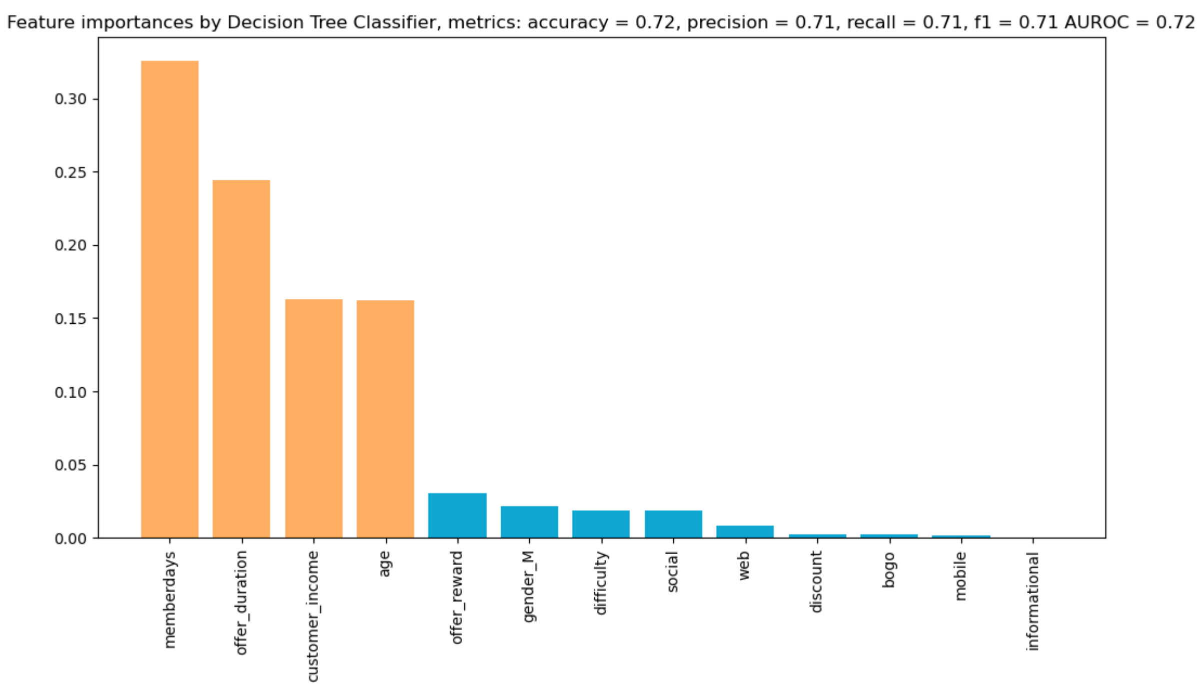
```
offers = transcript.copy().groupby(['customer_id', 'offer_id']).sum()[[ 'viewed',  'received', 'completed', 'transaction']].reset_index
offers['percent_completed'] = offers['completed'] / offers['received']

df_ = offers.merge(portfolio, on='offer_id', how='inner').merge(profile, on='customer_id', how='inner')

df_['offer_completed'] = df_['percent_completed'].apply(lambda x: 1 if x > 0.5 else 0)
df_['offer_recieved']  = df_['received'].apply(lambda x: 1 if x > 0 else 0)
df_['transaction_made'] = df_['transaction'].apply(lambda x: 1 if x > 0 else 0)

df_ =df_.query('offer_recieved == 1')

df_ = df_[df_['imcomplete_data'] == False]
df_.drop(['imcomplete_data', 'became_member_date','gender'], axis=1, inplace=True)
df_.drop(['gender_0'], axis=1, inplace=True)
df_.drop(['customer_id', 'offer_id'], axis=1, inplace=True)
df_.drop(['index','viewed','received','completed','transaction','percent_completed','transaction_made','offer_recieved','gender_F'], ax

df_.shape
```

	offer_reward	difficulty	offer_duration	mobile	social	web	bogo	discount	informational	age	customer_income	memberdays	gender_M	offer_completed
0	5	5	7	1	0	1	1	0	0	52	71000.0	2868	1	0
1	0	0	3	1	1	0	0	0	1	52	71000.0	2868	1	0
2	2	10	7	1	0	1	0	1	0	52	71000.0	2868	1	1
3	5	5	7	1	0	1	1	0	0	32	37000.0	1944	1	0
4	10	10	7	1	1	0	1	0	0	32	37000.0	1944	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
63282	5	20	10	0	0	1	0	1	0	59	61000.0	3226	1	0
63283	5	20	10	0	0	1	0	1	0	56	35000.0	1848	0	0
63284	5	20	10	0	0	1	0	1	0	25	73000.0	2605	1	1
63286	5	20	10	0	0	1	0	1	0	64	72000.0	1820	1	0
63287	5	20	10	0	0	1	0	1	0	45	63000.0	2180	0	0

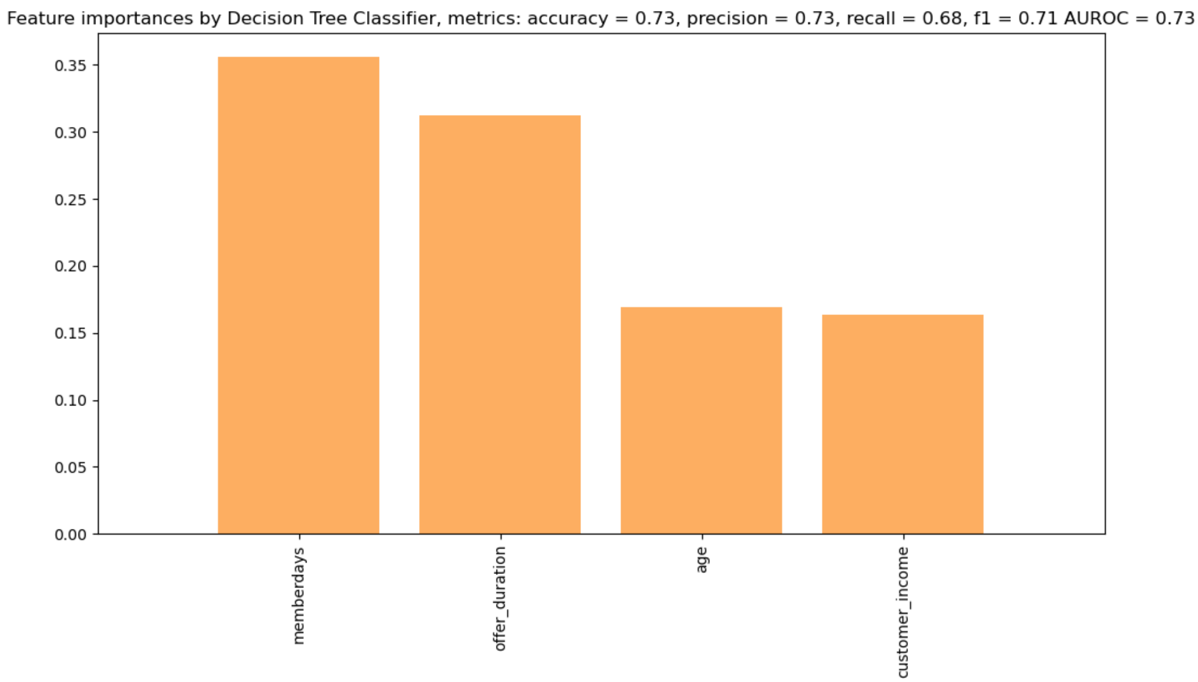
4. Model development

4.1 Metrics and baseline model

To start exploring the prediction power of the created dataset and to be confident the the usage of the mode complex models is relevant, is important to first define a simple benchmark model with a calculated metric that the final model should be able to beat. Since is a classification problem, one possible approach is to verify the most important features with a single decision tree and verify how well our model performs using only those.



Considering the business context of the data, sometimes the company goal could be to maximaze the number of accepted offers, for this scenario the recall of model is critical, and in othe situation could be to minimize the amount of orders sent keeping only those more likely to to succeeded. For that reason, the area under the receiver operating characteristic (ROC) curve was chosen to evaluate and compare the models to be created. By this metric, the model trained only by the most important features performed slightly better than the previous one, defining an benchmark value of 0.73.



4.2 Trying to beat the benchmark model

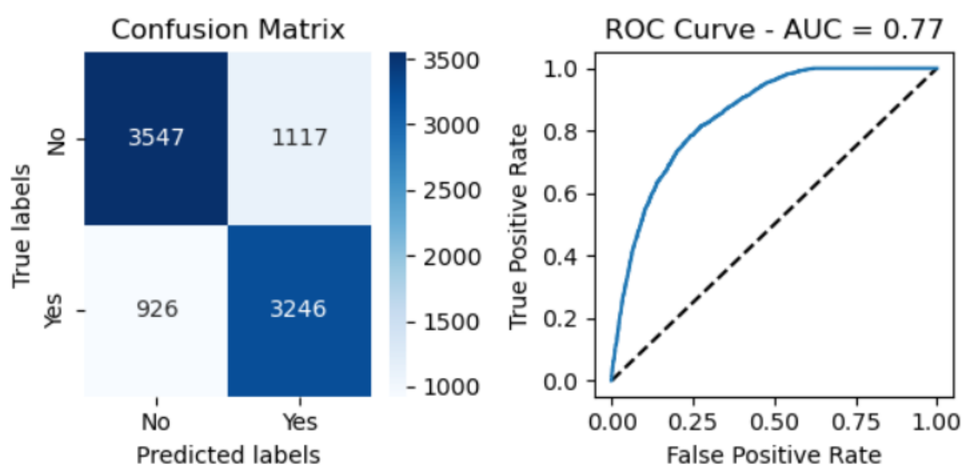
The model chosen to test with the increasing of complexity is beneficial was the XGBoost classifier implemented as indicated above.

```
# creating a function to train and evaluate the model
def train_evaluate_model(model, X_train, y_train, X_val, y_val):
    # training the model
    model.fit(X_train, y_train)

    # predicting the model
    y_pred = model.predict(X_val)

    # evaluating the model
    accuracy = accuracy_score(y_val, y_pred)
    precision = precision_score(y_val, y_pred)
    recall = recall_score(y_val, y_pred)
    f1 = f1_score(y_val, y_pred)
    roc_auc = roc_auc_score(y_val, y_pred)

    # printing the metrics
    print('Accuracy: {:.2f}%'.format(accuracy*100))
    print('Precision: {:.2f}%'.format(precision*100))
    print('Recall: {:.2f}%'.format(recall*100))
    print('F1 Score: {:.2f}%'.format(f1*100))
    print('ROC AUC: {:.2f}%'.format(roc_auc*100))

    # plotting the confusion matrix and ROC AUC curve side by side
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(6, 3))

    # Confusion Matrix
    cm = confusion_matrix(y_val, y_pred)
    sns.heatmap(cm, annot=True, ax=ax1, cmap='Blues', fmt='g')
    ax1.set_xlabel('Predicted labels')
    ax1.set_ylabel('True labels')
    ax1.set_title('Confusion Matrix')
    ax1.xaxis.set_ticklabels(['No', 'Yes'])
    ax1.yaxis.set_ticklabels(['No', 'Yes'])
```

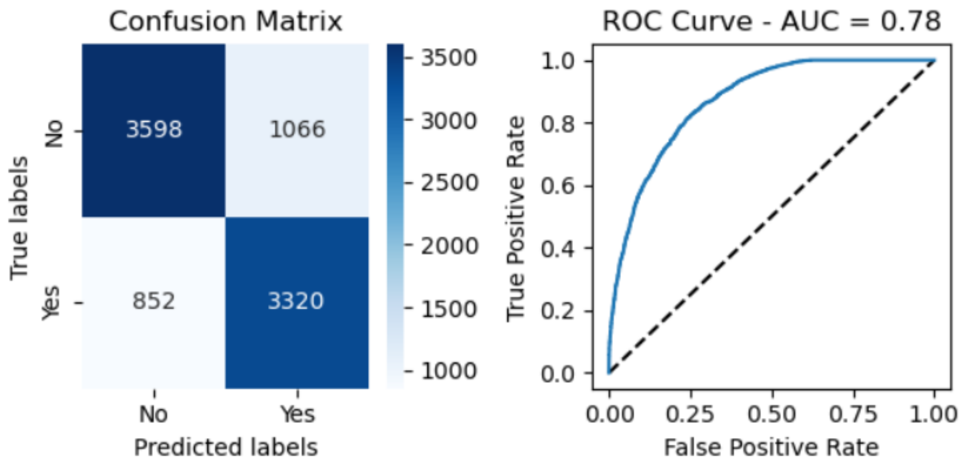
```
    # ROC Curve
    y_pred_proba = model.predict_proba(X_val)[:, 1]
    fpr, tpr, thresholds = roc_curve(y_val, y_pred_proba)
    ax2.plot([0, 1], [0, 1], 'k--')
    ax2.plot(fpr, tpr)
    ax2.set_xlabel('False Positive Rate')
    ax2.set_ylabel('True Positive Rate')
    ax2.set_title('ROC Curve')

    # Adjust the spacing between plots
    plt.tight_layout()

    # Show the plots
    plt.show()

# training and evaluating the model
xgb = XGBClassifier(random_state=42)
train_evaluate_model(xgb, X_train, y_train, X_val, y_val)
```

As was made in the definition of the benchmark model, two models were trained, one using only the more important features and the other one with all variables in the dataset. Diverging from the decision tree implementation, the model that considered more features had a superior performance in all the metrics calculated.

```
XGBoost Classifier with most important features:
Accuracy: 76.88%
Precision: 74.40%
Recall: 77.80%
F1 Score: 76.06%
ROC AUC: 76.93%
```



```
XGBoost Classifier with all features:
Accuracy: 78.29%
Precision: 75.70%
Recall: 79.58%
F1 Score: 77.59%
ROC AUC: 78.36%
```

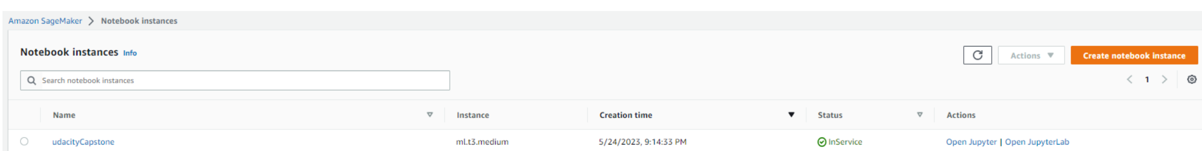


With an accuracy and ROC AUC of 78%, the XGBoost with all the features modeling is considered satisfactory. The next step is to prepare the environment for deploying the solution with AWS.

5. AWS Model model training and deployment.

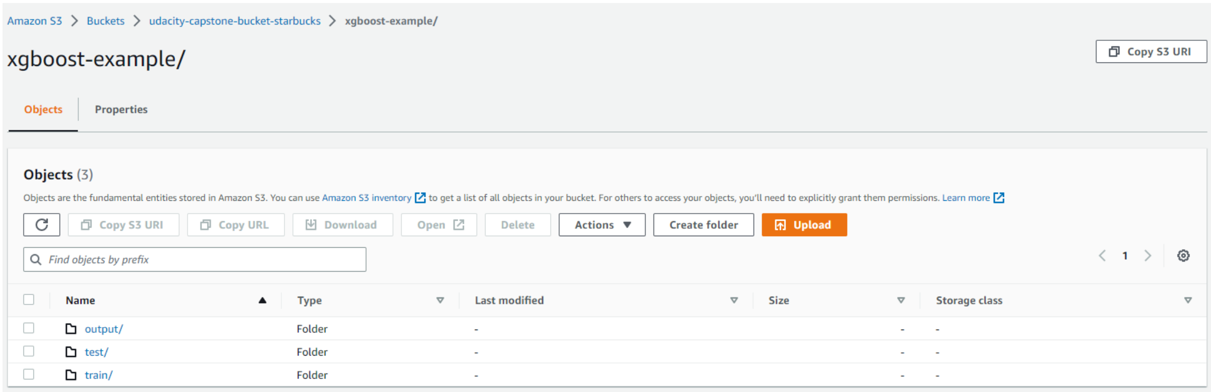
5.1. Data setup in S3

The first step in AWS was to executed the code that was first run locally in the notebook instance created. An instance type ml.t3.medium was chosen.



After that, train and test data were saved in the instance in order to be sent to the S3 bucket created to this project.

```
train_data = pd.concat([y_train,X_train], axis=1)
train_data.to_csv('train_data.csv', index=False,header=False)

test_data = pd.concat([y_test,X_test], axis=1)
test_data.to_csv('test_data.csv', index=False,header=False)

prefix = 'xgboost-example'
input_train = sagemaker_session.upload_data(path='train_data.csv', bucket=bucket, key_prefix=prefix + '/train')
input_test = sagemaker_session.upload_data(path='test_data.csv', bucket=bucket, key_prefix=prefix + '/test')
```

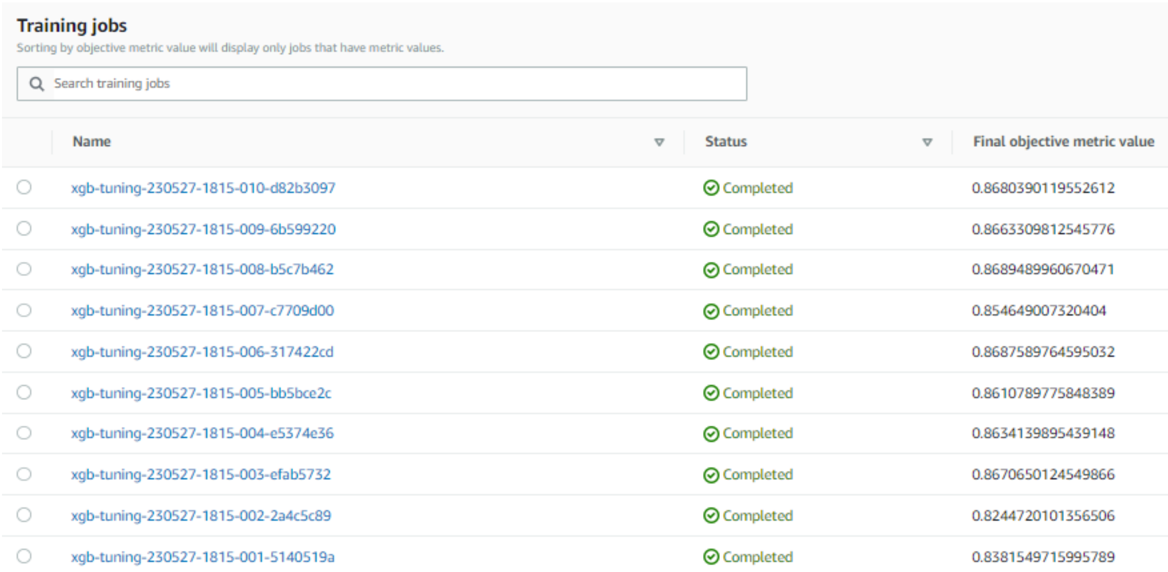


5.2. Create estimator and improve model with hyperparameter tunning.

In an effort to obtain a final model that performs better than the one with 0.78 ROC AUC, hyperparameter tuning was performed with a wide range of parameters.

```
container = get_image_uri(boto3.Session().region_name, 'xgboost')

role = get_execution_role()

xgb = sagemaker.estimator.Estimator(container,
                                    role,
                                    instance_count=1,
                                    instance_type='ml.m4.xlarge',
                                    output_path=f's3://{bucket}/{prefix}/output',
                                    sagemaker_session=sagemaker_session)

train_data = sagemaker.inputs.TrainingInput(s3_data=input_train, content_type='csv')
test_data = sagemaker.inputs.TrainingInput(s3_data=input_test, content_type='csv')

data_channels = {'train': train_data, 'validation': test_data}

# Set the hyperparameters to tune
hyperparameter_ranges = {
    'max_depth': IntegerParameter(1, 10),
    'eta': ContinuousParameter(0.01, 0.2),
    'min_child_weight': IntegerParameter(1, 10),
    'subsample': ContinuousParameter(0.5, 0.9),
    'gamma': ContinuousParameter(0, 5),
    'num_round': IntegerParameter(1, 100)
}

# Create a hyperparameter tuner
tuner = HyperparameterTuner(
    estimator=xgb,
    objective_metric_name='validation:auc',
    hyperparameter_ranges=hyperparameter_ranges,
    max_jobs=10,
    max_parallel_jobs=2,
    objective_type='Maximize',
    base_tuning_job_name='xgb-tuning'
)

# Launch the hyperparameter tuning job
tuner.fit(data_channels)
```

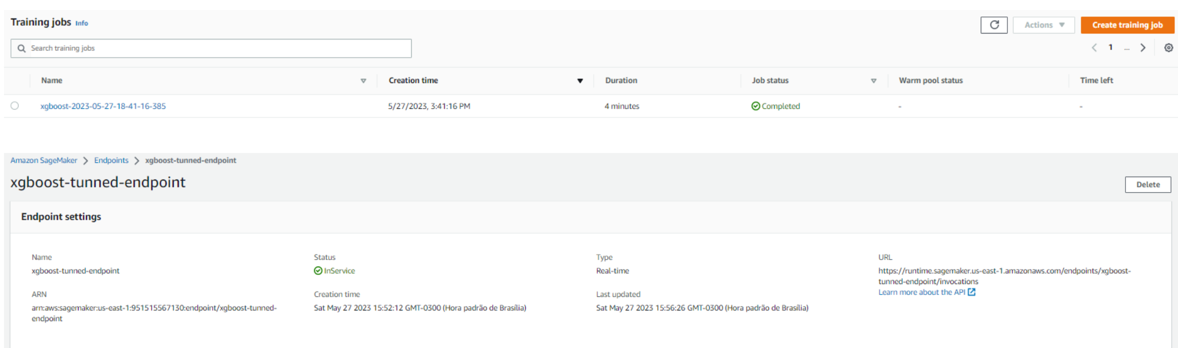
The hyperparameter tinning could achieve a value of almost 0.87 for our benchmark metric what confirms the importance if the process.



Name	Status	Final objective metric value
xgb-tuning-230527-1815-010-d82b3097	Completed	0.8680390119552612
xgb-tuning-230527-1815-009-6b599220	Completed	0.8663309812545776
xgb-tuning-230527-1815-008-b5c7b462	Completed	0.8689489960670471
xgb-tuning-230527-1815-007-c7709d00	Completed	0.854649007320404
xgb-tuning-230527-1815-006-317422cd	Completed	0.8687589764595032
xgb-tuning-230527-1815-005-bb5bce2c	Completed	0.8610789775848389
xgb-tuning-230527-1815-004-e5374e36	Completed	0.8634139895439148
xgb-tuning-230527-1815-003-efab5732	Completed	0.8670650124549866
xgb-tuning-230527-1815-002-2a4c5c89	Completed	0.8244720101356506
xgb-tuning-230527-1815-001-5140519a	Completed	0.8381549715995789

5.3. Deploying and testing final model and testing endpoint.

The last steps in Sagemaker were to train the model with the better hyperparameters, deploy it and then make a inference to test the endpoint. Since the model is small, a ml.t2.medium instance was used for the endpoint.



For testing, I hardcoded some parameters and made adjustiments to the csv format to be inputted in the model. All the prediction attempts were successful and al the results were coherent with the data comprehension obtained with the initial exploration.

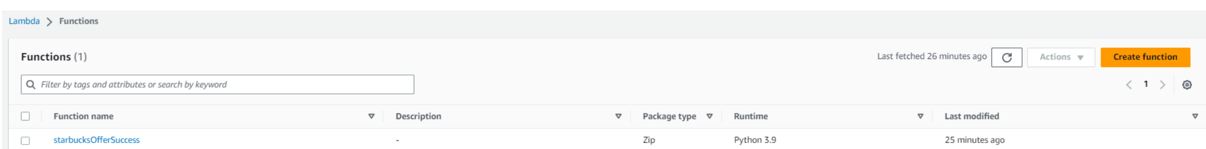
```
import json
# Hardcoded data for prediction
hardcoded_data = {
"offer_reward":30.0,
"difficulty":30.0,
"offer_duration":30.0,
"mobile":1.0,
"social":1.0,
"web":1.0,
"bogo":1.0,
"discount":15.0,
"informational":1.0,
"age":58.0,
"customer_income":55000.0,
"memberdays":600.0,
```

```
"gender_M":1.0
}

# Convert the hardcoded data to a list of values
input_data = [list(hardcoded_data.values())]

# Create a low-level SageMaker client
sagemaker_client = boto3.client('sagemaker-runtime')

# Specify the endpoint name
endpoint_name = 'xgboost-tunned-endpoint'

# Convert the input data to CSV format
input_data_csv = ','.join([str(val) for val in input_data[0]])

# Make a request to the endpoint
response = sagemaker_client.invoke_endpoint(
    EndpointName=endpoint_name,
    ContentType='text/csv',
    Body=input_data_csv
)


# Parse the response
prediction = response['Body'].read().decode()
prediction = json.loads(prediction)

if prediction > 0.5:
    print('The offer will likely be completed. (probability: {:.2f}%)'.format(prediction*100))
else:
    print('The offer will likely not be completed. (probability: {:.2f}%)'.format(prediction*100))
```

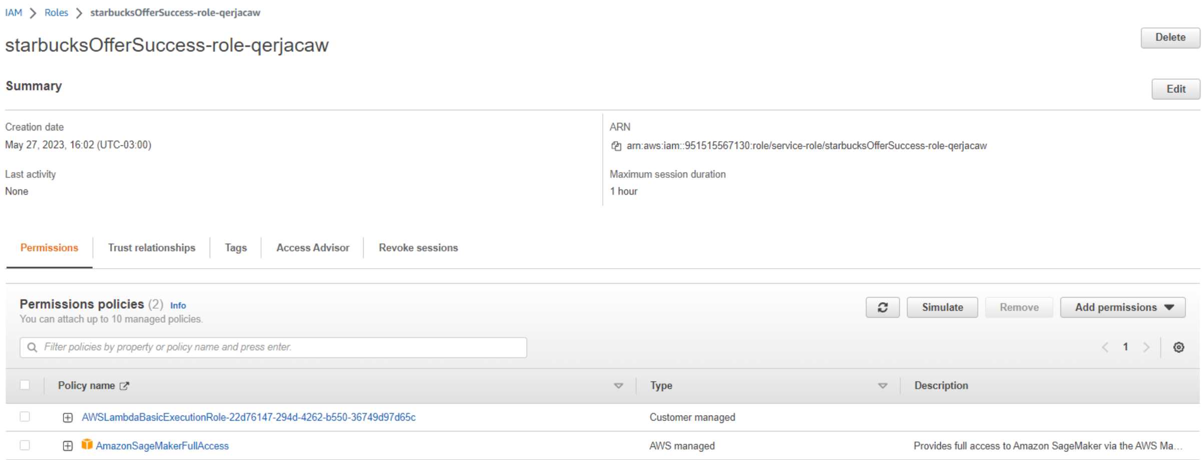
```
The offer will likely be completed. (probability: 84.73%)
```

6. Inferencing with Lambda

To finish this project, the integration with the deployed endpoint was made possble using a Lambda function whose input are the parameters related to the offer. This function should answer if this offer would be sucessull or not. The function created was named “starbucksOfferSuccess”.



By defalt, the function is not allowed to invoke endpoints. To solve that the ‘AmazonSageMakerFullAccess’ policy was attached to the function.



Finaly, the implementation of the function was made using two files ‘lambda_function.py’ and ‘inference.py’ and the test was successfull as shown above.

8. Conclusion

In this capstone project, as an AWS machine learning engineer, I developed a Starbucks offer acceptance forecast model using AWS services and machine learning techniques. By leveraging the provided data and applying data preprocessing and feature engineering, I built a model to predict whether a customer is likely to accept a Starbucks offer.

Starting with a baseline model using a decision tree, I achieved a benchmark ROC AUC score of 0.73. The final model surpassed the benchmark achieving a value of 0.87, demonstrating improved accuracy and ROC AUC score. Also the model was deployed in a endpoint and could be accesed outside sagemeker by a lambda function.

Overall, this project showcased the AWS machine learning engineer's proficiency in leveraging various AWS services, such as Amazon SageMaker, S3, IAM and AWS Lambda, to build a end-to-end solution. The utilization of machine learning techniques, combined with effective data preprocessing and feature engineering, resulted in a model that provided accurate predictions for Starbucks offer acceptance.