Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

Project Overview

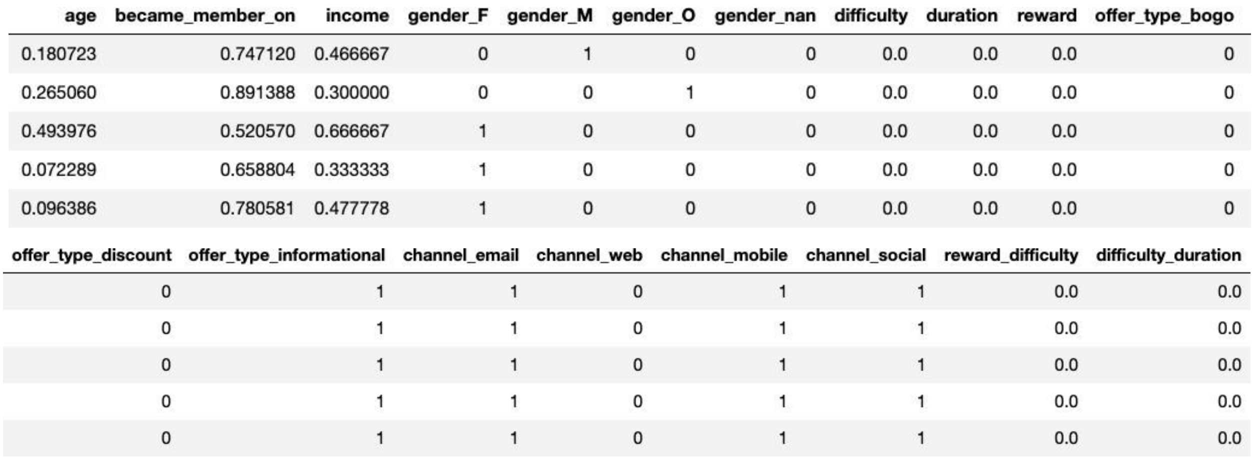
Starbucks is an American coffeehouse chain. Once every few days, Starbucks sends out an offer to users via different ways such as mobile app. An offer can be merely an advertisement for a drink or an actual offer such as a discount or BOGO (buy one get one free). Some users might not receive any offer during certain weeks. An important characteristic regarding this capstone is that not all users receive the same offer. As part of marketing strategy, we always want to figure out if a customer will spend more by giving a sound offer. Providing right offer to right customer could help build loyalty of the brand and product and as a result increasing sales margins in the long run.
The goal is to create a predictor to answer a question, that is, if a customer will response and complete a given offer?
The data is contained in three files. The files are in data folder in this repo:

- portfolio.json: offer ids and meta data about each offer (duration, type, etc.)
- profile.json: demographic data for each customer
- transcript.json: records for transactions, offers received, offers viewed, and offers completed.

These files are cleaned, processed, transformed and joined into one table which contains demographic data of a customer, attributes of the offer and whether the customer complete the offer.

The final dataset is 76277 * 20 in shape and columns or features are age, became_member_on, income, gender_F, gender_M, gender_O, gender_nan, difficulty, duration, reward, offer_type_bogo, offer_type_discount, offer_type_informational, channel_email, channel_web, channel_mobile, channel_social, reward%difficulty, difficulty%duration. Labels values are balanced because the number of occurrences of positive label is 34809 while the number is 41468.

Below are the first 5 rows of the dataset. The first column is label. The rest are features.



age	became_member_on	income	gender_F	gender_M	gender_O	gender_nan	difficulty	duration	reward	offer_type_bogo
0.180723	0.747120	0.466667	0	1	0	0	0.0	0.0	0.0	0
0.265060	0.891388	0.300000	0	0	1	0	0.0	0.0	0.0	0
0.493976	0.520570	0.666667	1	0	0	0	0.0	0.0	0.0	0
0.072289	0.658804	0.333333	1	0	0	0	0.0	0.0	0.0	0
0.096386	0.780581	0.477778	1	0	0	0	0.0	0.0	0.0	0

offer_type_discount	offer_type_informational	channel_email	channel_web	channel_mobile	channel_social	reward_difficulty	difficulty_duration
0	1	1	0	1	1	0.0	0.0
0	1	1	0	1	1	0.0	0.0
0	1	1	0	1	1	0.0	0.0
0	1	1	0	1	1	0.0	0.0
0	1	1	0	1	1	0.0	0.0

Previous researches on same datasets are found. A research, Who Might Respond to Starbucks' offer? try to solve similar question by AdaBoostClassifier. When processing transcript dataset, it simply removed offers that are completed but no viewed and ignore more complex case such as a offer that is completed and then viewed, etc. Another research Starbucks Capstone Challenge Dataset Customer Offer Success Prediction uses random forest model by creating features that describe an offer's success rate as a function of offer difficulty, duration and reward. Our benchmark model is inspired by this research. XGBoost, a implementation of boosting random forest model is a good candidate for comparing our solution's performance. Thus, in our research, we try another popular model, neural network and we do see the new model bring improvements on the prediction.

Problem Statement

I chose to build a model that predicts whether or not a customer will complete an offer, meaning that the customer will receive a offer, view the offer and finish the offer before expire day. Thus, to solve this problem, I will establish a binary classifier.

One potential solution has 3 steps:

1. Preprocess combined transaction, demographic and offer data. This dataset describes an offer’s attributes, the user's demographic data and whether the offer was successful. Also, split datasets into train and test datasets.

2. Training XGBoost Model as benchmark model.

3. Training PyTorch deep learning model and improve the results.

Metrics

The evaluation metric is the Receiver Operating Characteristic Curve (ROC AUC) score from prediction scores. It computes area under the Receiver Operating Characteristic Curve. This will quantify the performance of both the benchmark model and the solution model. The reason is that the datasets are balanced and also, we only care about the final class predictions and we don’t want to tune threshold.

II. Analysis

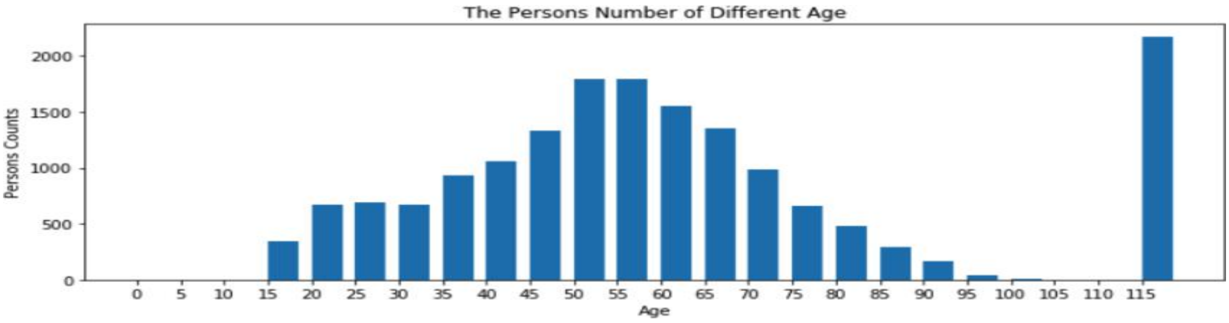
Data Exploration and Visualization

Portfolio Data

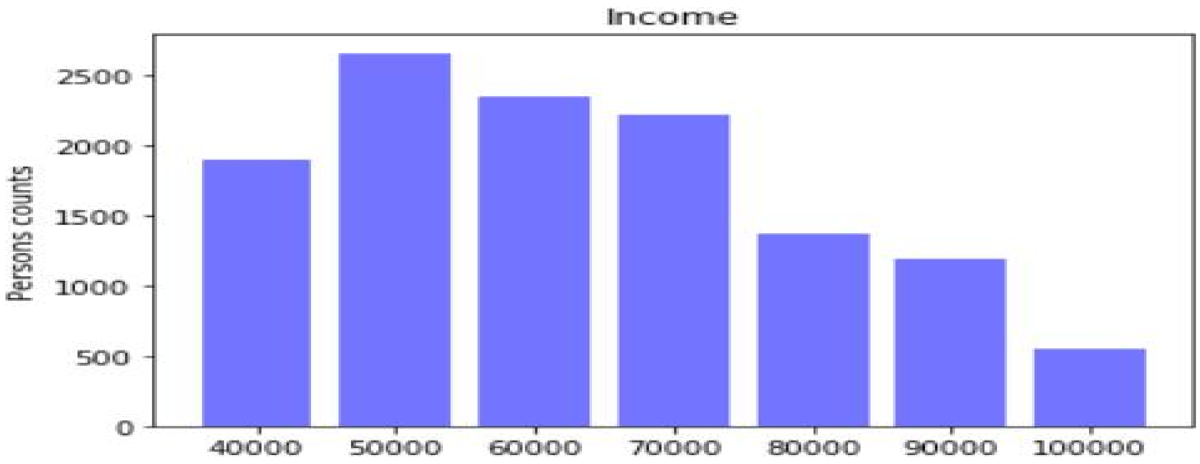
This dataset is about offers sent during 30-day test period. There are totally 10 offers. 4 of them are BOGO, 4 are discount and 2 are informational. All offers are distributed via email. By contrast only 6 offers are showed in social networks.

Profile Data

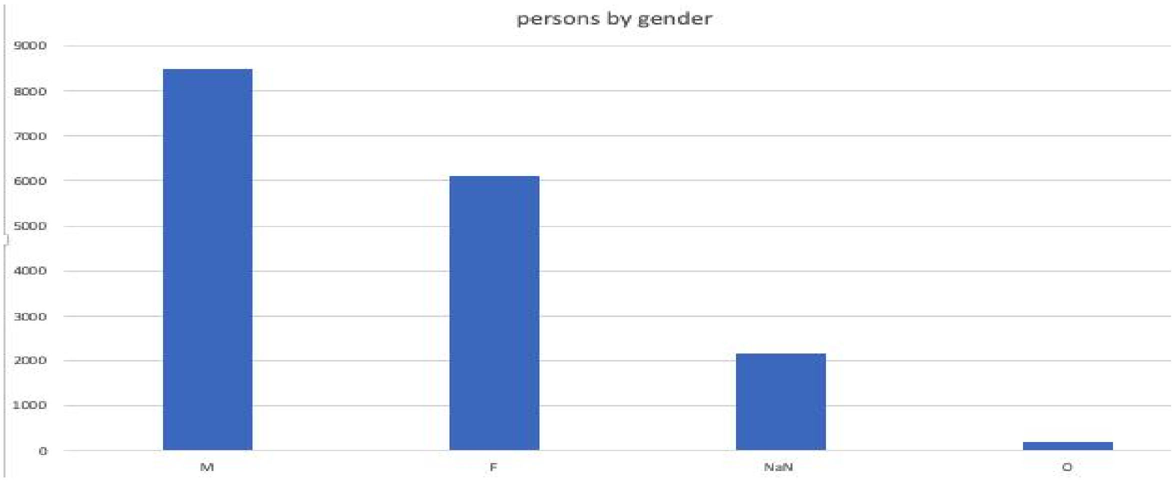
This dataset describes rewards program users, 17000 users totally. We show customers' age in the interval of 5 years. The missing value is encoded as 118, which is more than 2000 data points. Most of the customers fall in the age range from 50 to 60 years old.



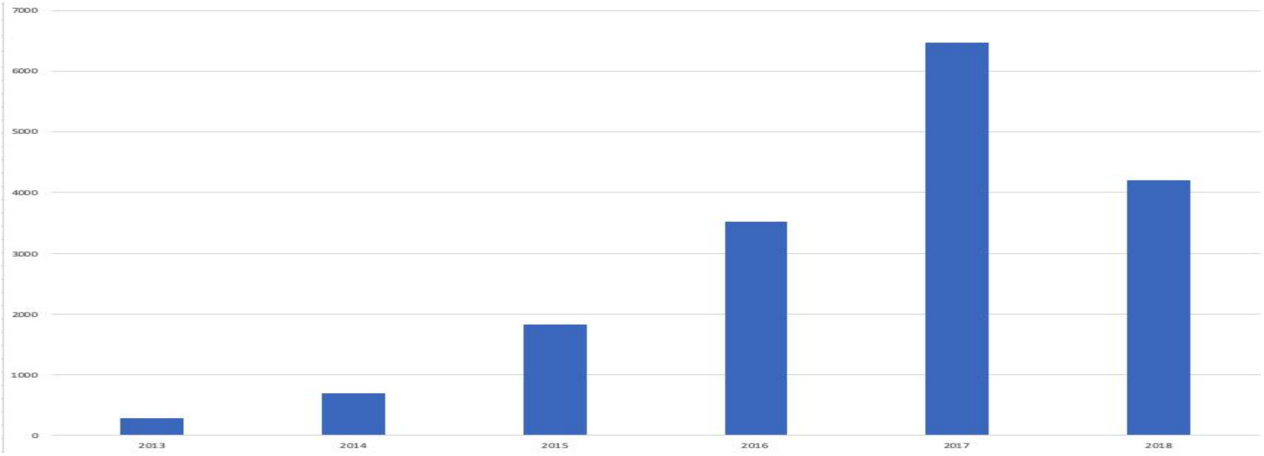
Most of the customers fall in the income range between 50000 and 60000. The income ranges from 40000 to 120000.



As for gender, there are two other categories than female and male. Male customers are more than female customers and gender O is smallest in number.

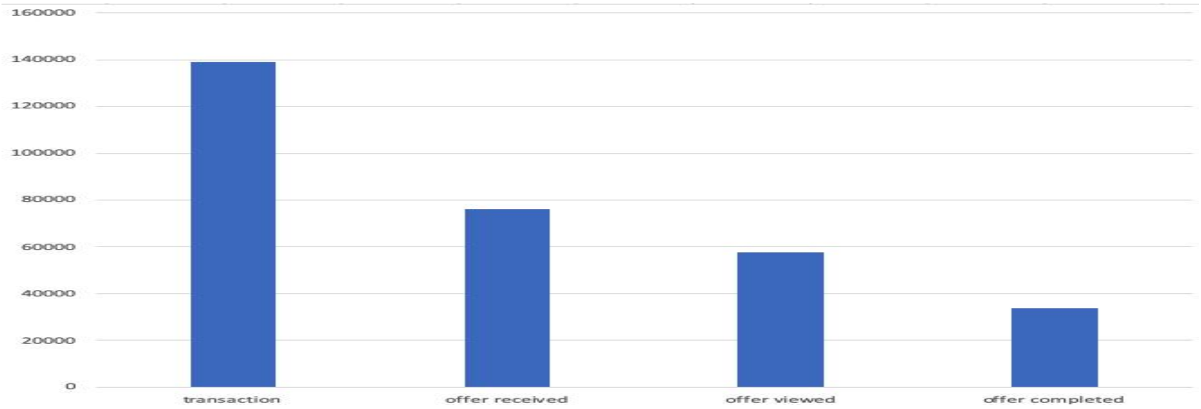


Member grows by year and get to the peak at 2017. The plot suggest that most customers recently joined the rewards program.

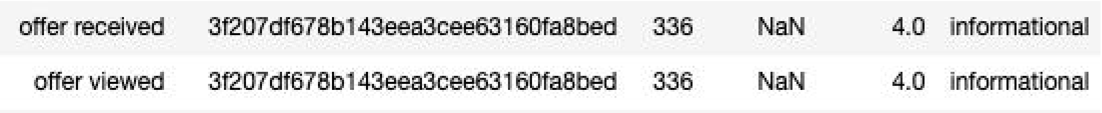


Transcript Data

This dataset contains event log. There are 306648 events. Similarly, we will explore insights of transactions.There are four events, offer received, offer viewed, transaction, offer completed. We could see the amount of completed offer is around half of that of offer received. Offer viewed is a bit lower than offer received. It hints the dataset would not be perfectly balanced.

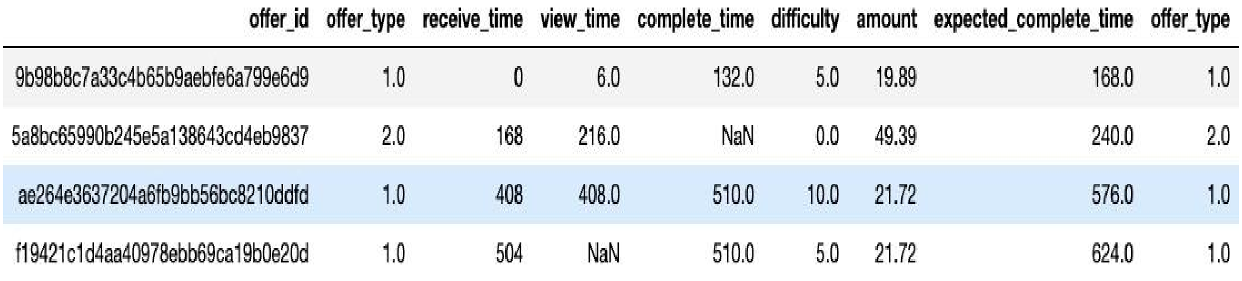


When discovering this dataset, we do see some abnormalities. For example, offer type informational usually don't have a complete event. See below summary for one person. The second row shows after viewing this offer, a user spends 49.39 dollars. We think such behavior should be consider a success offer, thus we adjust the class to completed offer. We also see behavior like no money spent after viewing informational offer. We don't category this to completed offer. Example is provided following:

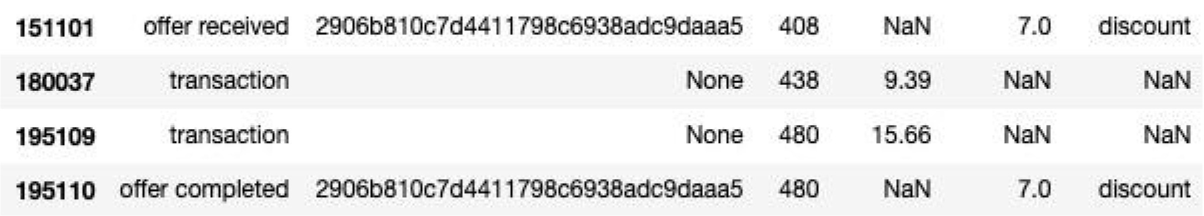


offer received	3f207df678b143eea3cee63160fa8bed	336	NaN	4.0	informational
offer viewed	3f207df678b143eea3cee63160fa8bed	336	NaN	4.0	informational

According to the instruction of this project, we should not consider offer complete if people didn't view it. See below to find this case.

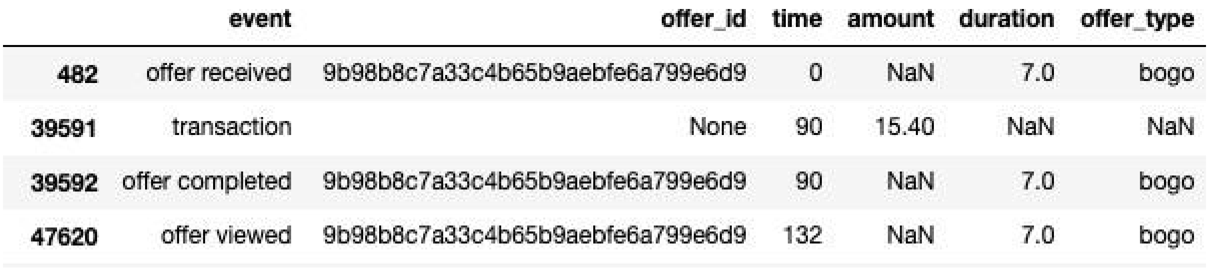


offer_id	offer_type	receive_time	view_time	complete_time	difficulty	amount	expected_complete_time	offer_type
9b98b8c7a33c4b65b9aebfe6a799e6d9	1.0	0	6.0	132.0	5.0	19.89	168.0	1.0
5a8bc65990b245e5a138643cd4eb9837	2.0	168	216.0	NaN	0.0	49.39	240.0	2.0
ae264e3637204a6fb9bb56bc8210ddfd	1.0	408	408.0	510.0	10.0	21.72	576.0	1.0
f19421c1d4aa40978ebb69ca19b0e20d	1.0	504	NaN	510.0	5.0	21.72	624.0	1.0



151101	offer received	2906b810c7d4411798c6938adc9daaa5	408	NaN	7.0	discount
180037	transaction	None	438	9.39	NaN	NaN
195109	transaction	None	480	15.66	NaN	NaN
195110	offer completed	2906b810c7d4411798c6938adc9daaa5	480	NaN	7.0	discount

We could clearly see the offer id 290 is received and completed without view event. However, we see interesting behavior like offer viewed after offer completed. See below records:



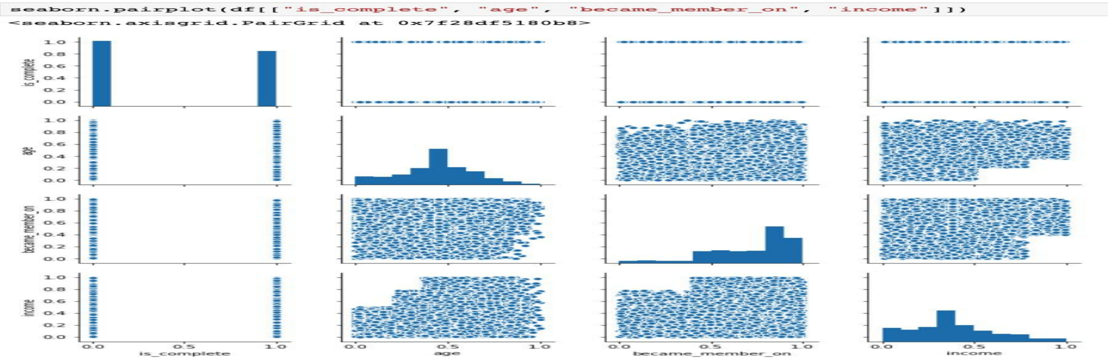
	event	offer_id	time	amount	duration	offer_type
482	offer received	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	NaN	7.0	bogo
39591	transaction	None	90	15.40	NaN	NaN
39592	offer completed	9b98b8c7a33c4b65b9aebfe6a799e6d9	90	NaN	7.0	bogo
47620	offer viewed	9b98b8c7a33c4b65b9aebfe6a799e6d9	132	NaN	7.0	bogo

The offer is viewed after completion. We also observe that the time offer viewed is still in valid duration and amount after offer received exceed difficulty (required amount). We consider this case also completed offer because customer may see the offer summary (not detail) and didn't take any response to it timely. But we don't consider the offer is completed if any requirements such as duration or difficulty are satisfied.

Descriptive statistics

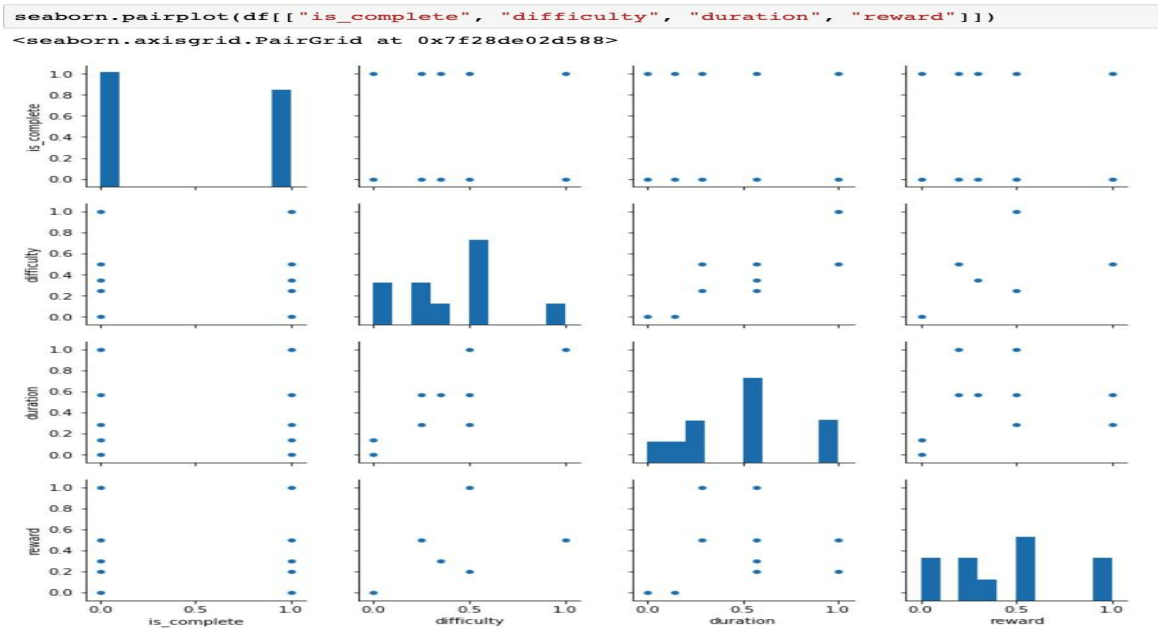
Feature distribution is a critical characteristic that influences models greatly. We would like to visualize pairwise relationships in our dataset. This creates a matrix of axes and shows the relationship for each pair of columns and also draws the uni-variate distribution of each variable on the diagonal axe. Below are plots on features we are interested on.

1.seaborn.pairplot(df[["is_complete", "age", "became_member_on", "income"]]). We can see become_member_on skews towards right while income skews towards left. And age data is distributed normally. We could also tell young people don't have higher income, which may be a common sense. And we observe that higher income group are getting to join reward programs. This may be a good signal of revenue growing.



```
seaborn.pairplot(df[["is_complete", "age", "became_member_on", "income"]])
<seaborn.axisgrid.PairGrid at 0x7f28df5180b8>
```

2. seaborn.pairplot(df[["is_complete", "difficulty", "duration", "reward"]]). Offer's sample size is too small, but we still see normal distribution on thediagrams. Other fact is as difficulty increase, duration and rewards tend to increase too.



```
seaborn.pairplot(df[["is_complete", "difficulty", "duration", "reward"]])
```

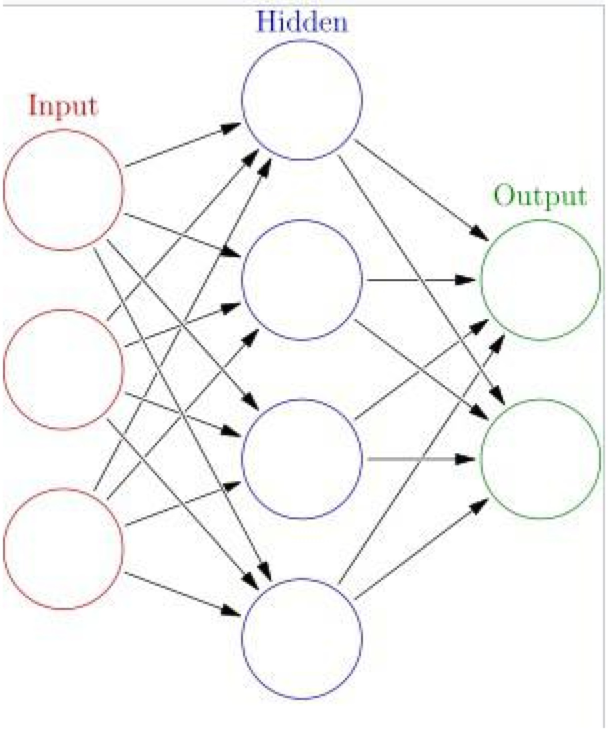
```
<seaborn.axisgrid.PairGrid at 0x7f28de02d588>
```

In summary, we do see some relationships among different features. But their relationship with our object is complete an offer is not so clear. It makes sense because each feature may only contribute little or nothing to describe the object. Thus, our model should have such an ability to capture all valuable information from all those features.

Algorithms and Techniques

Our solution for this problem is a custom PyTorch neural network classifier. Neural networks are a kind of supervised learning model. It computes systems that are inspired by, but not necessarily identical to, the biological neural networks that constitute animal brains. Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. Our model will have one hidden layer between input and output layer. And nodes are fully connected with linear regression model. The output layer go through sigma function to produce scalar value.

See below image for the graph:



There are other factors impact our model such as dropout, optimizer and criterion. A dropout function is added because we would like to avoid over-fitting. In training process, some data points may drop out with a certain probability. We use Adam Optimizer which is a common one in PyTorch. The object of using an optimizer is that We want the model to get trained to reach the state of maximum accuracy given resource constraints like time, computing power, memory etc. As for loss function, we choose BCEloss which measures the Binary Cross Entropy between the target and the output.

Benchmark

We use XGBoost model as benchmark. Hyperparameters are
max_depth = 5,
eta = 0.2,
gamma = 4,
min_child_weight = 6,
subsample = 0.8,
objective = 'binary:logistic',
The ROC-AUC score is 0.71594. This result will be used as the threshold to determine the improvement of solution model of which the ROC-AUC score is higher.

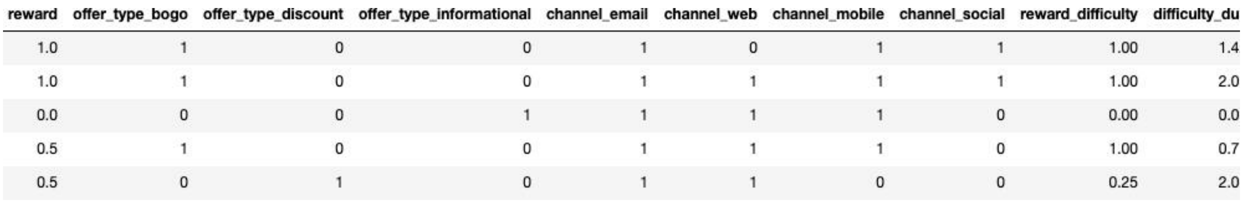
III. Methodology

Data Preprocessing

In this section, we will preprocess three datasets and deal with abnormalities data points and combine them to the dataset which will be used for training and testing models. The development codes are in starbucks notebook and in scripts folder.

Portfolio Dataset

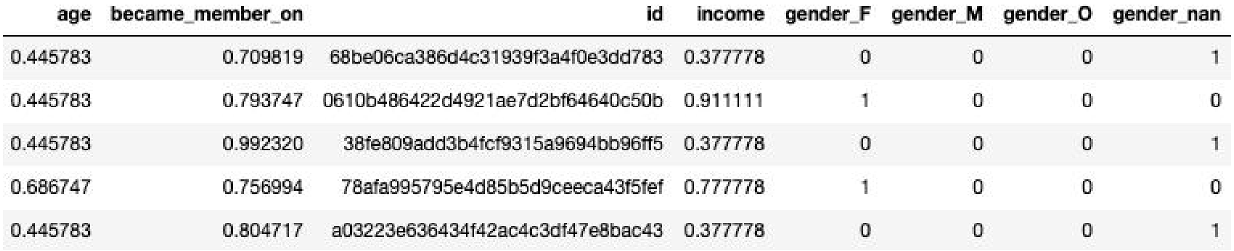
In this dataset, we found two columns are category data, offer_type and channels. We first break out these two columns by using one hot encoding. Second, all columns are numeric data except id and columns like difficulty, reward are measured on different scales comparing to one hot encoding columns. We adjust those values by performing normalization on them. Third, since we do normalization, we may lose value as being absolute value. We add two more features, that is, the ratio of reward against difficulty and the ratio of difficulty against duration. The former represents the ratio of return by completing an offer. You could image the higher the value, the higher probability a custom tend to response it. The latter shows the ratio of on average how much to pay to finish an offer. The lower is more attractive. The below image shows the processed portfolio dataset. There are 10 features.



reward	offer_type_bogo	offer_type_discount	offer_type_informational	channel_email	channel_web	channel_mobile	channel_social	reward_difficulty	difficulty_du
1.0	1	0	0	1	0	1	1	1.00	1.4
1.0	1	0	0	1	1	1	1	1.00	2.0
0.0	0	0	1	1	1	1	0	0.00	0.0
0.5	1	0	0	1	1	1	0	1.00	0.7
0.5	0	1	0	1	1	0	0	0.25	2.0

Profile Dataset

As for profile, similar to portfolio dataset, we have one category column, gender. We apply one hot encoding to this column. Then, we need to deal with NaN in income and age. We choose median to fill in because we saw the distribution of those two columns are skewed so that median maybe a better choice than average. Next, we have a date type column, become_member_on. This value matters but the actual value is not necessary. We convert the data to unix timestamp so we only keep the distance in timeline. Lastly, all columns are numeric now. They need be in same scale. Thus, we do normalization on all columns. Here is the processed dataset.



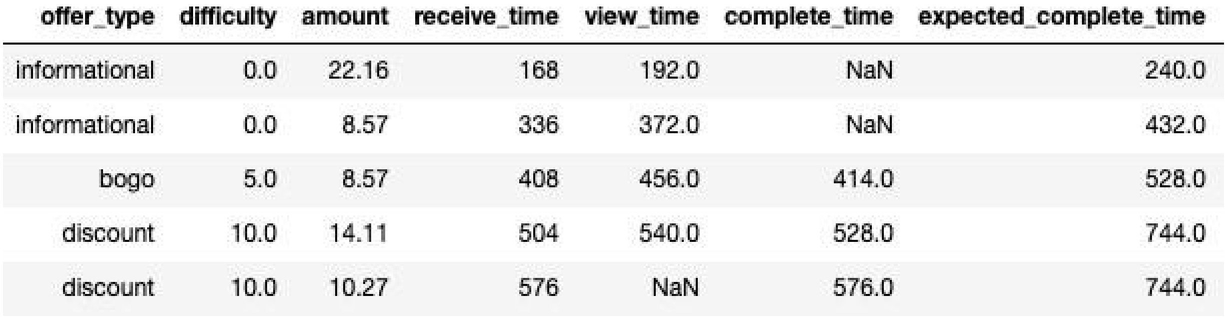
age	became_member_on	id	income	gender_F	gender_M	gender_O	gender_nan
0.445783	0.709819	68be06ca386d4c31939f3a4f0e3dd783	0.377778	0	0	0	1
0.445783	0.793747	0610b486422d4921ae7d2bf64640c50b	0.911111	1	0	0	0
0.445783	0.992320	38fe809add3b4fcf9315a9694bb96ff5	0.377778	0	0	0	1
0.686747	0.756994	78afa995795e4d85b5d9ceeca43f5fef	0.777778	1	0	0	0
0.445783	0.804717	a03223e636434f42ac4c3df47e8bac43	0.377778	0	0	0	1

Transcript Dataset

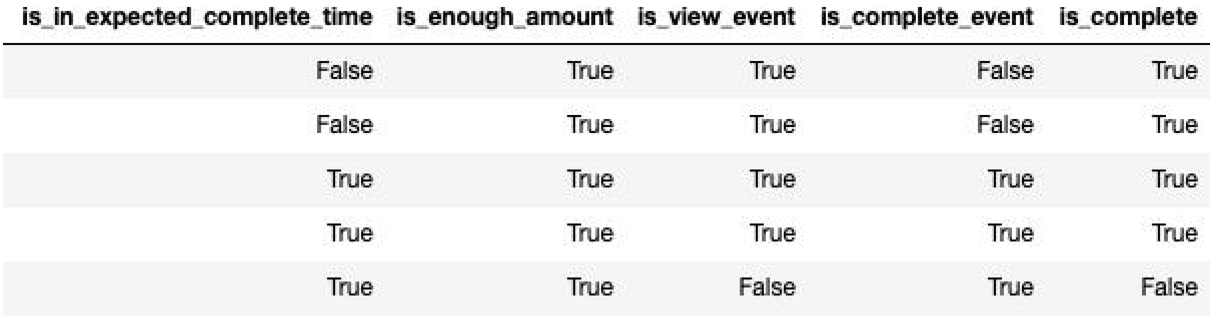
In terms of transcript, our goal is to create a label dataset. First of all, we need clean this dataset. We saw a complex dictionary data structure in value column so that the value column breaks out into two columns, offer_id and amount (we don't care reward here). Then, we need combine transcript and portfolio dataset because we need difficulty, duration and offer type to help judge if an offer is completed or not. Next, we have aprocess_one_customer_transcript. In this method, first step is to group by person and offer and calculate amount spent, receive time, view time, expected complete time and complete time (see detailed comments in scripts/process_transcript.py). We follow several rules to tell an offer is completed,

1. if offer has received event, viewed event and completed event in order.
2. if offer has received event, completed event and viewed event in order and viewed event happened before expire date and amount spent is reached.
3. if offer is informational and offer has received event and view event and also they happened before expire date and amount spent is reached.

The follow is processed transcript dataset. The final column is label column, which will then convert to integer. 1 is complete while 0 is incomplete.



offer_type	difficulty	amount	receive_time	view_time	complete_time	expected_complete_time
informational	0.0	22.16	168	192.0	NaN	240.0
informational	0.0	8.57	336	372.0	NaN	432.0
bogo	5.0	8.57	408	456.0	414.0	528.0
discount	10.0	14.11	504	540.0	528.0	744.0
discount	10.0	10.27	576	NaN	576.0	744.0



is_in_expected_complete_time	is_enough_amount	is_view_event	is_complete_event	is_complete
False	True	True	False	True
False	True	True	False	True
True	True	True	True	True
True	True	True	True	True
True	True	False	True	False

Combined Dataset

We need a combined dataset for model feeding. This final dataset is achieved using pandas merge functionality. We also removed useless columns such as offer id, person id and extra columns in transcript. In the end, there are 76277 data points and 19 features: is_complete, age, became_member_on, income, gender_F, gender_M, gender_O, gender_nan, difficulty, duration, reward, offer_type_bogo, offer_type_discount, offer_type_informational, channel_email, channel_web, channel_mobile, channel_social, reward_difficulty, difficulty_duration.

Train and Test Dataset

We wrote a train_test_split split the whole dataset into train and test datasets with decimal fraction 0.7 and random seed 666. Thus, the dataset could be reproduced.

Implementation

This section will state detailed implementation step by step:

1. Load data to S3. The data includes train.csv and test.csv files with features and class labels we prepared in previous section. The reason is SageMaker estimater will normally read data from S3.

2. Modeling

    1. Define NN model(see detail in pytorch/model.py). Since we use PyTorch neural network, we need define the network graph in forward method. Here we use two layers network and the output layer is a sigmod function which produce one dimensional data.

2. Write a train script (see detail in pytorch/train.py). A train program is needed because this model is customized one. In this script, we load training data, parse hyperparameters, initialize the customized model, train this model and finally save model articles for later deployment and predictions.

3. Create an estimator. Still, a custom SageMaker estimator is created with specified entry point which is the model.py in pytorch file. In this step, we give hyperparameters, 30 hidden dim, to evaluate the model.

4. Train the estimator with train data in S3.

5. Deploy the trained model. pytorch/predict.py file as an entry point.

3. Evaluate the trained model. After the model is deployed, we could simply call predict method to get the result. And then we use roc_auc_sore function from sklearn metrics to calculate the metric ROC AUC score.
4. Hyperparameter tuning. In this stage, we choose different options for hyperparameters, such as lower hidden dim, increase epochs and modify drop rate, etc. We chose a model with lowest loss value.
5. Evaluate best trained model. Similar to previous evaluation. We evaluate test with best trained model.
6. Clean up Resources including entrypoints, S3 files and unless files in SageMaker notebook.

We faced few complications during the coding process. The most challenge is to process transcript data. This dataset will be transformed into a category data from a series of events for 17,000 users. We first break this problem to a sub problem for each user. A user may have maximum 52 events in transcript data, which is relatively small than 30,0000 events. Then, we go through each user's events and category event to each offer's entry including receive time, view time, complete time, expected complete time, amount spent during offer valid. In this program, a challenge is how to maintain each offer's status and different offer timeline may overlap. Our solution is having a data structure for each user's each offer. Be caution that even same offer for each user are considered different offer. The final step is to judge an offer is completed by applying three rules we mentioned in data preprocessing section. The script can be found in scripts folder. Other challenge is that it needs patient and caution to keep all model related variables unique and naming those variables meaningfully, such as SageMaker session, S3 location and model name.

Refinement

We refine the model by tuning hyperparameters. We have two configurable parameters. Adding hidden dimensions could help capture changes on different dimensions. We could see this change would help reduce the loss value a lot. Epochs is another essential parameter. It controls how many iterators to improve the model based on loss function. We could see longer epochs will help increase the final score. Drop out is more avoiding over-fitting. Since our goal is to achieve better score. We here reduce the number a little bit to reflect a better performance. From below table, we could clearly see the model's score increasing from 0.7052 to 0.7343. Also, it beats the number of XGBoost model.

hiddendim	epochs	drop out	loss value	ROC AUC
30	100	0.25	0.5635	0.6952
15	100	0.25	0.5717	0.7056
15	200	0.25	0.5708	0.7111
100	100	0.15	0.4545	0.7605
190	200	0.15	0.4426	0.7843

IV. Results

This section will discuss the final model's qualities and metric result. Also, we will compare the result to that of our benchmark model.

Model Evaluation and Validation

Final model is a PyTorch neural network model with

- hidden dimensions = 190,
- epochs = 200
- drop out = 0.15

In order to show the robustness of this model, I also randomly generate other test datasets with same size of data points from the whole datasets. We could see the ROC AUC score are stable at around 0.78. The loss value is similar across datasets.

hiddendim	epochs	drop out	loss value	ROC AUC
190	200	0.15	0.4426	0.7843
190	200	0.15	0.4519	0.7845
190	200	0.15	0.4403	0.7819

Justification

The final model above shows a better score than XGBoost. In number, 0.78 vs 0.71. The improvement is not that big, but is already significate boost. Actually we also try a little bit fewer hidden dim and epochs like 150 and 180 respectively. The score didn't go down dramatically. Thus, the model is to adequately solve the problem.

Reference:

1. Pytorch tutorial
2. Pytorch NN
3. Artificial Neural Network
4. Pytorch dropout
5. Pytorch Adam
6. BCEloss
7. Hyperparameter tuning
8. Hyperparameter optimization
9. Seaborn doc