Starbucks Capstone Project Proposal

By

Shankhadeep Banerjee

Machine Learning Nanodegree Program

I. Definition

Project Overview

Nowadays Understanding user behaviour and taking actions based on data is a key for customer success and profitability. Starbuck coffee, a coffee chain in America has successfully developed a mobile application platform to achieve this. Once every few days, Starbuck sends out an offer to users of the mobile app. An offer can be merely an advertisement of a drink or an actual offer such as a discount or BOGO (buy one get one free). Some users might not receive any offers during certain weeks.

Problem Statement

It is important for marketers to be able tell how well an offer will perform in order to run effective campaigns. This problem can break down to multiple sections, such as choosing the right parameter for a target audience, finding the audience that can give the most outcome, analysing user behaviour after they used an offer, predicting how many users will use a certain offer. In this project, I will build a model which can give prediction on whether or not a user will complete the offer or not by using machine learning predictors. The model is going to be binary classifier because the outcome we want to expect is binary, if a user will complete the offer or not. The model will take an offer as input and gives how much percent of users will complete the offer. In order to achieve this, I will first explore the dataset to have better understanding. Secondly, I will clean up the dataset so that machine learning models can utilize the data, which includes normalization. Once the dataset is ready, I will use DummyClassifier provided by the scikit learn library. Finally, I will use other models, such as the support vector machine, the logistic regression, the k-nearest neighbors vote, to compare the performance suited for our purpose to predict offer completion.

Metrics

I will use the accuracy score and the receiver operating characteristic (ROC), specifically ROC-AUC. The accuracy score is provided by scikit learn library, which gives exact match with the test data and prediction. ROC-AUC is a graphical plot using the true positive rate (TPR) and the false positive rate (FPR) at various threshold to illustrate optimal model. ROC-AUC is suited for balanced data because TPR and FPR only depends on positives and if the data set is imbalanced ROC-AUC won't capture precision. In this case, data set is balanced as shown in data exploration section and we can use ROC-AUC as the main metric.

II. Analysis

Data Exploration

The dataset is provided by Udacity and downloaded to my project. There is three files.

- portfolio.json - containing 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

Here is the schema and explanation of each variable in the files:

portfolio.json

- id (string) - offer id
- offer_type (string) - type of offer ie BOGO, discount,
- informational difficulty (int) - minimum required spend to
- complete an offer reward (int) - reward given for completing an
- offer duration (int) - time for offer to be open, in days channels
- (list of strings)

There is three kinds of offer type:

- bogo
- informational
- discount

For channels, we have below as value:

- web
- email
- mobile
- social

Portofolio data contains 10 rows and the data looks like below:

:

	channels	difficulty	duration	id	offer_type	reward
0	[email, mobile, social]	10	7	ae264e3637204a6fb9bb56bc8210ddfd	bogo	10
1	[web, email, mobile, social]	10	5	4d5c57ea9a6940dd891ad53e9dbe8da0	bogo	10
2	[web, email, mobile]	0	4	3f207df678b143eea3cee63160fa8bed	informational	0
3	[web, email, mobile]	5	7	9b98b8c7a33c4b65b9aebfe6a799e6d9	bogo	5
4	[web, email]	20	10	0b1e1539f2cc45b7b9fa7c272da2e1d7	discount	5
5	[web, email, mobile, social]	7	7	2298d6c36e964ae4a3e7e9706d1fb8c2	discount	3
6	[web, email, mobile, social]	10	10	fafdcd668e3743c1bb461111dcafc2a4	discount	2
7	[email, mobile, social]	0	3	5a8bc65990b245e5a138643cd4eb9837	informational	0
8	[web, email, mobile, social]	5	5	f19421c1d4aa40978ebb69ca19b0e20d	bogo	5
9	[web, email, mobile]	10	7	2906b810c7d4411798c6938adc9daaa5	discount	2

Sample of protfolio.json **profile.json**

- age (int) - age of the customer
- became_member_on (int) - date when customer created an app account
- gender (str) - gender of the customer (note some entries contain 'O' for other rather than M or
- F) id (str) - customer id

- income (float) - customer's income

The data sample looks like below:

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

Sample of profile.json **transcript.json**

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

This json file contains 4 types of events. Those events represents key events for offer completion.

- transaction
- offer received
- offer viewed
- offer
completed

Each of these has different dictionary value set in the value column. For example, for transaction event, the dictionary contains amount of money transacted, and for offer completed, it's offer id.

The data has 306534 rows and the data sample looks like this.
] :

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

Sample of transcript.json

Exploratory Data

Analysis **portfolio.json**

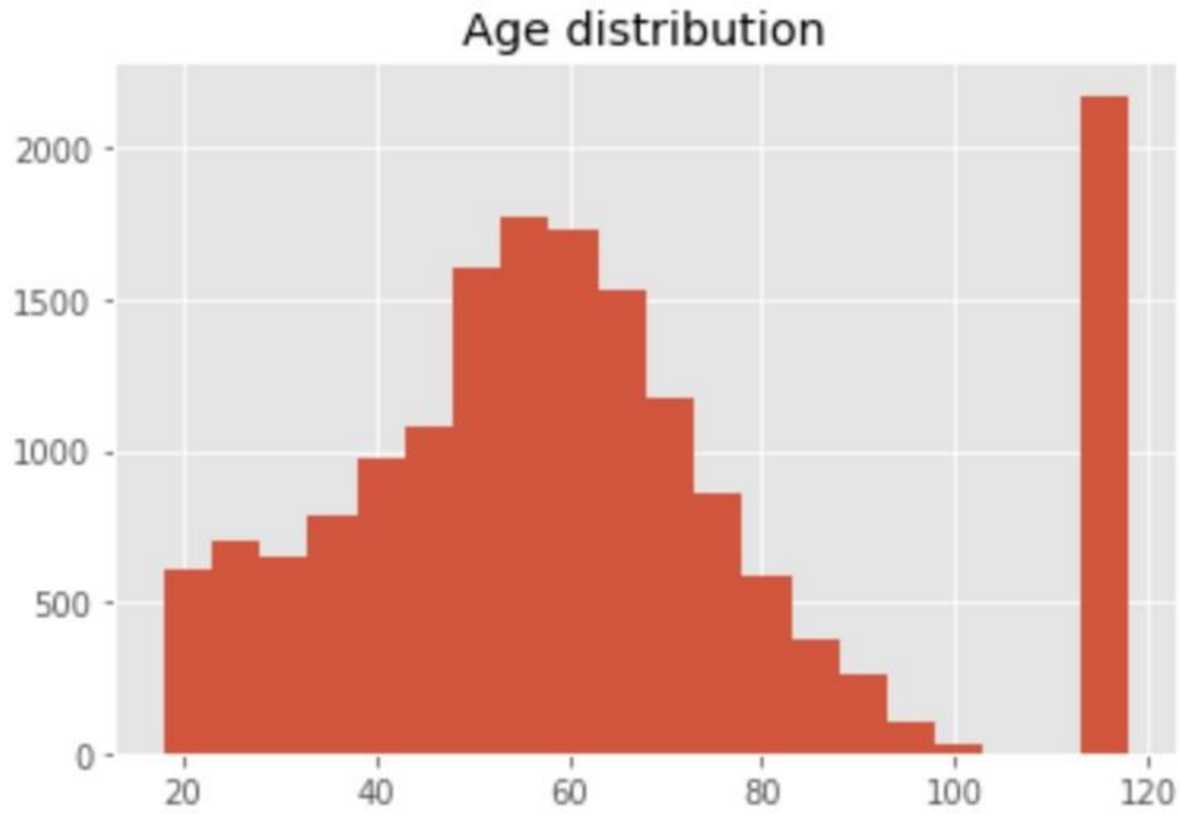
This data only contains 10 rows.

Channel row contains arrays of strings, and this is not machine learning model friendly, although it is expected that different channel have different influence on users. I will have to separate them to separate columns.

profile.json

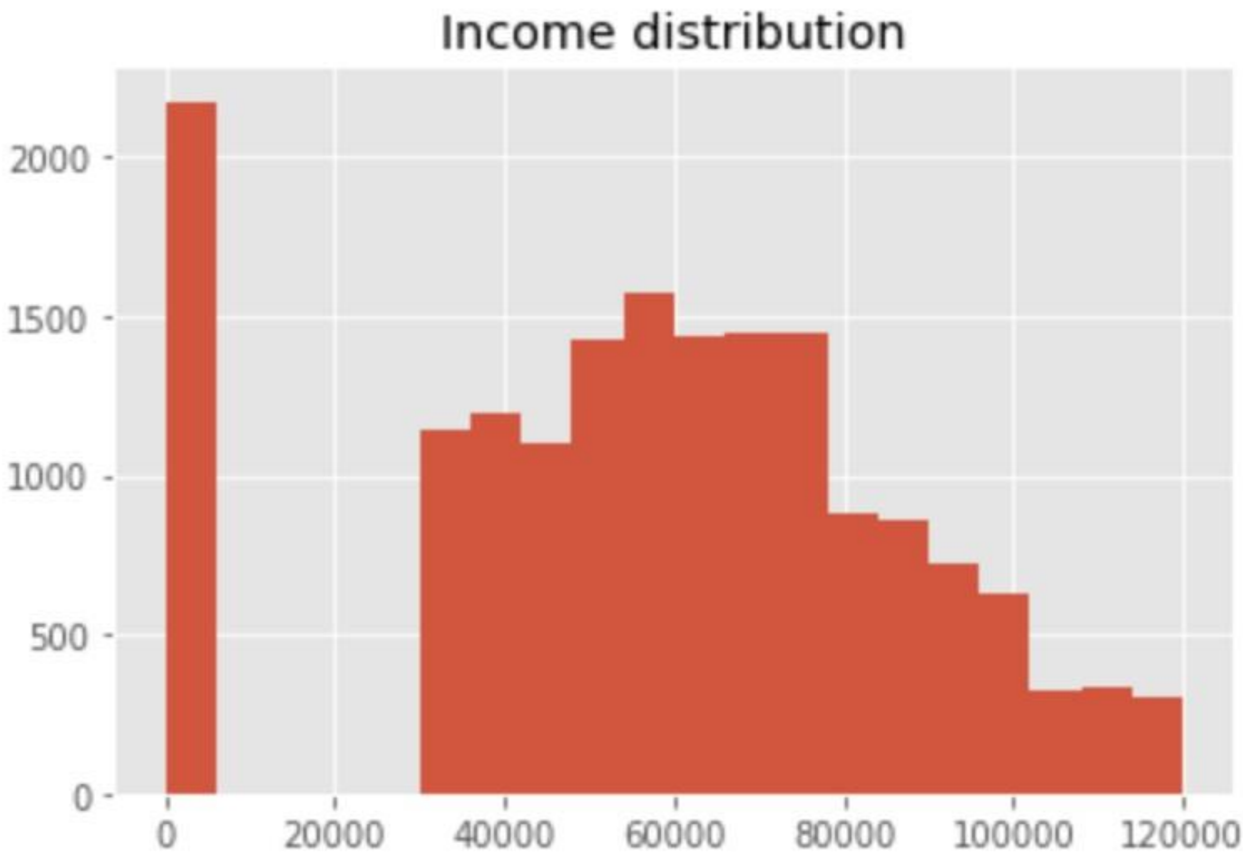
We have 17000 customer data set. The data seems incomplete because some data contains 118 for age, None for gender and NaN for income. Let's take a look at distribution of each features.

Age distribution is shown below. This shows people who is over 118 years old is the biggest population, which seems not realistic given average life expectancy in the U.S. is 72 years old. It is most likely the default value set by the system. I will replace this value with the average in the data preprocessing phase.



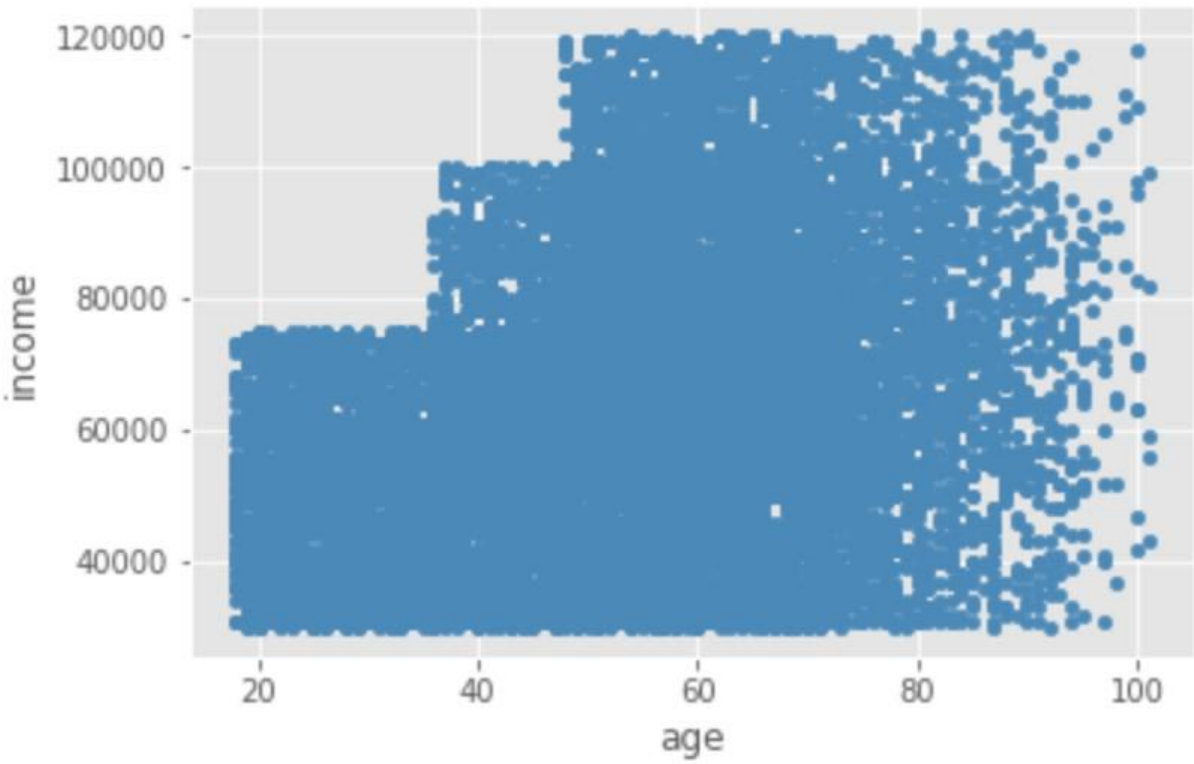
Age distribution in profile.json

The income distribution is shown below, and it seems reasonably distributed given it looks like normal distribution except for `NaN` rows. I will replace this `NaN` values with the average.



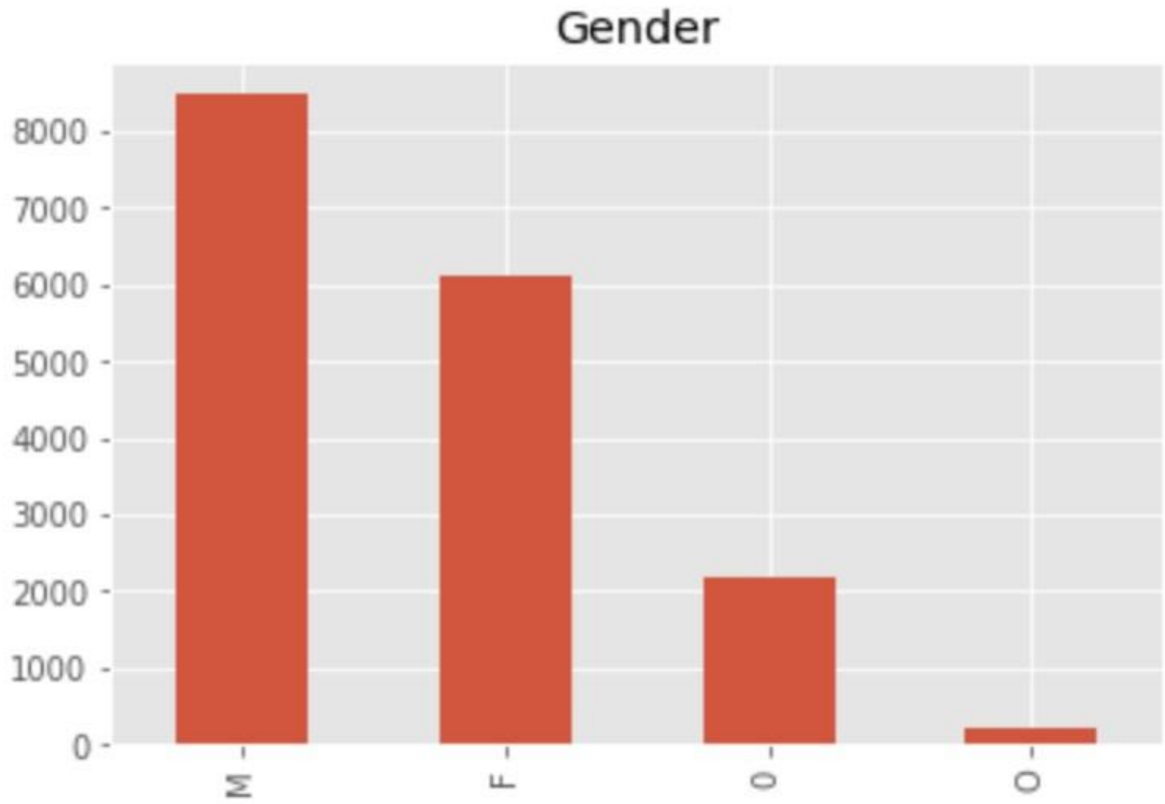
Income distribution in profile.json

The image above is a scatter plot with income and age. This highlights that there is income cut off for each age groups. For example, people in 20s and 30s have income cutoff somewhere around 750K. This indicates that the profile data is arbitrarily created. This may make prediciton simpler because user segmentation is clearler.



Income and age scatter plot from profile.json

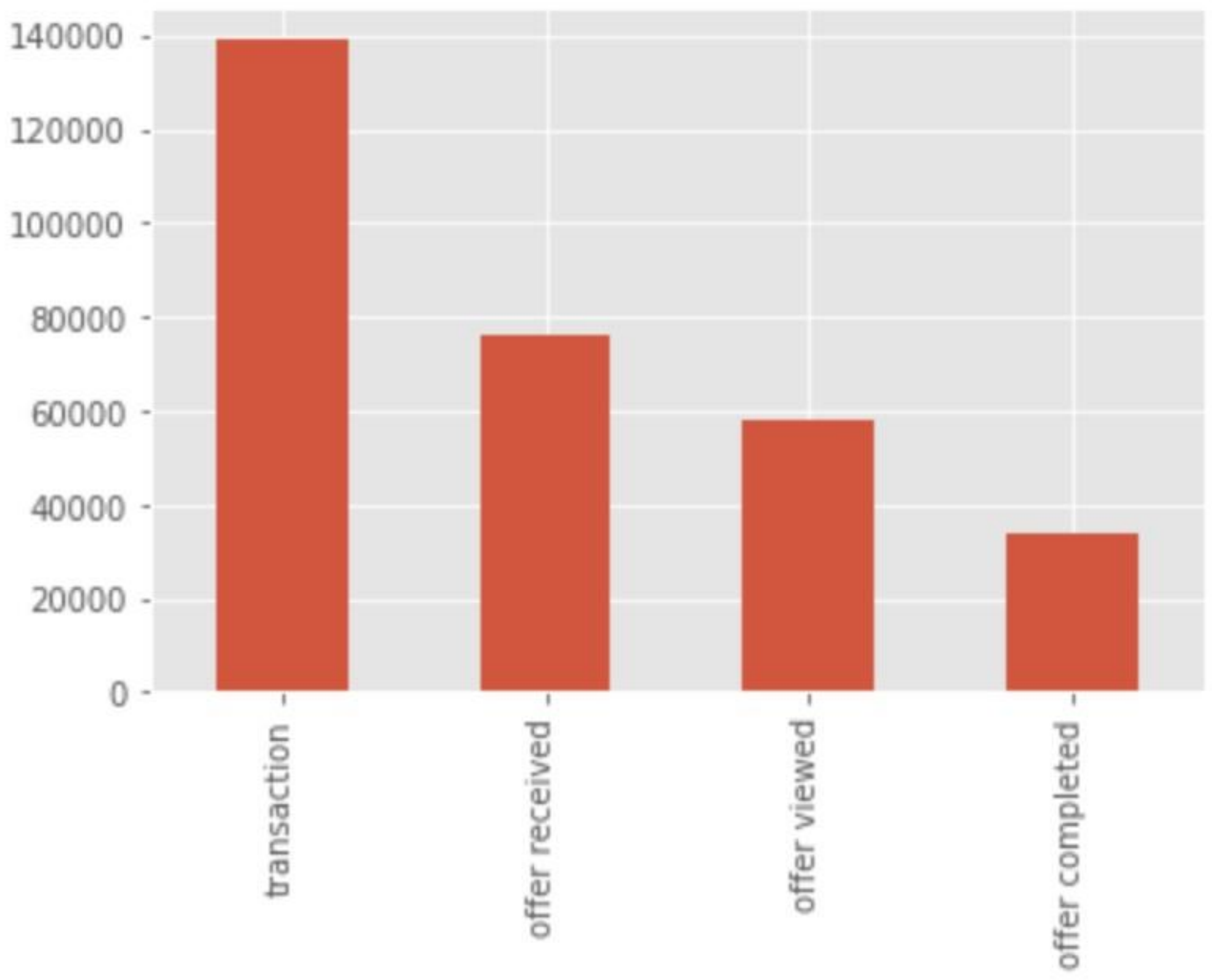
The chart below is gender distribution from profile.json. This shows gender column has some anomally values, 0 and O. I made an assumption they are default vaue or indicates user has not selected gender.



Gender distribution in profile.json **transcript.json**

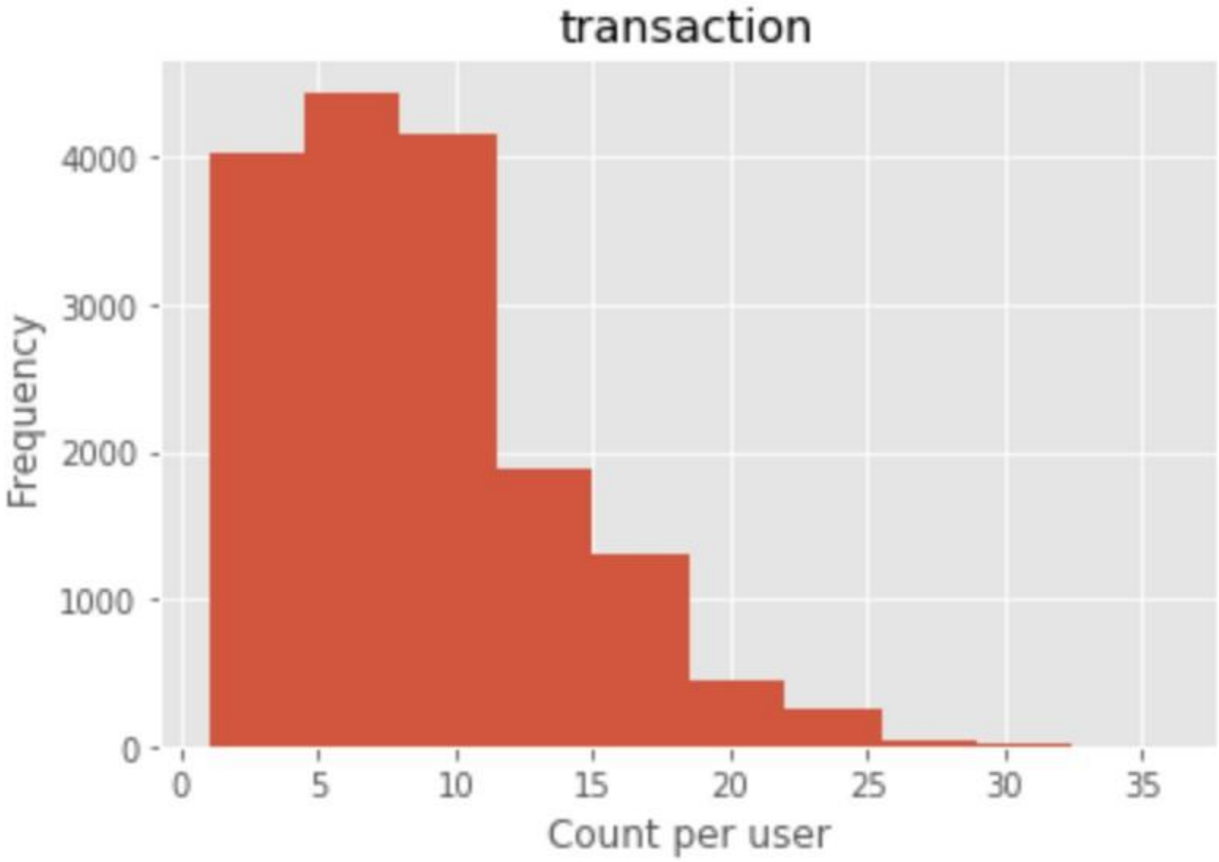
The data has 306534 rows. This transcript data contains for types of events and each event has different values. Therefore, we will need to separate them during data preprocessing.

Let's first take a look at number of each event as shown below. As expected, the number of events decrease as offer funnel proceeds from offer received to offer completed. Additionally, although transaction has the biggest data, this event should be treated differently because the nature of the event is different from other events.



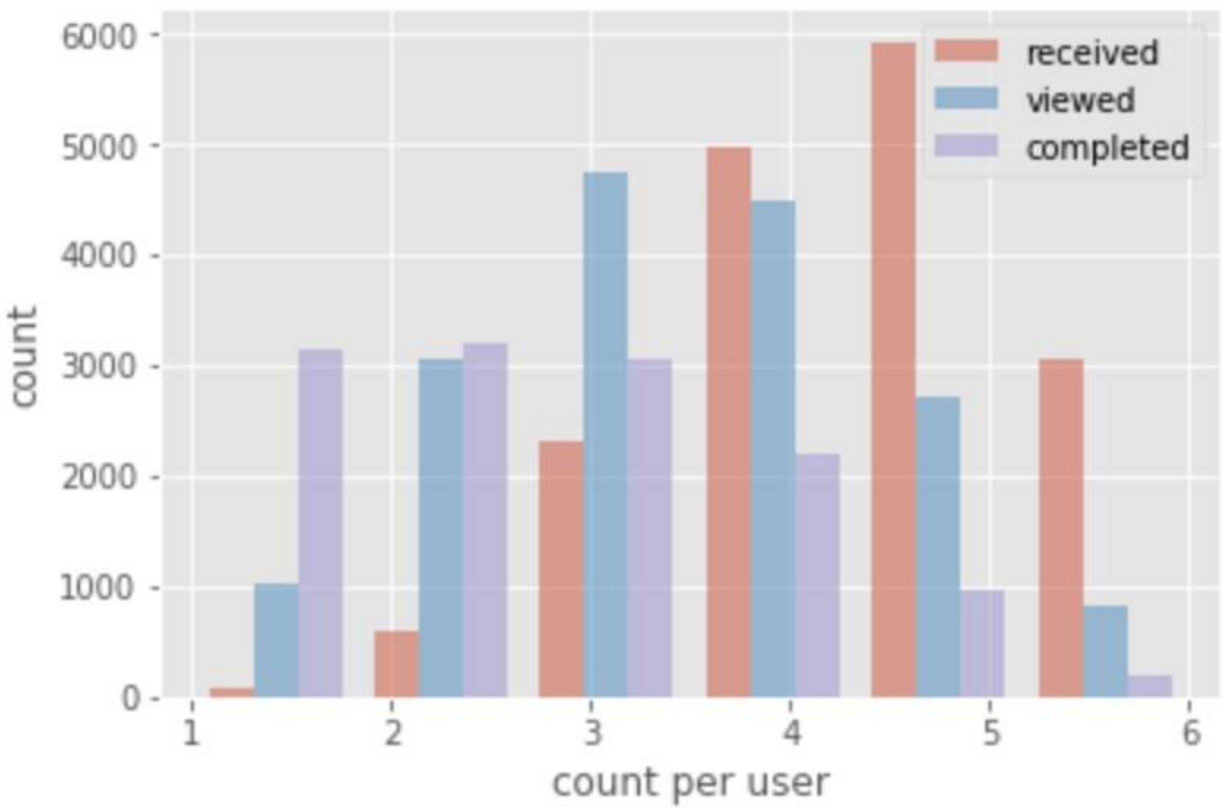
Event distribution in transcript.json

Here is distribution of transaction count per user. More users had a few transaction and less users had many transactions as expected.



Distribution of transaction count in transcript.json

The box graph below shows distribution of offer event including received, viewed and completed per user. As expected number is skewed high for the received, middle for the viewed and low for completed. This indicates that offer events has very realistic distribution. Additionally, the number of offer received data is 76277 and the number offer completed is 33579. This indicates that data is balanced.



Distribution of offer event count in transcript.json

Algorithms and Techniques

The goal for this project is to come up with a model that can accurately predict wether user will complete the offer or not. This is supervised binary classification problem.

I will use the logistic regression model, multi layer perceptron, random forrest classifier, the k-nearest neighbors vote, support vector machine and AdaBoost classifier.

Logistic regression is a probability model which is used for 0/1 problems. This model is used in variety of field such as medical and engineering.In this model, sigmoid function is used. It takes takes in user profile and offer data as input and gives an steep curve at which y value changes. an arbitral threshold is selected and depends on the threshold you can change sensitiveness of the model. I will use `LogisticRegression()` in sklearn for this problem.

Multi layer perceptron is consists of multiple layer of perceptorons as the name suggests. Perceptron is mathematic model represented by an activation function such as a step function or a sigmoid function, which sends output to the next layer if it hits certain threshold. The benefit of the model is it can learn non-linear models, which allows us to create complex models. However, this is sensitive to to feature scaling. Hence, we will normalize the data in preprocessing. `MLPClassifier()` in sklearn is used in this paper.

Random forrest classifier is a classification method uses multiple decision trees from randomly selected subset of training data. Sometimes simple random forest classifier performs better than other complicated models. `RandomForestClassifier()` from sklearn is used in the implementation.

The k-nearest neighbors vote classifies using majority vote of it's neighbors, with the object being assigned to the class most common to its k-nearest neighbor. The main feature of this model is being non-parametric method.

This makes the model suitable for data with a lot of unknowns and outliers. `KNeighborsClassifier()` from sklearn will be used in the implementation.

Additionally, support vector machine is a classifier model which finds a hyper plane which separates one or the other of two categories. It is represented as `SVN()` in sklearn.

And finally AdaBoost classifier is a classifier used in conjunction of bunch of weak learners. The benefit of the class is this model provides relatively accurate predictions without much of parameter tuning. However, AdaBoost is sensitive to outlier and noisy data. `AdaBoostClassifier()` class from sklearn is used in this project.

To simplify the problem, I'm not considering time series of user behavior. For example, it's natural to think an user who has transaction every month would not come back to a store til next month, taking it account would help improve the model. However, for this iteration, I will use user profile and offer information to tell if an user is likely to react to offers.

Benchmark

I used DummyClassifier in scikit learn. According to the documentation, DummyClassifier is a classifier that makes predictions using simple rules. The model is initialized with strategy parameter shown below:

```
model = DummyClassifier(strategy="most_frequent")
```

This model will always predict most frequent labels in the training set. This DummyClassifier is suitable for this project because I designed the pipeline in a way it's easy to accommodate new sklearn classifiers.

The result provided by the model is

Model name	Accuracy score	AUC
Dummy Classifier	0.541	0.541

III. Methodology

Data Preprocessing

THe first step was to clean up each data to remove anomaly and convert some data to easier to digest format for models. Then I combined those data to generate input features and label. Finally, combined data is normalized.

Portfolio

For portfolio, we first need to convert channels to binary columns from arrays of strings. Additionally, I converted `offer_type` to binary columns based on the value of the original column. This way all models can digest those values well. I also replaced `id` with `offer_id` to concatenate other data. The function I used to clean up looks like below:

```
def clean_portfolio(data):
    p = data.copy()
    p['web'] = p['channels'].apply(lambda x: 1 if 'web' in x else 0)
p['email'] = p['channels'].apply(lambda x: 1 if 'email' in x else 0)
p['mobile'] = p['channels'].apply(lambda x: 1 if 'mobile' in x else 0)
p['social'] = p['channels'].apply(lambda x: 1 if 'social' in x else 0)
    p.drop(['channels'], axis=1, inplace=True)
    p['bogo'] = p['offer_type'].apply(lambda x: 1 if 'bogo' in x else 0)
p['discount'] = p['offer_type'].apply(lambda x: 1 if 'discount' in x else
0)
    p['informational'] = p['offer_type'].apply(lambda x: 1 if
'informational' in x else 0)
    p.drop(['offer_type'], axis=1, inplace=True)
    p['offer_id'] = p['id']
    p.set_index('offer_id', inplace=True)
    p.drop(['id'], axis=1, inplace=True)
return p
```

The sample data of cleaned portfolio looks like below. `offer_id` will be used for concatenation.

offer_id	difficulty	duration	reward	web	email	mobile	social	bogo	discount	informational
ae264e3637204a6fb9bb56bc8210ddfd	10	7	10	0	1	1	1	1	0	0
4d5c57ea9a6940dd891ad53e9dbe8da0	10	5	10	1	1	1	1	1	0	0
3f207df678b143eea3cee63160fa8bed	0	4	0	1	1	1	0	0	0	1
9b98b8c7a33c4b65b9aebfe6a799e6d9	5	7	5	1	1	1	0	1	0	0
0b1e1539f2cc45b7b9fa7c272da2e1d7	20	10	5	1	1	0	0	0	1	0

Cleaned portfolio data

Profile

As mentioned above, age column has the default value 118, and it will be treated as anomaly if I leave it as is. I converted age to the mean of values that is not 118. Likewise, I took mean of income as well.

Gender is also missing some data. First, I created three columns for gender instead, `male`, `female` and `no_gender` and they take binary integer. I replaced all genders to those 3 columns and used `no_gender` if the value is not `F` or `M`. `id` was replaced with `profile_id` for concatenation.

I replaced `become_member_on` with `member_days` which shows number of days since you became member.
This makes it a single integer value and makes it easier to understand for ML models.

Here is the function I used to clean profile data:

```
def clean_profile(df):
    p = df.copy()
    p['age'] = p['age'].apply(lambda x: np.nan if x == 118 else x)
    p['age'] = p['age'].fillna(p['age'].mean())

    p['income'] = p['income'].fillna(p['income'].mean())

    p['male'] = p['gender'].apply(lambda x: 1 if x == 'M' else 0)
p['female'] = p['gender'].apply(lambda x: 1 if x == 'F' else 0)
p['no_gender'] = p['gender'].apply(lambda x: 1 if x != 'F' and x !=
'M' else 0)
    p.drop(['gender'], axis=1, inplace=True)
    p['profile_id'] = p['id']
    p.drop(['id'], axis=1, inplace=True)
    p.set_index('profile_id',inplace=True)
    p['member_days'] = (datetime.datetime.today().date() -
pd.to_datetime(p['became_member_on'], format='%Y%m%d').dt.date).dt.days
    p.drop(['became_member_on'], axis=1, inplace=True)
return p
```

And here is the sample converted data:

profile_id	age	income	male	female	no_gender	member_days
68be06ca386d4c31939f3a4f0e3dd783	54.393524	65404.991568	0	0	1	1102
0610b486422d4921ae7d2bf64640c50b	55.000000	112000.000000	0	1	0	949
38fe809add3b4fcf9315a9694bb96ff5	54.393524	65404.991568	0	0	1	587
78afa995795e4d85b5d9ceeca43f5fef	75.000000	100000.000000	0	1	0	1016
a03223e636434f42ac4c3df47e8bac43	54.393524	65404.991568	0	0	1	929

Cleaned profile data

Transaction

For transaction, I separate data to transaction and offer related based on `event` field. The leaning model I used does not consider historical transaction data. Therefore, we can ignore transaction events. Of course, to improve the model, we can potentially use this data with time series analysis.

I clean offer by first replacing `person` column name with `profile_id`. Then, extract `offer_id` from `value` field to concatenate eventually. Then instead of `event`, I created 3 columns for corresponding value using binary values, `offer_completed`, `offer_received` and `offer_viewed`.

I dropped `time` because I'm not considering timeline of transaction and user behavior in this model.

Here is the code used to clean offers.

```
def clean_offer(df):
    d = df.copy()
    d['profile_id'] = d['person']

    d.drop(['person'], axis = 1, inplace = True)
    d['offer_id'] = d['value'].apply(lambda x: x['offer id'] if 'offer id'
in x.keys() else x['offer_id'] if 'offer_id' in x.keys() else np.nan)

    d['event'] = d['event'].apply(lambda x: x.replace(" ", "_"))
event_df = pd.get_dummies(d['event'])          d = pd.concat([d,
event_df], axis=1)

    d.drop(['value', 'time', 'event'], axis = 1, inplace = True)
    d.reset_index(drop=True, inplace = True)
return d
```

Here is cleaned transaction:

	profile_id	offer_id	offer_completed	offer_received	offer_viewed
0	78afa995795e4d85b5d9ceeca43f5fef	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	1	0
1	a03223e636434f42ac4c3df47e8bac43	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	1	0
2	e2127556f4f64592b11af22de27a7932	2906b810c7d4411798c6938adc9daaa5	0	1	0
3	8ec6ce2a7e7949b1bf142def7d0e0586	fafdcd668e3743c1bb461111dcafc2a4	0	1	0
4	68617ca6246f4fbc85e91a2a49552598	4d5c57ea9a6940dd891ad53e9dbe8da0	0	1	0

Cleaned transaction data

Concatenation and normalization

The data is concatenated using `offer_id` and `profile_id`. When you aggregate, I can take summation for `offer_completed`, `offer_received` and `offer_viewed` because it's possible that users receive the same offer multiple times. However, to simplify, I didn't take the number of offer received in consideration and dropped the column. I separated `offer_completed` to used it as label.

After that the data is normalized using `MinMaxScaler` in sklearn for non-binary values, `age`, `income`, `difficulty`, `duration`, `reward`, and `member_days`.

At the end, we get features looks like below:

	difficulty	duration	reward	web	email	mobile	social	bogo	discount	informational	age	income	male	female	no_gender	member_days
0	0.50	0.571429	0.2	1	1	1	0	0	1	0	0.180723	0.466667	1	0	0	0.25288
1	0.00	0.142857	0.0	1	1	1	0	0	0	1	0.180723	0.466667	1	0	0	0.25288
2	0.00	0.000000	0.0	0	1	1	1	0	0	1	0.180723	0.466667	1	0	0	0.25288
3	0.25	0.285714	0.5	1	1	1	1	1	0	0	0.180723	0.466667	1	0	0	0.25288
4	0.50	1.000000	0.2	1	1	1	1	0	1	0	0.180723	0.466667	1	0	0	0.25288

Cleaned features

Implementation

I wrote a function which takes sklearn model and runs training and validation, which looks like below.

```
def train_predict(model, X_train, y_train, X_test, y_test):
    print('Name: {}'.format(model.__class__.__name__))

    model.fit(X_train, y_train)
y_pred = model.predict(X_test)

    score = model.score(X_test, y_test)
print('Test score: {:.3f}'.format(score))
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy score: {:.3f}'.format(accuracy))

    probs = model.predict_proba(X_test)[:, 1]
auc = roc_auc_score(y_test, probs)
print('AUC: %.2f' % auc)
    fpr, tpr, _ = roc_curve(y_test, probs)
        return {'y_pred': y_pred, 'auc': auc, 'fpr': fpr, 'tpr': tpr,
'score': score, 'accuracy': accuracy}
```

This function fit the model using training data and gives prediction based on test data. Afterwords it calculates test score and accuracy score. Additionally, AUC is also returned. At the end those two values are used as main measurements of model performance.

All models are defined in sklearn library, and in general, default value is used for the sake of simplicity. The model definition is below.

```
from sklearn.linear_model import LogisticRegression from
sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier from
sklearn.neighbors import  KNeighborsClassifier from
sklearn.neural_network import MLPClassifier from
sklearn.ensemble import RandomForestClassifier from
sklearn.ensemble import AdaBoostClassifier
 models =
[]
models.append(SVC(probability=True))
models.append(MLPClassifier()) models.append(LogisticRegression())
models.append(KNeighborsClassifier())
models.append(SVC(kernel='linear',probability=True))
models.append(RandomForestClassifier())
models.append(AdaBoostClassifier())
```

I take this array of models and for looped them to train the model. During the for loop, it keeps track of the best score and gives best method and best score based on it. Additionally, it plots ROC-AUC curves. The code is shown below.

```
best_score = 0
best_method = ""

for model in models:
    result = train_predict(model, X_train, y_train, X_test, y_test)
    fpr, tpr, auc = result['fpr'], result['tpr'], result['auc']
    plt.plot(fpr,tpr,label="{}, auc={}".format(model.__class__.__name__,
str(auc)))

    if result['score'] > best_score:
        best_method = model.__class__.__name__
        best_score = result['score']

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()

print('---------------------------------')
print('best_method :', best_method)
print('best_score :', best_score)
```

Refinement

I started off with using Sagemaker Estimator objects to optimize model learning process by using GPU instances. However, it turned out sklearn provides much simpler interface which allows me to reuse code and simplify the process. Additionally, since I simplified the problem, machine learning fitting process does not take long time. Therefore, I sticked with sklearn and added more models than I originally planned.

IV.Results

Model Evaluation and Validation

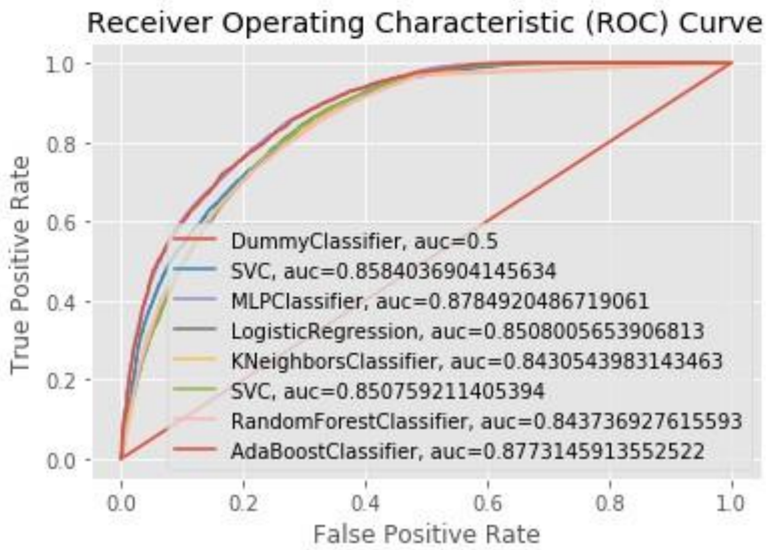
The table below is the result of test score and AUC for each model. ROC curve chart is provided as well. The numbers do not vary marginally, and almost within the error range. All the models performed better than the benchmark, and it shows machine learning models successfully learned training data.

MLP Classifier and AdaBoostClassifier performed slightly better than other models.

In order to verify the models are not overfitting, I conducted cross validation using `cross_val_score()` function in sklearn. Both MLPClassifier and AdaBoostClassifier gave pretty similar score as the original experiment. Given we have 33579 offer completed data, this result indicates the model is not overfitting.

Model name	Accuracy score	AUC
Dummy Classifier (Benchmark)	0.541	0.541
SVC (linear)	0.767	0.86
MLPClassifier	0.784	0.88

Model name	Accuracy score	AUC
LogisticRegression	0.765	0.85
KNeighborsClassifier	0.764	0.84
SVC	0.766	0.85
RandomForestClassifier	0.763	0.85
AdaBoostClassifier	0.782	0.88



ROC curve

Given all of this MLPClassifier seems the best model within the models I tested by a small margin. MLPClassifier also has a lot of flexibly in hyperparameter tuning like other models. We can use this this flexibility for further improvement using grid search (`GridSearchCV`) or random search (`RandomizedSearchCV`).

V. Conclusion

The result showed the machine learning models successfully came up with predictions better than the benchmark model. MLPClassifier performed slightly better with default settings in scikit learn library. As further improvement, we can conducted hyperparameter optimization which was not done for the sake of simplicity. Additionally, we can build models using models considers time-series such as DeepAR because user behavior is highly likely dependent on their previous activity.

Reference

- ROC and AUC, Clearly Explained!
- Receiver operating characteristic
- Logistic regression
- scikit-learn
- Machine Learning101
- AdaBoost
- Otto Group Product Classification Challenge