Machine Learning Capstone Report

Rajashekar Chintalapati
July 11, 2020

1. Definition

1.1 Project Overview

This report that was done on dataset of Starbucks which contains simulated data that mimics customer behavior collected from Starbucks rewards mobile app. To increase sales and customer satisfaction, Starbucks often give promotions (like BOGO - Buy one Get one, rebate & reward programs) to customers, so that customer come back more often. By identifying customer purchase patterns, companies more precisely can target the users who purchase less frequently. By doing analysis like given an offer, we can find out user conversion rate.

1.2. Problem statement

The problem I choose to solve given an offer and demographic data, whether user will complete the offer or not. By using given data, we can find the buyer pattern, what factors are impacting the sales. This data was provided by Udacity and is a simplified version of real Starbucks app.

1.3. Metrics

Will use accuracy and f1 score to evaluate each model score because accuracy tells us how many are correctly labeled and f1 score considers both precision and recall simultaneously (harmonic average between precision and recall), this gives a better measure on how many are not correctly classified. And will use feature importance using Random Forest model to define which features were important to decide whether will user will accept the offer or not.

2. Analysis

2.1 Data Exploration

There are 3 datasets provided.

i) Portfolio Dataset - which contains offer ids and meta data about each offer (duration, type, etc.). This dataset has 10 records, out of them 4 has offer type as bogo, 4 has offer type has discount and 2 has offer type has informational.

- 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)

In this dataset, I will be considering all above features, as this will help on identify which feature of offer has weight so that user completed the offer.

ii) Profile Dataset - which contains demographic data for each customer. This dataset has 17,100 records out of them 2175 records have NaN values, after removing those records, total came to 14925 records with 4 features (excluding id).

- 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

became_member_on has date, this was converted to days to calculate tenure.

iii) Transcript Dataset - which contains records for transactions, offers received, offers viewed, and offers completed. This data set has 306534 records and 4 features. I removed all informational offers as this transactions does not end up with offer complete. After removing I got 280468 records. Among that 138953 records are of transactional data which has user amount transactions.

- 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

From transactional data, amount spent till now, number of transactions done and time spent in test will be known.

There are total 16928 customers received offer, out of them 16578 customers made amount transactions. 16523 viewed the offer and 12774 customer completed the offer.

2.2 Exploratory Visualization

2.1.1 Portfolio dataset

In Portfolio dataset, there are 3 offer types

- 4 bogo (buy one get one)
- 4 discount (get some amount off or percent off)
- 2 informational

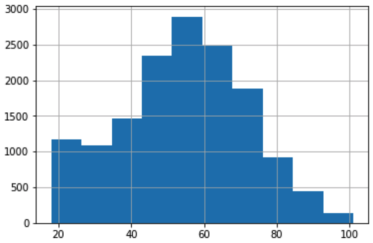
offer_type	reward	channels	difficulty	duration	id
bogo	4	4	4	4	4
discount	4	4	4	4	4
informational	2	2	2	2	2

Group by on offer type

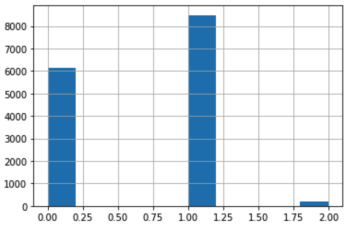
2.1.2 Profile Dataset

For the features like gender, age, income there are Nan values, there are 2175 records that are null, dropping all null values.

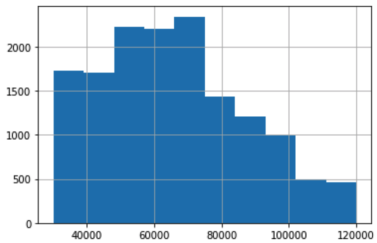
Below are the data distribution for Age, Gender and Income.



Age



Gender



Income

From **became_member_on** we can find the tenure - how long the customer is with Starbucks.

Below is the distribution of became_member_on per year.

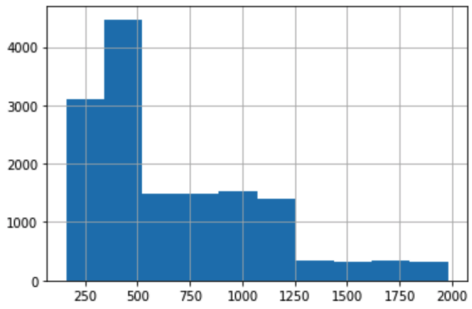
```
profile_conv['became_member_on'].apply(lambda x: str(x)[:4]).value_counts()
```

```
2017    5599
2018    3669
2016    3024
2015    1597
2014     662
2013     274
Name: became_member_on, dtype: int64
```

became_member_on per year distribution

became_member_on was given YYYYMMDD, this needs to be converted to date and get number of days, from above data we can see that we got users from 2013 to 2018. To find tenure, number of days user is with starbucks, I will use 2019-01-01 as the end date.

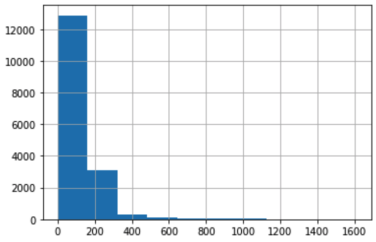
Below is the distribution of tenure.



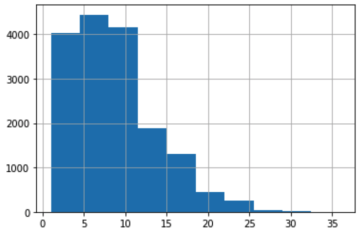
Tenure

2.1.3 Transcript Dataset

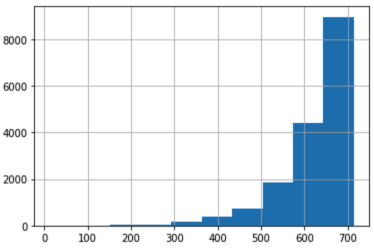
From Transaction data - Amount, number of transactions and time spent in test.



Amount

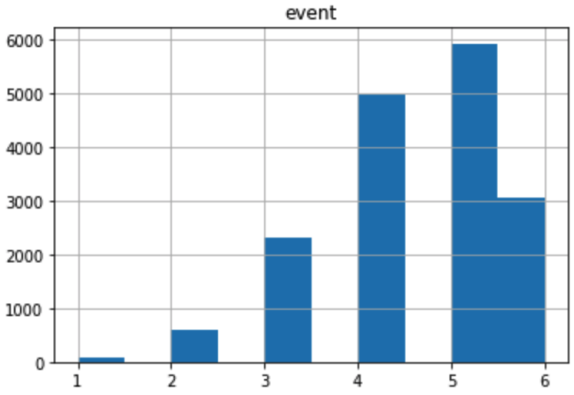


Number of transactions

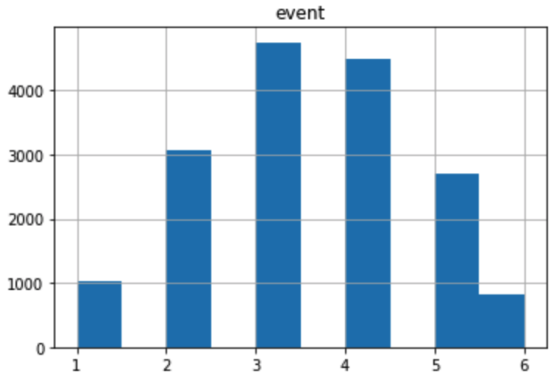


Time spent in test

Number of offers received and number of offers viewed

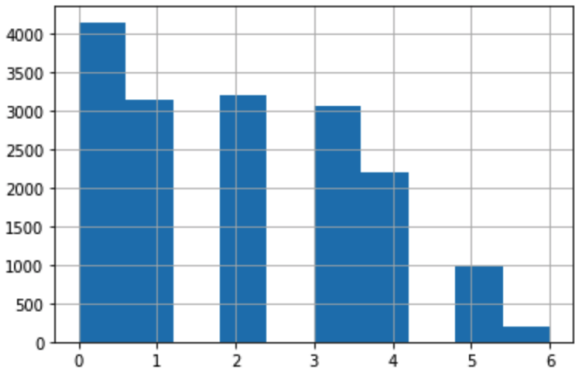


Offer received

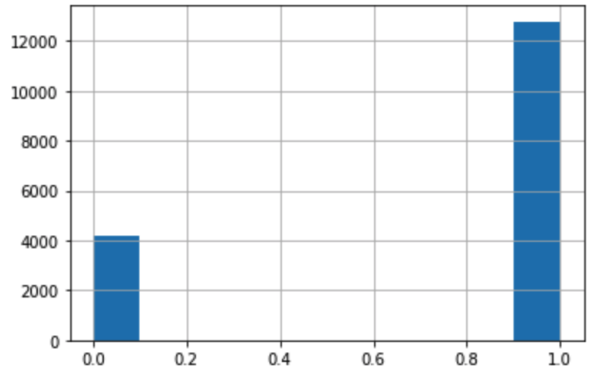


Offer Viewed

Number of offers completed and offer success rate.



Offer Completed



Offer success rate

2.3 Algorithms and Techniques

By going through data, first analyze data, process and prepare the data for training like removing NaN records and removing any unnecessary features, do one-hot encoding where ever necessary, once the data is ready with all required features, identify which feature is the output in this case it would be offer completed. And then split the data into train and test, and use supervised machine learning algorithms like Naive Bayes classifer, sklearn ensemble methods like AdaBoost, Bagging, Random Forest algorithms to train the data and will use evaluation metrics like accuracy, precision, recall and f1 score to find out each model score.

2.4 Benchmark

Using Logistic regression which is extremely efficient mechanism for calculating probabilities especially incases like binary classifications.

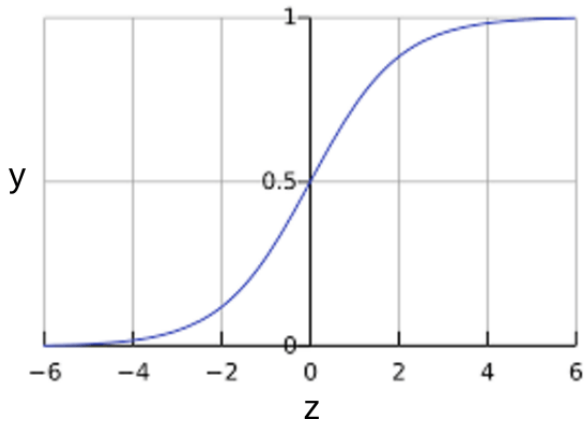
> In many cases, you'll map the logistic regression output into the solution to a binary classification problem, in which the goal is to correctly predict one of two possible labels (e.g., "spam" or "not spam") [3]

If z represents output of linear layer of a model trained with logistic regression, then sigmoid(z) will yield a value between 0 & 1.

$$y^{'} = \frac{1}{1 + e^{-z}}$$

$y^{'}$ is output of logistic regression model

z is $b + w_1 x_1 + w_2 x_2 + ... + w_N x_N$



3. Methodology

3.1 Data Preprocessing and Implementation

3.1.1 Portfolio dataset

For information offer the reward is 0, so this feature might not appeal to customers to convert, so will remove any informational offers at later point.

```
mlb = MultiLabelBinarizer()
channels_onehot = pd.DataFrame(mlb.fit_transform(portfolio['channels']),columns=mlb.classes_, index=portfolio.index)
```

```
offertype_onehot = pd.get_dummies(portfolio['offer_type'])
portfolio_conv = pd.concat((portfolio, channels_onehot, offertype_onehot), axis=1)

# Drop channels & offer_type
portfolio_conv.drop(['channels','offer_type'], axis = 1, inplace=True)

# rename to offer_id
portfolio_conv.rename(columns={'id': 'offer_id'}, inplace=True)
```

After applying one-hot encoding on channels and offer_type, below are the all the records after encoding. (After encoding the offer_type and channels features are removed).

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

Portfolio Dataset

3.1.2 Profile Dataset

For the features like gender, age, income there are Nan values, there are 2175 records that are null, dropping all null values.

```
profile_conv = profile.dropna(axis=0)
```

From **became_member_on** we can find the tenure - how long the customer is with Starbucks.

Below is the distribution of became_member_on per year.

```
profile_conv['became_member_on'].apply(lambda x: str(x)[:4]).value_counts()
```

```
2017    5599
2018    3669
2016    3024
2015    1597
2014     662
2013     274
Name: became_member_on, dtype: int64
```

became_member_on per year distribution

became_member_on was given YYYYMMDD, this needs to be converted to date and get number of days, from above data we can see that we got users from 2013 to 2018. To find tenure, number of days user is with starbucks, I will use 2019-01-01 as the end date.

```
def convertDateToDays(dateint):
    to_date = datetime.strptime(str(dateint),'%Y%m%d')
    from_date = datetime.strptime('20190101','%Y%m%d')
    duration = from_date - to_date
    return duration.days

# Convert to number of days
profile_conv['tenure'] = profile_conv['became_member_on'].apply(lambda x: convertDateToDays(x))
profile_conv['tenure'].hist()
```

Processing gender

```
profile_conv['gender'].replace({'F':0,'M':1,'O':2}, inplace=True)

# rename id to person_id
profile_conv.rename(columns={'id': 'person_id'}, inplace=True)
```

Final profile data, after processing data

	gender	age	person_id	income	tenure
1	0	55	0610b486422d4921ae7d2bf64640c50b	112000.0	535
3	0	75	78afa995795e4d85b5d9ceeca43f5fef	100000.0	602
5	1	68	e2127556f4f64592b11af22de27a7932	70000.0	250
8	1	65	389bc3fa690240e798340f5a15918d5c	53000.0	326
12	1	58	2eeac8d8feae4a8cad5a6af0499a211d	51000.0	416

Profile

3.1.3 Transcript Dataset

Removing information transactions as these records wont help in identifying whether user had taken offer or not. After removing these records the count came to 280468.

```
off_view_or_receive = transcript[(transcript['event'] == 'offer received') | (transcript['event'] == 'offer viewed')]

informational_offers = portfolio_conv[portfolio_conv['informational'] == 1]['offer_id'].values

inf_off_1 = off_view_or_receive[off_view_or_receive['value'] == {'offer id': informational_offers[0]}]
inf_off_2 = off_view_or_receive[off_view_or_receive['value'] == {'offer id': informational_offers[1]}]

transcript.drop(inf_off_1.index, inplace=True)
transcript.drop(inf_off_2.index, inplace=True)
```

3.1.3.1 Processing transactional data

Getting only transaction data. There are 138953 records.

```
transaction_data = transcript[transcript['event'] == 'transaction']
transaction_data['amount'] = transaction_data['value'].apply(lambda x: x['amount'])
transaction_data.drop(['event', 'value'], axis=1, inplace=True)
```

	person	time	amount
12654	02c083884c7d45b39cc68e1314fec56c	0	0.83
12657	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	0	34.56
12659	54890f68699049c2a04d415abc25e717	0	13.23
12670	b2f1cd155b864803ad8334cdf13c4bd2	0	19.51
12671	fe97aa22dd3e48c8b143116a8403dd52	0	18.97
...	...	...	...
306529	b3a1272bc9904337b331bf348c3e8c17	714	1.59
306530	68213b08d99a4ae1b0dcb72aebd9aa35	714	9.53
306531	a00058cf10334a308c68e7631c529907	714	3.61
306532	76ddbd6576844afe811f1a3c0fbb5bec	714	3.53
306533	c02b10e8752c4d8e9b73f918558531f7	714	4.05

138953 rows × 3 columns

User transactions

From above data, calculating how much amount was spent by each customer, number of transaction made, number of hours users was in this test.

```
# getting amount spent per customer
transaction_final = transaction_data.groupby('person').sum().drop('time', axis=1)
# getting number of transactions made by customer
transaction_final['no_of_trans'] = transaction_data.groupby('person').count().drop('time', axis=1)
# getting time spent in test by customer
transaction_final['time_spent_in_hrs'] = transaction_data.groupby('person').max().drop('amount', axis=1)

transaction_final.reset_index(level=0, inplace=True)
transaction_final.rename(columns={'person': 'person_id'}, inplace=True)
```

	person_id	amount	no_of_trans	time_spent_in_hrs
0	0009655768c64bdeb2e877511632db8f	127.60	8	696
1	00116118485d4dfda04fdbaba9a87b5c	4.09	3	474
2	0011e0d4e6b944f998e987f904e8c1e5	79.46	5	654
3	0020c2b971eb4e9188eac86d93036a77	196.86	8	708
4	0020ccbbb6d84e358d3414a3ff76cffd	154.05	12	672
...	...	...	...	...
16573	fff3ba4757bd42088c044ca26d73817a	580.98	11	552
16574	fff7576017104bcc8677a8d63322b5e1	29.94	6	696
16575	fff8957ea8b240a6b5e634b6ee8eafcf	12.15	5	576
16576	fffad4f4828548d1b5583907f2e9906b	88.83	12	678
16577	ffff82501cea40309d5fdd7edcca4a07	226.07	15	648

16578 rows × 4 columns

3.1.3.2 Processing offer received and viewed

Since offer completed will be the actual output event we are looking for, we can convert this to number of offers customer received and viewed.

```
offer_received = pd.DataFrame(transcript[transcript['event'] == 'offer received'].groupby('person').count()['event'])
offer_received.reset_index(level=0, inplace=True)

offer_viewed = pd.DataFrame(transcript[transcript['event'] == 'offer viewed'].groupby('person').count()['event'])
offer_viewed.reset_index(level=0, inplace=True)
```

	person	event
0	0009655768c64bdeb2e877511632db8f	3
1	00116118485d4dfda04fdbaba9a87b5c	2
2	0011e0d4e6b944f998e987f904e8c1e5	3
3	0020c2b971eb4e9188eac86d93036a77	4
4	0020ccbbb6d84e358d3414a3ff76cffd	3
...	...	...
16923	fff3ba4757bd42088c044ca26d73817a	4
16924	fff7576017104bcc8677a8d63322b5e1	5
16925	fff8957ea8b240a6b5e634b6ee8eafcf	2
16926	fffad4f4828548d1b5583907f2e9906b	3
16927	ffff82501cea40309d5fdd7edcca4a07	6

16928 rows × 2 columns

Offer received

	person	event
0	0009655768c64bdeb2e877511632db8f	2
1	00116118485d4dfda04fdbaba9a87b5c	2
2	0011e0d4e6b944f998e987f904e8c1e5	3
3	0020c2b971eb4e9188eac86d93036a77	2
4	0020ccbbb6d84e358d3414a3ff76cffd	3
...	...	...
16518	fff3ba4757bd42088c044ca26d73817a	2
16519	fff7576017104bcc8677a8d63322b5e1	4
16520	fff8957ea8b240a6b5e634b6ee8eafcf	2
16521	fffad4f4828548d1b5583907f2e9906b	3
16522	ffff82501cea40309d5fdd7edcca4a07	6

16523 rows × 2 columns

Offer received

Offer received is superset, all received offer, but only few people viewed or done transactions

- offer_received has 16928 records
- transaction_final has 16578 records
- offer_viewed has 16523

```
# renaming columns for merge
offer_received.rename(columns={'person': 'person_id', 'event': 'offers_received'}, inplace=True)
offer_viewed.rename(columns={'person': 'person_id', 'event': 'offers_viewed'}, inplace=True)

# merging offer_viewed to offer_received
offer_details = pd.merge(pd.merge(offer_received, offer_viewed, on='person_id', how="left"), \
         transaction_final, on='person_id', how="left")

# fill nan values with 0
offer_details = offer_details.fillna(0)
```

	person_id	offers_received	offers_viewed	amount	no_of_trans	time_spent_in_hrs
0	0009655768c64bdeb2e877511632db8f	3	2.0	127.60	8.0	696.0
1	00116118485d4dfda04fdbaba9a87b5c	2	2.0	4.09	3.0	474.0
2	0011e0d4e6b944f998e987f904e8c1e5	3	3.0	79.46	5.0	654.0
3	0020c2b971eb4e9188eac86d93036a77	4	2.0	196.86	8.0	708.0
4	0020ccbbb6d84e358d3414a3ff76cffd	3	3.0	154.05	12.0	672.0
...	...	...	...	...	...	...
16923	fff3ba4757bd42088c044ca26d73817a	4	2.0	580.98	11.0	552.0
16924	fff7576017104bcc8677a8d63322b5e1	5	4.0	29.94	6.0	696.0
16925	fff8957ea8b240a6b5e634b6ee8eafcf	2	2.0	12.15	5.0	576.0
16926	fffad4f4828548d1b5583907f2e9906b	3	3.0	88.83	12.0	678.0
16927	ffff82501cea40309d5fdd7edcca4a07	6	6.0	226.07	15.0	648.0

16928 rows × 6 columns

After merging transactional data, offer received and offer viewed

3.1.3.3 Processing event

After processing transaction, offer received and offer viewed, now we look into offer completed data. There are 16928 members got offer, 16523 viewed the offer, 12774 persons completed offer. All this offer completed data has dictionary object which has what offer was completed and what reward was given to the user.

```
# convert to one hot encoding
transcript_conv = pd.concat((transcript, pd.get_dummies(transcript['event'])), axis=1)

transcript_conv['offer'] = transcript_conv['value'].apply(lambda x: x['offer_id'])
transcript_conv['reward_earned'] = transcript_conv['value'].apply(lambda x: x['reward'])
transcript_conv['reward_earned'] = transcript_conv['reward_earned'].fillna(0)

# drop time, event, value columns
transcript_conv.drop(['time', 'event', 'value'], axis=1, inplace=True)

# rename to person_id and offer_id
transcript_conv.rename(columns={'person': 'person_id', 'offer': 'offer_id'}, inplace=True)
transcript_conv.head()
```

	person_id	offer completed	offer_id	reward_earned
12658	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	1	2906b810c7d4411798c6938adc9daaa5	2
12672	fe97aa22dd3e48c8b143116a8403dd52	1	fafdcd668e3743c1bb461111dcafc2a4	2
12679	629fc02d56414d91bca360decdfa9288	1	9b98b8c7a33c4b65b9aebfe6a799e6d9	5
12692	676506bad68e4161b9bbaffeb039626b	1	ae264e3637204a6fb9bb56bc8210ddfd	10
12697	8f7dd3b2afe14c078eb4f6e6fe4ba97d	1	4d5c57ea9a6940dd891ad53e9dbe8da0	10

After processing offer completed and rewards earned

3.1.3.4 Merging all datasets

Merge portfolio and transcript data.

```
transcript_conv = pd.merge(transcript_conv, portfolio_conv, on='offer_id')
```

Grouping records so that we have only one entry for each user. Calculating count for columns to know how many emails, mobile, social, web, bogo, discount, offer completed happened for each user. And we also calcualted the sum of rewards earned, reward, difficulty and duration.

```
transcript_conv = pd.merge(transcript_conv.groupby('person_id').count()\
    [['email', 'mobile', 'social', 'web', 'bogo', 'discount', 'offer completed']].reset_index(level=0),\
        transcript_conv.groupby('person_id').sum()\
  [['reward_earned', 'reward', 'difficulty', 'duration']].reset_index(level=0), on='person_id')
```

I see that rewards_earned & rewards are same so deleting rewards_earned.

Merge offer details and transcript details

```
final = pd.merge(offer_details, transcript_conv, on='person_id', how='left')
```

For those who have not completed the offer, fill with zero.

```
final['offer completed'] = final['offer completed'].fillna(0)
```

Now calculate output feature - offer success - 0 means user have not completed the offer, 1 means user completed the offer

```
final['offer_success'] = final['offer completed'].apply(lambda x: 1 if x>0 else 0)
```

Finally merge above final data with profile data

```
# Merging profile data to transcript_conv
final = pd.merge(final, profile_conv, on='person_id', how='left')
final = final.fillna(0)
# drop person_id & offer completed
final.drop(['person_id', 'offer completed'], axis=1, inplace=True)
```

The final data after processing all data, it has 16928 records with 18 features and 1 output feature

1) offer_received - number of offers received

2) offer_viewed - number of offers viewed

3) amount - Amount spent till now

4) no_of_trans - Number of transactions made

5) time_spent_in_hrs - Time spent in hours in test

6) email - Number of offers received through emails

7) mobile - Number of offers received through mobile

8) social - Number of offers received through social

9) web - Number of offers received through web

10) bogo - Number of bogo offers completed

11) discount - Number of discount completed

12) reward - Total rewards received

13) difficulty - Total number of amount spend to complete the offer

14) duration - Total number of days offer was open

15) gender - Customer Gender

16) age - Customer age

17) income - Customer Income

18) tenure - Number of days user is with Starbucks

Output feature -

1) offer_success - User successfully completed the offer or not

3.2 Split data

Separating offer success data and splitting data 70% for training and 30% for testing.

```
X = final.drop('offer_success', axis=1)
y = pd.DataFrame(final['offer_success'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Finding success rate distribution in both train and test

```
# train success percent - 75%
y_train[y_train['offer_success'] == 1.0].count()/(y_train[y_train['offer_success'] == 0.0].count()\
                                                  +y_train[y_train['offer_success'] == 1.0].count())
```

```
offer_success    0.756435
dtype: float64
```

```
# test success percent - 75%
y_test[y_test['offer_success'] == 1.0].count()/(y_test[y_test['offer_success'] == 0.0].count()\
                                                  +y_test[y_test['offer_success'] == 1.0].count())
```

```
offer_success    0.750345
dtype: float64
```

Above shows in both train and test, success rate distribution is 75%

4. Results

4.1 Model Evaluation and Validation

4.1.1 Benchmark

```
from sklearn.linear_model import LogisticRegression
logistic = LogisticRegression(random_state=42).fit(X_train, y_train)
logistic_preds = logistic.predict(X_test)
print_metrics(y_test, logistic_preds, 'logistic')
```

Below is the accuracy and F1 score

```
Accuracy score for logistic : 0.999212443394369
F1 score logistic : 0.9994754786257539
```

Logistic regression gave 99% as the benchmark.

4.1.2 Training model

4.1.2.1 Using Naive Bayes

```
# Instantiate our model
naive_bayes = MultinomialNB()

# Fit our model to the training data
naive_bayes.fit(X_train, y_train)
```

4.1.2.2 Using sklearn ensemble

```
# Instantiate a BaggingClassifier with:
# 200 weak learners (n_estimators) and everything else a default values
bagging_mod = BaggingClassifier(n_estimators=200)

# Instantiate a RandomForestClassifier with:
# 200 weak learners (n_estimators) and everything else a default values
random_mod = RandomForestClassifier(n_estimators=200)

# Instantiate an a AdaBoostClassifier with:
# With 300 weak learners (n_estimators) and a learning_rate of 0.2
adaboost_mod = AdaBoostClassifier(n_estimators=300, learning_rate=0.2)

# Fit your BaggingClassifier to the training data
bagging_mod.fit(X_train, y_train)
random_mod.fit(X_train, y_train)
adaboost_mod.fit(X_train, y_train)
```

4.1.3 Testing model

Below is the method which calculates accuracy and f1 score

```
def print_metrics(y_true, preds, model_name=None):
    '''
    INPUT:
    y_true - the y values that are actually true in the dataset (NumPy array or pandas series)
    preds - the predictions for those values from some model (NumPy array or pandas series)
    model_name - (str - optional) a name associated with the model if you would like to add it to the print statements

    OUTPUT:
    None - prints the accuracy, precision, recall, and F1 score
    '''
    if model_name == None:
        print('Accuracy score: ', format(accuracy_score(y_true, preds)))
        print('F1 score: ', format(f1_score(y_true, preds)))
        print('\n\n')
```

```
    else:
        print('Accuracy score for ' + model_name + ' :' , format(accuracy_score(y_true, preds)))
        print('F1 score ' + model_name + ' :', format(f1_score(y_true, preds)))
        print('\n\n')
```

Predicting using Naive Bayes & Ensemble methods - bagging, random forest and adaboost.

```
# Predict using Naive bayes on the test data
predictions = naive_bayes.predict(X_test)

# Predict using BaggingClassifier on the test data
bag_preds = bagging_mod.predict(X_test)

# Predict using RandomForestClassifier on the test data
rf_preds = random_mod.predict(X_test)

# Predict using AdaBoostClassifier on the test data
ada_preds = adaboost_mod.predict(X_test)

# Print Bagging scores
print_metrics(y_test, bag_preds, 'bagging')

# Pring Random Forest scores
print_metrics(y_test, rf_preds, 'random_forest')

# Print AdaBosst scores
print_metrics(y_test, ada_preds, 'adaboost')

# Print Bayes Classifier scores
print_metrics(y_test, predictions, 'naive_bayes')
```

Naive Bayes gave 94% accuracy and F1 score as 96%

```
Accuracy score for naive_bayes : 0.9484150423311676
F1 score naive_bayes : 0.9663671373555841
```

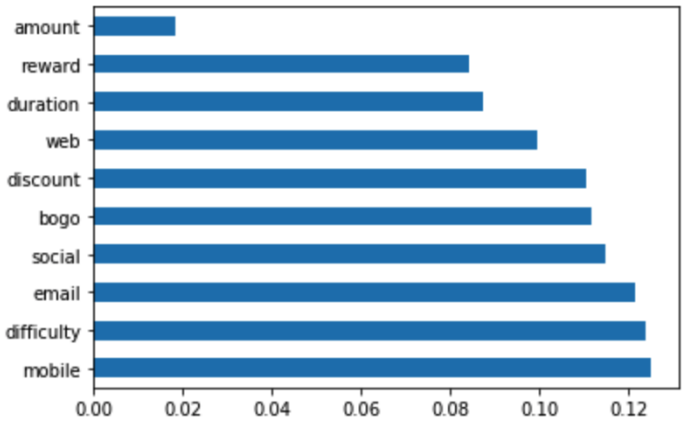
Where as ensemble methods - bagging, random forest & adaboost gave 100% on accuracy & F1 score.

```
Accuracy score for bagging : 1.0
F1 score bagging : 1.0

Accuracy score for random_forest : 1.0
F1 score random_forest : 1.0

Accuracy score for adaboost : 1.0
F1 score adaboost : 1.0
```

4.1.4 Feature importance using Random Forest

```
feature_importances = pd.DataFrame(random_mod.feature_importances_,
                                   index = X_train.columns,
                                    columns=['importance']).sort_values('importance',ascending=False)

(pd.Series(random_mod.feature_importances_, index=X_train.columns)
```

```
    .nlargest(10)
    .plot(kind='barh'))
```



Feature importance

4.2 Justification

Given user demographic data like gender, age etc and promotion data like bogo or discount and on what channels the offer was offered, the Naive Bayes was able to predict 94% of time and when used sklearn ensemble methods like Ada Boost, Bagging and Random Forest was able to predict 100% of the time.

By using feature importance, we can say that, below features played important role in offer to get complete

- mobile - When offer was offered in mobile channel
- difficulty - minimum required spend to complete an offer
- email - When offer was offered in email channel
- social - When offer was offered in social channel
- bogo - When offer of type bogo was offered
- discount - when offer with discount was offered

5. References

1. https://scikit-learn.org/stable/modules/ensemble.html
2. https://scikit-learn.org/stable/modules/naive_bayes.html
3. https://developers.google.com/machine-learning/crash-course/logistic-regression/calculating-a-probability
4. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html
5. https://scikit-learn.org/stable/modules/generated/sklearn.metrics.precision_recall_fscore_support.html