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Starbucks Capstone Project Report

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Jan 2021

I. Overview

This Starbucks Capstone project is part of the Udacity Machine Learning Engineer Nanodegree. Udacity partnered with Starbucks provide a real-world business problem and simulated data that mimics their customer behavior.

Starbucks has a reward program that allows customers earning points for purchases. There is also a phone app for their reward program where they send exclusive personalized offers based on customers spending habits.

This project is focused on tailoring personalized offers to the customers who are most likely to use them. The Machine Learning terminology for this is "propensity modeling". Propensity models are "often used to identify the customers most likely to respond to an offer".

With the well-organized related data, machine learning becomes a useful tool to improve revenues for business but also to offer better services. With the smartphone revolution, there are many applications for business services, and those apps collect insightful data about the user behaviors browsing the app that help predicting their needs and provide them the right offers.

This project is a wonderful example, it is a case of study to analyze related data provided by Starbucks and Udacity to make decisions for sending offers to the client.

My goal is analyzing this type of data to apply the same ideas in other similar projects in real productions.

Here is my blog post.

II. Problem Statement

We want to determine the classes of customers which complete valuable offers to success – in this project we concentrate on two types of offer: *bogo* and *discount*. Some customers do not want to receive offers and might be turned off by them, some do not view the offers and maybe some fulfill the offer although they never view the offer.

III. Evaluation Metrics

In the first step, as a prototype model, we use only *accuracy score* metric for sklearn Logistic Regression models.

In the second and third steps, with the powerful Autogluon Tabular we use many types of compatible metrics, such as the scores of *accuracy, balanced accuracy, roc_auc, f1, precision, recall*.

IV. Data Exploration

We use the dataset provided by Starbucks and Udacity. The data consists of 3 files containing simulated data that mimics customer behavior on the Starbucks Rewards mobile app.

1. portfolio.json: information about the offers,
2. profile.json: information about the customers,
3. transcript.json: info about customer purchases and relationships with the offers.

We read all 3 files and transform into the pandas DataFrame type for efficient processing data.

Process data from portfolio.json:

We transform data in this file into a pandas DataFrame *port_df* for processing data. First here, there exist 10 rows, 6 columns, and no null values .

```
RangeIndex: 10 entries, 0 to 9
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   reward      10 non-null     int64
 1   channels    10 non-null     object
 2   difficulty  10 non-null     int64
 3   duration    10 non-null     int64
 4   offer_type  10 non-null     object
 5   id          10 non-null     object
dtypes: int64(3), object(3)
```

	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

- id: is string type, we replace by number to have good view data, we have 10 ids got number from 0 to 9. We change name "id" into a meaningful name "offer_id".
- channel: has 4 values email, web, mobile, social, we write a small function to encode to 4 binary columns.

```
def encode_df_col(df, col):
    '''
    df: DataFrame
    col: an encoded column of df
    '''
    sep_cols =
pd.get_dummies(df[col].apply(pd.Series).stack()).groupby(level=0).sum()
    return pd.concat([df, sep_cols], axis=1)
```

- reward: compatible value reward of the offer.
- difficulty: the minimum amount spending to have the compatible reward. We change "difficulty" into a meaningful name "min_spend"
- duration: effective time of the offer.
- offer_type: 3 types of "bogo", "discount", and "informational", we use our function to encode 3 columns " bogo", "discount", and "informational".
- We write a function to move column 'offer_id" to the first columns of this dataframe for a good view.

```
def move_col_first(df, col_name):
    '''
    df: pandas DataFrame
    col_name: column is moved to the first column in df
    '''
    vals = df.pop(col_name)
    df.insert(0, col_name, vals)
```

- We remove the columns "channels", "offer_type", "email". The "email" value is always a constant 1, so it is not useful for our research.

```
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   offer_id       10 non-null     int64
 1   reward         10 non-null     int64
 2   min_spend      10 non-null     int64
 3   duration       10 non-null     int64
 4   mobile         10 non-null     uint8
 5   social         10 non-null     uint8
 6   web            10 non-null     uint8
 7   bogo           10 non-null     uint8
```

```
 8   discount       10 non-null     uint8
 9   informational  10 non-null     uint8
dtypes: int64(4), uint8(6)
```

Now a quick look of our port_df dataframe:

	offer_id	reward	min_spend	duration	mobile	social	web	bogo	discount	informational
0	0	10	10	7	1	1	0	1	0	0
1	1	10	10	5	1	1	1	1	0	0
2	2	0	0	4	1	0	1	0	0	1
3	3	5	5	7	1	0	1	1	0	0
4	4	5	20	10	0	0	1	0	1	0
5	5	3	7	7	1	1	1	0	1	0
6	6	2	10	10	1	1	1	0	1	0
7	7	0	0	3	1	1	0	0	0	1
8	8	5	5	5	1	1	1	1	0	0
9	9	2	10	7	1	0	1	0	1	0

Process data from profile.json

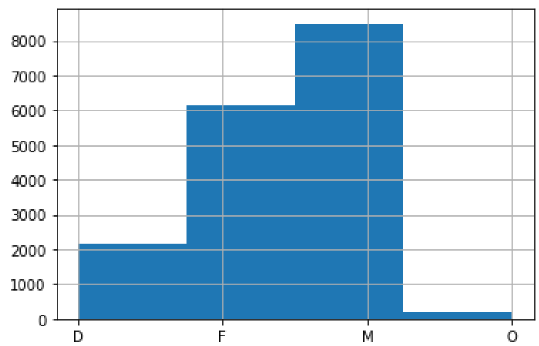
Here, there exist 17,000 customers with related information: *gender, age, id, become_memger_on, and income*. We examine each field later.

```
RangeIndex: 17000 entries, 0 to 16999
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   gender            14825 non-null  object 
 1   age               17000 non-null  int64  
 2   id                17000 non-null  object 
 3   became_member_on  17000 non-null  int64  
 4   income            14825 non-null  float64
dtypes: float64(1), int64(2), object(2)
```

- "id": is the customer id, we change it into meaningful name *customer_id*, and we change its values from a long string to an integer number value to have a good view and easy to process.
- "gender": here, there exist 3 types F, M, O (Female, Male, Other) and there are null values in this column, we fill the null value by D (Difference) to have full meaning data of gender, after that we encode into 4 other binary columns *F, M, O,* and *D.*

```
Number of null value: 2175
M    8484
F    6129
O     212
Name: gender, dtype: int64
```

After fill the null value by D, the histogram of gender is as following:



- "age": we will return to parse this values when we examine the combined data to fine the relationship with offers. There is no null value here, but people that do not declare gender set age 118.

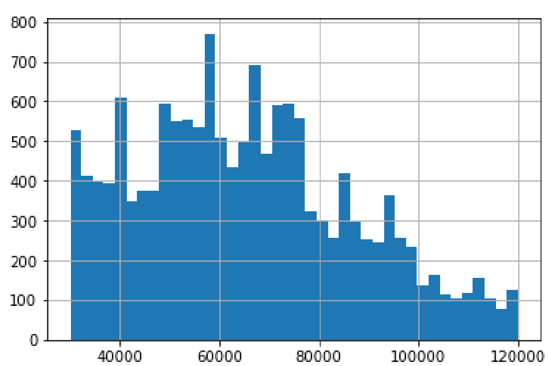
```
prof_df['gender'][prof_df['age'] == 118].unique()
```

```
      array(['D'], dtype=object)
```

- "income": its values are from 30,000 to 120,000 and there are 2175 null values.

```
Number of null income:  2175
count     14825.000000
mean      65404.991568
std       21598.299410
min       30000.000000
25%       49000.000000
50%       64000.000000
75%       80000.000000
max      120000.000000
Name: income, dtype: float64
```

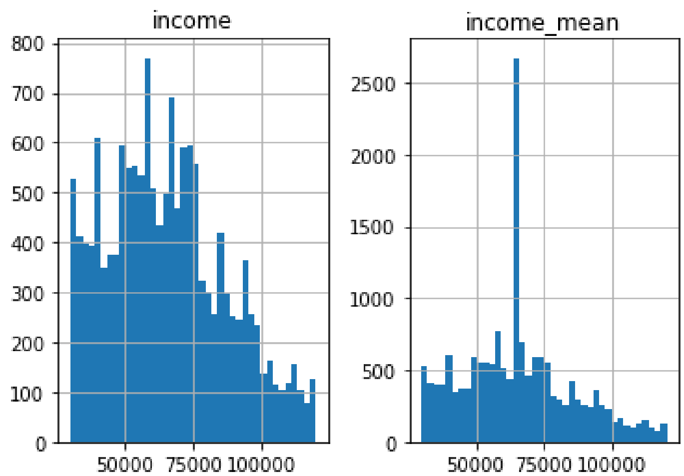
Here is the histogram of income values.



We have many methods to fill in the null values to utilize these data. Now we display two popular methods:

1. ***mean value***:

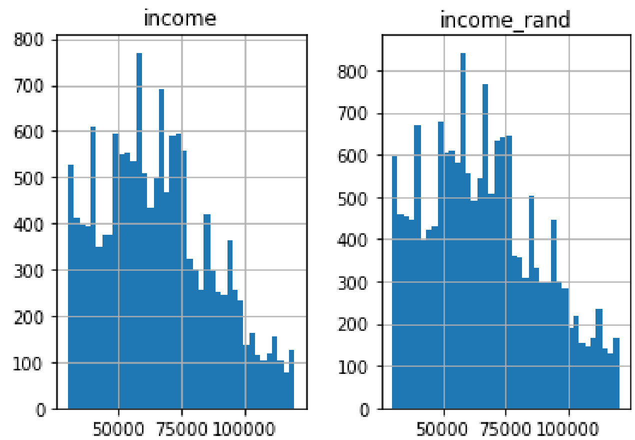
```
# Try setting mean value for null income
mean_inc = round(prof_df['income'].mean(), -3)
prof_df['income_mean'] = prof_df['income'].fillna(mean_inc)

# Histograms
prof_df[['income_mean', 'income']].hist(bins=40)
```



2. ***random values*** in the range of min and max

   We write some code to implement this null values filling.

```
max_inc = max(prof_df['income'].dropna())//1000
min_inc = min(prof_df['income'].dropna())//1000

null_income_indexs = prof_df['income'].isnull()

new_incomes = (np.random.randint(min_inc, max_inc,
size=sum(null_income_indexs))*1000).tolist()

prof_df['income_rand'] = prof_df['income'].copy()

indexs = []
i = 0
for k, val in enumerate(null_income_indexs):
    if val == True:
        indexs.append(k)
        prof_df['income_rand'][k] = new_incomes[i]
        i += 1

# Histograms
prof_df[['income_rand', 'income']].hist(bins=40)
```



Compare two plots, we see that the *income_rand* histogram is similar to the original *income* one. So, we choose the income_rand values for next steps.

- " *became_member_on*": datetime that the customer was a member. We change the name into a meaningful name '*time_on*'.

  We move the column *customer_id* to the first position to have a good order and remove the columns *income* and *income_mean* to have a neat and useful data for next steps. Summarize our changes.

```
RangeIndex: 17000 entries, 0 to 16999
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   customer_id  17000 non-null  int64
 1   gender       17000 non-null  object
 2   age          17000 non-null  int64
 3   time_on      17000 non-null  datetime64[ns]
 4   income_rand  17000 non-null  float64
 5   D            17000 non-null  uint8
 6   F            17000 non-null  uint8
 7   M            17000 non-null  uint8
 8   O            17000 non-null  uint8
```

Process data from transcript.json

Here, there exist 306,534 purchases with 4 columns with information related to the offers and customers.

```
RangeIndex: 306534 entries, 0 to 306533
Data columns (total 4 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   person  306534 non-null  object
```

```
 1   event   306534 non-null  object
 2   value   306534 non-null  object
 3   time    306534 non-null  int64 
dtypes: int64(1), object(3)
```

1. *person:* this is customer_id in profile data, we substitute it by the name and the numeric value of *customer_id*.
2. *event*: there are 4 types of event.

```
# Examine the event data
tran_df['event'].unique()
```

```
array(['offer received', 'offer viewed', 'transaction', 'offer completed'],
      dtype=object)
```

We encode event into 4 binary columns *offer_received, offer_viewed, offer_completed,* and *transaction*.

3. *value*: this is a complicated field; each value is a dictionary data. Write some code, we find there are four types of value data:

```
{'reward', 'offer id', 'offer_id', 'amount'}
```

Examine real data, 'offer id' and 'offer_id' are the same, it contain the offer_id in portfolio data. Here we do not know exactly what is the amount, because there is not a clear explain in the document, but it may be useful for our prediction models.

We encode this column into three columns *offer_id, amount,* and *reward*. Write some code, we can read the values in reward column, we see that sometime they do not record the reward value as in portfolio, so we *remove this column* to get the data consistency, because the offer_id implies the reward value.

```
{3: [0, 5], 4: [0, 5], 9: [0, 2], 6: [0, 2], 1: [0, 10], 8: [0, 5], 5: [0, 
3], 2: [0], 0: [0, 10], 7: [0]}
```

4. *time:* time in hours since start of test. The data begins at time t = 0.

After processing and cleaning the data, moving *customer_id* to the first column, we have the dataframe info as following:

```
RangeIndex: 306534 entries, 0 to 306533
Data columns (total 8 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   customer_id      306534 non-null  int64
 1   time             306534 non-null  int64
 2   offer_completed  306534 non-null  uint8
 3   offer_received   306534 non-null  uint8
 4   offer_viewed     306534 non-null  uint8
```

```
 5   transaction      306534 non-null  uint8
 6   offer_id         306534 non-null  int64
 7   amount           306534 non-null  float64
dtypes: float64(1), int64(3), uint8(4)
```

Combine data from 3 above dataframes

First we combine data from profile and transcript on value *customer_id.*

```
# Merge tran_df and prof_df
data = pd.merge(tran_df, prof_df, on='customer_id')
```

Second we combine new data with portfolio data on value *offer_id*.

```
# Merging on 'offer_id'
data = pd.merge(data, port_df, on='offer_id', how='left')
```

Process combined data

There are null values in new combined data:

```
reward             138953
min_spend          138953
duration           138953
mobile             138953
social             138953
web                138953
bogo               138953
discount           138953
informational      138953
```

These null values attached with the false *offer_id 10* – (informational transaction) when we process the transaction data.

```
# Find sample null value
data['offer_id'][data['bogo'].isnull()].value_counts()
```

```
10    138953
Name: offer_id, dtype: int64
```

We can remove all 138953 data rows of offer_id 10.

We change column name *offer_comleted* as *success* to have a meaningful name and move it to the first position in dataframe.

```
Int64Index: 167581 entries, 0 to 306532
Data columns (total 25 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   success         167581 non-null  uint8
 1   customer_id     167581 non-null  int64
```

```
 2   time            167581 non-null  int64
 3   offer_received  167581 non-null  uint8
 4   offer_viewed    167581 non-null  uint8
 5   transaction     167581 non-null  uint8
 6   offer_id        167581 non-null  int64
 7   amount          167581 non-null  float64
 8   gender          167581 non-null  object
 9   age             167581 non-null  int64
 10  time_on         167581 non-null  datetime64[ns]
 11  income_rand     167581 non-null  float64
 12  D               167581 non-null  uint8
 13  F               167581 non-null  uint8
 14  M               167581 non-null  uint8
 15  O               167581 non-null  uint8
 16  reward          167581 non-null  float64
 17  min_spend       167581 non-null  float64
 18  duration        167581 non-null  float64
 19  mobile          167581 non-null  float64
 20  social          167581 non-null  float64
 21  web             167581 non-null  float64
 22  bogo            167581 non-null  float64
 23  discount        167581 non-null  float64
 24  informational   167581 non-null  float64
dtypes: datetime64[ns](1), float64(11), int64(4), object(1), uint8(8)
```

We save data in the file *raw_data.csv* for backup and reuse later.

We can see the ratio of *success, bogo,* and *discount* on *gender*.

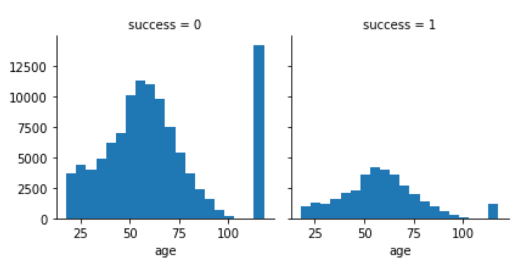
	gender	success
1	F	0.285180
3	O	0.273173
2	M	0.235094
0	D	0.073845

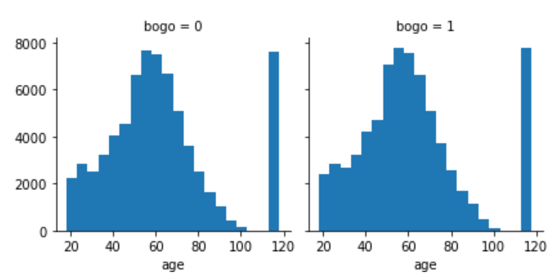
	gender	bogo
1	F	0.508909
0	D	0.506376
2	M	0.504012
3	O	0.498364

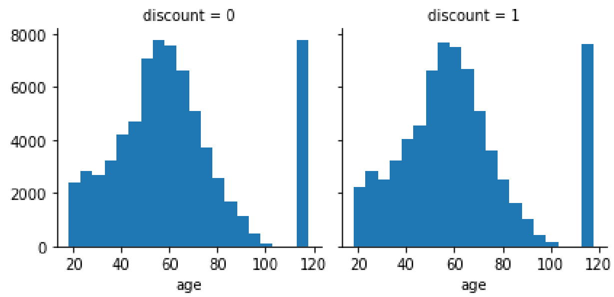
	gender	discount
3	O	0.501636
2	M	0.495988
0	D	0.493624
1	F	0.491091

The difference between female and male is not much.

Now we review the histograms of success, bogo, and discount over age to see how we can combine age values into some compatible age classes for better prediction.





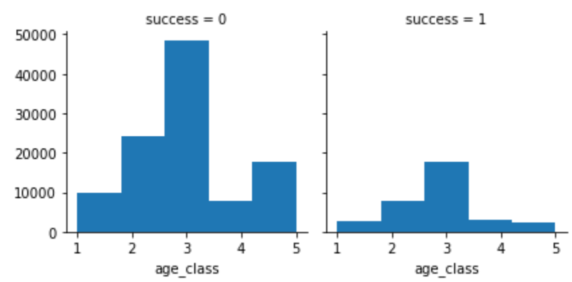


From these plots, we can set five classes of age:

$$[1, 2, 3, 4, 5] = [\ < 30,\ < 50,\ < 75,\ < 85, \text{rest}\ ]$$

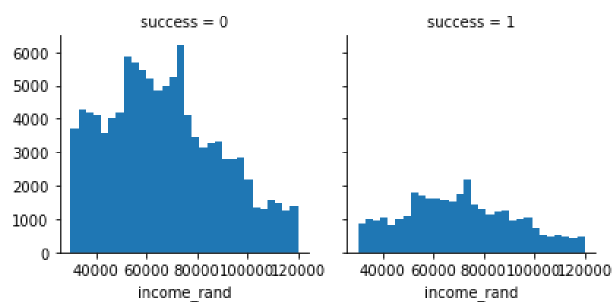
and we can see the distribution of *success* on *age_class*:

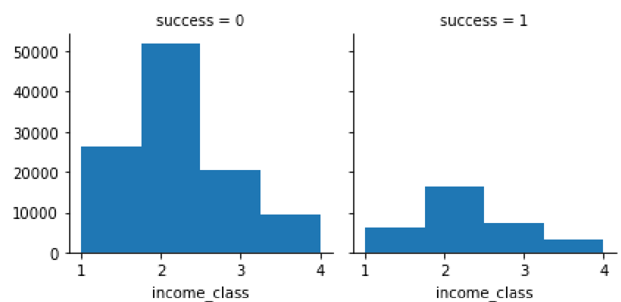
```
3    17623
2     7868
4     2876
1     2706
5     2506
Name: age_class,
dtype: int64
```



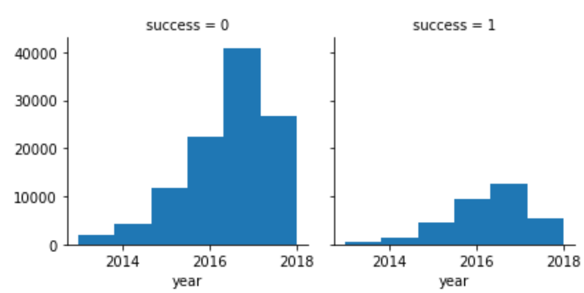
Similarly, we can create four income classes:

$$[1, 2, 3, 4] = [< 50.000, < 80.000, < 100.000, \text{rest}]$$





From the column *time_on*, we can extract value *year* to check its effect on the ratio of *success*.



So, we extract year value from time_on and encode into columns to use in our dataframe.

After many steps of encoding and cleaning unnecessary data, we save the new data in the file *pdata.csv*.

```
Int64Index: 141515 entries, 0 to 306532
Data columns (total 26 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   success       141515 non-null  uint8
 1   customer_id   141515 non-null  int64
 2   time          141515 non-null  int64
 3   offer_viewed  141515 non-null  uint8
 4   offer_id      141515 non-null  uint8
 5   time_on       141515 non-null  datetime64[ns]
 6   D             141515 non-null  uint8
 7   F             141515 non-null  uint8
 8   M             141515 non-null  uint8
 9   O             141515 non-null  uint8
 10  reward        141515 non-null  uint8
 11  min_spend     141515 non-null  uint8
 12  duration      141515 non-null  uint8
 13  mobile        141515 non-null  uint8
 14  social        141515 non-null  uint8
 15  web           141515 non-null  uint8
 16  bogo          141515 non-null  uint8
 17  discount      141515 non-null  uint8
 18  age_class     141515 non-null  uint8
 19  income_class  141515 non-null  uint8
 20  2013          141515 non-null  uint8
 21  2014          141515 non-null  uint8
 22  2015          141515 non-null  uint8
 23  2016          141515 non-null  uint8
 24  2017          141515 non-null  uint8
 25  2018          141515 non-null  uint8
dtypes: datetime64[ns](1), int64(2), uint8(23)
```

Conclusion

After these steps of analyzing and processing the data relationship, from the supplied data, if Starbucks wants to have more success in offers bogo and discount, they need to concentrate on customers that are in:

- gender of female and male.
- age_class from 30 to 50.
- income_class from 50.000 to 80.000.
- Although the customers engaged in year 2017 had the most success offers, we can't conclude easily because the data of year 2018 is too small.

Separate data for bogo and discount training models

We need some adjustment to separate the data into two parts. For prediction model, we change *time_on* data type as int64, normalize data columns *'time'*, *'reward'*, *'min_spend'*, *'duration'*, and *'time_on'*.

Now we are ready to create bogo and discount data.

```
# Seperate two instant dataframes for bogo and discount
bogo = data[data['bogo'] == 1]
discount = data[data['discount'] == 1]

# Save data into csv files
bogo.to_csv(DIR+'bodo.csv', index=False)
discount.to_csv(DIR+'dicsount.csv', index=False)
```

Prepare data for sklearn Logistic Regression models.

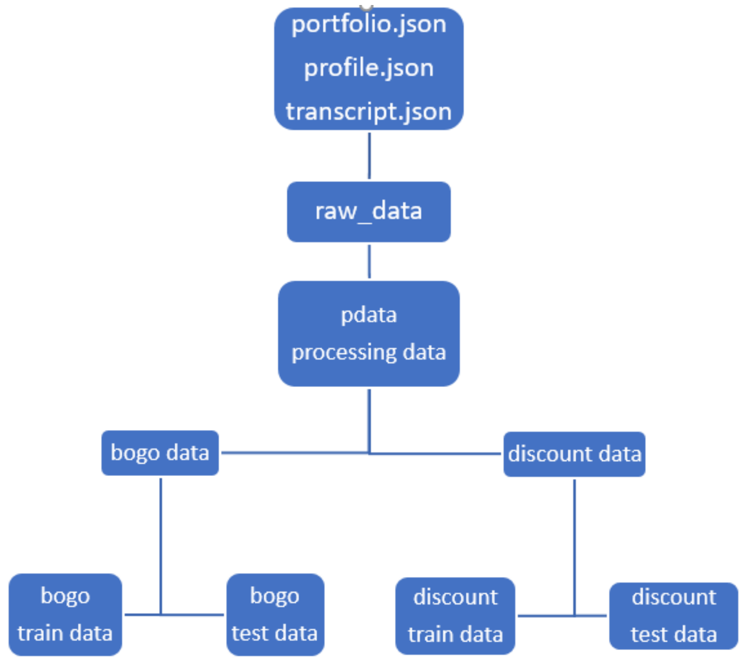
```
# Predict the success bogo, we delete unrelated rows
Y_bogo = bogo['success']
X_bogo = bogo.drop(axis=1,
    columns=['discount', 'success',])

# Predict the success discount, we delete unrelated rows
Y_disc = discount['success']
X_disc = discount.drop(axis=1,
    columns=['bogo', 'success',])
X_bogo.info()
X_disc.info()
```

By sklearn train_test_split, we create train set and test set for our models. We also use these train set and test for two local training models: Sklearn Logistic Regression and Autogluon Tabular

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

X1_train, X1_test, Y1_train, Y1_test = train_test_split(X_bogo, Y_bogo, test_size=0.2, random_state=18)
X2_train, X2_test, Y2_train, Y2_test = train_test_split(X_disc, Y_disc, test_size=0.2, random_state=18)
```

When we create data for Autogluon Tabular models on Aws Sagemaker, we will use the function sample of Pandas to separate our data to train set and test set.

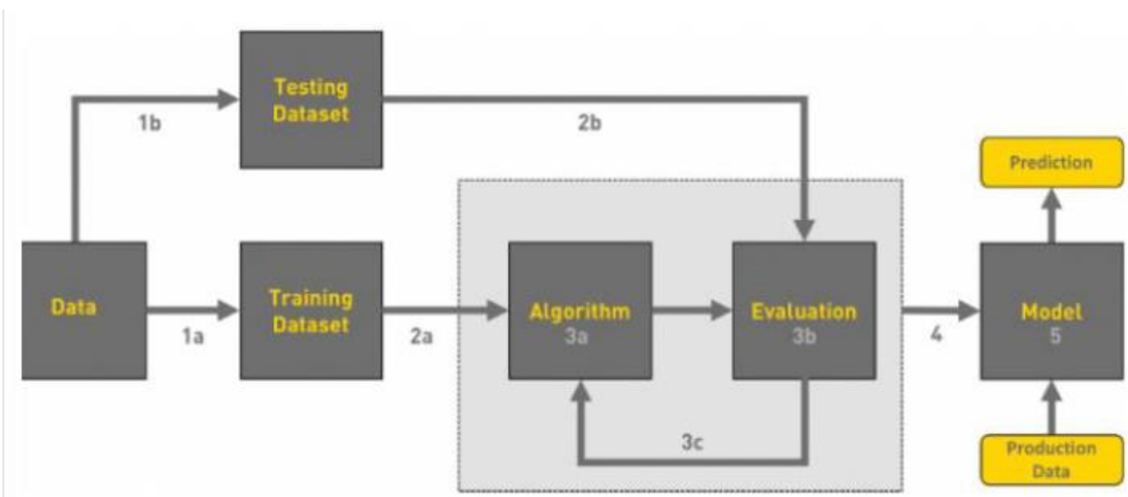
We can describe in the following workflow.



Data workflow

V. Train the models

The workflow of machine learning can be displayed in the following chart.



[Overview of Machine Learning flowchart](#).

We deploy our training process through three steps.

1. Sklearn Logistic Regression models

The first bogo model.

```
bogo_clf = LogisticRegression(random_state=18, max_iter= 1000).fit(X1_train, Y1_train)
bogo_predictions = bogo_clf.predict(X1_test)
print('Train accuracy: ', bogo_clf.score(X1_train, Y1_train),
      '\n---\nTest accuracy: ', bogo_clf.score(X1_test, Y1_test))
```

We have the accuracy:

```
Train accuracy:  0.7852093624002933
---
Test accuracy:  0.7872102764590896
```

The second discount model.

```
disc_clf = LogisticRegression(random_state=18, max_iter= 1000).fit(X2_train, Y2_train)
disc_predictions = disc_clf.predict(X2_test)
print('Train accuracy: ', disc_clf.score(X2_train, Y2_train),
      '\n---\nTest accuracy: ', disc_clf.score(X2_test, Y2_test))
```

We have the accuracy:

```
Train accuracy:  0.751672091276512
---
Test accuracy:  0.7533619456366237
```

Very good results for sklearn Logistic Regression models.

2. Autogluon Tabular models on local

Now we adjust data a little bit for compatible Autogluon Tabular models.

```
# Set category type for category columns
X_bogo = pd.concat([Y1_train,X1_train], axis=1)
cat_cols = ['success', 'mobile', 'social', 'web', 'customer_id', 'offer_id',
       'bogo', 'D', 'F', 'M', 'O', 'age_class', 'income_class', 2013, 2014,
       2015, 2016, 2017, 2018]
X_bogo[cat_cols] = X_bogo[cat_cols].astype('category')
X_disc=pd.concat([Y2_train,X2_train], axis=1)
disc_cat_cols = ['success', 'mobile', 'social', 'web', 'customer_id', 'offer_id',
       'discount', 'D', 'F', 'M', 'O', 'age_class', 'income_class', 2013, 2014,
       2015, 2016, 2017, 2018]
X_disc[disc_cat_cols] = X_disc[disc_cat_cols].astype('category')
```

And now we are ready for training our bogo model.

```
from autogluon.tabular import TabularPredictor
bogo_predictor = TabularPredictor(label='success', problem_type='binary',
    verbosity = 1).fit(X_bogo, presets='best_quality', time_limit=600)
```

We get the leaderboard, and sort the score_val values.

```
bogo_leaderboard = bogo_predictor.leaderboard(X_bogo, silent=True)
bogo_leaderboard['score_val'].sort_values(ascending=False)
```

We get such an impressive result:

```
15    0.980294
14    0.980294
13    0.980294
11    0.979893
12    0.979875
9     0.979579
10    0.979561
8     0.979160
6     0.978636
5     0.978636
4     0.978636
7     0.978287
3     0.970520
1     0.864556
0     0.863770
2     0.841272
16    0.781614
17    0.781544
Name: score_val, dtype: float64
```

With the test set:

```
bogo_predictor.evaluate(pd.concat([Y1_test,X1_test], axis=1))
```

```
{'accuracy': 0.9773806199385646,
 'balanced_accuracy': 0.952397164785564,
 'mcc': 0.9323110209968879,
 'roc_auc': 0.9914061353237994,
 'f1': 0.945325683428957,
 'precision': 0.9852268730214562,
 'recall': 0.9085306519623743}
```

The accuracy is 97.74%, the minimum is recall 90.85% and the maximum is roc_auc 99.14%.

All the score results are much better than sklearn models ones.

Similarly, we train the discount model.

```
disc_predictor = TabularPredictor(
    label='success', problem_type='binary',
    verbosity = 1).fit(X_disc,
          presets='best_quality', time_limit=600)
```

We get the leaderboard, and sort the score_val values.

```
disc_leaderboard = disc_predictor.leaderboard(X_disc, silent=True)
disc_leaderboard['score_val'].sort_values(ascending=False)
```

Result:

```
12    0.981008
11    0.981008
16    0.980972
15    0.980936
13    0.980918
9     0.980901
14    0.980865
10    0.980811
6     0.980132
5     0.980132
7     0.980132
8     0.979935
4     0.972978
0     0.856790
3     0.855431
2     0.838442
1     0.836761
19    0.788923
18    0.786938
17    0.786688
Name: score_val, dtype: float64
```

With the test set:

```
disc_predictor.evaluate(pd.concat([Y2_test, X2_test], axis=1))
```

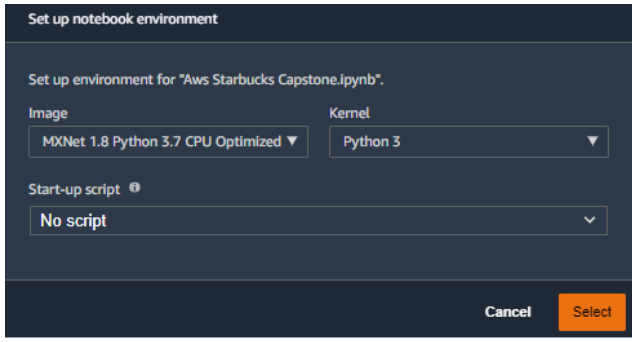
```
{'accuracy': 0.9828326180257511,
 'balanced_accuracy': 0.9673226683523406,
 'mcc': 0.9548884574734777,
 'roc_auc': 0.9939625410074887,
 'f1': 0.9654278305963699,
 'precision': 0.9973214285714286,
 'recall': 0.9355108877721943}
```

The accuracy is 98.28%, the minimum is recall 93.55% and the maximum is roc_auc 99.40%.

We get the very good results with Autogluon Tabular models on local model training processing.

3. Autogluon with Aws Sagemaker

From Aws gateway, we run Amazon Sagemaker Studio. Because this project is executed with Autogluon Tabular prediction models, we must run our notebook on the most compatible instance type. We select the low cost instance type *ml.t3.medium* with suitable powerful kernel *MXNet 1.8 Python 3.7 CPU Optimized*.



According to the guide in Cloud Training with AWS SageMaker - AutoGluon and Cloud Deploying AutoGluon Models with AWS SageMaker, we implement as following:

1. Prepare python code and config file for entry points to create and deploy Autogluon Tabular TabularPredictor models:
    a. ag_model.py
    b. tabular_train.py
    c. tabular_serve.py
    d. config.yaml
2. Create data for bogo models. We get data from *bogo.csv* that we create from previous steps and use pandas sample to separate into train set and test set with the fraction 80% and 20%. From these data, we create compatible csv files to upload into our s3 bucket.

```
DIR = 'data/'
bogo = pd.read_csv(DIR + 'bogo.csv')
bg_train = bogo.sample(frac = 0.8, random_state = 18)
bg_test = bogo.drop(bg_train.index)
bg_train_file = 'bg_train.csv'
bg_test_file = 'bg_test.csv'
bg_train.to_csv(bg_train_file, index=False)
bg_test.to_csv(bg_test_file, index=False)
train_input = ag.sagemaker_session.upload_data(
    path=os.path.join("data", "bg_train.csv"), key_prefix=s3_prefix)
eval_input = ag.sagemaker_session.upload_data(
    path=os.path.join("data", "bg_test.csv"), key_prefix=s3_prefix)
config_input = ag.sagemaker_session.upload_data(
    path=os.path.join("config", "config.yaml"), key_prefix=s3_prefix)
```

Next we create AutoGluon tabular model:

```
from ag_model import (
    AutoGluonTraining,
    AutoGluonInferenceModel,
    AutoGluonTabularPredictor,
)
```

```
ag = AutoGluonTraining(
    role=role,
    entry_point="tabular_train.py",
    region=region,
    instance_count=1,
    instance_type="ml.m5.2xlarge",
    framework_version="0.3.1",
    base_job_name="autogluon-tabular-train",
)
```

We create training job and train our bogo model:

```
job_name = utils.unique_name_from_base("autogluon-sm")
ag.fit(
    {"config": config_input, "train": train_input, "test": eval_input},
    job_name=job_name,)
```

…

In the config file, it set time_limit = 600 (second), then after successfully training, we get the message:

```
2022-01-10 16:13:58 Completed - Training job completed
Training seconds: 907
Billable seconds: 907
```

We have another training with no time_limit, it takes much time:

```
2022-01-10 17:30:14 Completed - Training job completed
Training seconds: 4052
Billable seconds: 4052
```

When comparing the metrics score, we see the differences are very small. We can conclude *time_limit = 600* is enough for our data with low cost.

After training, we prepare a little bit of data for deploying the model. We copy the model image *model.tar.gz* to the data directory of the endpoint:

```
s3_deploy = f"ag_sm_deploy/{utils.sagemaker_timestamp()}"
output_path = f"s3://{bucket}/{s3_deploy}/output/"
endpoint_name = sagemaker.utils.unique_name_from_base("sg-ag-deploy")

# Copy model image to endpoint data directory
!aws s3 sync s3://sagemaker-us-east-1-503563512855/autogluon-sm-1641831565-ea74/output/
         s3://sagemaker-us-east-1-503563512855/sg-ag-deploy-1641837746-719b/models
```

We setup the process to deploy the endpoint:

```
instance_type = "ml.m5.2xlarge"
```

```
model = AutoGluonInferenceModel(model_data=model_data,
    role=role,
    region=region,
    framework_version="0.3.1",
    instance_type=instance_type,
    entry_point="tabular_serve.py",)

bogo_predictor = model.deploy(initial_instance_count=1,
                         serializer=CSVSerializer(),
                         instance_type=instance_type)
```

We prepare test data for our bogo model.

```
bg_test_data = pd.read_csv('data/bg_test.csv')

bg_success = bg_test_data.loc[1:,0].tolist()
bg_success = [int(item) for item in bg_success]

bg_test_data.shape
```

```
(14324, 25)
```

There are 14.324 test data rows. We try a test prediction of 500 data test row:

```
bg_test_data.drop(columns=['mobile', 'bogo', 'discount','success'], axis=1,
      inplace=True)
bg_predictions = bogo_predictor.predict(bg_test_data[:500].values)
bg_predictions[:5]
```

```
[[0.0, 0.9517540335655212, 0.04824599251151085],
 [1.0, 0.008261322975158691, 0.9917386770248413],
 [0.0, 0.9948185682296753, 0.005181452259421349],
 [1.0, 0.008979439735412598, 0.9910205602645874],
 [0.0, 0.9975728392601013, 0.0024271896108984947]]
```

The endpoint execution can't response to the large test data – timeout problem, so we write some code to get the result of all test data predictions.

```
NUM_TEST = bg_test_data.shape[0]
SEGMENT = 500
ITER = NUM_TEST // SEGMENT
bg_preds = []
for k in range(ITER):
    preds=bogo_predictor.predict(bg_test_data[k*SEGMENT:(k+1)*SEGMENT].values)
    bg_preds.extend(preds)

preds = bogo_predictor.predict(bg_test_data[ITER*SEGMENT:].values)
bg_preds.extend(preds)

bg_predictions = [int(item[0]) for item in bg_preds]
```

Using sklearn metrics to get the prediction metric scores from our prepared data *bg_predictions* and *bg_success*.

```
from sklearn.metrics import (accuracy_score, f1_score, balanced_accuracy_score,
                             precision_score, recall_score, roc_auc_score)
print('Bogo predictions test scores',
     '\naccuracy_score: ', accuracy_score(bg_predictions, bg_success),
     '\nbalanced_accuracy_score: ', balanced_accuracy_score(bg_predictions,
bg_success),
     '\nprecision_score: ', precision_score(bg_predictions, bg_success),
     '\nrecall_score: ', recall_score(bg_predictions, bg_success),
     '\nf1_score: ', f1_score(bg_predictions, bg_success),
     '\nroc_auc_score', roc_auc_score(bg_predictions, bg_success))
```

```
Bogo predictions test scores
accuracy_score:  0.9867346226349228
balanced_accuracy_score:  0.9891488181708774
precision_score:  0.945617402431222
recall_score:  0.9932795698924731
f1_score:  0.9688626679777124
roc_auc_score 0.9891488181708775
```

The accuracy is 98.67 %, the minimum is precision 94.56% and the maximum is recall 99.33%.

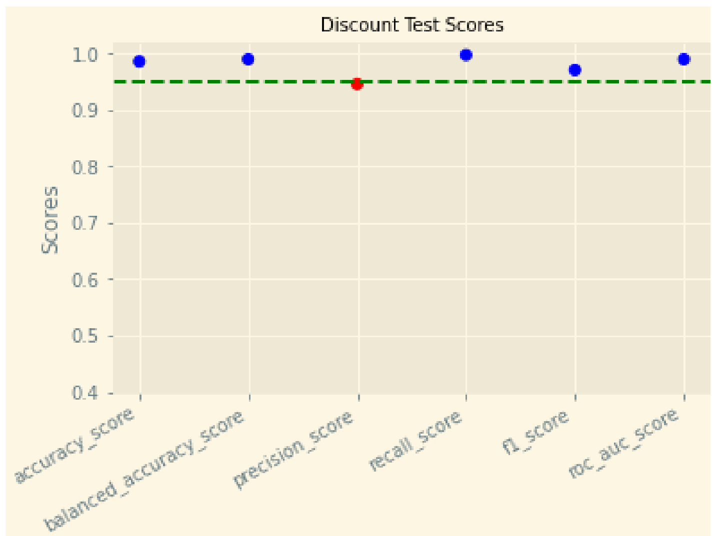
3. Similarly, we create our discount Autogluon tabular model and get the same results – reference to my notebook *my_Starbucks_Capstone.ipynb*.

```
Discount predictions test scores
accuracy_score:    0.9851931330472103
balanced_accuracy_score: 0.9890291251091365
precision_score:   0.9451631046119235
recall_score:            0.9964423361992292
f1_score:          0.9701255592437581
roc_auc_score:           0.9890291251091367
```

The accuracy is 98.52 %, the minimum is precision 94.52% and the maximum is recall 99.64%. We write some code to plot these scores to have more interesting results.

```
metric = ['accuracy_score', 'balanced_accuracy_score', 'precision_score',
          'recall_score', 'f1_score', 'roc_auc_score']
disc_score = [accuracy_score(disc_predictions, disc_success),
         balanced_accuracy_score(disc_predictions, disc_success),
         precision_score(disc_predictions, disc_success),
         recall_score(disc_predictions, disc_success),
         f1_score(disc_predictions, disc_success),
         roc_auc_score(disc_predictions, disc_success)]
df = pd.DataFrame.from_dict({'metric': metric, 'score': disc_score})
df
```

```
x,y = df['metric'], df['score']
plt.scatter(x, y, c=['r' if k<.95 else 'b' for k in y ])
plt.axhline(y=0.95, color='g', linestyle='--')
plt.ylim(bottom=.4,top=1.02)
# Add labels
plt.ylabel("Scores")
# plt.suptitle("Bogo Test Scores", size=14)
plt.title("Discount Test Scores", size=10)
# Give it some pizzaz!
plt.style.use("Solarize_Light2")
plt.gcf().autofmt_xdate()
plt.show()
```



Very impressive scores. These scores prove that our Autogluon tabular are the most effective models for these problems.

4. Research

When researching on the Internet, there was a paper solved the same problem with ours, and the author implemented on three models, he got the results as following:

The author got the scores from three models.

Model	Accuracy	F1 Score	F2 Score	TP	FP	TN	FN
Logistic Regression **[test set]**	0.71208	0.79208	0.83016	4838	1737	1444	803
Support Vector Machines **[test set]**	0.72463	0.78873	0.80353	4534	1391	1858	1038
Neural Network (Final) **[test set]**	0.71163	0.79726	0.84863	5002	1905	1276	639

Final Metrics using the Test Set

[Starbucks Capstone Project Stephen – Stephen Blystone | Medium]

VI. Conclusion

1. We examine and analyze three json files to combine a useful related data.
2. We can see the ratio success offers from customers with details in gender, age classes, income classes.
3. We separate our data into two distinct parts for two prediction models of bogo and discount offers.
4. We implement successful Sklearn Logistic Regression Models and train them to get the good accuracy score about 78% and 75%
5. We implement successful Autogluon Tabular Models on local and train them to get the very impressive results about 98% (the above results).
6. We implement successful Autogluon Tabular Models on Aws Sagemaker and train them to get the very impressive results about 98% (the above results).
7. Autogluon Tabular Model is much better than Sklearn Logistic Regression Model. Autogluon Tabular Model is the most effective model for these similar problems.

VII. Improvement

1. We can examine if informational data has an effect on other offers.
2. We can use unsupervised model to prepare our data more effective to get more interesting results about various classification of customers – combining gender, age, income, time to become member.
3. We can use other compatible machine learning models to learn more with these wonderful datasets.

VIII. References

1. Propensity model.
2. Sklearn Logistic Regression.
3. Autogluon Tabular.
4. Deploying AutoGluon Models with AWS SageMaker.
5. Code-free machine learning: AWS Machine Learning Blog.
6. AutoGluon Tabular with SageMaker Examples.
7. Cloud Training with AWS SageMaker - AutoGluon.