Machine learning Engineer Nanodegree

Capstone Project Report

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Introduction

Starbucks Corporation is an American coffee company and coffeehouse chain which opened the doors to its first store in Seattle, Washington in 1971. While successful, this first shop originally only sold prepackaged coffee beans with no opportunity for customers to sit and enjoy a cup of coffee in a public setting.

Imagine pulling into a Starbucks drive-thru and seeing not just your drink order but your name on the screen and to your smartwatch —are serving suggestions generated by artificial intelligence of what foods you might like with your drink, automatically generated by the weather, your buying history, and the choices that others with similar preferences have made.

In reality, the Starbucks app sends out various types of promotional offers to customers, either discounts (BOGO or 50% off during happy hours) or Star Dash/menu challenges (completing required purchases to earn star rewards). Sometimes it also informs customers about limited-time drinks, such as those colorful Instagram Frappuccinos. As a marketing strategy, the goal of these promotional offers is to encourage customers to buy drinks at Starbucks and build loyalty among customers in the long run. Since Starbucks has a variety of products and customers' tastes also vary, it is important to send the right offer to the right customer by building a highly personalized recommendation system.

It's all part of the coffee giant's plan to use AI and the cloud to drive sales and growth.

Problem definition

- The first of Starbucks' challenges is figuring out how the chain will continue to stay relevant to their customers. With 27,000 locations across over 70 countries, it's a large undertaking that involves all parts of the organization and requires creative thinking.

- Secondly, the incredible success of Starbucks' mobile ordering has led to a large amount of orders, creating a need to make the Baristas' job simpler.

Our approach is to incorporate AI technology to make the Baristas' production more seamless. By helping their employees do their jobs more efficiently, Starbucks improves the customer experience.

In a simulated environment, Starbucks sends out three types of offers (BOGO, discount and informational) via multiple channels. Customers' responses to offers and transactions are recorded.

Data

The data is provided by Starbucks and Udacity, in three JSON files:

profile.json

Rewards program users (17000 users x 5 fields)

- gender: (categorical) M, F, O, or null age:
- (numeric) missing value encoded as 118 id:
- (string/hash)
- became*member*on: (date) format YYYYMMDD

- income: (numeric) **portfolio.json**

Offers sent during 30-day test period (10 offers x 6 fields)

- reward: (numeric) money awarded for the amount spent
- channels: (list) web, email, mobile, social difficulty: (numeric)
- money required to be spent to receive reward duration:
- (numeric) time for offer to be open, in days offer_type: (string)
- bogo, discount, informational id: (string/hash)

transcript.json

Event log(306648 events x field)

- Person: (string/hash)
- Event: (string) offer received, offer viewed, transaction, offer completed.
- Value: (dictionary) different values depending on event type

- Offer id: (string/hash) not associated with any “transaction”
- Amount: (numeric) amount spent on “transaction”
- Time: (numeric) hours spent after start of test

Proposed solution

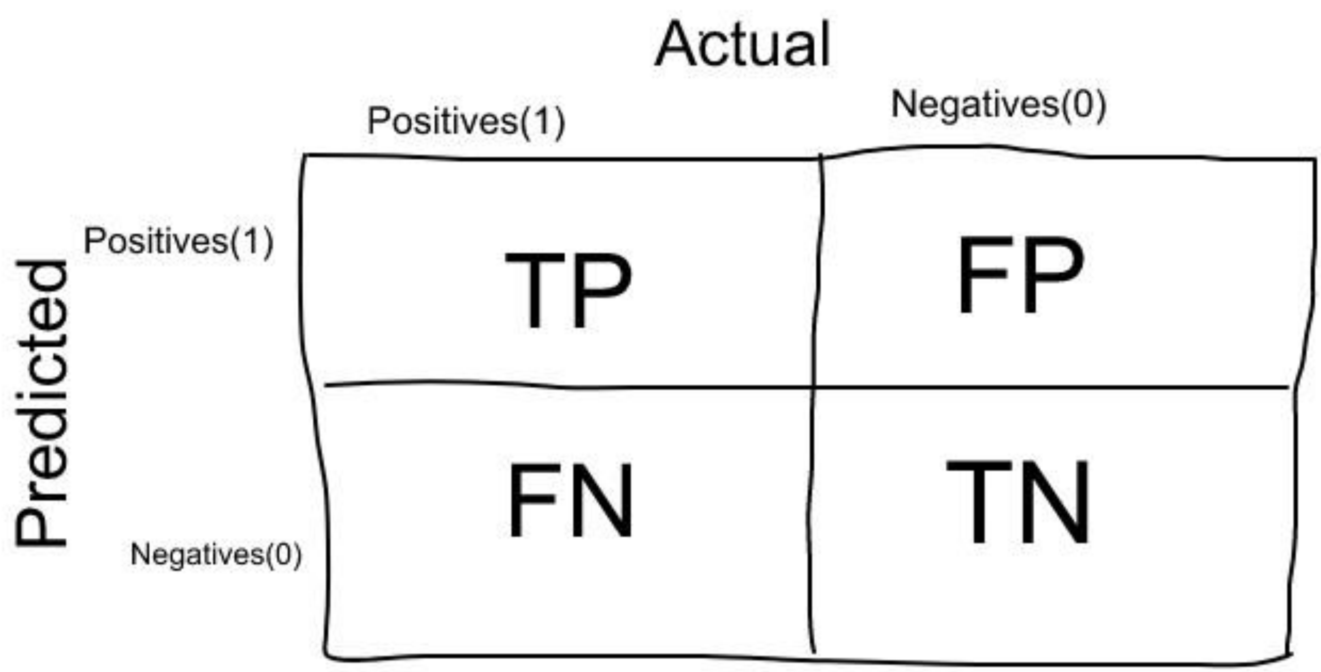
The solution to the above problem can be solved using Reinforcement Learning. Starbucks as a coffee retailer knows every nuance of it’s customer’s coffee habits through it’s in-house Artificial Intelligence technology.

With a core focus on Customer centricity, Starbucks sends a customized email to any customer who hasn’t visited Starbucks recently with offers drawn from the customer’s previous history. For Starbucks, AI will be going through the mounds of data it already has in areas like scheduling, inventory, and restaurant traffic. Scheduling and inventory are necessary tasks, but monotonous and uncreative, innovation is the name of the game, and today, there is more pressure than ever for companies to bring new products to market.

The transcript will be processed to extract the responses from customers towards the promotional offers sent to them. With the response as labels, and properties of each customer and offer pair as features, a binary classifier can be trained to predict whether a customer will positively respond to a promotional offer.

Metrics

The performance of solutions will be evaluated on a large unseen dataset. For a binary classification problem, the relationship between prediction and ground truth can be visualized by the confusion matrix,



where all data is sliced into four groups:

- True positive (TP): both prediction and ground truth are positive class
- True negative (TN): both prediction and ground truth are negative class
- False positive (FP): predicted to be positive, but in fact negative
- False negative (FN): predicted to be negative, but in fact positive

Many scalar metrics can be derived from the confusion matrix. Defined by the ratio of correct predictions, accuracy can be expressed as:

- Accuracy = (TP + TN) / (TP + FP + FN + TN)

Accuracy is a good measure when the target classes are nearly balanced. It will become less effective facing highly imbalanced data. For instance, in fraud detection, the positive rate could be lower than 1%. A naive model predicting all instances to be negative will yield an accuracy above 99%, but will never get the job done.
In this case, metrics like precision and recall are more sensitive.

- Precision (P) = TP / (TP + FP) Recall (R)
- = TP / (TP + FN)

One can also consider both precision and recall at the same time using F1 score.

- F1 = 2 * P * R / (P + R)

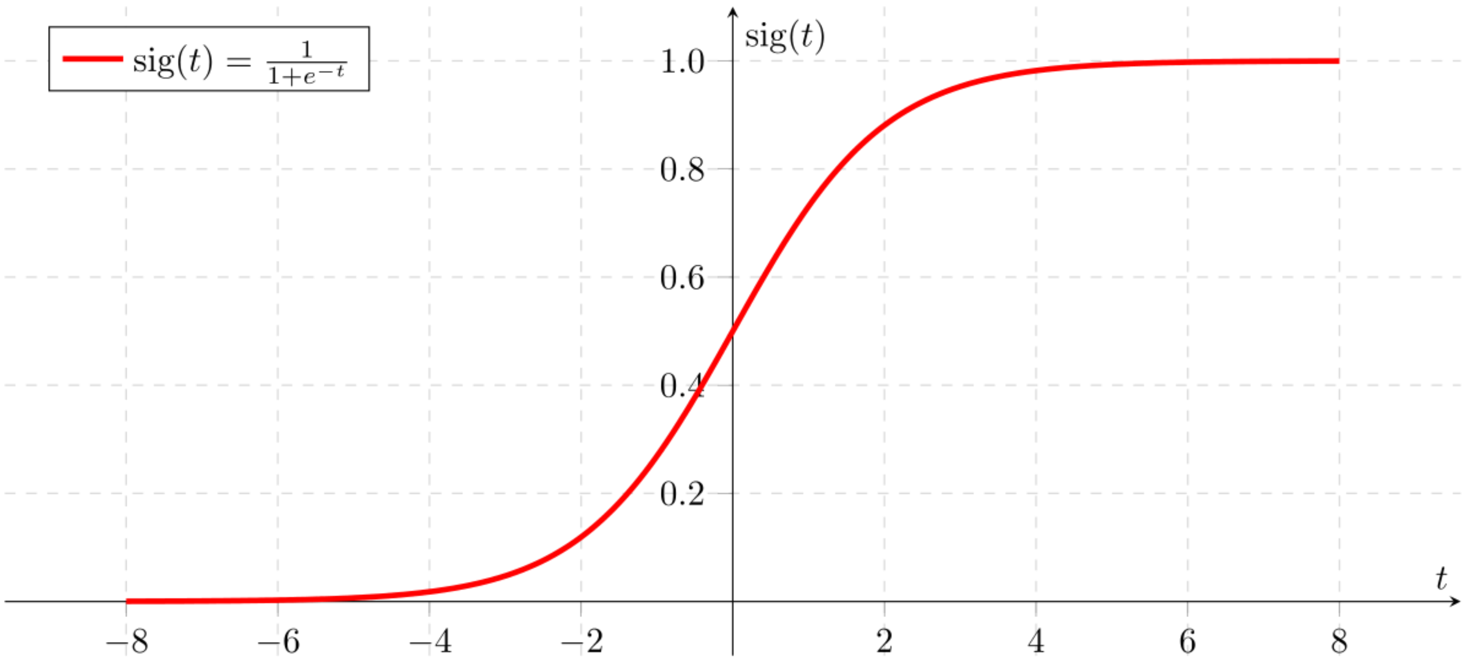
In this project, I proposed to use accuracy as the primary metric. In case the data is highly imbalanced, F1 score will be used instead.

Benchmark model

For this project, Starbucks-Analyze the Coffee Innovation, the benchmark model would be the reinforcement learning algorithm.

A logistic regression will serve as the benchmark model, since it is possibly the most popular algorithm for binary classification problems in industry.

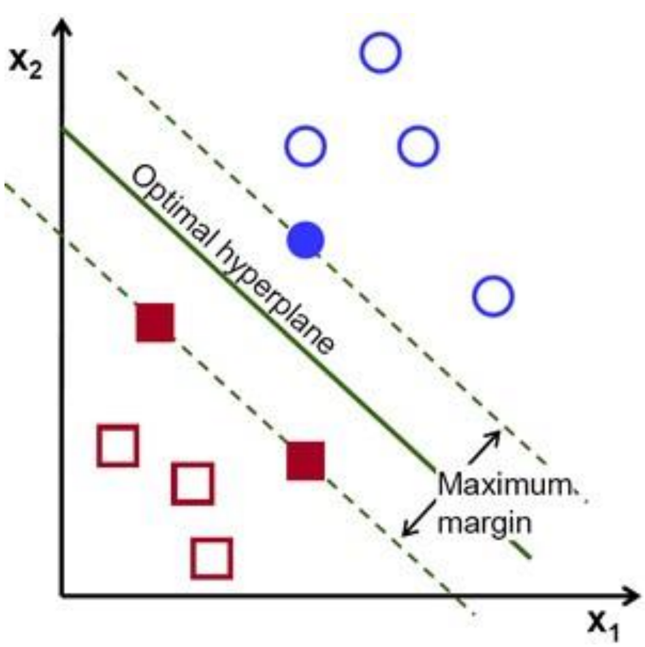
A logistic regression model estimates the probability of an instance belonging to the positive class using the logistic function, with the input being a linear model.



Algorithms beyond the benchmark

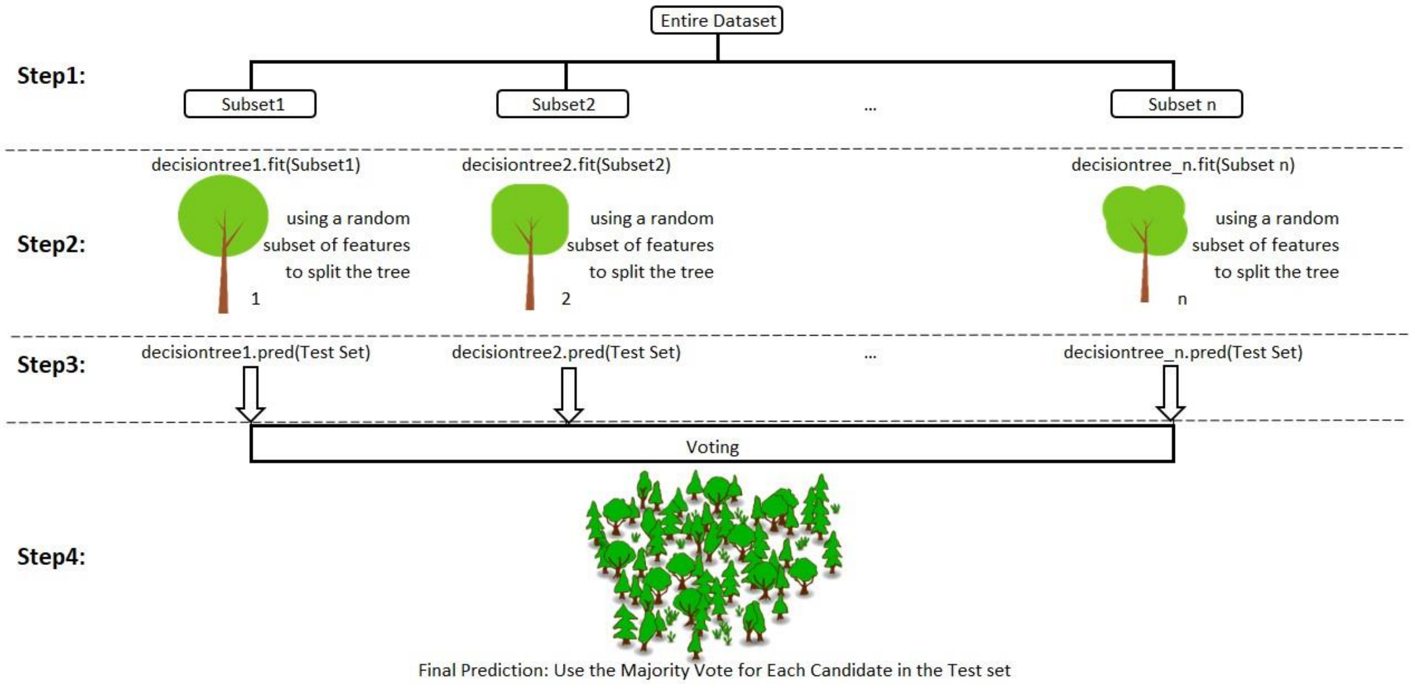
Support vector machine (SVM)

The objective of the support vector machine algorithm is to find a hyperplane in feature space that distinctly classifies the data points. For classification problems, the optimal hyperplane stays as far away from the closest training instances as possible to maximize the margin.



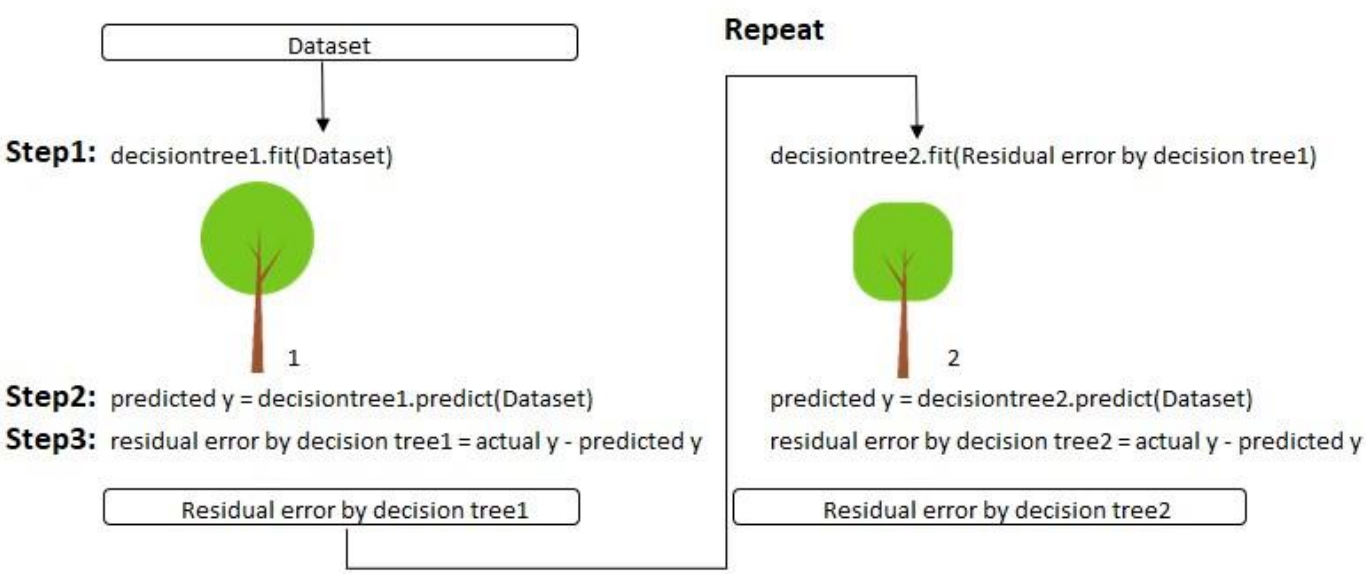
Random forest

Random forest is an extension of decision tree bagging, with additional randomness in selecting subset of features.



Gradient boosting

In gradient boosting, a new decision tree is added to the ensemble by learning from the residual directly. It is an extremely popular solution in online machine learning competitions.



Data analysis

`portfolio`

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

`portfolio` contains 10 different offers, categorized into 3 types (BOGO, discount and informational).

`profile`

gender	age	id	became_member_on	income
	118	68be06ca386d4c31939f3a4f0e3dd783	20170212	nan
F	55	0610b486422d4921ae7d2bf64640c50b	20170715	112000
	118	38fe809add3b4fcf9315a9694bb96ff5	20180712	nan
F	75	78afa995795e4d85b5d9ceeca43f5fef	20170509	100000
	118	a03223e636434f42ac4c3df47e8bac43	20170804	nan

`profile` contains information of each customer. There are notable NaNs found for gender, age and income. Strategies to deal with these NaNs will be discussed in the next section.

`transcript`

Take a look at the transcript of a particular customer.

person	event	value	time
78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	0

78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	6
78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 19.89}	132
78afa995795e4d85b5d9ceeca43f5fef	offer completed	{'offer_id': '9b98b8c7a33c4b65b9aebfe6a799e6d9', 'reward': 5}	132
78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 17.78}	144
78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': '5a8bc65990b245e5a138643cd4eb9837'}	168
78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': '5a8bc65990b245e5a138643cd4eb9837'}	216
78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 19.67}	222
78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 29.72}	240
78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 23.93}	378
78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	408
78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	408
78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	504
78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 21.72}	510
78afa995795e4d85b5d9ceeca43f5fef	offer completed	{'offer_id': 'ae264e3637204a6fb9bb56bc8210ddfd', 'reward': 10}	510
78afa995795e4d85b5d9ceeca43f5fef	offer completed	{'offer_id': 'f19421c1d4aa40978ebb69ca19b0e20d', 'reward': 5}	510
78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 26.56}	534
78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	582

By looking at activities of one customer, one can easily find four types of events recorded in transcript , transactions and three types of offer activities.

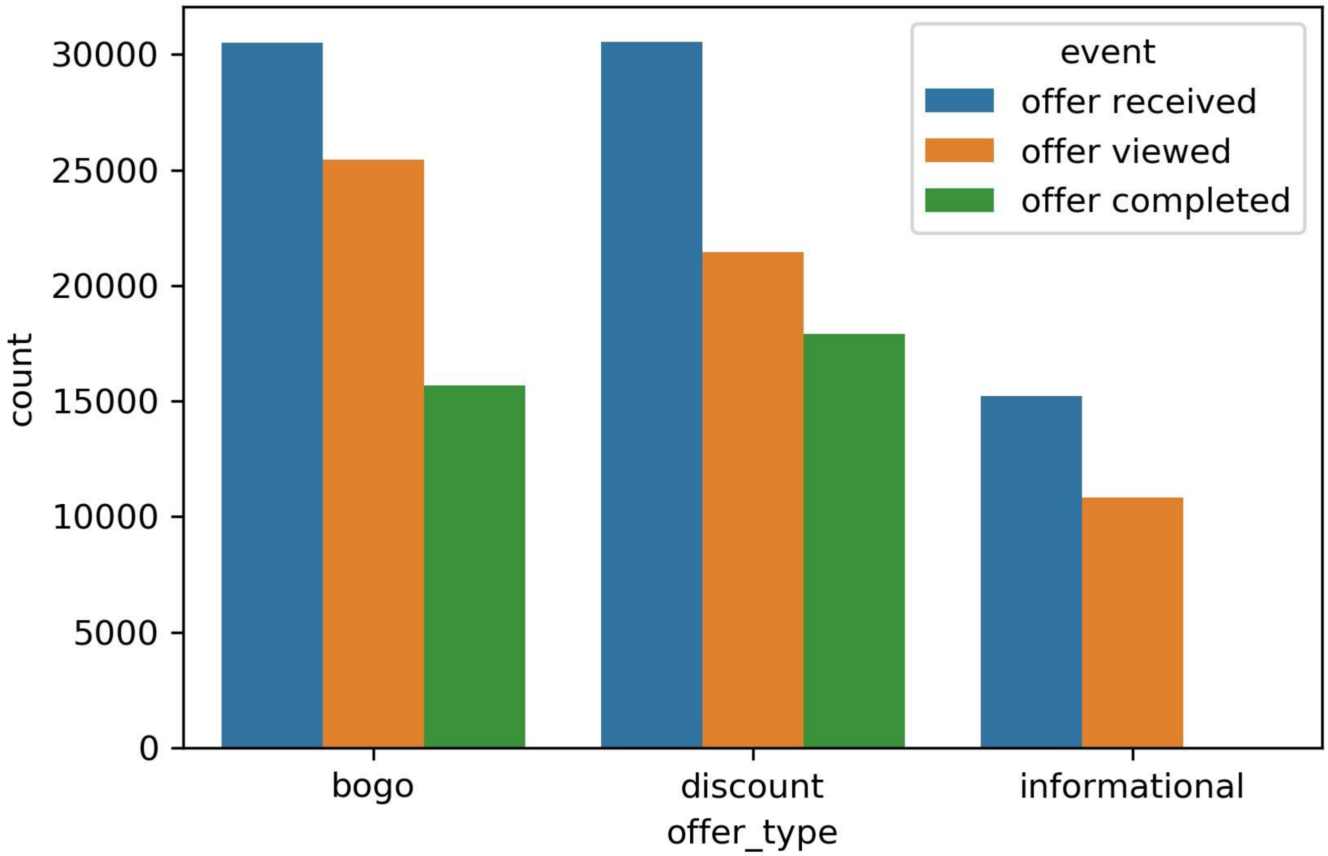
The reinforcement model can be evaluated based on various measures. The agent interacts with environment in repeating sequences of time t, observing the environment state s1, taking action a1, receiving rewards r1.

- 'offer received' marks the time when Starbucks sends the offer to the customer, and the offer becomes effective instantly regardless whether the customer has viewed it or not.
- 'offer viewed' marks the time when customer views the offer or becomes aware of it. Note that the customer can still view the offer even if he/she has already completed without knowing it, as long as the time is still within the offer's duration.
- 'offer completed' marks the time when the customer makes qualified transaction meeting the requirement. The dict in the 'value' column has an additional key 'reward', which is associated with the offer id in portfolio

```
>>> offer_log = transcript[transcript['event'].str.startswith('offer')] >>>
offer_log.loc[:, 'offer'] = offer_log['value'].apply(lambda c: c['offer id'] if '
```

```
offer id' in c else c['offer_id']) >>> offer_log.drop(['value'], axis=1,
inplace=True)
```

After filtering out transactions using the code above, I further analyzed offer activities with different offer types considered. From the count plot of events for different types of offers, one can easily observe that informational offers do not have completion events, possibly because there is no reward to claim. This is a key observation, as it will ultimately determine how transcript will be processed for different types of offers.



Here are the **rules** I propose to label responses:

- A positive response requires both customer's awareness (viewed) and offer completion. The former must occur before the latter.
- For informational offers, the response is determined from the number of transactions within the effective time window between viewed time and offer expiration. No transactions simply indicate a negative response.

All the offer-customer pair will be traced from all the 'offer received' events.

```
>>> offer_receive = offer_log[offer_log['event'] == 'offer
received'] >>> offer_receive['time'].unique() / 24 array([ 0.,  7.,
14., 17., 21., 24.])
```

During the 30-day simulation, Starbucks only sends out six waves of offers.

The time interval between offer waves varies from three days to a week. At time t, the reinforcement learning agent observes the state of the environment St**.** The agent's behavior and ability to learn is greatly influenced by the state and it's definition.

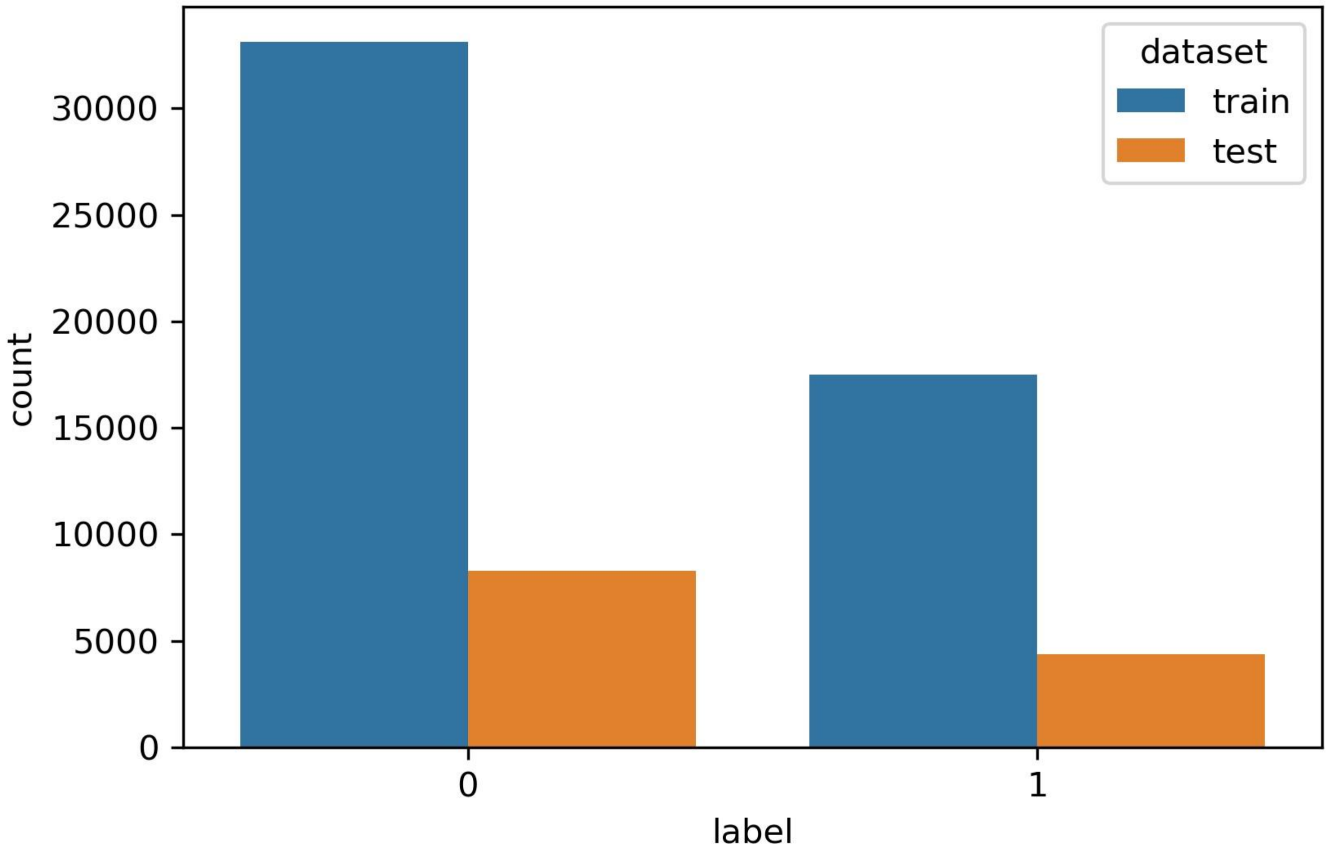
There are chances that multiple offers are effective in one customer's account since the offer durations are generally longer than the minimum interval. Processing transcript by person and unique offer id may reduce such complexity, but it is still tricky if the person has more than one active offers with the same id.

```
>>> tmax = transcript.iloc[-1]['time']
>>> tmax / 24
29.75
```

In addition, the final wave of offers arrives on the 24th day, leaving less than six days in `transcript`. Some offers have longer duration and the final response remains unknown if they are not completed by the final time mark in `transcript`. Those offers will be dropped during processing.

```
>>> offer_receive.groupby(['person', 'offer']).count()['event'].value_counts()
1    51570
2    10523
3     1124
4       66
5        5
Name: event, dtype: int64
```

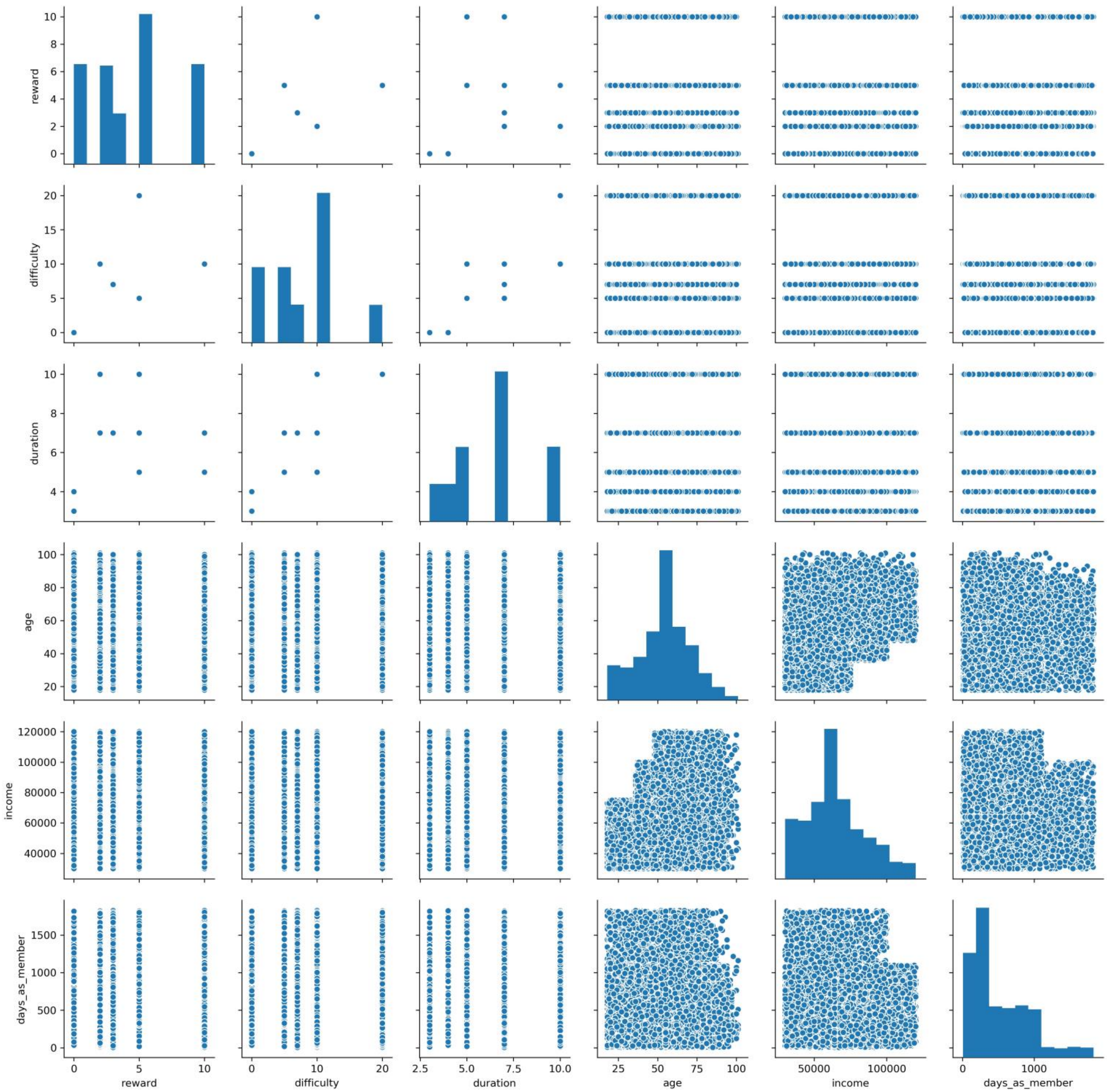
As a final remark for data processing, a unique customer-offer pair may have different responses since there are customers getting the same offer for more than once. Their responses may not necessarily remain the same. After observing state s1, the agent chooses an action a1, it also has the effect of putting more weight on large errors. After observing state s1, and taking action a1, the agent receives a scalar reward r1, from the environment. The reward is the feedback for how 'good' the action a1, was in state s1. Many rewards have been proposed for reinforcement learning. However, a model predicting customer-offer match should yield a unique output based on the input. Here I made a simple assumption that a customer likes an offer as long as a positive response is collected for more than once.



After finishing data processing and putting together data for modeling, I did another round of EDA before jumping into training the classifier. The target label (positive as 1 and negative as 0) has a 2:1 ratio in both training and test set, i.e., the data is not highly imbalanced. In this case, **accuracy** alone is good enough to measure the model performance, and F1 score will not be used.

```
>>> train_X.columns
Index(['reward', 'difficulty', 'duration', 'channel_web', 'channel_mobile',
       'channel_social', 'type_bogo', 'type_discount',
'type_informational',        'age', 'income', 'profile_nan',
'days_as_member', 'gender_F',        'gender_M', 'gender_O', 'gender_U'],
dtype='object')
```

There are 17 features available from customer or offer characteristics. These features can be grouped into two types, binary labeled (including some one-hot encoded ones) and numerical.



A straightforward observation from the pair plot of numerical features is that all offer attributes are discrete while customer ones are continuous. Moreover, no clear correlation can be observed between any pair of customer attributes- The agent here is the entity, through repeated interaction with the environment that implements and improves the policy. Therefore, the features will be used as is, with a bit of preprocessing to scale them in case the algorithm is distance based (e.g., SVM).

Solution implementation

Data cleaning

1. Handle missing values in profile

Based on my observations, all the rows with NaNs in profile have gender and income as NaN, and age of 118. As already mentioned in the data source, 118 is the encoded missing value for age. Therefore, imputation is required for gender, age and income. The median of numerical fields (age and income) is used, and another label ('U' for unknown) is applied for gender. Finally, since the three fields are either all missing or full, only one column 'profile_nan' is added as an indication of missing values. profile after imputation is shown below.

gender	age	id	became_member_on	income	profile_nan
U	55	68be06ca386d4c31939f3a4f0e3dd783	20170212	64000	1
F	55	0610b486422d4921ae7d2bf64640c50b	20170715	112000	0
U	55	38fe809add3b4fcf9315a9694bb96ff5	20180712	64000	1
F	75	78afa995795e4d85b5d9ceeca43f5fef	20170509	100000	0
U	55	a03223e636434f42ac4c3df47e8bac43	20170804	64000	1

2. Process transcript to label responses

Implement a label_response method to process transcript with one particular customer-offer pair as the unit. First, add a 'positive_response' column to offer_receive with starting value 0 (negative), and then loop label_response through all appearing customers and offers sent to each one of them to label positively responded offers to 1. A few key ideas in addition to the proposed **rules** reflected in label_response :

- Use a queue to store active offers represented by a list [t_receive, t_expire, t_viewed] since offers have FIFO nature. Go through the offer activities by time, and pop offers completed or expired. • Treat informational offers differently. Besides the way a positive response is determined, the way to decide which offer is viewed when multiple offers (with same id) active. Label earlier BOGO, discount offers as viewed as offer chasers will complete them first to maximize their rewards. On the other hand, label later informational offers as viewed to extend the effective time window.

Once the loop finishes, group offer_receive by 'person' and 'offer' using logic OR. After dropping other columns, a three-column dataframe appears to be the skeleton of the final dataset.

```
response = offer_receive.groupby(['person', 'offer']).any().reset_index()
response.drop(columns=['event', 'time'], inplace=True)
```

person	offer	positive_response
0009655768c64bdeb2e877511632db8f	2906b810c7d4411798c6938adc9daaa5	False
0009655768c64bdeb2e877511632db8f	3f207df678b143eea3cee63160fa8bed	False
0009655768c64bdeb2e877511632db8f	5a8bc65990b245e5a138643cd4eb9837	False
0009655768c64bdeb2e877511632db8f	f19421c1d4aa40978ebb69ca19b0e20d	False
0009655768c64bdeb2e877511632db8f	fafdcd668e3743c1bb461111dcafc2a4	False

Pre-processing

3. Encode categorical variables and assemble dataset

Before merging `portfolio` and `profile` onto the skeleton, further process them to encode columns not suitable as inputs for a model, and drop the original columns. These include:

`portfolio`

- Expand channels into four columns representing different media where the offer is sent. Drop the email column since all offers have this option.
- Use one-hot encoding for 'offer_type'.

`profile`

- Convert 'became_member_on' (date) to membership days counted from a later date (2018-08-01).
- Use one-hot encoding for 'gender'.

Finally, join processed `portfolio` and `profile` onto the skeleton and drop all hash columns (customer and offer id). Create a test set with 20% data for final metric evaluation.

4. Scale DataFrames

Implement `NumericalTransformer` to preprocess numerical columns, leveraging on the scikit-learn api. The discrete ones are scaled using `MinMaxScaler`, while the continuous ones are scaled using `StandardScaler`. Note that this preprocessing step is completely optional for tree-based algorithms since they are non-distance based.

Modeling

5. Select optimal classification algorithm

Use out-of-the-box classifiers to select optimal classification algorithm. The score is taken from the mean of 5fold cross validation accuracy.

Logistic regression (benchmark)

```
>>> from sklearn.linear_model import LogisticRegression
>>> logistic = make_pipeline(NumericalTransformer(), LogisticRegression()) >>>
cross_val_score(logistic, train_X, train_y, scoring='accuracy', cv=5, n_jobs=-1).
mean()
0.7365592954908515
```

Support vector machine with linear kernel

```
>>> from sklearn.svm import LinearSVC
>>> svm = make_pipeline(NumericalTransformer(), LinearSVC(dual=False))
>>> cross_val_score(svm, train_X, train_y, scoring='accuracy', cv=5, n_jobs=-1).mean(
)
0.7346828966249379
```

Non-linear kernels are not considered since the algorithm scales poorly with number of instances.

Random forest

```
>>> from sklearn.ensemble import RandomForestClassifier >>>
cross_val_score(RandomForestClassifier(n_estimators=100), train_X, train_y, scori
ng='accuracy', cv=5, n_jobs=-1).mean()
0.7380603720566018
```

Gradient boosting

```
>>> from lightgbm import LGBMClassifier
>>> cross_val_score(LGBMClassifier(), train_X, train_y, scoring='accuracy', cv=5, n_j
obs=-1).mean()
0.7637567343733975
```

Gradient boosting implemented in LightGBM is the algorithm for the optimal model. Here LightGBM is choose over XGBoost not only because of better performance, but also the early stopping feature. As a strategy to significantly reduce training time, both XGBoost and LightGBM support early stopping. However, with early stopping enabled, LightGBM always returns the optimal ensemble while XGBoost only returns the final ensemble.

6. Tune hyperparameters

Tuning hyperparameters for gradient tree boosting itself is a high dimensional problem. Here I followed a guide on hyperparameter tuning on XGBoost to break it down to a few steps of low dimensional grid search:

1. Keep a high learning_rate (0.1) until the final step. Find optimal parameters controlling the growth of an individual tree (num_leaves and max_depth).
2. Tune other parameters related to tree growth (min_data_in_leaf and min_sum_hessian_in_leaf).
3. Tune "random forest" parameters (bagging_fraction and feature_fraction).
4. Tune regularization parameters (lambda_l1 and lambda_l2).
5. Try lowering learning_rate and more rounds of iterations to see if the score further improves.

The entire process is leveraged on the cross validation API from LightGBM, with early stopping enabled and number of iterations returned. Here is the final optimal set of hyperparameters, and default values are used for those not mentioned.

```
>>> lgbm = LGBMClassifier(num_leaves=127, max_depth=14, n_estimators=98)
```

Results

After training both benchmark and optimal models on the entire training set, evaluate their performance on the test set.

Model	LogisticRegression	LightGBM
Accuracy	0.737	0.766

To validate model robustness with no additional data, reshuffle the training and test data with different random states and evaluate performance on the new test data using the model trained from the new training data. The accuracy score seems stable regardless how the dataset splits, suggesting the solution is robust.

```
>>> scores = []
>>> for seed in [8, 24, 13, 10, 41, 35, 7, 30]:
...     train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.2, rando
m_state=seed)
...     lgbm.fit(train_X, train_y)
...     lgbm_y = lgbm.predict(test_X)
...     scores.append(accuracy_score(lgbm.predict(test_X), test_y))
...
>>> scores
[0.7622847211249802,
 0.7657607836941065,
 0.7595986727761099,
 0.7721598988781798,
 0.7664717964923369,
 0.763943750987517 8,
 0.7649707694738506,
 0.7659977879601833]
```

Overall, the optimal LightGBM model has minor improvement in predicting accuracy comparing with the benchmark logistic regression model. Both models solve the problem, predicting whether a customer will positively responds to a promotional offer based on their characteristics. The benchmark model is already a good starting point, and the improvement may seem marginal at first glance. But its impact will be amplified considering the business revenue of Starbucks, a worldwide coffee retailer.

References

- Performance Metrics for Classification problems in Machine Learning
- Logistic Regression - Detailed Overview
- Support Vector Machine - Introduction to Machine Learning Algorithms
- Decision Tree Ensembles - Bagging and Boosting
- LightGBM Python API
- LightGBM Parameters
- Complete Guide to Parameter Tuning in XGBoost with codes in Python