Capstone Project 1

Introduction

The Problem:
The modern-day lifestyle has turned into one that revolves around the subscription business model. Nowadays, you can get fresh ingredients delivered to your door, clothes to update your wardrobe, movies and TV shows to watch across different online devices, and even access to a variety of music to listen to during long commutes; all for a reasonable recurring monthly fee. The critical business question is no longer just “How will I find customers for my product?” but will also include “How will I retain my customers?”

KKBOX, Taiwanese subscription based music streaming service, shared their customer data on Kaggle to learn more about predicting churning. When users signs up for our service, users can choose to either manually renew or auto-renew the service. Users can actively cancel their membership at any time. For this project, the criteria of "churn" is no new valid service subscription within 30 days after the current membership expires.

The Inquiry:
Can we predict if a user will make a new service subscription transaction within 30 days after the current membership expiration date based on their behaviors and interactions with the product?

The Client:
The client is KKBOX. KKBOX will be able to use this information to offer special deals to customers who are likely to churn or on the verge of churning.

The Data:
KKBOX has provided 4 datasets:

1. Train Set, contains the user ids and whether they have churned for March 2017
    a. msno: user id
    b. is_churn: This is the target variable. Churn is defined as whether the user did not continue the subscription within 30 days of expiration. is_churn = 1 means churn, is_churn = 0 means renewal.
2. Transactions Data, contains the transactions data until 3/31/2017
    a. msno: user id
    b. payment_method_id: payment method
    c. payment_plan_days: length of membership plan in days
    d. plan_list_price: in New Taiwan Dollar (NTD)
    e. actual_amount_paid: in New Taiwan Dollar (NTD)
    f. is_auto_renew
    g. transaction_date: format %Y%m%d
    h. membership_expire_date: format %Y%m%d
    i. is_cancel: whether or not the user canceled the membership in this transaction.
3. User Logs Data, contains listening behaviors of a user until 3/31/2017
    a. msno: user id
    b. date: format %Y%m%d

    c. num_25: # of songs played less than 25% of the song length
    d. num_50: # of songs played between 25% to 50% of the song length
    e. num_75: # of songs played between 50% to 75% of of the song length
    f. num_985: # of songs played between 75% to 98.5% of the song length
    g. num_100: # of songs played over 98.5% of the song length
    h. num_unq: # of unique songs played
    i. total_secs: total seconds played
4. Members Data, contains user information
    a. msno
    b. city
    c. bd: age
    d. gender
    e. registered_via: registration method
    f. registration_init_time: format %Y%m%d

Data Wrangling

The data provided were all very large files.

- Train set contained 992,931 rows
- Members data contained 6,769,473 rows
- Transactions data contained 21,547,746 rows
- User log data contained 400,000,000+ rows

The train set is extremely biased with only a 6.4% churn rate. Having an extremely biased train set means that there's a high chance of not churn and it would be pretty accurate to label all users as not churn. Therefore, the majority group needs to be downsampled. There are 63,471 users marked as churned who are all kept in the new train set. I have randomly sampled 75,000 users from the not churned group to be included in the new train set as well. The resulting churn rate of the new train set is now 45.8%, which is a lot more balanced than before. All the other datasets will also only reflect those in this new train set.

All columns with date data were converted into datetime objects for easier manipulation and feature engineering relative to time.

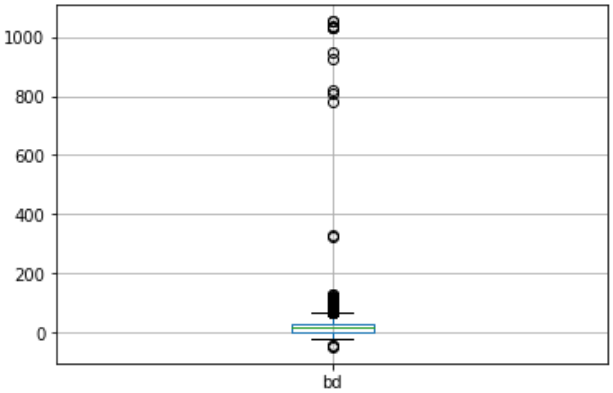
Members Data

The resulting members data has 123,815 rows meaning that we do not have member information for all of those in the train set.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 123815 entries, 0 to 123814
Data columns (total 6 columns):
msno                    123815 non-null object
city                    123815 non-null int64
bd                      123815 non-null int64
gender                  63206 non-null object
registered_via          123815 non-null int64
registration_init_time  123815 non-null int64
```

The only column with missing values is gender. I will hold off filling in missing values until I build the model because the exploratory data analysis should be based off the data provided.

Another problematic column is age (bd). The age column contains outliers that have negative values and positive values larger than 100.



Outliers under 1 year old and over 100 years old were removed, leaving only 63,188 data points. Although more than half of the data points were removed, those outliers heavily skewed the mean. It is more accurate to only keep data that makes logical sense.

Transactions Data

The resulting transactions data has 1,909,676 rows, at least 1 per user. The transaction records in the data spans over 3 years (2015/01/01 to 2017/02/28). Oddly, 'payment_plan_days', 'plan_list_price', and 'actual_amount_paid' had minimum as 0. However, after further investigation, it seems like transactions with 0 as 'payment_plan_days' are all back in 2015. They might have not had payment plan day options back then. As for the plan price and actual amount paid with 0 values, these transactions does not seem to be a temporal issue since the most recent occurrence happened 2017-02-02. This might just mean that the user received a free trial.

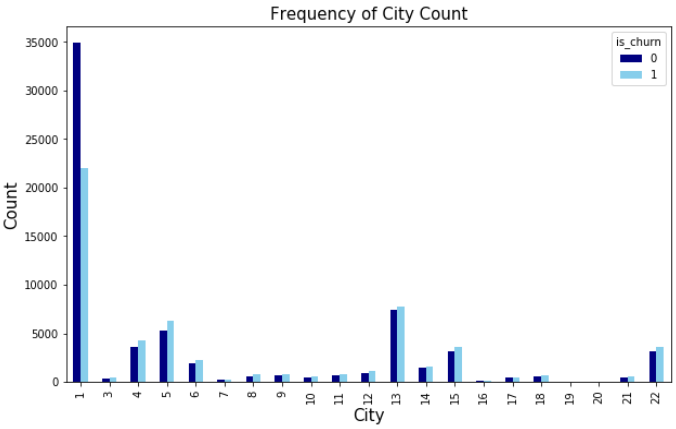
User Logs Data

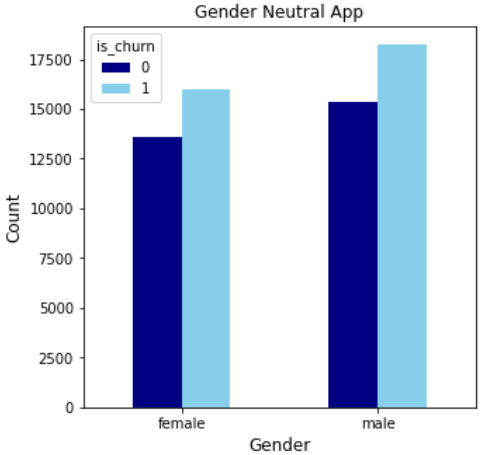
The resulting user logs data has 10,927,697 rows, and it does not have activity logged for all users in the train data, only 115,730 users. The activity log also spans over the same time period as the transaction data (2015/01/01 to 2017/02/28). For some reason, there are 1,564 rows in which total seconds played had negative values. This occurred for data between 2015/04/22 and 2016/04/18.

Exploratory Data Analysis

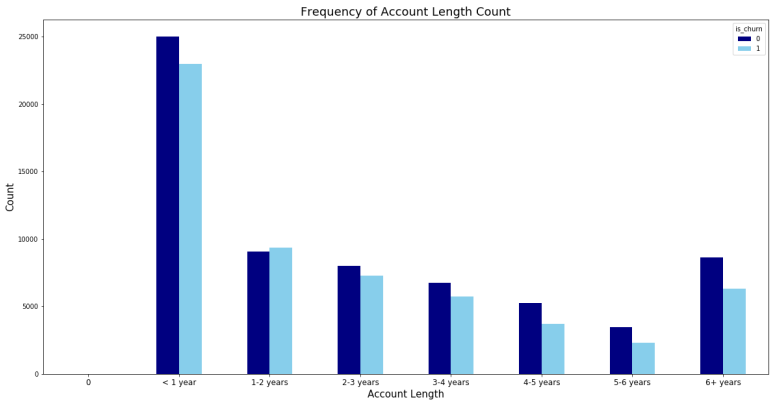
The exploratory data analysis focuses on comparing different variable distributions between the churn group and the group that did not churn to see if certain distributions differ between the 2 groups.

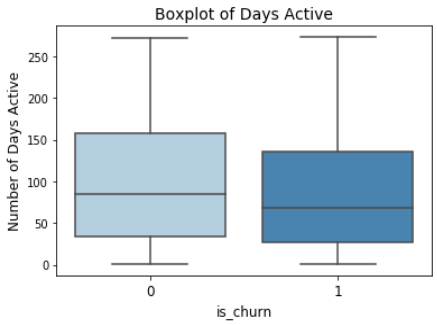
The two groups are actually pretty similar in demographics. Users in both groups are mostly in city labelled as "1". I would think that it represents Taipei. Also, there's an even ratio between males and females who use the app.

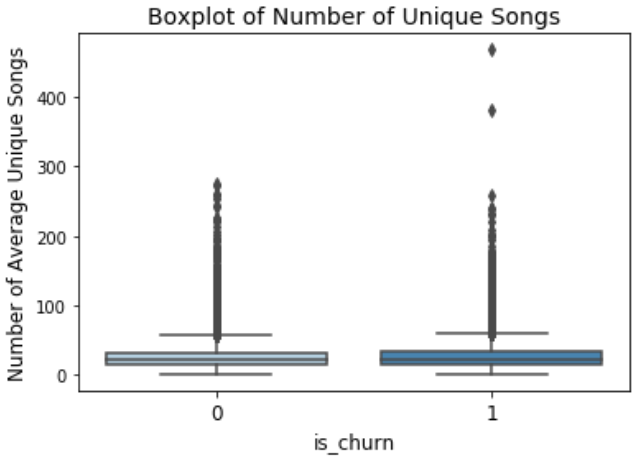


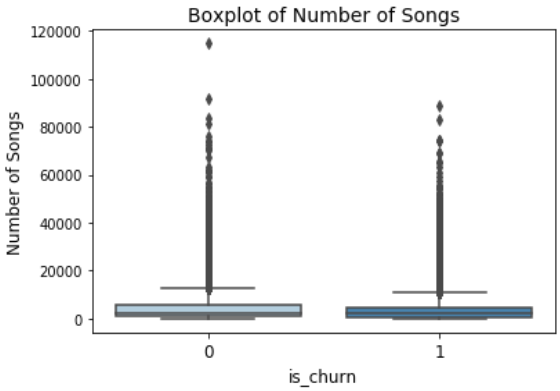


Most users are new and have had accounts for less than a year. Also, on average, they seem to be active on similar amount of days and listened to the same amount of songs.

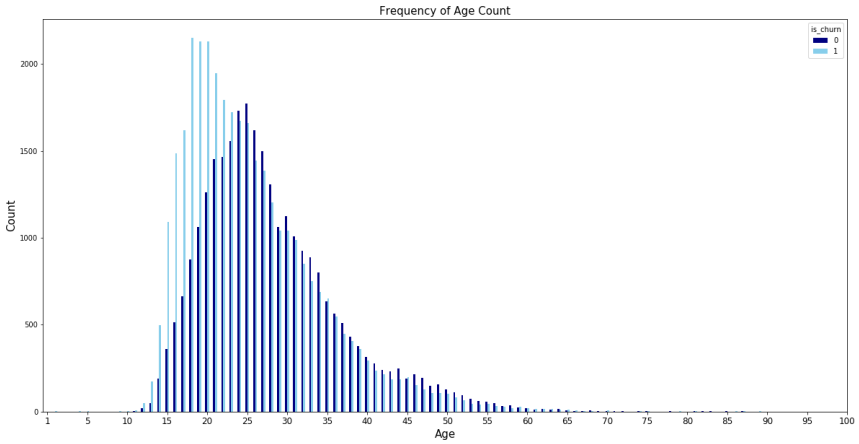




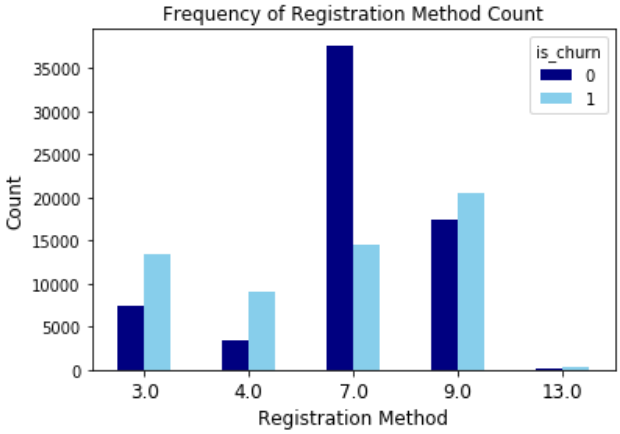




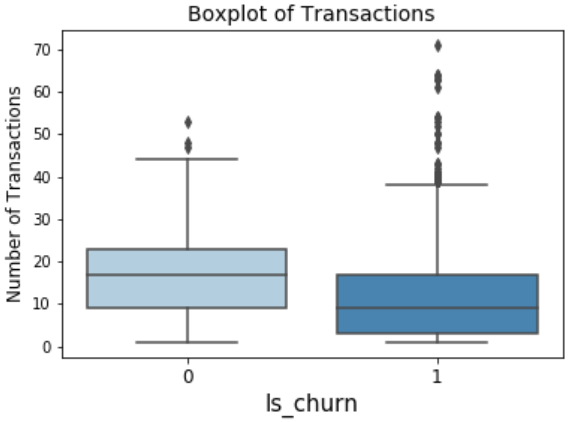
However, there are a few variables with distributions that seem to differ between the churn group and did not churn group. First off, the churn group seems to be comprised of younger users. Most of churned users are in their early 20s while users who did not churn are mostly in their late 20s.

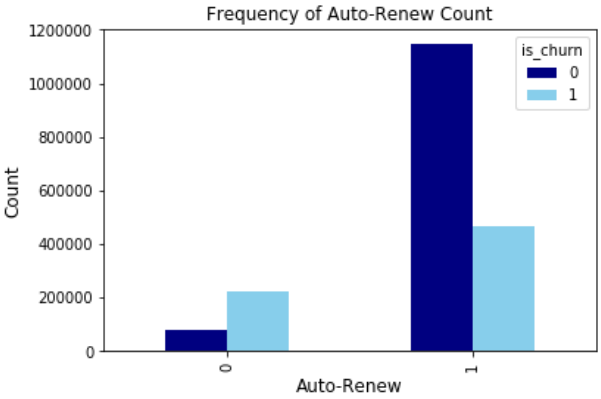


The method they used to register also differed. Users who did not churn mostly signed up via registration method 7 while most churned users registered via method 9. Unfortunately, we do not know what these numbers actual represent.



The number of transactions made also seemed to differ. Those who did not churn seemed to have made more transactions than those that churned. Also, from those transactions, the users who used the auto-renew feature tend to be less likely to churn.





Hypothesis Testing

Although the distributions may seem to look like they differ visually, these hypotheses should be tested to see if the difference is statistically significant. I have tested 5 different variables to see if these differences happened by chance or if they can actually explain chances of churning.

The first hypothesis is regarding the age distribution.

H_0: There's no difference in the age between user who churned and did not churn.

H_A: Users who did not churn are older than users who churned.

```
Mean Difference: 2.5739036785245375
Margin of error: 0.13734545113421098
95% Confidence Interval: [2.4365582273903263, 2.7112491296587486]
```

There is a mean difference of 2.574 in age between the group that churn and did not churn. The confidence interval does not contain 0; therefore, we are 95% confident that there is a difference. After conducting a bootstrap test, the null hypothesis was rejected due to a p-value

of 0. This means that there is an age difference between the two groups, and that younger users are more likely to churn.

The next hypothesis is regarding the distribution of users who use the auto-renew feature.

H_0**:** There's no difference in auto-renewal rate between user who churned and did not churn.

H_A**:** Users who did not churn have a higher auto-renewal rate.

```
Mean Difference: 0.44100533658159546
Margin of error: 0.004210435379622165
95% Confidence Interval: [0.4367949012019733, 0.44521577196121764]
```

There was a difference of 0.441 in mean auto renewal rate between those that churned and did not churn. The confidence interval is very narrow [0.437, 0.445], meaning it is not likely that there is no difference in auto renewal rate. The bootstrap test had a p-value of 0; therefore, the null hypothesis was rejected. There is statisically significant difference in auto renewal rate between the churn and not churn group. On average, those who did not churn were 44% more likely to have their subscription auto-renewed.

I also tested the hypothesis regarding the number of transactions made.

H_0: There's no difference in the number of transactions between user who churned and did not churn.

H_A: Those who did not churn made more transactions than those who churned.

```
Mean Difference: 5.5200867432370675
Margin of error: 0.08865758164061524
95% Confidence Interval: [5.431429161596452, 5.608744324877683]
```

On average, those who did not churn made 5.52 more transactions than those that churned. The 95% confidence interval is [5.431, 5.609]. The bootstrap test resulted in a p-value of 0.0, meaning that the null hypothesis can be rejected. Therefore, we can say that there were more transactions made by those who did not churn.

Although the boxplots showed that the distributions for listening behavior seemed to be similar in the two groups, I still wanted to perform hypothesis testing to see if a difference in the mean was significant.

One hypothesis I tested was regarding the total number of seconds listened.

H_0**:** There's no difference in the total number of seconds listened between user who churned and did not churn.

H_A**:** There's a difference between the groups.

```
Mean Difference: 21891093981546.016
Margin of error: 18958175174543.344
95% Confidence Interval: [2932918807002.672, 40849269156089.36]
```

** Note: Absolute value was used to compute difference*

There seems to be a difference in the total number of seconds listened. After conducting the bootstrap test, we fail to reject the null hypothesis at 0.01 significance level. This means that number of total seconds listened may not differ between those that churned and did not churn.

The last hypothesis tested was regarding average number of unique songs listened per session.

H_0: There's no difference in the number of unique songs listened per session between user who churned and did not churn.

H_A: There's a difference between the groups.

```
Mean Difference: -1.093376972354637
Margin of error: 0.2055256639861163
95% Confidence Interval: [-1.2989026363407532, -0.8878513083685207]
```

On average, those that churned listened to one more unique song per session than those that did not churn. The confidence interval does not contain 0, so we are 95% confident this finding is significant. After conducting the bootstrap test, we are able to reject the null hypothesis since we received a p-value of 0.0.

Out of the 5 variables we've tested, 4 of the variables were proven to have statisically significant differences in distribution. These variables should be included in the predictor model:

- Age
- Auto-Renew
- Number of Transactions
- Number of Unique Songs

Classification Model

To take advantage of the temporal aspect of the data, we will split the dataset into 2 separate time periods for training and testing data:

- Training Data: February (2017/02/01 - 2017/02/28)
- Testing Data: March (2017/03/01 - 2017/03/31)

Just like the training data, the testing data is very biased (~9% churn rate). I have downsampled the majority group so that the testing data has about a 50% churn rate.

Feature Engineering

Categorical features need to be numerical in order to be incorporated into the model. The following features were transformed into dummy variables. The first categorical class of every category was dropped due to the issue of perfect collinearity.

- Members Data Set
    - City
    - Gender
    - Registration Method
- Transactions Data Set
    - Payment Plan (7 or 30)

Temporal features needed to be transformed so that it is relative to the time period being modelled. I will use the relative refactoring method,which involves mapping a date-driven feature into a new feature space which is not anchored in any particular time-series, but is instead relative to a selected point in time. This ensures the feature is relatively comparable across different time periods. I have

chosen to compute the difference in days between the date element and the end of the time period. For example, the training data has information for those that churned in February; therefore, the end of the period is 2/28/17. I have created 2 features using this method:

- Days since registered
- Days since last logged in

For the transactions data and the user log data, there are multiple lines per user according to how much they interact with the service. I found the average of these values for each user. For the transactions data, I am interested in the ones 3 month prior to the month of interest. As for the user log data, I am only interested in the activity for the month prior.

In the end, I have a total of 48 features to be used in the model.

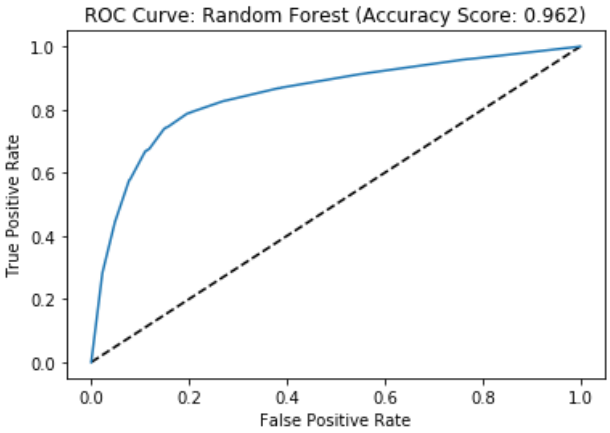
Data Preprocessing

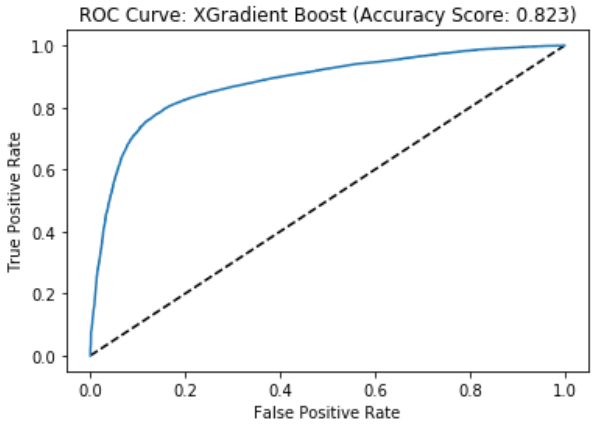
Once I began merging all the data sets together, I realized that we did not have all the information for those we had the churn data for. I had kept all the users that had a record of their account information. If the user did not have any transactions data, the transactions count feature was filled with 0. If the user did not have any user log data, the days since log in was filled with 31. All the other features were just the average of of all records on file; therefore, the users without any transactions or user log data was filled the sample mean for the column. Since the values for each feature vary in range, all the data was normalized prior to fitting the model.

Building the Model

I had fit 5 different classification models on the data using the default parameters to see which classifier was the most effective. Log loss was used as the model metric because not only do I care if the predictions are accurate, but I also care about the confidence in the labels produced. Log loss penalizes errors that are correct but not confident as well as incorrect but confident. The following are the results from the 5 fold cross validation:

Classification Model	**Average Log Loss**
Logistic Regression	0.463
Random Forest	1.464
Adaptive Boosting	0.681
Gradient Boosting	0.428
Extreme Gradient Boosting	0.427





As shown by the graph and results, Random Forest had an extremely high log loss, but performed the best in terms of accuracy (log loss: 1.464, accuracy score: 0.962). Extreme Gradient Boosting, on the other hand, had the lowest log loss of 0.427 and an accuracy score of 0.823. I have fine-tuned the hyperparameters of the Extreme Gradient Boosting to finalize the model. After performing a grid-search cross validation on a range of values, the following had proven to be the best parameter: colsample_bytree = 0.8, learning_rate = 0.05, and max_depth = 8. This model results in 83.9% accuracy and a log loss of 0.388, which is a slight improvement from the default model.

Feature Selection

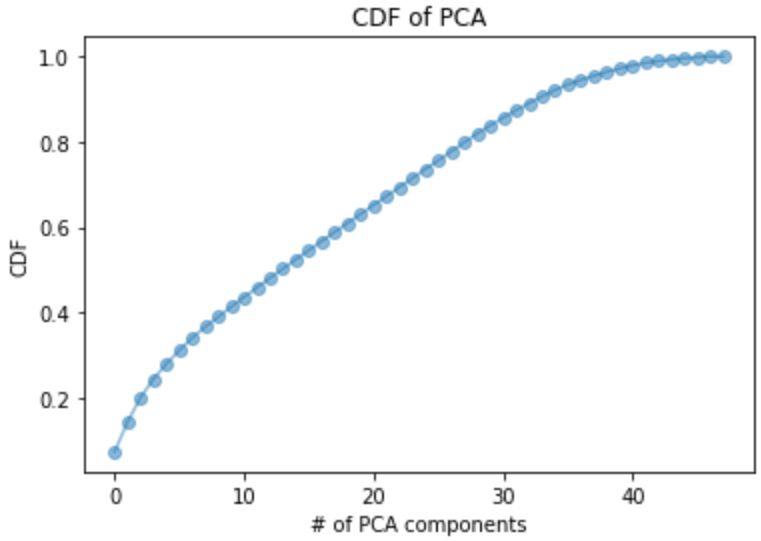
Feature selection is the method of selecting the most important features to be used in the model. The scoring method used to rank each feature is Mutual Information. Mutual information measures the dependency between the variables. It is equal to zero if and only if two random variables are independent, and higher values mean higher dependency. Only features with low mutual information should be included in the model because if knowing one of these variables reduces uncertainty about the other, there is no need to include both variables. Only the variable that explains more of the target variable should be kept.

Number of Top Features Kept	**Log Loss Score**
30	0.3919
32	0.3901
35	0.3896
40	0.3907
42	0.3899
All 48	0.3887

According to the results, we would only keep the top 35 features to be used in the model. It is where the log loss score is at the lowest before opting to keep all the features.

Principal Component Analysis

An alternative to reducing the number of features used in the model is performing principal component analysis (PCA). Unlike feature selection, PCA reduces dimensionality through a linear transformation into a lower dimension. Below is the cumulative distribution graph of the variance explained by each PCA component.



In order to have enough components to explain 80% - 95% of the variance in the target variable, the model must include 29-37 of the PCA components. I have ran the model with that range of PCA components to see which one would give me the best score.

Number of PCA Components	Log Loss Score
29	0.4062
30	0.4067
31	0.405
32	0.4055
33	0.4038
34	0.4023
35	0.3998
36	0.3974
37	0.3958

According to the results, the more number of PCA components used in the model, the better the model. The goal was to reduce the number of features; therefore I continued to fit the final model using the results from feature selection.

Results of the Final Model

The final model consists of the extreme gradient boosting classifier used on the top 35 features of the model. Applying the final model on the training data resulted on an accuracy score of 83.7% and log loss of 0.3934. Once applied on the testing data, the predictions had an accuracy score of 78.9% and log loss of 0.4655. This is reasonably lower than its performance on the training data. It is good to know that the model did not overfit to the training data.

Limitations and Further Opportunities

There are a few limitations in the model that could be improved if someone else were to replicate this project. The model could be vastly improved if the analysis was done on a computer with higher CPU. An alternative to balancing out the biased data would be keeping all the data points and putting higher weights on the minority group (in this case, the churn group). Also, fine tuning more hyperparameters of the classifiers might better fit the model and result in lower log loss. More feature engineering could be done given more guidance on how the values of certain columns were derived. There were lots of outliers that did not seem to make sense. For example, extreme negative values when the value should strictly be positive such as age and total seconds listened.

A model with a low log loss allows accurate prediction of the likelihood of churning. Therefore, as user behaviors start to yield a high probability of churning, KKBox can offer promotions proven to stir behaviors back to user behaviors with low likelihood of churning. Clustering similar users together in terms of demographics and activity can pave the opportunity of a recommender system of which promotion would be most effective.