# Capstone Project 1

## KKBox Customer Churn Prediction

# How will I retain my customers?

- Most companies utilize subscription business model, including KKBox
- KKBox shared their customer data on Kaggle to learn more about predicting churn rates.
- **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?

# KKBox is a Taiwan-based music streaming software

# Data Provided

| Train Dataset |
| --- |
| msno |
| is_churn |

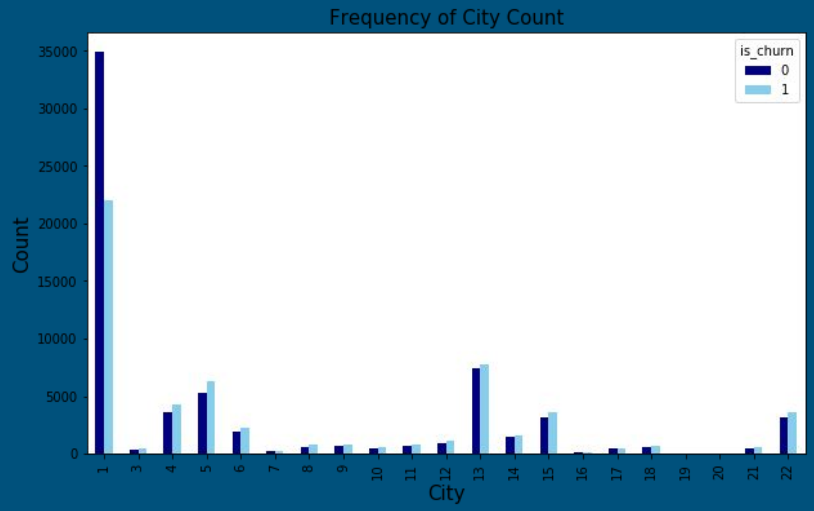
| Member Data |
| --- |
| msno |
| city |
| bd |
| gender |
| registered_via |
| registration_init_time |

| Transactions Data |
| --- |
| msno |
| payment_method_id |
| payment_plan_days |
| plan_list_price |
| actual_amount_paid |
| is_auto_renew |
| transaction_date |
| membership_expire_date |
| is_cancel |

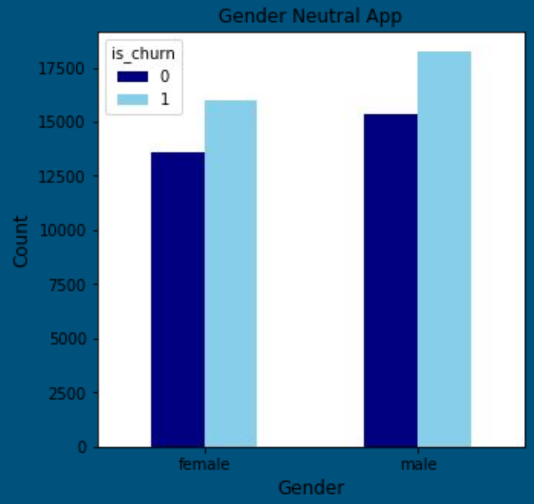
| User Log Data |
| --- |
| msno |
| date |
| num_25 |
| num_50 |
| num_75 |
| num_985 |
| num_100 |
| num_unq |
| total_secs |

# Exploratory Data Analysis: Churn vs Not Churn

Both groups are similar in certain demographics.



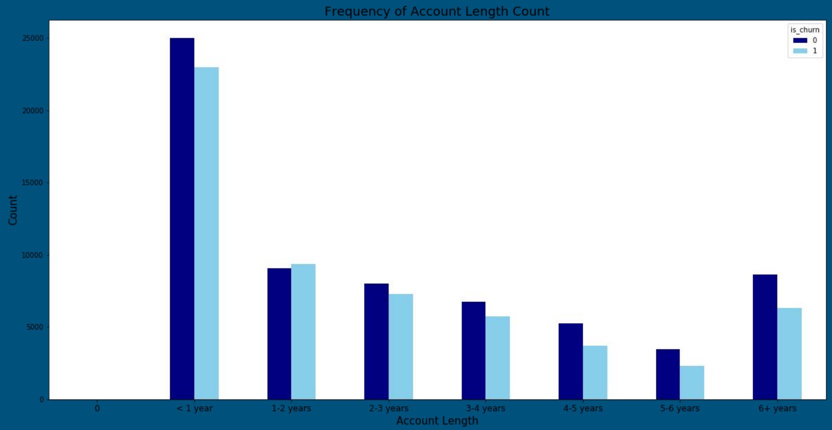

Most live in city 1

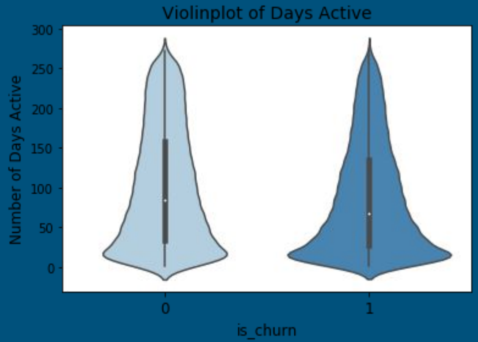


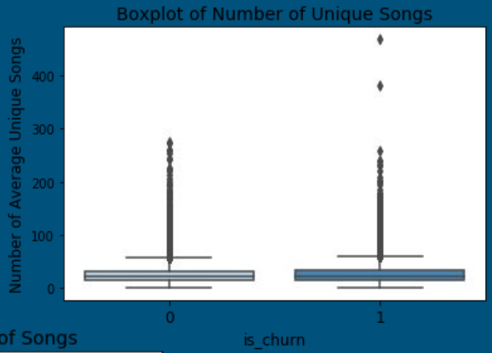

Even gender ratio

# Exploratory Data Analysis: Churn vs Not Churn

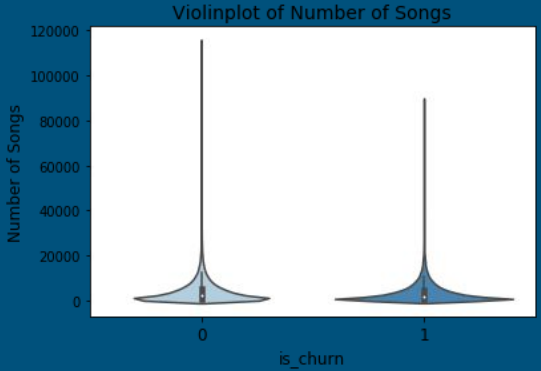
Their behaviors with the app was also similar.



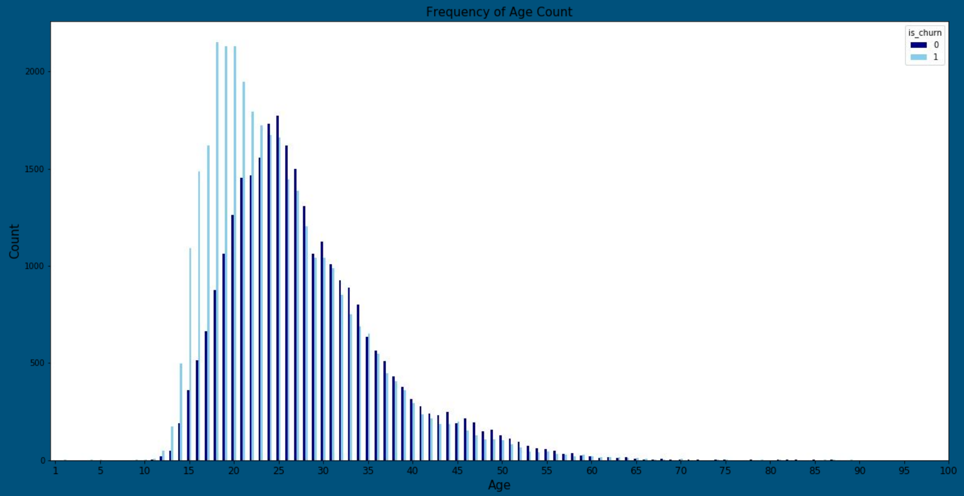

Similar length of account distribution



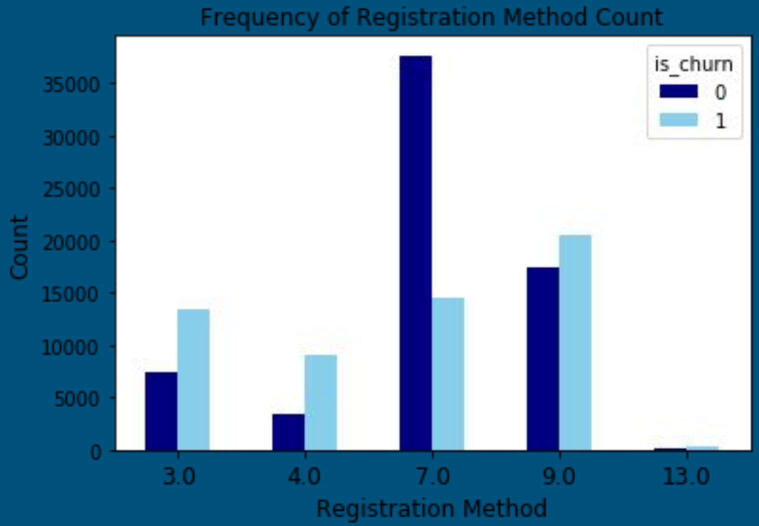

There's not much difference in the distribution of number of days and songs.

# Exploratory Data Analysis: Churn vs Not Churn

A few demographics features did vary between the 2 groups.



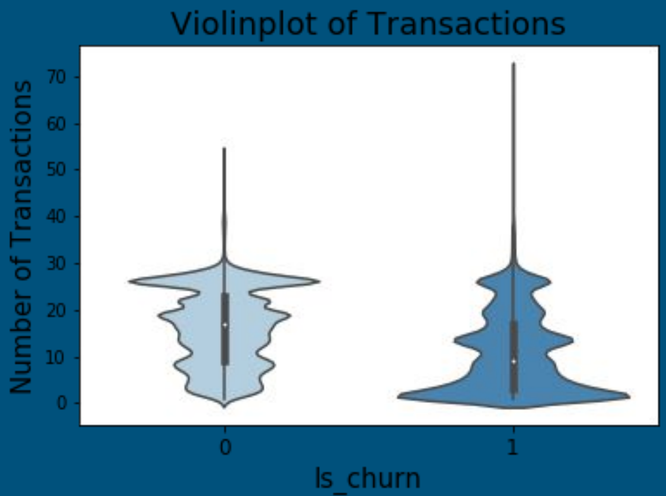

Most of churned users are in their early 20s while users who did not churn are mostly in their late 20s.



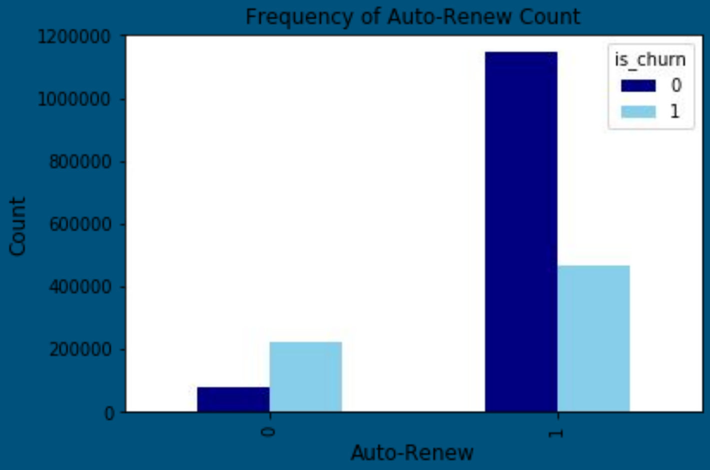

Users who did not churn mostly signed up via registration method 7 while most churned users registered via method 9.

# Exploratory Data Analysis: Churn vs Not Churn

They also differed in the monetary transactions made.




Those who did not churn seemed to have made more transactions than those that churned.




The users who used the auto-renew feature tend to be less likely to churn.

# Inferential Statistics

Although the distributions may seem to look like they differ visually, these hypotheses should be tested to see if the difference is statistically significant

Method used: Permutation (Bootstrap) Hypothesis Testing

| Null Hypothesis | Mean Difference | 95% Confidence Interval | P-value | Reject $H0$ |
|---|---|---|---|---|
| There's no difference in the age between user who churned and did not churn. | 2.574 | [2.437, 2.711] | 0 | True |
| There's no difference in auto-renewal rate between user who churned and did not churn. | 0.441 | [0.437, 0.445] | 0 | True |
| There's no difference in the number of transactions between user who churned and did not churn. | 5.520 | [5.431, 5.609] | 0 | True |
| There's no difference in the number of unique songs listened per session between user who churned and did not churn. | -1.093 | [-1.299, -0.888] | 0 | True |

# Building the 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)

# Feature Engineering

| Transactions Data |
| --- |
| msno |
| payment_method_id |
| payment_plan_days |
| plan_list_price |
| actual_amount_paid |
| is_auto_renew |
| transaction_date |
| membership_expire_date |
| is_cancel |

| Transactions Data |
| --- |
| msno |
| avg_actual_amount_paid |
| avg_is_auto_renew |
| avg_is_cancel |
| avg_payment_plan_7 |
| avg_payment_plan_30 |
| avg_discount_received |
| trans_count |

| Member Data |
| --- |
| msno |
| city |
| bd |
| gender |
| registered_via |
| registration_init_time |

| Member Data |
| --- |
| msno |
| age |
| gender_male |
| registered_via |
| days_since_reg |
| city_3 |
| city_4 |
| city_5 |
| city_6 |
| city_7 |
| city_8 |
| city_9 |
| city_10 |
| city_11 |
| city_12 |
| city_13 |
| city_14 |
| city_15 |
| city_16 |
| city_17 |
| city_18 |
| city_19 |
| city_20 |
| city_21 |
| city_22 |
| registered_via_4 |
| registered_via_7 |
| registered_via_9 |
| registered_via_13 |

# Feature Engineering

| User Log Data |
| --- |
| msno |
| date |
| num_25 |
| num_50 |
| num_75 |
| num_985 |
| num_100 |
| num_unq |
| total_secs |

→

| User Logs Data |
| --- |
| msno |
| avg_num_25 |
| avg_num_50 |
| avg_num_75 |
| avg_num_985 |
| avg_num_100 |
| avg_num_unq |
| avg_rate_num_25 |
| avg_rate_num_50 |
| avg_rate_num_75 |
| avg_rate_num_985 |
| avg_rate_num_100 |
| total_secs |
| log_count |
| days_since_login |

In total, there are 48 features.

# Data Preprocessing

Not all users in the training data and testing data that had churn information had records of transactions or user activity.

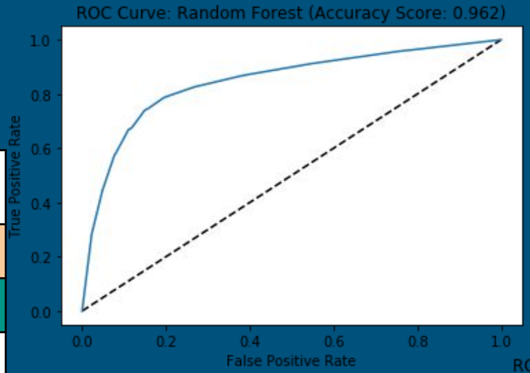
- If the user did not have any transactions data, the transactions count feature was filled with 0.
- If the user did not have any user log data, the days since log in was filled with 31.
- All the other features were filled with the sample mean for the column.

In the end, all the values were normalized.

# Selecting Classification Model

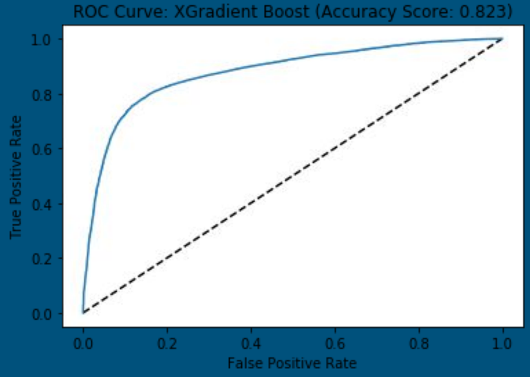
Fit 5 different classification models on the data using the default parameters and utilized log loss as the model metric.

| 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 |




Random Forest
Accuracy Score: 0.962

XGBoosting
Accuracy Score: 0.823



# Fine Tuning Hyperparameters

Utilized GridSearch cross validation to select best parameters for both models:

- Extreme Gradient Boosting
  - colsample_bytree = 0.8
  - learning_rate = 0.05
  - max_depth = 8
- Logistic Regression
  - penalty = ‘l2’
  - dual = False
  - C=1
  - max_iter = 100

# Interpreting Logistic Regression Coefficients

| Feature | Coefficient |
|---|---|
| avg_is_cancel | 0.905624 |
| avg_payment_plan_7 | 0.362903 |
| avg_discount_received | 0.165612 |
| avg_is_auto_renew | -0.947160 |
| trans_count | -0.848782 |
| log_count | -0.192631 |
| registered_via_7 | -0.145023 |

The features with the highest effect mostly seem to relate to the transactions dataset.

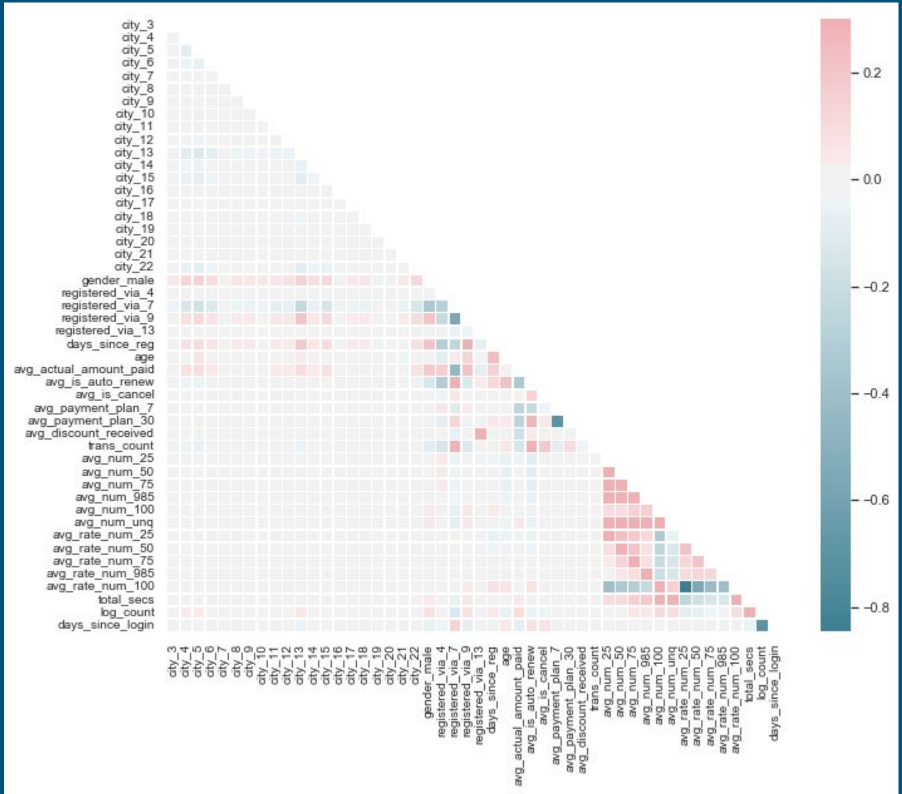
- Those that opted to use the auto-renewal feature are less likely to churn (coefficient of -0.947)
- The more number of transactions made, the less likely the user would churn (coefficient of -0.849).
- Those who had a payment plan of 7 days were more likely to churn. (coefficient of 0.363)
- The registration method also seemed to matter since those that registered via method 7 were less likely to churn. (coefficient of -0.145)

# Feature Selection

Feature selection is the method of selecting the most important features to be used in the model. There are multiple ways to perform feature selection:

1. Drop one of the variables that is highly correlated to another
2. Use the recursive feature elimination method to see dropping which features would affect the model the least
3. Perform feature importance to see which features are the most important for the model

# Feature Selection: Multicollinearity




As shown by this pairwise scatter plot, there are 3 pairs of variables that are highly negatively correlated.

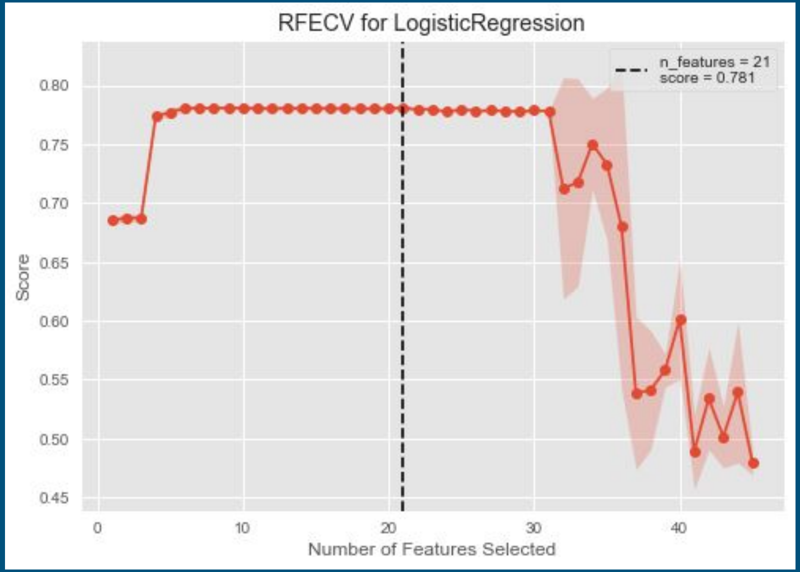
- avg_payment_plan_30 and avg_payment_plan_7
- avg_rate_num_25 and avg_rate_num_100
- log_count and days_since_login.

Dropped the following features since produced the better score:

- 'Avg_payment_plan_30'
- 'Avg_rate_num_25'
- 'days_since_login'

The log loss score after dropping these variables was 0.463304.

# Feature Selection: Recursive Feature Elimination




RFE is able to work out the combination of attributes that contribute to the prediction on the target variable (or class).

As the graph suggests, the ideal number of features to keep is 21.

# Feature Selection: Recursive Feature Elimination

| Column name | Keep |
|---|---|
| city_7 | True |
| city_8 | True |
| city_9 | True |
| city_10 | True |
| city_16 | True |
| city_18 | True |
| city_19 | True |
| city_20 | True |
| registered_via_7 | True |
| registered_via_9 | True |
| registered_via_13 | True |
| avg_is_auto_renew | True |
| avg_is_cancel | True |
| avg_payment_plan_7 | True |
| avg_payment_plan_30 | True |
| trans_count | True |
| avg_rate_num_25 | True |
| avg_rate_num_50 | True |
| avg_rate_num_75 | True |
| avg_rate_num_985 | True |
| avg_rate_num_100 | True |

Here are the 21 features to be kept.

A majority of the features kept are regarding the demographics of the user. The other half of the features is composed of the nature of the user's transactions (type of payment plan, number of transactions, auto-renewal, cancellation) and the average rate of how much of the song the user actually listens to. The number of active days did not seem to make it onto the list.

The log loss score after dropping these variables worsened to 0.468988.

# Feature Selection: Feature Importance

The scoring method used to rank each feature is Mutual Information.

| Number of Top Features Kept | Log Loss Score |
|---|---|
| 18 | 0.4674 |
| 20 | 0.4642 |
| 24 | 0.4634 |
| 28 | 0.4634 |
| 30 | 0.4634 |

# Feature Selection: Feature Importance

| Feature | MI Score |
|---|---|
| avg_is_auto_renew | 0.190177 |
| trans_count | 0.145051 |
| avg_actual_amount_paid | 0.123797 |
| avg_is_cancel | 0.088513 |
| avg_payment_plan_7 | 0.075063 |
| avg_discount_received | 0.064310 |
| registered_via_7 | 0.061058 |
| age | 0.023075 |
| registered_via_4 | 0.020251 |
| avg_payment_plan_30 | 0.015818 |
| days_since_reg | 0.013782 |
| registered_via_9 | 0.011532 |
| gender_male | 0.010578 |
| city_14 | 0.005798 |
| city_5 | 0.005577 |
| city_4 | 0.005511 |
| log_count | 0.004673 |
| city_15 | 0.004220 |
| city_13 | 0.004218 |
| city_12 | 0.004160 |
| avg_num_985 | 0.004034 |
| city_17 | 0.003831 |
| avg_rate_num_25 | 0.003822 |
| city_6 | 0.003816 |

Here are the 24 features to be kept.

The top 6 features all seem to relate to the details of the transactions the users have made. The most important feature is the average auto renewal rate.

The features kept due to feature importance is very similar to the features kept due to recursive feature elimination. They are comprised of features related to transactions details and user demographic information. The user activity does not seem to be that important as only 3 of the features are from the user activity dataset.

The log loss score is slightly better through this method with a log loss score of 0.46393.

# Principal Component Analysis

Another way to improve the model is through adding more variance into the model. Principal Component Analysis (PCA) linearly transforms the features into a lower dimension while keeping the most important components of the feature. The larger the variance the larger the amount of information the variable contains. Since the Recursive Feature Elimination method and the Feature Importance both removed many features from the dataset, the variance in the dataset was reduced. I have added the top 2 principal component into each of the features of the dataset to see if they would result in a better log loss score.

| Feature Selection Method | Log Loss Before PCA | Log Loss After PCA |
| --- | --- | --- |
| Recursive Feature Elimination | 0.4690 | 0.4677 |
| Feature Importance | 0.4639 | 0.4637 |

# Final Results

The final model uses the top 24 most important features as well as the 2 principal components to train on. The following are the results on the test data and train data:

| **Algorithm Used** | **Train Data Results** | **Test Data Results** |
|---|---|---|
| XG Boosting | Accuracy score: 0.8367<br>Log Loss: 0.3953 | Accuracy score: 0.8027<br>Log Loss: 0.4559 |
| Logistic Regression | Accuracy score: 0.8129<br>Log Loss: 0.4637 | Accuracy score: 0.8016<br>Log Loss: 0.4718 |

# Limitations and Further Opportunities

- Model can be improved using server with higher CPU
  - Solving issue of unbalanced dataset by assigning higher weight to users that churned so that all the data can be used to train model
  - Fine tune more hyperparameters
- Model can be improved in a better understanding of the variables provided
  - Extreme negative values in columns that should strictly be positive (age and total seconds listened)

A model with a low log loss allows accurate prediction of the likelihood of churning. Clustering similar users together in terms of demographics and activity can pave the opportunity of a recommender system that provides the most effective promotion for the user.