Predicting Customer Churn for a Music Streaming App

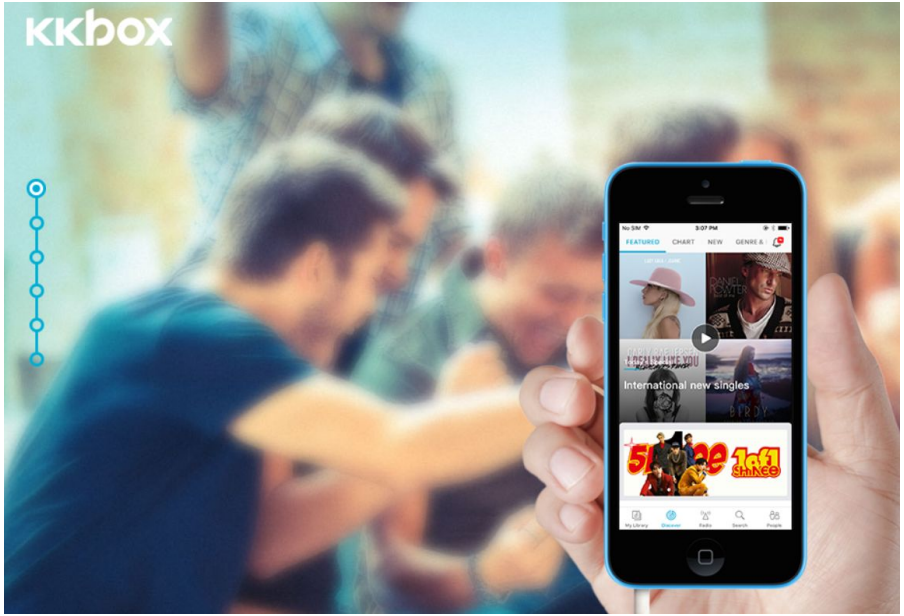
Providing Predictive Models and Data Insights to Aide in Targeted Marketing and Improve Customer Retention

Background: Business Problem

- For a subscription based business, customer churn refers to customers canceling their service
- The churn rate must be lower than the new subscriber rate for the company to grow
- Accurately predicting customer churn is critical for business projections and long term success
- Segmenting customers who have a high churn probability is very valuable to the marketing team to deploy targeted efforts to increase customer retention

Hypothetical Client

- KKbox is the biggest music streaming service in East Asia with a large library of Asian pop music
- Users can stream unlimited numbers of songs from their smartphones or other devices in exchange for a monthly fee
- Basically, it's Taiwanese Spotify



Data

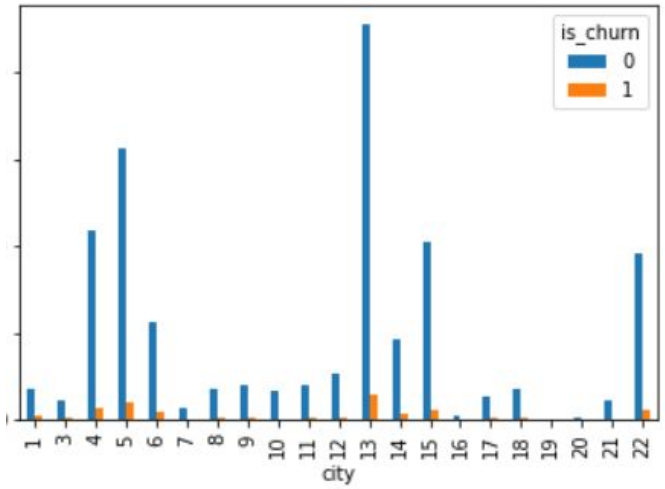
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000000 entries, 0 to 9999999
Data columns (total 9 columns):
msno          object
date          int64
num_25        int64
num_50        int64
num_75        int64
num_985       int64
num_100       int64
num_unq       int64
total_secs    float64
dtypes: float64(1), int64(7), object(1)
memory usage: 1.5 GB
```

- Kaggle provided their anonymized user data on the competition page.
- There were 4 different types of csv data tables: train/test, members, transactions, and user logs
- One column they all have in common is User ID (MSNO)
- Train/test and members files are indexed by User ID, while transactions and user logs are indexed by date
- Transactions file contain ~ 20 million records (@1.61 GB) and user logs file contains ~ 200 million (@ 22.4 GB) records
- This presents a challenge as most any laptop/desktop does not have enough RAM to hold these files in memory if using python packages such as Pandas taught in this course

Data Description (columns)

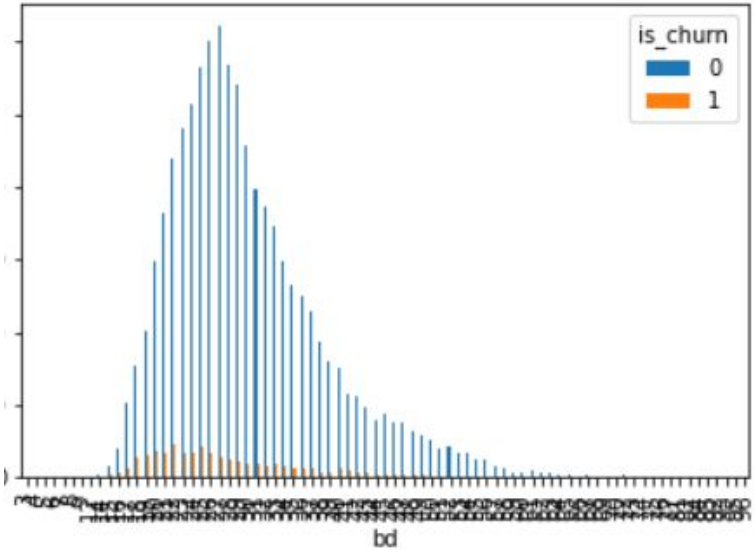
- Train/test
  - User ID
  - Churn (0 or 1)
- Members
  - User ID
  - Age
  - Gender
  - Registration method
  - Registration Date
- Transactions
  - Date
  - User ID
  - Payment method
  - Days in pay period
  - Payment plan list price
  - Actual amount payed
  - Auto renew (0 or 1)
  - Membership expire date
  - Cancellation (0 or 1)
- User Logs
  - Date
  - User ID
  - # of Songs played to 0-25%
  - # of Songs played to 25-50%
  - # of Songs played to 50-75%
  - # of Songs played to 75-98.5%
  - # of Songs played to 100%
  - # of unique songs played
  - Total seconds played

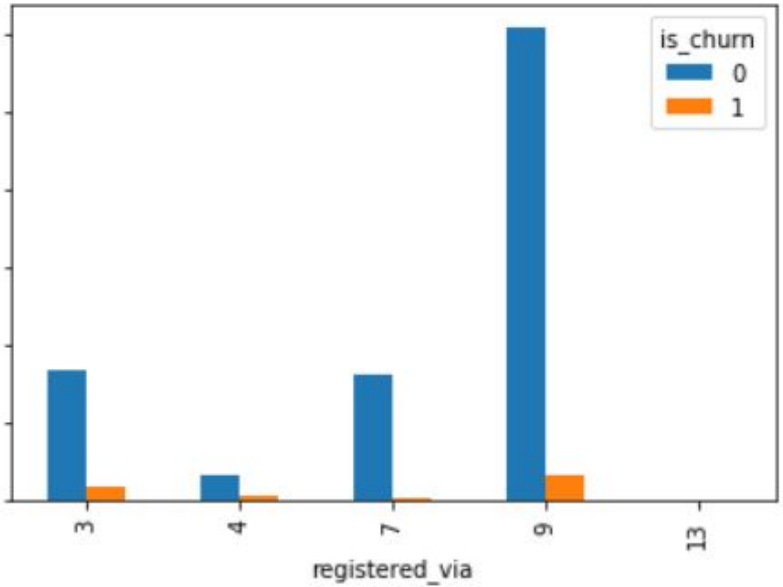
Exploratory Data Analysis



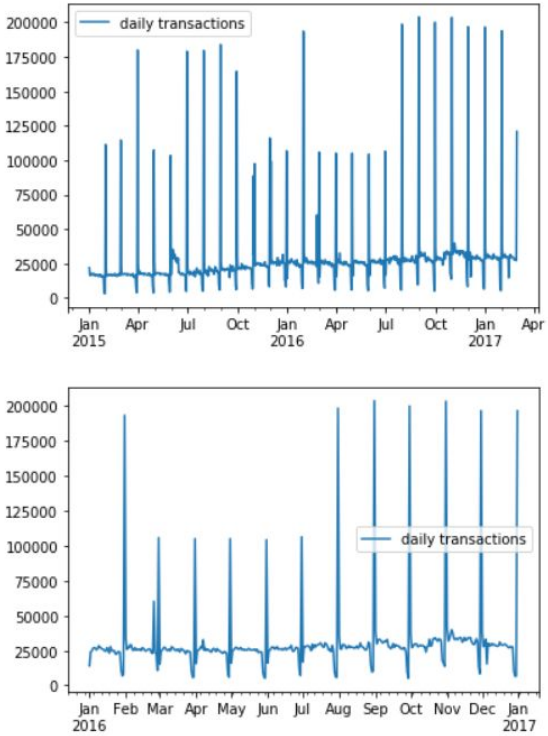

```
city
1     12.250000
3      7.203390
4      6.147186
5      5.772137
6      7.023411
7      3.875969
8      6.539510
9      5.450237
10     3.021148
11     5.825243
12     5.300353
13     5.732616
14     6.224490
15     5.050973
16     3.773585
17     5.535055
18     3.641457
19    28.571429
20     0.000000
21     4.803493
22     5.416051
Name: churn_percentage, dtype: float64
```

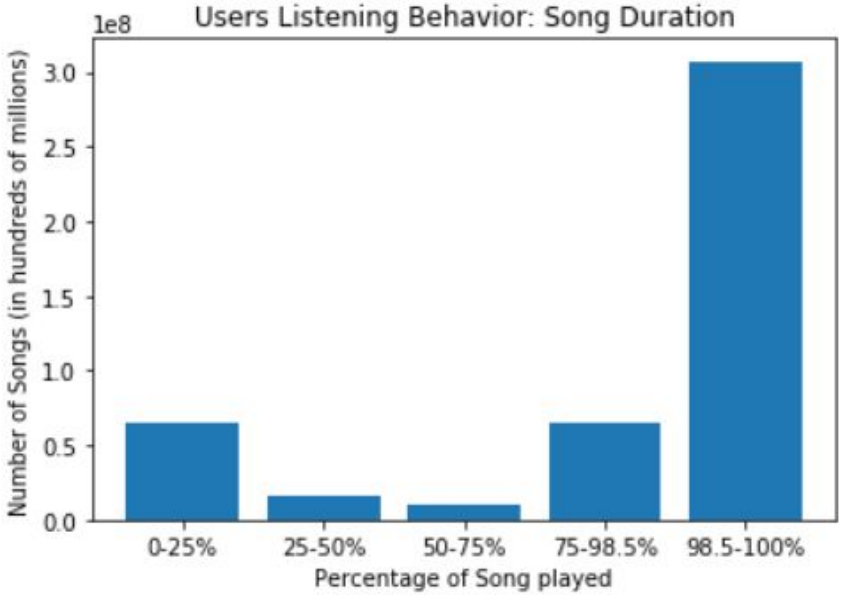
EDA con’td



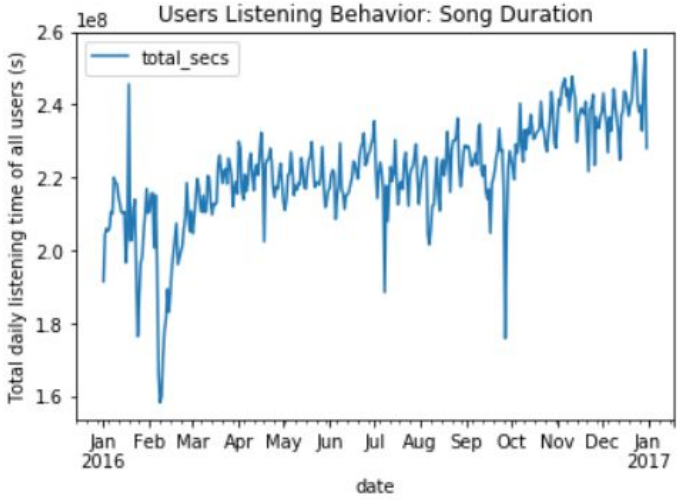


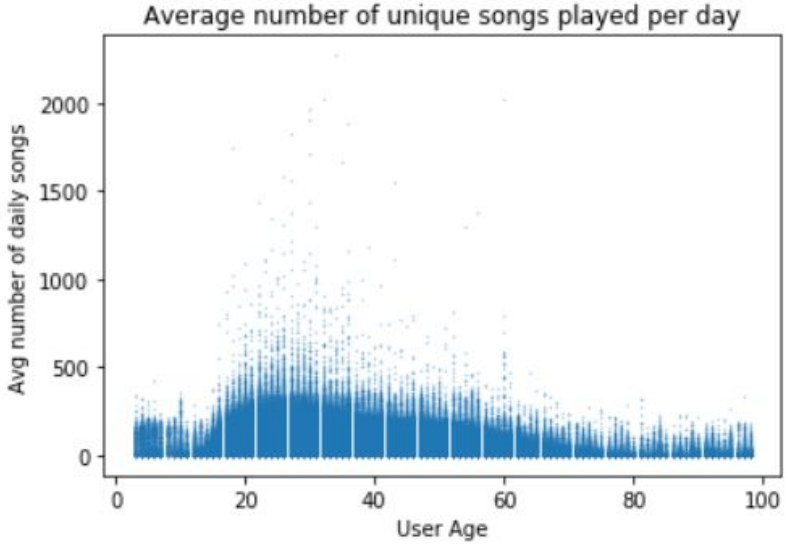
EDA con’td


daily transactions
200000
175000
150000
125000
100000
75000
50000
25000
0
Jan 2015
Apr
Jul
Oct
Jan 2016
Apr
Jul
Oct
Jan 2017
Apr
daily transactions
Jan 2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan 2017


Users Listening Behavior: Song Duration
1e8
Number of Songs (in hundreds of millions)
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0-25%
25-50%
50-75%
75-98.5%
98.5-100%
Percentage of Song played

EDA con’td

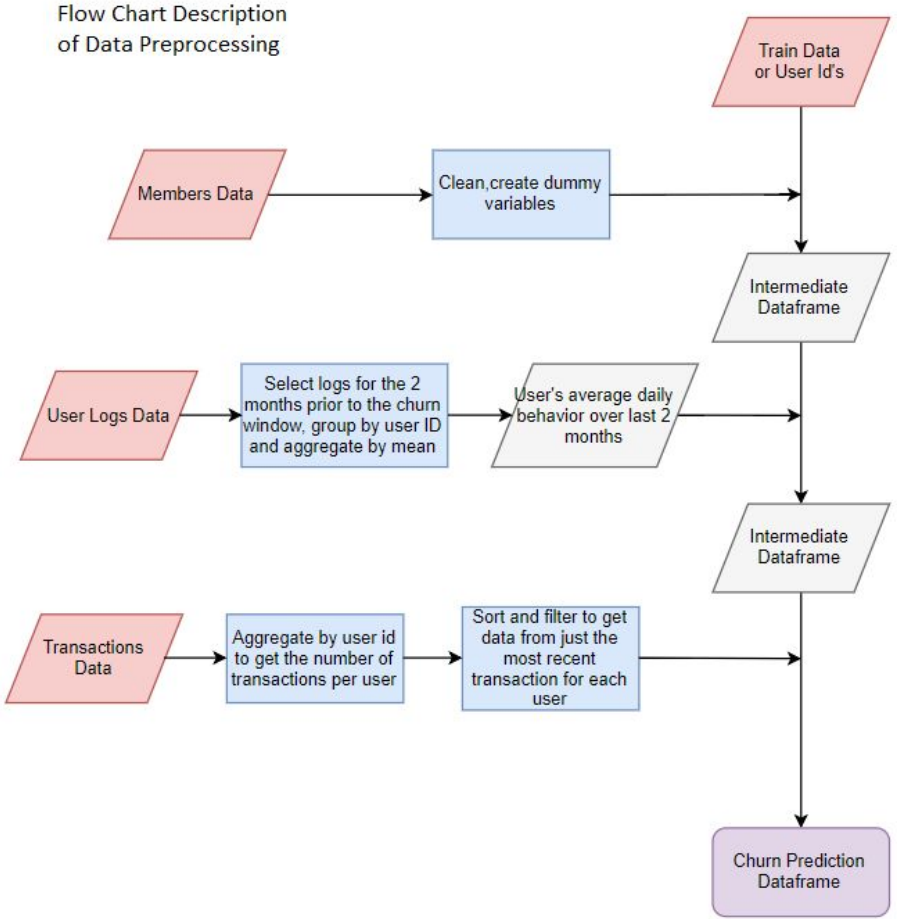

Users Listening Behavior: Song Duration
1e8
2.6
2.4
2.2
2.0
1.8
1.6
total_secs
Total daily listening time of all users (s)
Jan
2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
2017
date


Average number of unique songs played per day
2000
1500
1000
500
0
Avg number of daily songs
0
20
40
60
80
100
User Age

Correlation Matrix (Pearson R)

	city	bd	registered_via	is_churn	num_25	num_50	num_75	num_985	num_100	num_unq	total_secs	days_logged
city	1.000000	-0.020445	0.045767	-0.022499	0.001224	0.001040	-0.006339	0.001040	-0.000279	-0.000679	-0.002455	0.003994
bd	-0.020445	1.000000	0.209202	-0.071810	-0.089061	-0.090175	-0.086469	-0.090175	0.022526	-0.040294	0.010269	-0.035512
registered_via	0.045767	0.209202	1.000000	-0.073980	-0.031941	-0.031360	-0.021466	-0.031360	0.010942	-0.007058	0.007218	-0.019007
is_churn	-0.022499	-0.071810	-0.073980	1.000000	0.005029	0.003880	0.013094	0.003880	-0.022791	-0.013198	-0.022951	-0.046399
num_25	0.001224	-0.089061	-0.031941	0.005029	1.000000	0.533542	0.422364	0.533542	0.069331	0.414502	0.118600	0.021858
num_50	0.001040	-0.090175	-0.031360	0.003880	0.533542	1.000000	0.591780	1.000000	0.078209	0.325399	0.143024	0.032062
num_75	-0.006339	-0.086469	-0.021466	0.013094	0.422364	0.591780	1.000000	0.591780	0.102863	0.301384	0.173186	0.031214
num_985	0.001040	-0.090175	-0.031360	0.003880	0.533542	1.000000	0.591780	1.000000	0.078209	0.325399	0.143024	0.032062
num_100	-0.000279	0.022526	0.010942	-0.022791	0.069331	0.078209	0.102863	0.078209	1.000000	0.783419	0.982416	0.076924
num_unq	-0.000679	-0.040294	-0.007058	-0.013198	0.414502	0.325399	0.301384	0.325399	0.783419	1.000000	0.819015	0.068628
total_secs	-0.002455	0.010269	0.007218	-0.022951	0.118600	0.143024	0.173186	0.143024	0.982416	0.819015	1.000000	0.080310
days_logged	0.003994	-0.035512	-0.019007	-0.046399	0.021858	0.032062	0.031214	0.032062	0.076924	0.068628	0.080310	1.000000

Data Wrangling



Data Wrangling

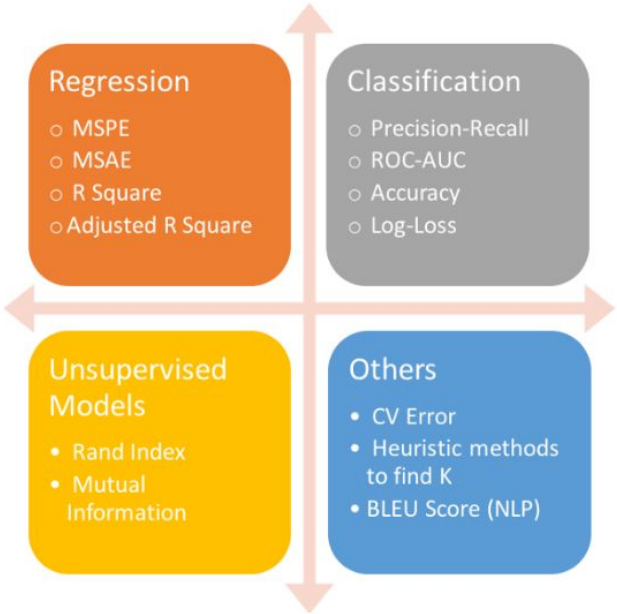
Out[12]:

msno	is_churn	bd	registration_init_time	num_25	num_50	num_75	num_985	num_100	num_unq	...	city_22.0	registered_via_0.0
)ZaoIqOUAZPsH1q0teWCg=	1	28.0	20131223.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0	0
Udr+E+3+oewvweYz9cCQE=	1	20.0	20131223.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0	0
hiRnAVvgibMyazbCxvWPcg=	1	18.0	20131227.0	5.166667	1.833333	1.500000	1.833333	8.000000	15.000000	...	0	0
/GCG2Ecrogbc2Vy5YhsfhQ=	1	0.0	20140109.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0	0
/w/XKpMgrEMdG2edFOxnA=	1	35.0	20140125.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0	0
)99M5vYB3CN2HzkEY+eM=	1	0.0	20140126.0	1.500000	0.000000	0.000000	0.000000	2.750000	5.000000	...	1	0
'LjFoxD1EcKYCc76F5IAWw=	1	0.0	20140129.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0	0
4dXMLk0jOn65d7a8tQ2Eds=	1	28.0	20140202.0	0.500000	0.166667	0.166667	0.166667	33.500000	17.666667	...	0	0
Jbsz0MXw3kay/1AlZCq3EbI=	1	21.0	20140212.0	14.857143	2.285714	1.571429	2.285714	46.285714	63.142857	...	0	0
eN3oaNmhdmTkoof2iRYEE=	1	0.0	20140228.0	47.500000	2.833333	0.166667	2.833333	21.666667	61.666667	...	0	0
Cezv5KBK7+DMujNibYgyIrs=	1	0.0	20140307.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0	0
K1Bc6g+7LFKzoNf+zlJtDoQ=	1	0.0	20140323.0	1.500000	1.000000	1.500000	1.000000	16.833333	21.333333	...	0	0
FerqTEgmno3x7Rc7YGwzw=	1	32.0	20140324.0	3.000000	1.285714	0.857143	1.285714	10.285714	14.285714	...	0	0
CVYPdek7K4Leu+aqbCRo8=	1	0.0	20140402.0	5.000000	2.000000	0.500000	2.000000	40.000000	32.125000	...	0	0
bZ9gChiSR4tWP4IvJGdxSM=	1	21.0	20140407.0	3.000000	1.600000	1.800000	1.600000	90.000000	91.200000	...	0	0
iKwhz0Za0yU2GIQtKa1JFk=	1	20.0	20140415.0	14.666667	4.000000	1.500000	4.000000	2.500000	21.666667	...	0	0
TsxP0VrzDsfB0Hdth12gqQE=	1	0.0	20140420.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0	0
ucgyuT2i8JIiJ87bOIsxtFvBw=	1	0.0	20140425.0	15.000000	2.500000	2.500000	2.500000	27.000000	44.000000	...	0	0
VnjzY7U1G24mVFNdzGNQ=	1	29.0	20140510.0	6.571429	1.285714	1.000000	1.285714	21.142857	27.857143	...	0	0
)fme2pHLE2y+RJ3eGcLT0k=	1	0.0	20140515.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0	0
RoSPuI6X2x5O+woVFDhnY=	1	0.0	20140605.0	3.333333	1.000000	0.500000	1.000000	14.166667	17.833333		0	0

Model Selection

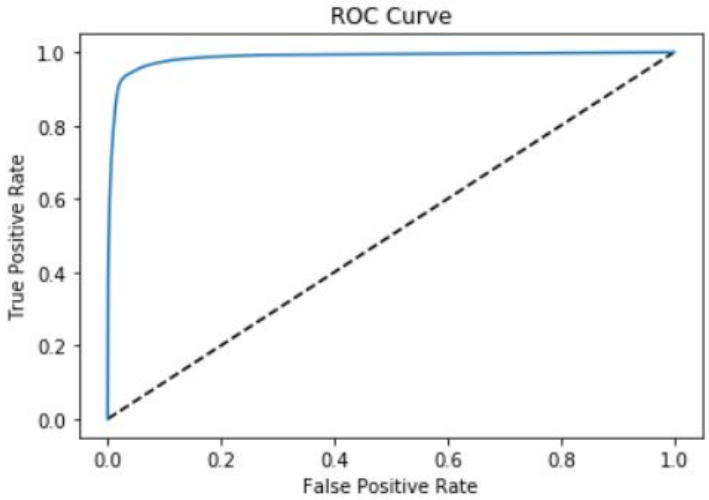
The evaluation metric for this competition is **Log Loss**

$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log(p_i) + (1-y_i)\log(1-p_i)\right)$$



Log loss of random guessing = ln(0.5) = 0.693
Log loss of hypothetical perfect model = 0.0

Model Performance: Random Forest



AUC: 0.9861211554440634

Confusion Matrix

```
[[174343   2371]
 [  2621  14857]]
```

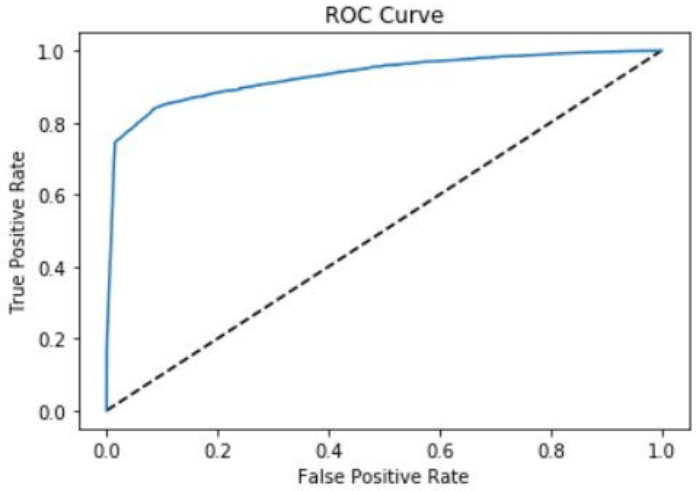
Evaluation Set:

```
#check log loss
log_loss(y_test,y_pred_prob)
```

```
0.09625370790222848
```

Competition Scoring: 0.30744

Model Performance: Logistic Regression with Grid Search Hyperparameter Optimization



AUC: 0.930369867332425

Confusion Matrix

```
[[174087   2627]
 [  4606  12872]]
```

Evaluation Set:

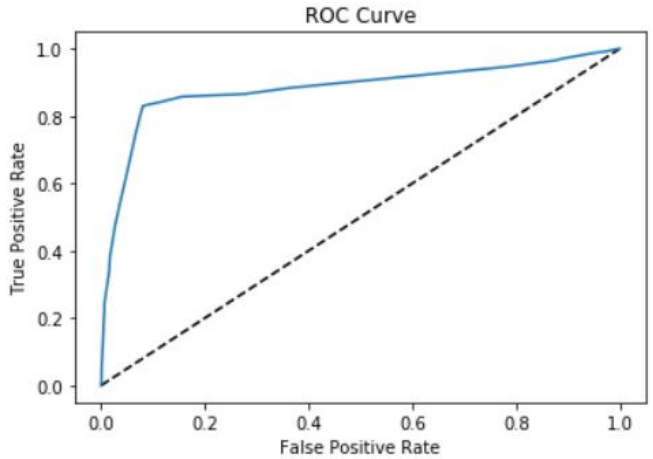
```
#check log loss
log_loss(y_test,y_pred_prob)
```

```
0.13416865382929385
```

Competition Scoring:

0.26963

Model Performance: Logistic Regression- ridge regression penalty with LASSO regression selected features (final model)



AUC: 0.8817120310353784

Confusion Matrix

```
[[173671   3043]
 [ 10788   6690]]
```

Evaluation Set:

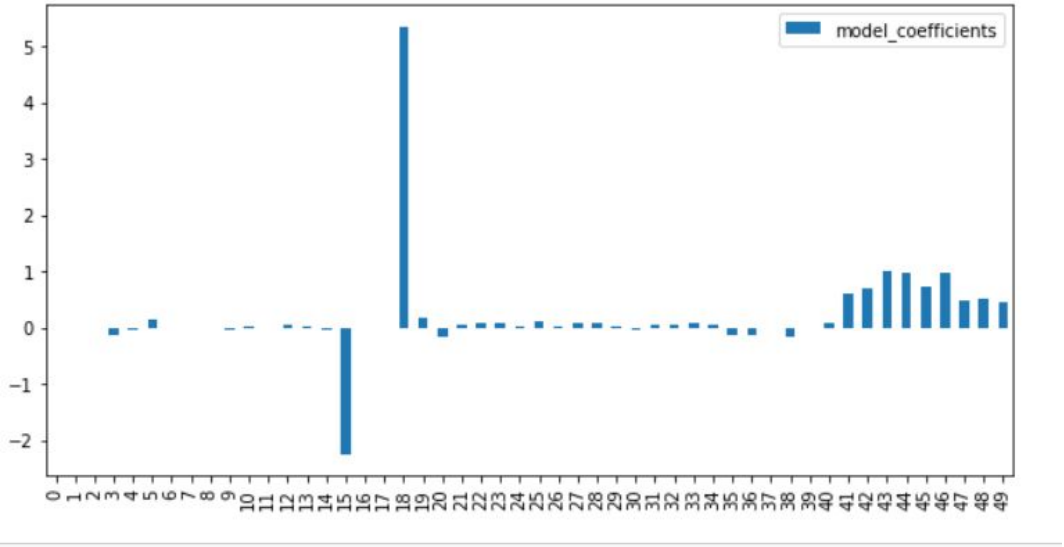
```
#check log loss
log_loss(y_test,y_pred_prob)
```

```
0.1738358467535548
```

Competition Scoring: **0.13673**

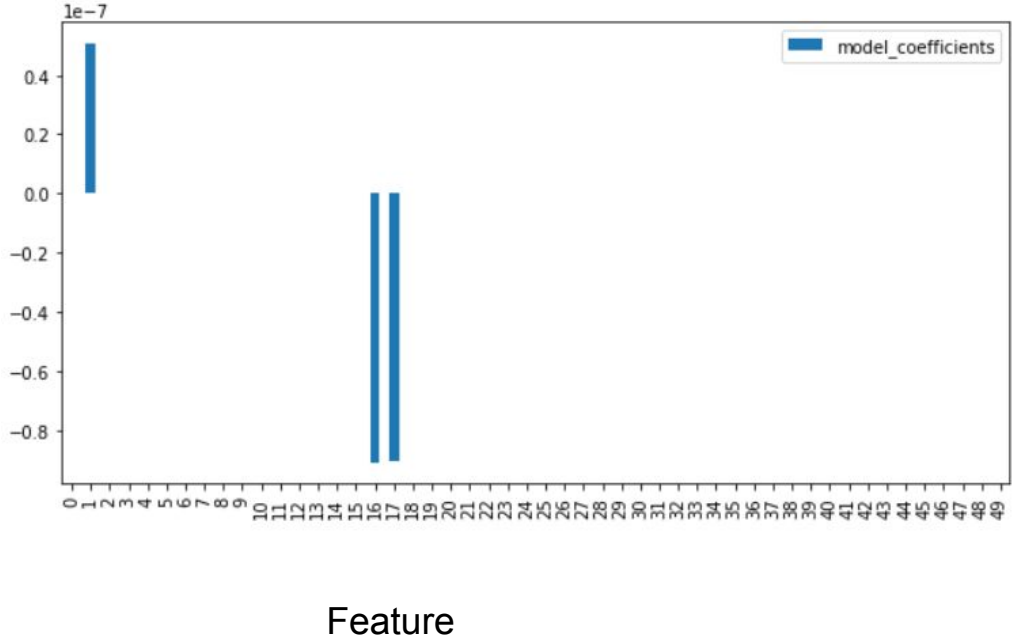
Features: LASSO Regression with All Features

Coefficient Value

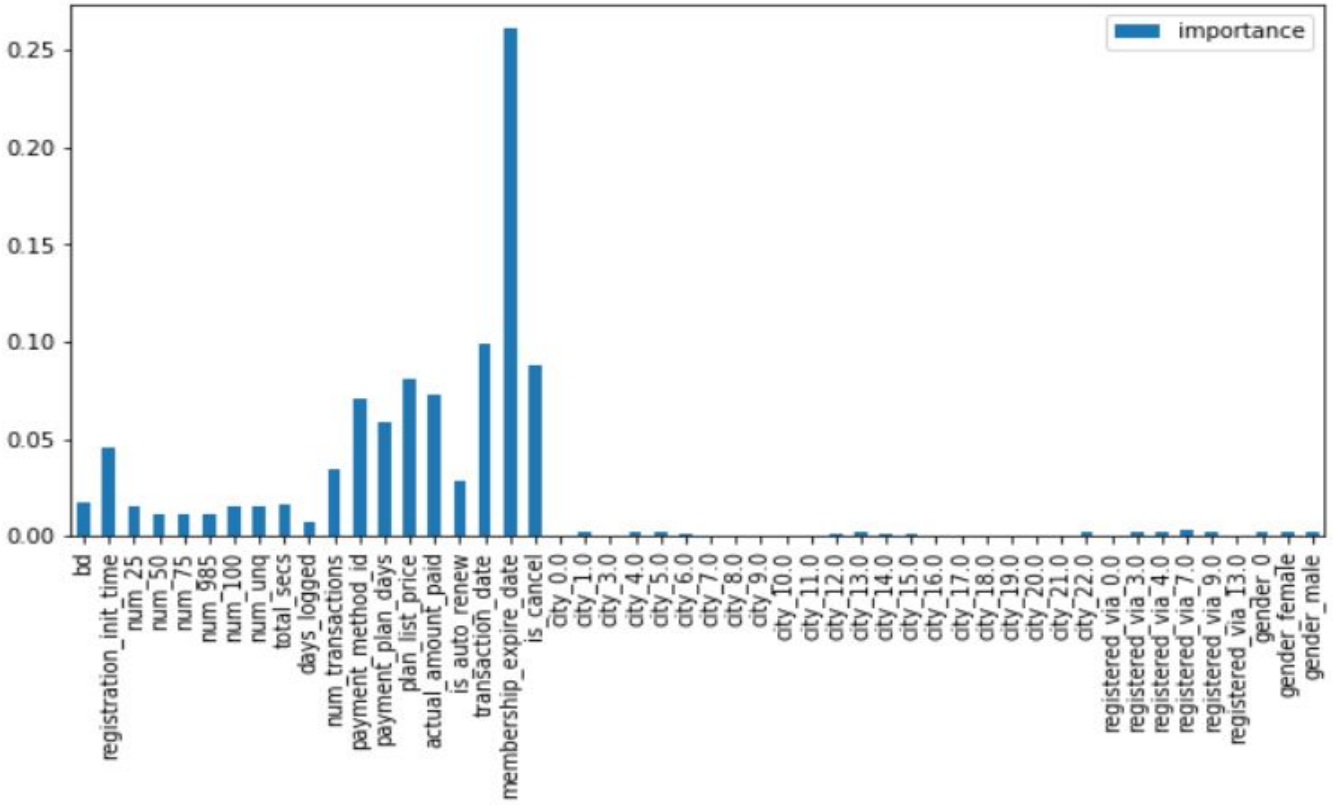


Feature

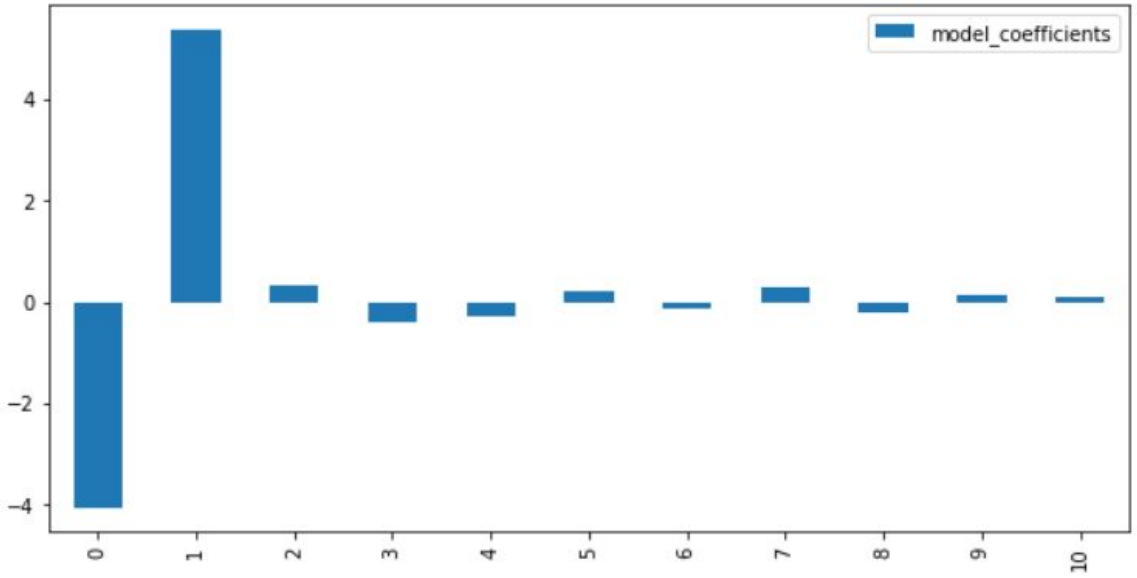
Features: Ridge Regression with All Features



Random Forest Feature Importance



Final Model Feature Coefficients



	features	model_coefficients
0	is_auto_renew	-4.052154
1	is_cancel	5.375505
2	registered_via_0.0	0.317831
3	registered_via_3.0	-0.394750
4	registered_via_4.0	-0.274589
5	registered_via_7.0	0.210269
6	registered_via_9.0	-0.119956
7	registered_via_13.0	0.286762
8	gender_0	-0.219702
9	gender_female	0.151013
10	gender_male	0.094256

Recommendation to Client:

- Apply targeting marketing strategies to customers with high churn probability
- Consider features of users that have significance to churning when implementing product improvements