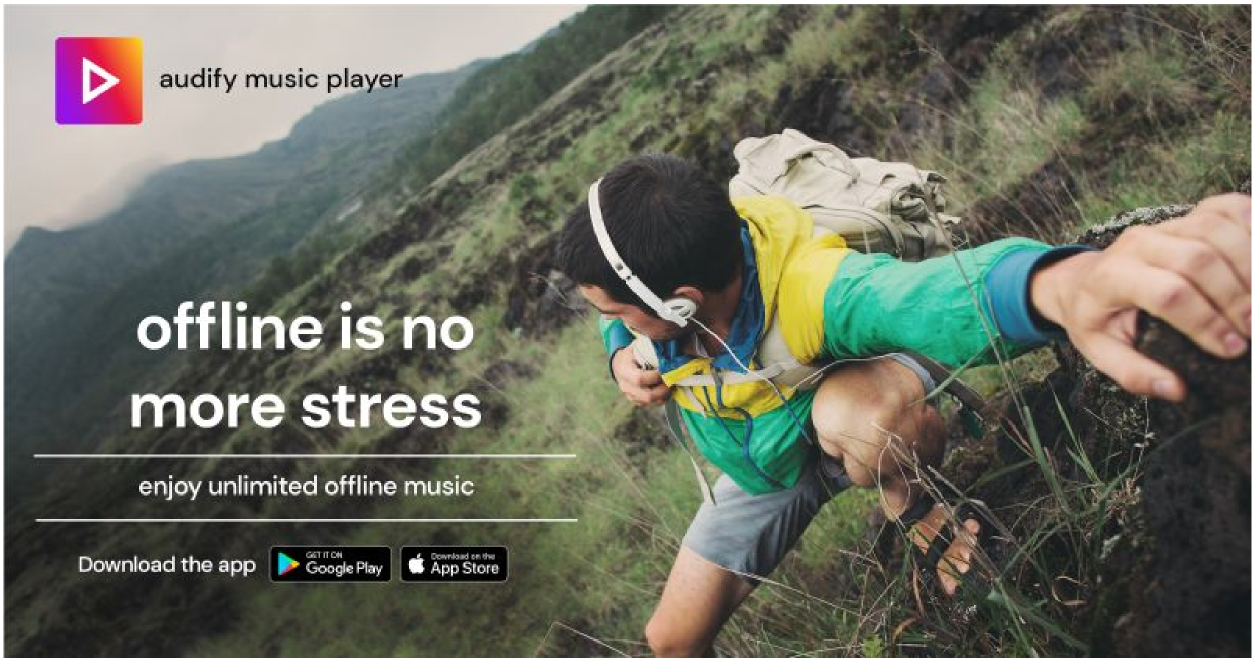
PGDBA PROJECT

HITESH MEENA

Audify App - Churn Analysis



GitHub Link : https://github.com/RubyOnNode/AUDIFY

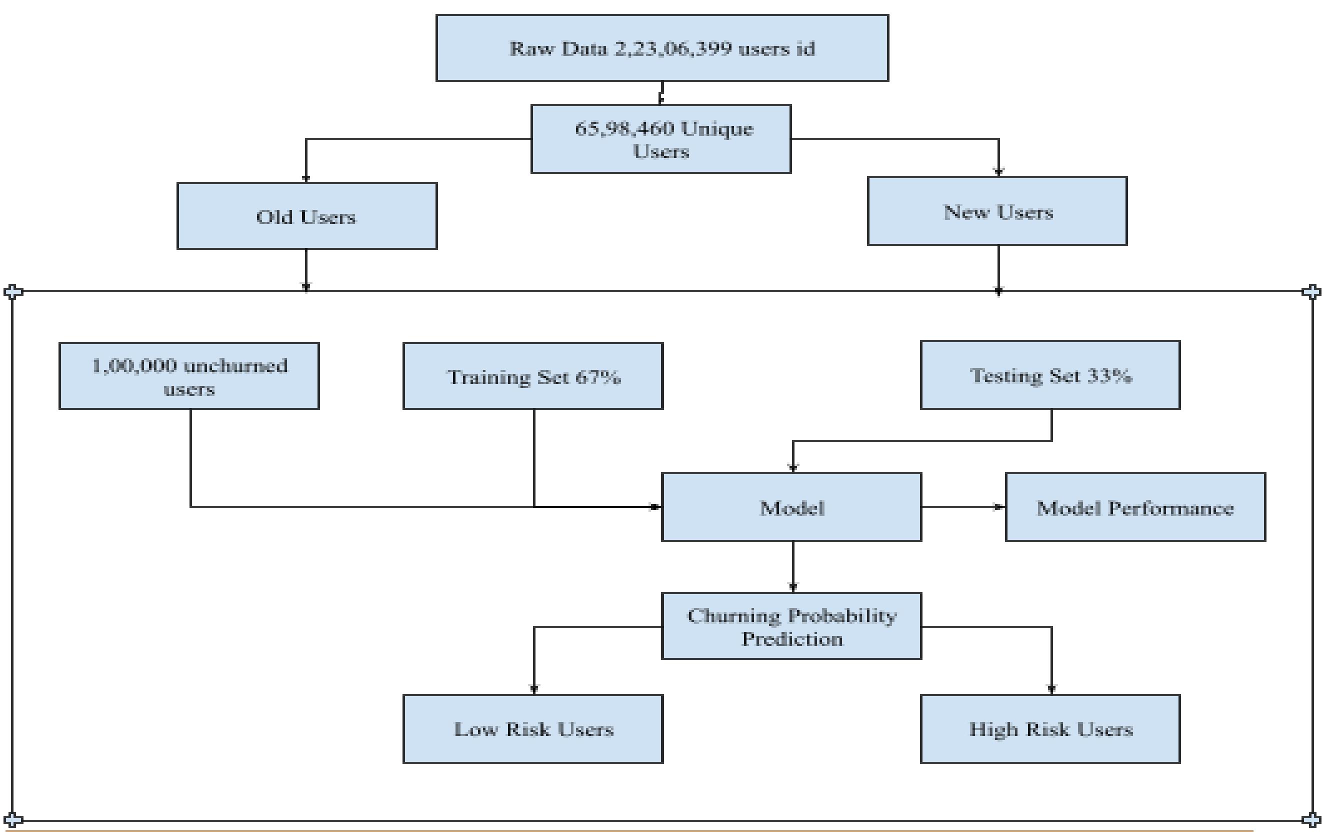
Problem Statement

Churning in the mobile application industry is one of the major challenges. We say a customer is churned when he or she has stopped using the services or buying the products of a firm, in our case a customer is churned when the user uninstalls the Audify application.

We need to do the analysis of the data that was collected from Firebase - Google Analytics. Find out the behavior of the users who are uninstalling the app. What factors or features are affecting the churning behavior of the users and how likely (probability) users are going to uninstall the app who have not yet uninstalled.

Brief overview of solution approach

- We will be using pyspark with hadoop for loading the data as we are dealing with big data. As we have multiple entries of a single user id, we will group them by user id and sum up all the features (underlying assumptions, please find them at the bottom of the report)
- Splitting of data in terms of old users and new users and building separate models for both for better decision making and analysis.
- Feature engineering, We have 56 total event columns, all these events will be clubbed together which shows similarity
- A global test set for (users who have not yet churned) of 1 lakh users for accessing the model when run in real time.
- Train Test split of the data points for training and testing of the models that we are going to impliment.
- SMOTE with undersampling for unbalanced class problem
- Grid search for hyperparameter tuning.
- Confusion matrix and ROC curves for evaluating the accuracy of models (Logistic Regression, KNN classifier and Xgboost)
- Calculation of Permutation importance and SHAP values for interpretation of tree based model xgboost that we used.



Exploratory Data Analysis

These data are for the range of date we are provided data with. 2,23,06,399 users interacted with the Audify app and 2,80,062 churned in this time frame.

Total data points	2,23,06,399
Total active users	65,98,460
Total churned users	2,80,062

Initial look into the head of the data

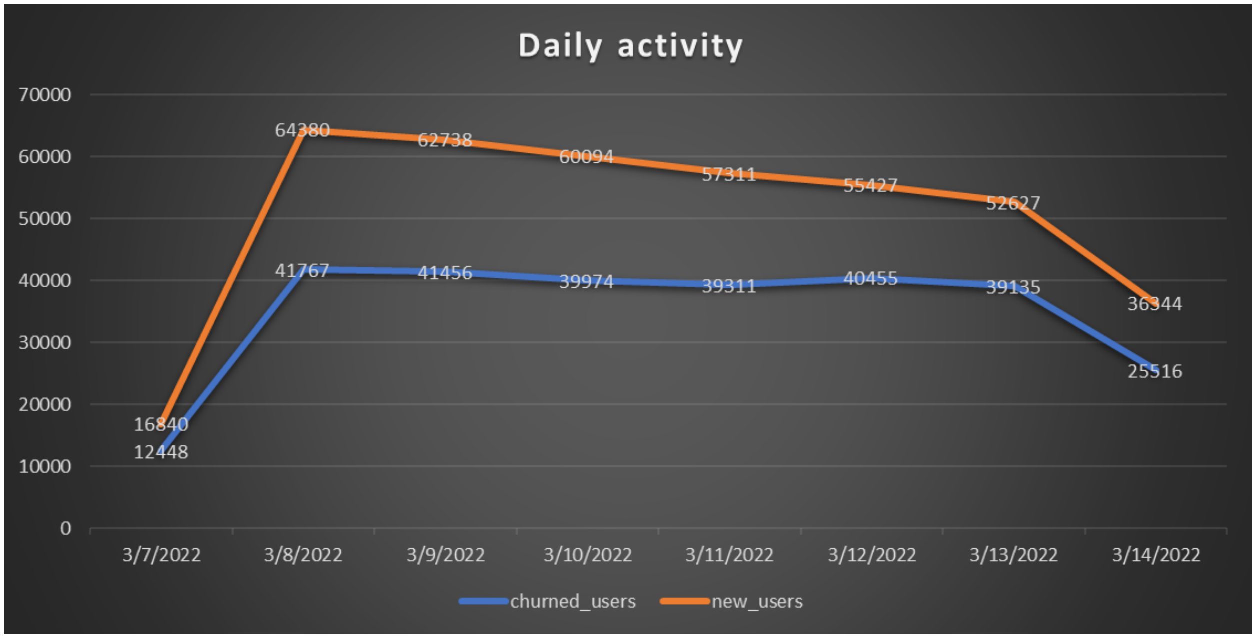
user_pseudo_id	totalEventCount	first_activity_time	last_activity_time	sessNum	engTime_sec
2a33e972f4731248662f28c714156551	1	2022-03-13 19:18:12.015 UTC	2022-03-13 19:18:12.015 UTC	null	null
11aa7d8c808a35c1566d41d184aa5145	1	2022-03-13 21:57:56.573 UTC	2022-03-13 21:57:56.573 UTC	null	null
cb56e3a8ef28723efc95ce7812974c7e	1	2022-03-13 21:38:07.461 UTC	2022-03-13 21:38:07.461 UTC	null	null
4fa298d11f984953ed45a3aa44715d63	6	2022-03-13 19:04:10.215 UTC	2022-03-14 17:16:19.524 UTC	null	null
fbbe3e8b5d3179dc78f8b7f079fdc14e	1	2022-03-13 23:37:57.811 UTC	2022-03-13 23:37:57.811 UTC	1.0	null

bottom_option_click_event	current_search_tab_event	edit_tags_page_events	equalizer_event	feature_popup_events
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0

The data is very sparse, most of the elements are zero and very few entries are greater than one. We can see Null Values also. Need to combine data of various users who are present multiple times in the rows.

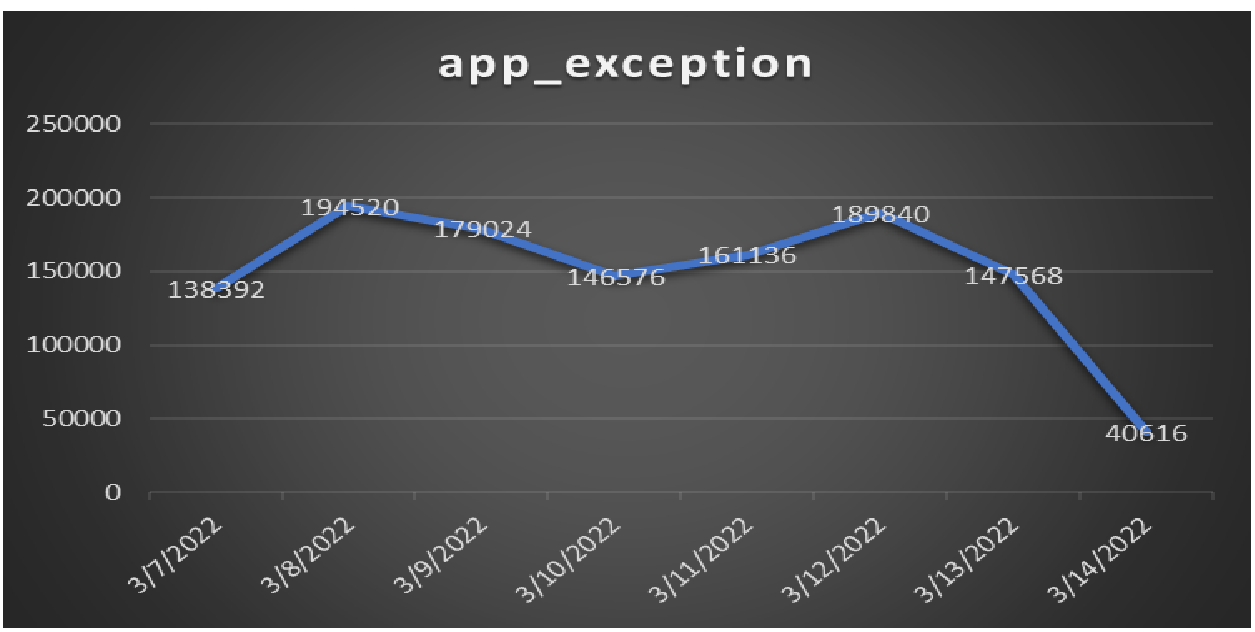
We will group together all the user id and sum up all the events. This will create a feature dataframe where each row will represent one user and all its features, like his total screen view, total events, total notifications he has seen. This is based on the underlying assumption that initially we had a session of users and what he did in that session.

daily churned users and new users who opens the app for the first time



We do not have full data of 7,March 2022 and 14, March 2022 as this was the slicing point for this dataset **. There is a declining trend in the number of users who open the app for the first time (new users) from 8, March 2022 to 13, March 2022**. Which might be little concerning as the number of churned users remains constant throughout this period.

App Crash or throws an exception daily data



Here are the frequency of visits each user has made.

user_pseudo_id	count
c75a7a99f51a8f4e578943bf9bb0b2ed	1
45f3e2ee9cc17dba89227869f8c6adf5	5
f1a38b974675019f7a1f63ea8a1c075d	3
045441ffe13ac1d934659a8c9a536914	3
2280b60eb3247cf54063e3d264e10172	1
221ab279ca417be5b9fca8a258423f56	5
e2688adbe119c58b1c6ae2a4a2b08d47	5
563bef316a43e461553b99c77d002d48	1
ff2bb4945badba76c426369104ae4abd	7
bc20e5d1c01cb21551909a30ee49dc5d	3
8aa1af3f87187e53760dbc3f5144faae	7
a6d454aab932dc5bb2af3effcc56e8dd	1
cab4f8c27c935c76bebc83506b683db8	7

We have null values in sessNum and engTime columns but these will disappear when we group by and sum the features.

```
#Count the Null values in the dataframe
from pyspark.sql.functions import col,isnan,when,count
df.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in df_columns]
   ).show()
```

```
-+-----------------+-------+-----------+---------+-------------+-------------+--------------+-
e|last_activity_time|sessNum|engTime_sec|appRemove|app_exception|app_clear_data|ad_close_event|a
-+-----------------+-------+-----------+---------+-------------+-------------+--------------+-
0|                 0| 743908|    1350672|        0|            0|             0|             0|
-+-----------------+-------+-----------+---------+-------------+-------------+--------------+-
```

Below is the computation of mean of all the features of users who have not churned yet and people who have churned already. As we can see, the values for people who are removed are much lower than those who are still active.

appRemove	0	1
widget_events	9.648398	0.369061
totalEventCount	357.395974	27.114028
bottom_mini_playing_bar_event	38.591762	2.133985
sessNum	8.380855	1.333212
notification_events	421.981833	17.812427
video_notification_event	0.853985	0.529083
app_clear_data	0.366268	0.081011
floating_player_event	1.616766	0.134142
interstitial_ad_events	110.447731	5.244439
lyrics_page_events	1.214717	0.178303
ad_close_event	6.520530	0.258086

New users are more likely to churn compared to old users.

This gives us the strong indication that we should segment the users by their total event count as old users and new users.

Then we can come up with two different strategies and models for analyzing their behavior. This way we will achieve user segmentation.

Why The choice of splitting on feature totalEventCount is good

We have data of a specific date range but total event count will reveal us how old is the user or how recently he has joined. Then we can segment the users based on some threshold value of this feature. The chosen threshold value will be 15 in our case and can be altered in future analysis.

Feature Engineering

We have 56 total events summed up for each unique user. Now can add up all the events that are relevant and can be described by a single feature which has the same semantic meaning as the event. **For example, events such as clicking the hamburger button, bottom option click event and all such events can be summed up can be called in_app_experience.** Few of the calculated features are given below. Total of 56 events will be scaled down to 10 features.

```
in_app_experience = [
 'album_art_change_event',
 'bottom_mini_playing_bar_event',
 'bottom_option_click_event',
 'current_search_tab_event',
 'edit_tags_page_events',
 'equalizer_event',
 'font_change_event',
 'genres_page_event',
 'ham_burger_click_event',
 'inside_page_events',
 'list_item_clicked_event',
 'playing_window_event',
 'playlist_event',
 'settings_page_events',
 'theme_event',
 'top_tab_event',
 'widget_events',
]
```

```
profile_visits = [
        'profile_page_events',
        'wellness_event',
]

special_features = [
       'floating_player_event',
       'lyrics_open_event',
       'lyrics_page_events',
       'mini_youtube_event',
       'ringtone_cutter_event',
       'voice_assistant_event',
       'youtube_event',
       'feature_popup_events',

]
```

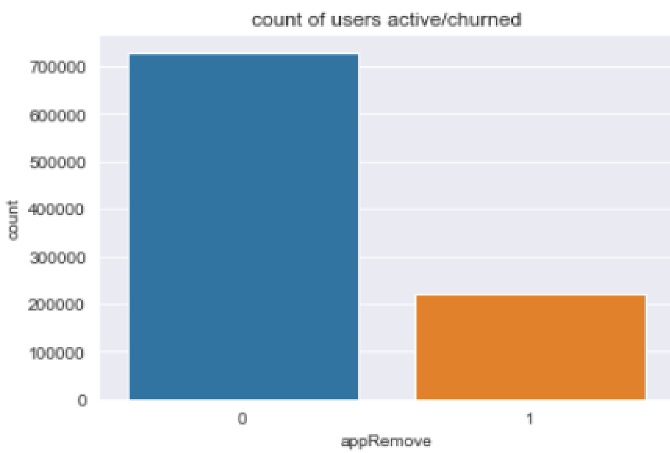
```
notification_events = [
    'notification_events',
    'video_notification_event',
]

adsEvents = [
     'ad_close_event',
     'remove_ads_purchase_event',
]


app_event = [
        'app_exception',
        'app_clear_data',
]
```

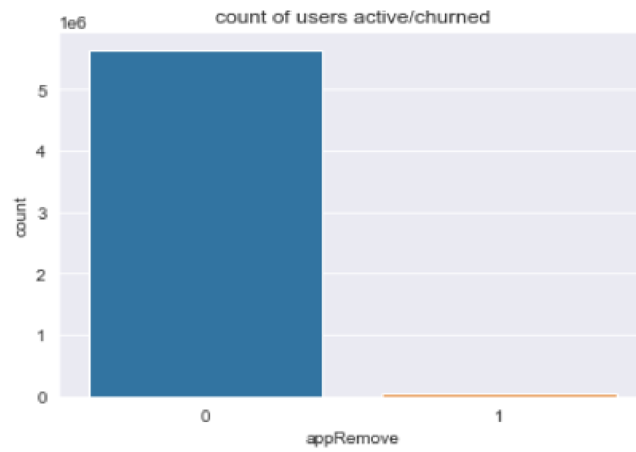
Correlation between features

	totalEventCount	sessNum	appRemove	screen_view	sum_in_app_exp	sum_special_features	sum_adsEvents
totalEventCount	1.000000	0.162095	-0.563956	0.898603	0.403640	0.098423	0.663884
sessNum	0.162095	1.000000	-0.124671	-0.002926	0.010645	0.004324	-0.025926
appRemove	-0.563956	-0.124671	1.000000	-0.535412	-0.183675	-0.072198	-0.384292
screen_view	0.898603	-0.002926	-0.535412	1.000000	0.339563	0.049980	0.601041
sum_in_app_exp	0.403640	0.010645	-0.183675	0.339563	1.000000	-0.020627	0.144499
sum_special_features	0.098423	0.004324	-0.072198	0.049980	-0.020627	1.000000	0.010709
sum_adsEvents	0.663884	-0.025926	-0.384292	0.601041	0.144499	0.010709	1.000000
sum_engagement_events	0.195790	0.027367	-0.112228	0.176404	0.090558	0.099135	0.092438
sum_notification_events	0.199844	0.009314	-0.127840	0.074602	0.164765	-0.016340	0.031242
sum_profile_visits	0.515295	-0.024046	-0.246685	0.470306	0.177150	-0.048785	0.320214

We can see we have a strong correlation of 0.89 between screen view and totalEventCount, which makes sense as more the screen view time of the user more will be the totalEventCount. We will be dropping the feature totalEventCount for the modeling purposes as it will create multicollinearity problems.

Churned new vs old users






```
df_low.appRemove.value_counts()/df_low.shape[0]
```

```
0     0.766134
1     0.233866
Name: appRemove, dtype: float64
```

```
df_high.appRemove.value_counts()/df_high.shape[0]
```

```
0     0.989785
1     0.010215
Name: appRemove, dtype: float64
```

When talking about new users 76 percent of the users have not uninstalled the app yet and 23 percent of the users have uninstalled the app. Clearly we have class unbalance.

In Old users the distribution of active users and churned users is highly unbalanced 98.9 percent of the users are still active and only 1.02 percent of the users has been churned.

This is one more indication that new users are almost 23 times more likely to to uninstall than an old user.

We have to go for sampling techniques and techniques that will handle these unbalanced class problems otherwise the model will be highly biased towards negative classes.

Outlier Detection

```
df_high.describe().transpose()
```

	count	mean	std	min	25%	50%	75%	max
widget_events	5697823.0	10.685507	179.483346	0.0	0.000	0.000	0.000	73864.000
totalEventCount	5697823.0	396.733188	807.067637	15.0	58.000	160.000	421.000	369546.000
bottom_mini_playing_bar_event	5697823.0	42.840411	130.077457	0.0	0.000	8.000	40.000	42048.000
sessNum	5692037.0	9.116987	9.486014	1.0	2.000	6.000	13.000	210.000

In the old users dataframe where we have data about the users who have high total event count we can see each one has abnormally high max values.

These are the outliers and need to be eliminated inter quartile range technique. Where we will eliminate only upper outliers values which are above 1.5 times above interquartile range.

```
cols = [ 'sessNum', 'screen_view', 'sum_in_app_exp', 'sum_adsEvents', 'sum_engagement_events',
        'sum_notification_events'] # one or more

Q1 = df_high[cols].quantile(0.25)
Q3 = df_high[cols].quantile(0.75)
IQR = Q3 - Q1

df_high = df_high[~( df_high[cols] > (Q3 + 1.5 * IQR)).any(axis=1)]
```

Sampling and Scaling

```
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline

# define pipeline
smote = SMOTE(sampling_strategy=0.5)
under = RandomUnderSampler(sampling_strategy=0.5)
steps = [('o', smote), ('u', under)]
pipeline = Pipeline(steps=steps)
# transform the dataset
X, y = pipeline.fit_resample(X, y)
```

First we have done oversampling of positive response data points using a technique called SMOTE (Synthetic Minority Oversampling TEchnique) where we have systematically generated new data points for minority classes, this was followed by undersampling of majority classes. These two techniques combined give better results.

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
fit = scaler.fit(X_train)
X_test = fit.transform(X_test)
X_train = fit.transform(X_train)
```

Since we will be dealing with algorithms which try to calculate the distance between the data points like KNN classifier and those which use gradient descent like logistic regression we have to scale the data points and then fit transform all the test points.

We are using min max scaling technique where each value in the vector will be scaled down to values between 0 and 1. This way we will make sure no single feature who just differs in domain of its values does not dominate in the modeling process.

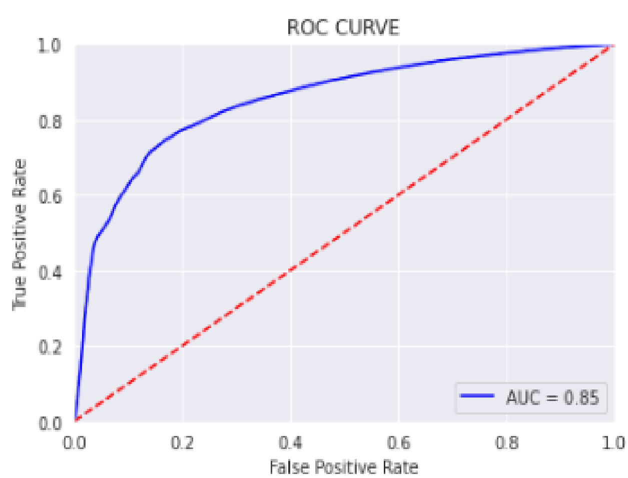
Modeling Results

So two models were trained, one for old users and the other for new users. 5 Fold cross validation technique was used for getting the appropriate test accuracies for each model.

Algorithm	5-Fold Test Accuracy	Test Accuracy	Area Under Curve(AUC)
Logistic Regression	79.51%	79%	0.85
Extreme Gradient Boosting	85.88%	86%	0.89
KNN classifier	83.42%	83%	0.86

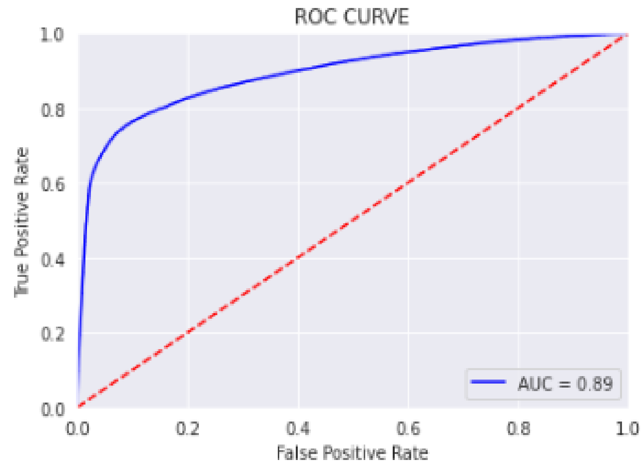
Results for Logistic Regression on test set

```
Confusion matrix :
 [[14467  4449]
 [ 6260 26634]]
Outcome values :
 26634 6260 4449 14467
Classification report :
              precision    recall  f1-score   support

           1       0.70      0.76      0.73     18916
           0       0.86      0.81      0.83     32894

    accuracy                           0.79     51810
   macro avg       0.78      0.79      0.78     51810
weighted avg       0.80      0.79      0.80     51810
```



Results for XGBoost on test set

```
Confusion matrix :
 [[13545  5371]
 [ 2031 30863]]
Outcome values :
 30863 2031 5371 13545
Classification report :
              precision    recall  f1-score   support

           1       0.87      0.72      0.79     18916
           0       0.85      0.94      0.89     32894

    accuracy                           0.86     51810
   macro avg       0.86      0.83      0.84     51810
weighted avg       0.86      0.86      0.85     51810
```



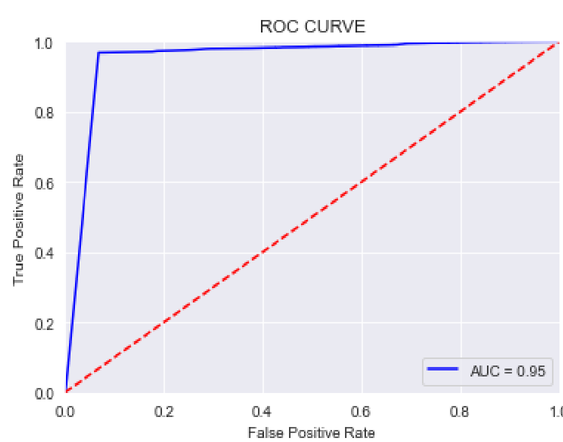
These are the results of modeling on old users.

For New users

Algorithm	5-Fold Test Accuracy	Test Accuracy	Area Under Curve(AUC)
Logistic Regression	92.4%	92%	0.95
Extreme Gradient Boosting	94.42%	96%	0.98
KNN classifier	95.42%	95%	0.96

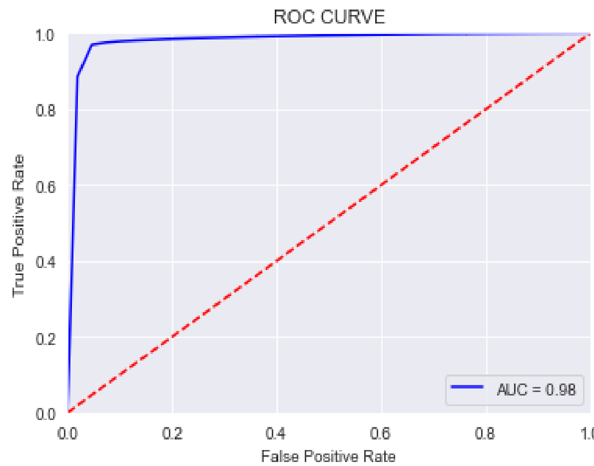
Extreme Gradient Boosting results

```
Confusion matrix :
 [[ 71101   2346]
 [ 21386 219003]]
Outcome values :
 219003 21386 2346 71101
Classification report :
              precision    recall  f1-score   support

           1       0.77      0.97      0.86     73447
           0       0.99      0.91      0.95    240389

    accuracy                           0.92    313836
   macro avg       0.88      0.94      0.90    313836
weighted avg       0.94      0.92      0.93    313836
```



Logistic regression results

```
Confusion matrix :
 [[ 65030   8417]
 [  4635 235754]]
Outcome values :
 235754 4635 8417 65030
Classification report :
              precision    recall  f1-score   support

           1       0.93      0.89      0.91     73447
           0       0.97      0.98      0.97    240389

    accuracy                           0.96    313836
   macro avg       0.95      0.93      0.94    313836
weighted avg       0.96      0.96      0.96    313836
```



Grid Search: For Xgboost

```
params = {
        'min_child_weight': [1, 5, 10],
        'gamma': [0.5, 1, 1.5, 2, 5],
        'subsample': [0.6, 0.8, 1.0],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [3, 4, 5]
        }
```

A total number of combinations for the set of parameters above is a product of options for each parameter (3 x 5 x 3 x 3 x 3 = 405). It also needs to be multiplied by 5 to calculate a total number of data-fitting runs as we will be doing 5-fold cross-validation. That gets to be a large number and will take so much time to fit all those models hence we are using randomized grid search with 5 fold cross validation.

```
 Best estimator:
XGBClassifier(colsample_bytree=0.8, gamma=1.5, learning_rate=0.02, max_depth=5,
              n_estimators=600, nthread=1, silent=True, subsample=0.6)

 Best normalized gini score for 3-fold search with 5 parameter combinations:
0.7948625597405481

 Best hyperparameters:
{'subsample': 0.6, 'min_child_weight': 1, 'max_depth': 5, 'gamma': 1.5, 'colsample_bytree': 0.8}
```

Grid Search: For logistic Regression

```
logreg_new = LogisticRegression(random_state=1)
parameters = [{'penalty':['l1','l2'],
               'solver':['liblinear'],
               'tol':[0.01,0.1],
                },
              {
                'penalty':['l2','none'],
               'solver':['lbfgs'],
               'tol':[0.01,0.1],
               'max_iter':[1000,500]
              },
              {
                'penalty':['elasticnet'],
                'l1_ratio':[0.2,0.4],
               'solver':['saga'],
               'tol':[0.01,0.1],
              }
]
```

Total models to fit : 4 + 8 + 4 = 16

Results of Grid Search :

```
Parameters that give the best results :

 {'max_iter': 1000, 'penalty': 'l1', 'solver': 'liblinear', 'tol': 0.1}


Estimator that was chosen by the search :

 LogisticRegression(max_iter=1000, penalty='l1', random_state=1,
                    solver='liblinear', tol=0.1)
```

Main Focus in Modeling:

Our main focus is to identify those users accurately which are going to uninstall the app. So negating the positive response will be our biggest mistake as it would mean we failed to identify the user. **This in technical terms is called FALSE NEGATIVE (we need to minimize the false negative). In other words it means we should have good recall value.**

This is exactly what we achieved using grid search on logistic regression. **Improving the recall value from 0.51 to 0.76 but this came with a cost of reduction in accuracy from 82 percent to 79**. The trade off is best because our foremost important task is to reduce the false negative.

	Predicted Churned	Predicted Not Churned
Actual Churned	True Positive TP High Risk users	False Negative FN Need to be minimized
Actual Not Churned	False Positive FP Not churned yet, May churn in future	True Negative TN Low risk users

Interpretation of results:

Let's analyze the results that we got and take the necessary inference and all the outcomes we need for our problem statement. We have to compare the results for both the segments.

Most important features to consider churning of user (according to XGB boost)

Old users.

Feature importance permutation(package)

Weight	Feature
0.0927 ± 0.0006	sessNum
0.0441 ± 0.0013	interstitial_ad_events
0.0432 ± 0.0019	personalization_assignment
0.0233 ± 0.0015	engTime_sec
0.0127 ± 0.0006	sum_adsEvents
0.0116 ± 0.0007	screen_view
0.0105 ± 0.0018	sum_notification_events
0.0086 ± 0.0007	sum_special_features
0.0070 ± 0.0008	user_engagement
0.0025 ± 0.0008	sum_in_app_exp
0.0018 ± 0.0001	sum_app_event
0.0003 ± 0.0001	sum_profile_visits

The values towards the top are the most important features, and those towards the bottom matter least.

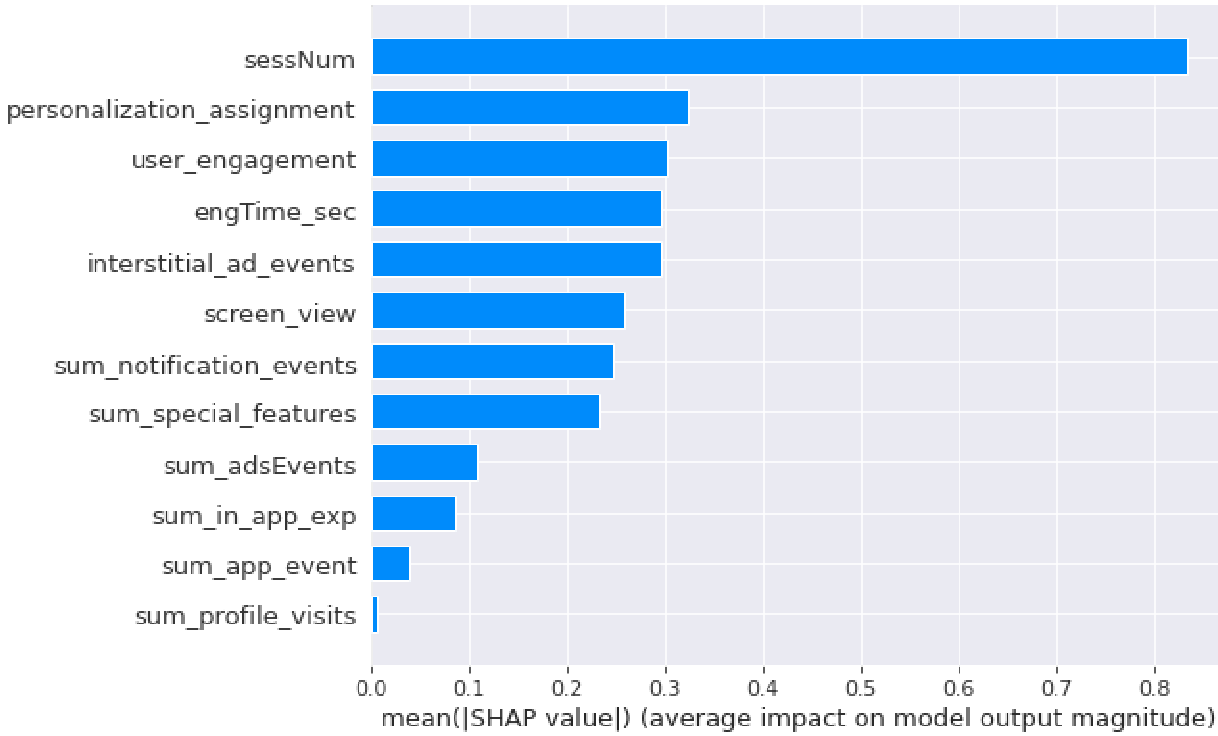
The first number in each row shows how much model performance decreased with a random shuffling (in this case, using "accuracy" as the performance metric).

There is some randomness to the exact performance change from shuffling a column. We measure the amount of randomness in our permutation importance calculation by repeating the process with multiple shuffles. The number after the ± measures how performance varied from one-reshuffling to the next.

These results tell us the feature importance, green results effects the most. We see that sessNum, interstitial_ad_events and personalization assignment features were most important . Where sum app events and profile visits had hardly any effect on old users .

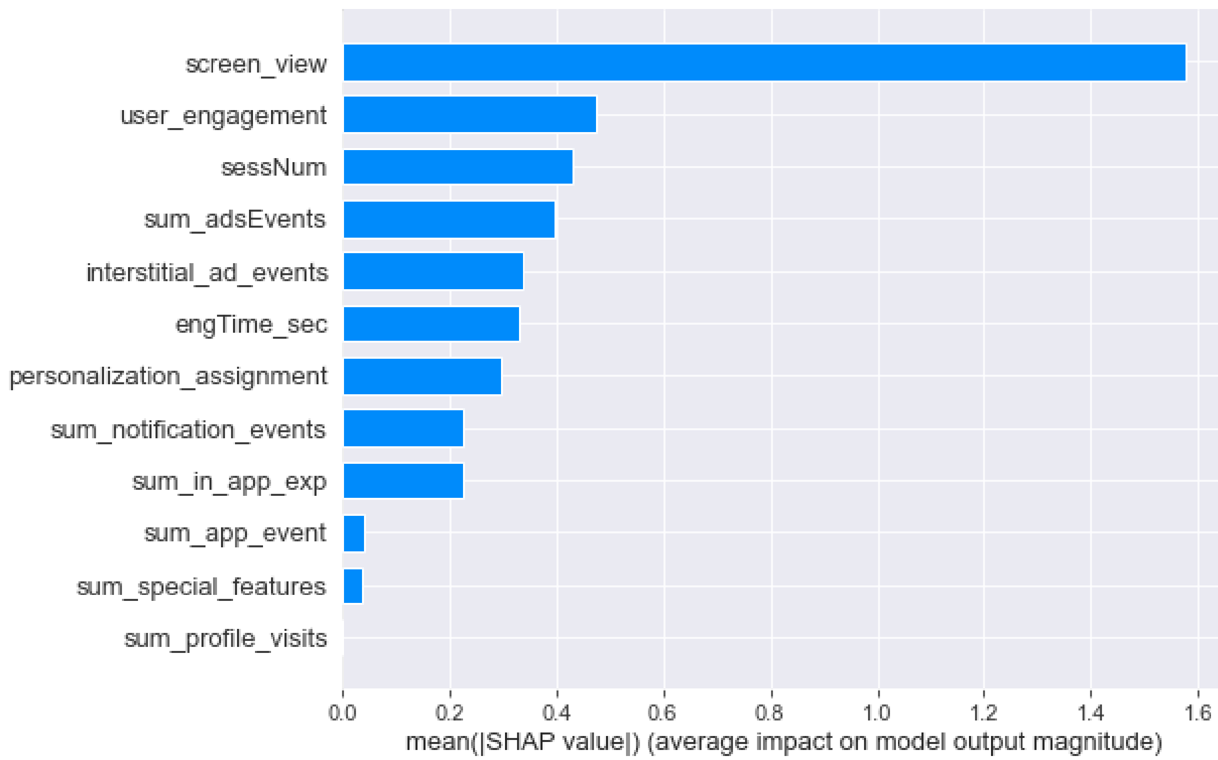
SHAP VALUES

SHAP values interpret the impact of having a certain value for a given feature in comparison to the prediction we'd make if that feature took some baseline value.



We see that seeNum has the most predictive power but as the problem suggests this is not in our control.**What's in our hand is the user's interaction with the audify app and what insights we can come up with these results.** Personalization assignment to special features had the same predictive power in the SHAP value graph, whereas from ads_Event to profile visits had the least predictive power.

New users



Weight	Feature
0.1588 ± 0.0009	screen_view
0.1212 ± 0.0011	user_engagement
0.1113 ± 0.0013	engTime_sec
0.0777 ± 0.0009	sum_adsEvents
0.0443 ± 0.0010	personalization_assignment
0.0421 ± 0.0005	interstitial_ad_events
0.0377 ± 0.0003	sessNum
0.0367 ± 0.0006	sum_in_app_exp
0.0359 ± 0.0005	sum_notification_events
0.0056 ± 0.0002	sum_app_event
0.0054 ± 0.0003	sum_special_features
0 ± 0.0000	sum_profile_visits

These results are quite different from the previous segment of old users. We can clearly see that screen_view , user_engagement, engTime_sec and advertisement had high predictive power.

App_event to profile visits had no contribution to predicting the probability of churning.

Findings from the feature importance results.

- **For new users most important features are screen view, engagement with the app and advertising events that they encounter. Profile visits and special features are low in feature importance which makes sense as well.**
- **Need to focus on screen time of users who install the app. Making efforts in increasing the screen time helps in reducing the probability of churning. Ad events have to be reduced to the minimum possible initially when the user installs for the first time.**
- **Notification events are also contributing to the predictions. More notifications makes the user come to the app. Which increases the engagement time and interaction with the app and in return reduces the churning probability.**
- **For old users engagements events, profile visits, notification events are quite important and in app experience seems to be less important than others. Reason can be that over time they get quite used to the interface already.**
- **Old users prefer personalization assignments and like to maintain their profile and playlist.**

user_pseudo_id	churn_probability	rank
d84f2558890c51ed063197349beb0be4	0.499998498	1
2208142c3b546d55306953845ecdd892	0.499993399	2
2EAECED8CBA142159729E4FB831B2BB7	0.499974953	3
0c089a858c5fcd0806807760000a41b5	0.499963135	4
ad20fddf5ada0075c01a9cecd038181f	0.499938818	5
1727f0655e0179a8c1db5b6de127ebf0	0.499928116	6
ea11919e4ee88a19ea5a0f03c131b43b	0.499921575	7
7ab5116f30b8b74f35f497c217e2dec0	0.499920313	8
34ca9ba84c16f791c5049a637d36dfe5	0.499908541	9
fedf1fe7f7d3d51ec9c88b6777d37961	0.499887441	10
d4c25ddc19cb1ef307fae2506c080a52	0.499887177	11
f3e44f2a05a880954473391526e1d859	0.499870805	12
a0e09916d2a2bbe5d45d06a8edff545a	0.49986768	13
c43b8f18f8c7dc2ef02ce691fca3d43b	0.499851635	14
0e4d8d4ca12a17dbb16439860eba4273	0.499839742	15

Please find the predictions excel files for risk probability of different types of users