About Dataset

In this competition you're tasked to build an algorithm that predicts whether a user will churn after their subscription expires. Currently, the company uses survival analysis techniques to determine the residual membership life time for each subscriber. By adopting different methods, KKBOX anticipates they'll discover new insights to why users leave so they can be proactive in keeping users dancing.

```
                    ***Tables-***
```

train.csv the train set, containing the user ids and whether they have churned.

msno: user id

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.

transactions.csv

transactions of users up until 2/28/2017.

msno: user id

payment_method_id: payment method

payment_plan_days: length of membership plan in days

plan_list_price: in New Taiwan Dollar (NTD)

actual_amount_paid: in New Taiwan Dollar (NTD)

is_auto_renew

transaction_date: format %Y%m%d

membership_expire_date: format %Y%m%d

is_cancel: whether or not the user canceled the membership in this transaction.

user_logs.csv daily user logs describing listening behaviors of a user. Data collected until 2/28/2017.

msno: user id

date: format %Y%m%d

num_25: # of songs played less than 25% of the song length

num_50: # of songs played between 25% to 50% of the song length

num_75: # of songs played between 50% to 75% of of the song length

num_985: # of songs played between 75% to 98.5% of the song length

num_100: # of songs played over 98.5% of the song length

num_unq: # of unique songs played

total_secs: total seconds played

members.csv user information. Note that not every user in the dataset is available.

msno

city

bd: age. Note: this column has outlier values ranging from -7000 to 2015, please use your judgement.

gender

registered_via: registration method

registration_init_time: format %Y%m%d

expiration_date: format %Y%m%d, taken as a snapshot at which the member.csv is extracted. Not representing the actual churn behavior.

```
# Import the neccessary modules for data manipulation and visual representation
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as matplot
import seaborn as sns
from datetime import datetime
```

```
#df=pd.read_csv('/content/drive/MyDrive/DS Aegis/PortFolio/KKBox Churn Prediction/train_fe
```

```
#df=df.sample(frac=0.1)
```

```
#df.to_csv('sampled merged KKBox churn dataset.csv')
```

```
df=pd.read_csv('/content/drive/MyDrive/DS Aegis/PortFolio/KKBox Churn Prediction/sampled m
```

```
df3=df.sample(frac=0.025)
```

```
df3.to_csv('kkboxchurnsample2.csv')
```

```
df.shape
```

```
(196389, 32)
```

```
df.head()
```

	Unnamed: 0	Unnamed: 0.1	msno	is_churn	t
0	1467196	1467196	KbnosFBjAPjGAMrTckIl9VLiaSk/3sYosF49L63i6s8=	0	
1	721020	721020	75WNi582TMGl1OMJb6G1ydFXOxjxD5CvFtWLBN8vKgo=	0	
2	1362157	1362157	8UQ3H39vR9b8UrBG0mnUMlFzHka27HgvSbfUMz8sOoQ=	0	
3	180078	180078	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	
4	1246023	1246023	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	

```
df=df.drop(['Unnamed: 0', 'Unnamed: 0.1'], axis=1)
```

```
pd.set_option('display.max_columns', None)
df.head()
```

	msno	is_churn	trans_count	logs_cou
0	KbnosFBjAPjGAMrTckIl9VLiaSk/3sYosF49L63i6s8=	0	17	
1	75WNi582TMGl1OMJb6G1ydFXOxjxD5CvFtWLBN8vKgo=	0	27	
2	8UQ3H39vR9b8UrBG0mnUMlFzHka27HgvSbfUMz8sOoQ=	0	7	2
3	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	27	1
4	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	18	

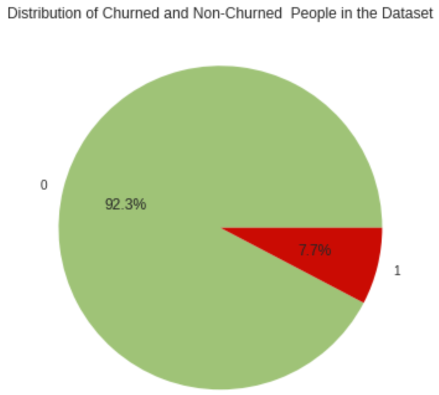
```
df.is_churn.value_counts() # checking the distribution of target variable
```

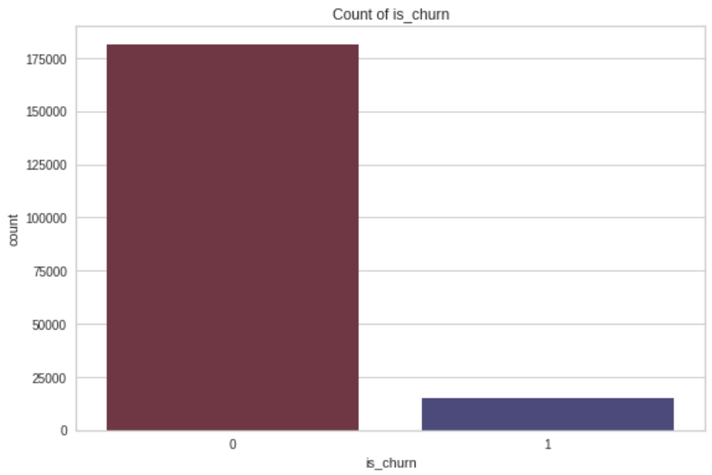
```
0    181310
1     15079
Name: is_churn, dtype: int64
```

```
plt.figure(figsize=(20,6))
plt.subplot(121)
plt.pie(x=df.is_churn.value_counts(), labels=df.is_churn.value_counts().index, autopct='%.
plt.title("Distribution of Churned and Non-Churned  People in the Dataset")

plt.subplot(122)
sns.countplot(data=df, x=df.is_churn,palette='icefire_r' )
plt.title('Count of is_churn')

plt.show()
```






```
df.isna().sum() # so we dont have any missing values in the sampled dataset
```

```
msno                        0
is_churn                    0
trans_count                 0
logs_count                  0
city_x                      0
bd_x                        0
gender_x                    0
registered_via_x            0
registration_init_time_x    0
city_y                      0
bd_y                        0
gender_y                    0
registered_via_y            0
registration_init_time_y    0
payment_method_id           0
payment_plan_days           0
plan_list_price             0
actual_amount_paid          0
is_auto_renew               0
transaction_date            0
membership_expire_date      0
is_cancel                   0
date                        0
num_25                      0
num_50                      0
num_75                      0
num_985                     0
num_100                     0
num_unq                     0
total_secs                  0
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 196389 entries, 0 to 196388
```

```
Data columns (total 30 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   msno                       196389 non-null  object 
 1   is_churn                   196389 non-null  int64  
 2   trans_count                196389 non-null  int64  
 3   logs_count                 196389 non-null  float64
 4   city_x                     196389 non-null  float64
 5   bd_x                       196389 non-null  float64
 6   gender_x                   196389 non-null  object 
 7   registered_via_x           196389 non-null  float64
 8   registration_init_time_x   196389 non-null  float64
 9   city_y                     196389 non-null  float64
 10  bd_y                       196389 non-null  float64
 11  gender_y                   196389 non-null  object 
 12  registered_via_y           196389 non-null  float64
 13  registration_init_time_y   196389 non-null  float64
 14  payment_method_id          196389 non-null  int64  
 15  payment_plan_days          196389 non-null  int64  
 16  plan_list_price            196389 non-null  int64  
 17  actual_amount_paid         196389 non-null  int64  
 18  is_auto_renew              196389 non-null  int64  
 19  transaction_date           196389 non-null  int64  
 20  membership_expire_date     196389 non-null  int64  
 21  is_cancel                  196389 non-null  int64  
 22  date                       196389 non-null  float64
 23  num_25                     196389 non-null  float64
 24  num_50                     196389 non-null  float64
 25  num_75                     196389 non-null  float64
 26  num_985                    196389 non-null  float64
 27  num_100                    196389 non-null  float64
 28  num_unq                    196389 non-null  float64
 29  total_secs                 196389 non-null  float64
dtypes: float64(17), int64(10), object(3)
memory usage: 44.9+ MB
```

```
df.registration_init_time_x=df.registration_init_time_x.astype('int64')
```

```
# We have a few repeated columns as we have merged different datasets, so lets get rid of
```

```
df=df.drop(['city_y','bd_y', 'gender_y', 'registered_via_y', 'registration_init_time_y'],
```

```
df.shape
```

```
(196389, 25)
```

EDA and Preprocessing

City

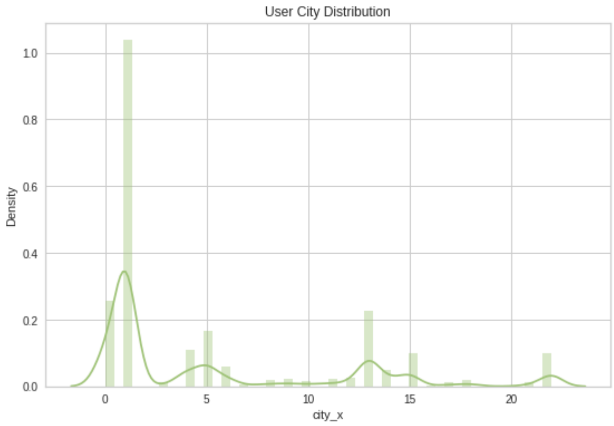
```
d=df.groupby('city_x').aggregate({'msno':'count'}).reset_index() # We have 21 unique citie
d
```

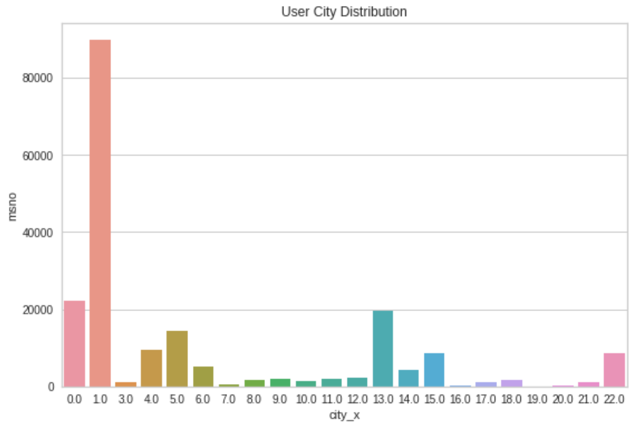
	city_x	msno
0	0.0	22314
1	1.0	89734
2	3.0	1029
3	4.0	9463
4	5.0	14262
5	6.0	5215
6	7.0	567
7	8.0	1558
8	9.0	1840
9	10.0	1329
10	11.0	1829
11	12.0	2272
12	13.0	19652
13	14.0	4214
14	15.0	8485
15	16.0	173
16	17.0	1118
17	18.0	1582
18	19.0	27
19	20.0	135
20	21.0	1063
21	22.0	8528

```
import warnings
warnings.filterwarnings('ignore')
```

```
plt.figure(figsize=(20,6))
plt.subplot(121)
sns.distplot(df.city_x, kde=True, color="g").set_title('User City Distribution')

plt.subplot(122)
sns.barplot(x='city_x', y='msno', data=d).set_title('User City Distribution')
plt.show()
```






```
##
```

Gender

```
for i in df.select_dtypes(include='object').columns:
  print(i, df[i].unique())
```

```
msno ['KbnosFBjAPjGAMrTckIl9VLiaSk/3sYosF49L63i6s8='
 '75WNi582TMGl1OMJb6G1ydFXOxjxD5CvFtWLBN8vKgo='
 '8UQ3H39vR9b8UrBG0mnUMlFzHka27HgvSbfUMz8sOoQ=' ...
 'y0bEWP5i+HFPwux8edRMneFAAfENDusY2m22sx06qzI='
 '++boFsOAGvAI3O+P4RG9O+p7e/dF7JdGb6/b+mf0ahk='
 'Kwe4HMBv16keDk6ri/k6I8xrdV6rbfobeo9I8yVAaRI=']
gender_x ['0' 'female' 'male']
```

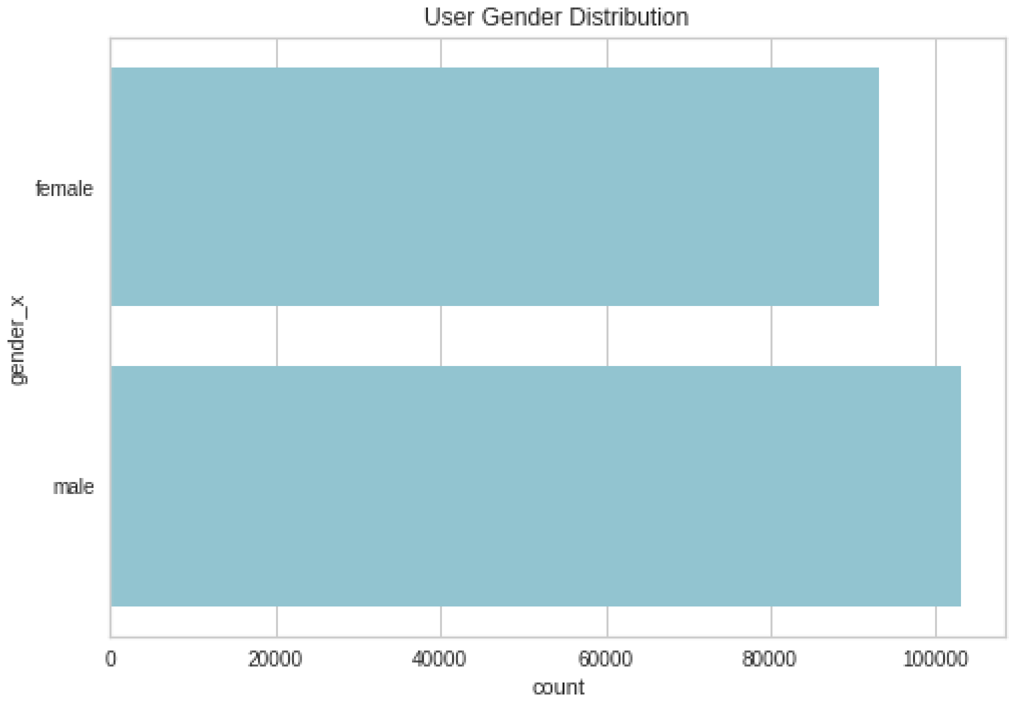
```
df.gender_x.replace('0',np.nan,inplace=True)
```

```
df.gender_x.fillna(method='ffill',inplace=True)
```

```
df.gender_x.value_counts()
```

```
male      103186
female     93200
Name: gender_x, dtype: int64
```

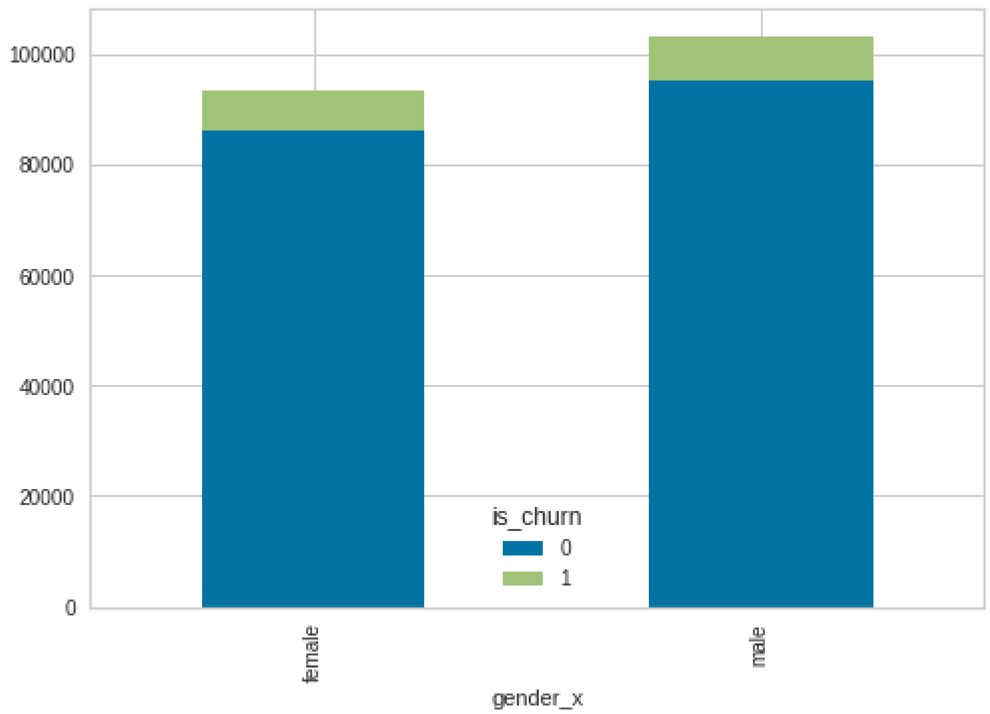
```
sns.countplot(y="gender_x", data=df, color="c").set_title('User Gender Distribution')
plt.show()
```




```
gender_crosstab=pd.crosstab(df['gender_x'],df['is_churn'])
gender_crosstab.plot(kind='bar', stacked=True)

gender_crosstab["Ratio"] =  gender_crosstab[1] / gender_crosstab[0]
gender_crosstab # so we can see that we have almost exual ratio of male and female churn i
```

is_churn	0	1	Ratio
gender_x			
female	86039	7161	0.083230
male	95268	7918	0.083113



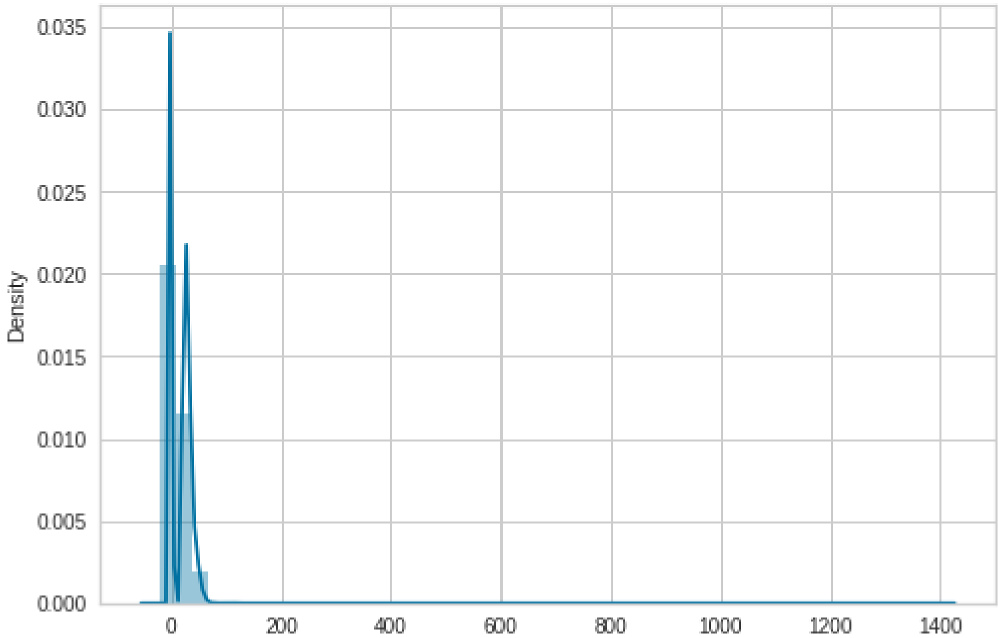
Age

```
df.bd_x.nunique() # 132 unique age values
```

```
132
```

```
sns.distplot(x=df.bd_x) # we have lot of outliers and 0 and negative values, lets treat th
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f15169d29d0>
```



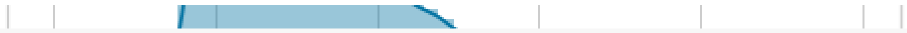

```
df['bd_x'] = df.bd_x.apply(lambda x: -1 if float(x)<=1 else x )
df['bd_x'] = df.bd_x.apply(lambda x: -1 if float(x)>=100 else x )
```

```
tmp_bd = df[(df.bd_x != "NAN") & (df.bd_x != -1)] # storing in temporary variable
sns.distplot(x=tmp_bd.bd_x)
plt.title("Frequency of BD Count without ouliers and NAN values", fontsize=12)
plt.show()
```

Frequency of BD Count without ouliers and NAN values

```
tmp_bd.bd_x.value_counts()
```

```
27.0    4654
26.0    4519
28.0    4173
25.0    4094
24.0    4023
        ...
86.0       1
92.0       1
84.0       1
81.0       1
90.0       1
Name: bd_x, Length: 92, dtype: int64
```



```
mean_age=tmp_bd.bd_x.mean()
print(mean_age)

median_age=tmp_bd.bd_x.median()
print(median_age)
```

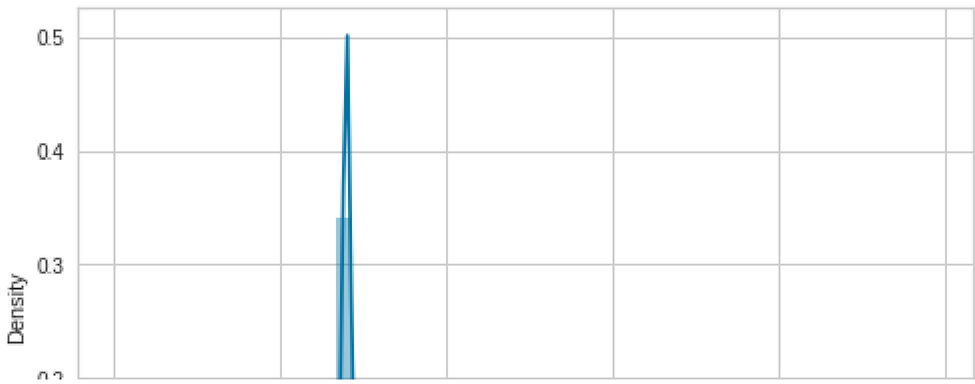
```
29.910092896735783
28.0
```

```
df.bd_x=df.bd_x.replace(-1, median_age)
```

```
df.bd_x.value_counts()
```

```
28.0    122626
27.0      4654
26.0      4519
25.0      4094
24.0      4023
          ...
86.0         1
92.0         1
84.0         1
81.0         1
90.0         1
Name: bd_x, Length: 92, dtype: int64
```

```
sns.distplot(x=df.bd_x)
plt.show()
```



registration methods

```
df.registered_via_x.unique() # We have 6 methods of registration
```

```
array([ 0.,  7.,  9.,  3.,  4., 13.])
```

```
df.registered_via_x.value_counts()
```

```
7.0     94643
9.0     47433
0.0     22314
3.0     21191
4.0     10126
13.0      682
Name: registered_via_x, dtype: int64
```

```
sns.countplot(y="registered_via_x", data=df, color="b").set_title('Registration Type Distr
plt.show() # Registration type 7 is the most common method prefered by the users in the da
```

Dates

```
df.head()
```

	msno	is_churn	trans_count	logs_cou
0	KbnosFBjAPjGAMrTckIl9VLiaSk/3sYosF49L63i6s8=	0	17	
1	75WNi582TMGl1OMJb6G1ydFXOxjxD5CvFtWLBN8vKgo=	0	27	
2	8UQ3H39vR9b8UrBG0mnUMlFzHka27HgvSbfUMz8sOoQ=	0	7	2
3	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	27	1
4	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	18	

```
df=df.drop('date', axis=1)
```

```
df.registration_init_time_x.replace(0,np.nan,inplace=True)
```

```
# lets convert Date to correct format
df.registration_init_time_x = pd.to_datetime(df.registration_init_time_x, format='%Y%m%d',
df.transaction_date = pd.to_datetime(df.transaction_date, format='%Y%m%d', errors='ignore'
df.membership_expire_date = pd.to_datetime(df.membership_expire_date, format='%Y%m%d', err
```

```
df.head()
```

	msno	is_churn	trans_count	logs_cou
0	KbnosFBjAPjGAMrTckIl9VLiaSk/3sYosF49L63i6s8=	0	17	
1	75WNi582TMGl1OMJb6G1ydFXOxjxD5CvFtWLBN8vKgo=	0	27	
2	8UQ3H39vR9b8UrBG0mnUMlFzHka27HgvSbfUMz8sOoQ=	0	7	2
3	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	27	1
4	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	18	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 196389 entries, 0 to 196388
Data columns (total 25 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   msno                       196389 non-null  object
 1   is_churn                   196389 non-null  int64
 2   trans_count                196389 non-null  int64
 3   logs_count                 196389 non-null  float64
 4   city_x                     196389 non-null  float64
```

```
 5   bd_x                       196389 non-null  float64
 6   gender_x                   196386 non-null  object
 7   registered_via_x           196389 non-null  float64
 8   registration_init_time_x  174075 non-null  datetime64[ns]
 9   payment_method_id          196389 non-null  int64
 10  payment_plan_days          196389 non-null  int64
 11  plan_list_price            196389 non-null  int64
 12  actual_amount_paid         196389 non-null  int64
 13  is_auto_renew              196389 non-null  int64
 14  transaction_date           196389 non-null  datetime64[ns]
 15  membership_expire_date     196389 non-null  datetime64[ns]
 16  is_cancel                  196389 non-null  int64
 17  date                       196389 non-null  float64
 18  num_25                     196389 non-null  float64
 19  num_50                     196389 non-null  float64
 20  num_75                     196389 non-null  float64
 21  num_985                    196389 non-null  float64
 22  num_100                    196389 non-null  float64
 23  num_unq                    196389 non-null  float64
 24  total_secs                 196389 non-null  float64
dtypes: datetime64[ns](3), float64(12), int64(8), object(2)
memory usage: 37.5+ MB
```

```
df.head()
```

	msno	is_churn	trans_count	logs_cou
0	KbnosFBjAPjGAMrTckIl9VLiaSk/3sYosF49L63i6s8=	0	17	
1	75WNi582TMGl1OMJb6G1ydFXOxjxD5CvFtWLBN8vKgo=	0	27	
2	8UQ3H39vR9b8UrBG0mnUMlFzHka27HgvSbfUMz8sOoQ=	0	7	2
3	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	27	1
4	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	18	

```
df.isna().sum()
```

```
msno                          0
is_churn                      0
trans_count                   0
logs_count                    0
city_x                        0
bd_x                          0
gender_x                      3
registered_via_x              0
registration_init_time_x  22314
payment_method_id             0
payment_plan_days             0
plan_list_price               0
actual_amount_paid            0
is_auto_renew                 0
transaction_date              0
membership_expire_date        0
is_cancel                     0
date                          0
```

```
num_25                  0
num_50                  0
num_75                  0
num_985                 0
num_100                 0
num_unq                 0
total_secs              0
dtype: int64
```

```
df.registration_init_time_x = pd.to_datetime(df.registration_init_time_x, format='%Y%m%d',
```

```
df.head()
```

	msno	is_churn	trans_count	logs_cou
0	KbnosFBjAPjGAMrTckIl9VLiaSk/3sYosF49L63i6s8=	0	17	
1	75WNi582TMGl1OMJb6G1ydFXOxjxD5CvFtWLBN8vKgo=	0	27	
2	8UQ3H39vR9b8UrBG0mnUMlFzHka27HgvSbfUMz8sOoQ=	0	7	2
3	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	27	1
4	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	18	

```
df=df.dropna()
```

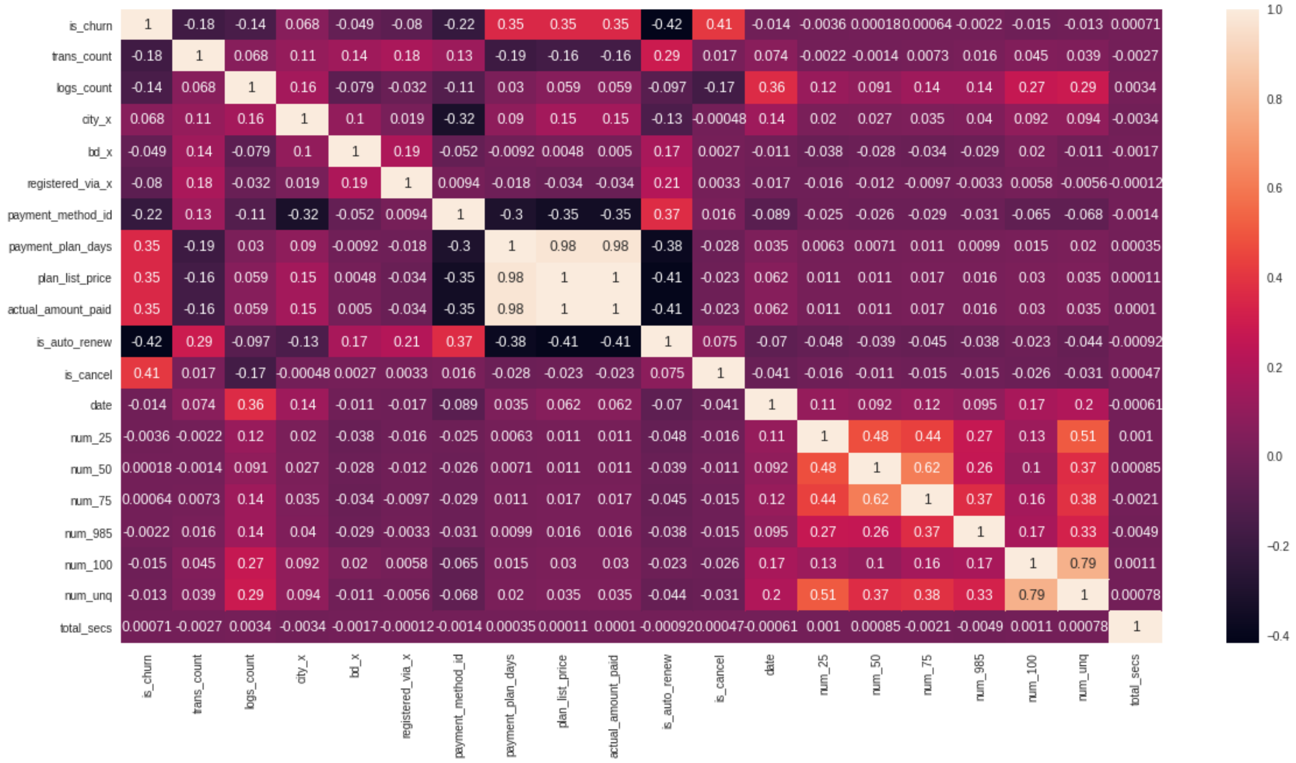
```
df.isna().sum()
```

```
msno                    0
is_churn                0
trans_count             0
logs_count              0
city_x                  0
bd_x                    0
gender_x                0
registered_via_x        0
registration_init_time_x    0
payment_method_id       0
payment_plan_days       0
plan_list_price         0
actual_amount_paid      0
is_auto_renew           0
transaction_date        0
membership_expire_date  0
is_cancel               0
date                    0
num_25                  0
num_50                  0
num_75                  0
num_985                 0
num_100                 0
num_unq                 0
total_secs              0
dtype: int64
```

```
df.shape
```

```
(174074, 25)
```

```
# lets check correlation
plt.figure(figsize=(20,10))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



Feature Extraction

Discount

```
df['discount'] = df['plan_list_price'] - df['actual_amount_paid']
df.discount.unique()
```

```
array([  0,  50, 149,  20, 180,  30, 120])
```

```
df['is_discount'] = df.discount.apply(lambda x: 1 if x > 0 else 0)
df.is_discount.value_counts()
```

```
0    173759
1       315
Name: is_discount, dtype: int64
```

Amount paid by user per day

```
df['amt_per_day'] = df['actual_amount_paid'] / df['payment_plan_days']
df['amt_per_day'].describe()
```

```
count    174074.000000
mean          4.385170
std           0.982959
min           0.000000
25%           3.300000
50%           4.966667
75%           4.966667
max           6.000000
Name: amt_per_day, dtype: float64
```

membership_duration

```
#--- difference in days ---
df['membership_duration'] = df.membership_expire_date - df.transaction_date
df['membership_duration'] = df['membership_duration'] / np.timedelta64(1, 'D')
df['membership_duration'] = df['membership_duration'].astype(int)
```

```
df['membership_duration'].value_counts() # mostly people prefer 30 days plan
```

```
31     75070
30     55132
32      9688
0       3472
33      3121
       ...
326        1
352        1
446        1
474        1
771        1
Name: membership_duration, Length: 474, dtype: int64
```

```
df.payment_plan_days.value_counts()
```

```
30     168319
410      1355
90        944
195       931
180       747
7         572
360       254
100       209
120       185
395       113
60         97
200        88
400        53
45         49
365        43
240        37
1          23
450        21
10         13
270         4
14          4
415         3
80          3
3           2
230         2
110         1
35          1
70          1
Name: payment_plan_days, dtype: int64
```

Registration duration

```
#--- difference in days ---
df['registration_duration'] = df.membership_expire_date - df.registration_init_time_x
df['registration_duration'] = df['registration_duration'] / np.timedelta64(1, 'D')
df['registration_duration'] = df['registration_duration'].astype(int)
```

```
df['registration_duration'].describe() # average of 1323 days since registered,
```

```
count    174074.000000
mean       1323.329722
std        1099.940520
min      -16352.000000
25%         456.000000
50%        1065.000000
75%        1896.000000
max        5328.000000
Name: registration_duration, dtype: float64
```

```
long_term_users=df[df['registration_duration']>365]
```

```
long_term_users # 142371 users have been using the app for more than a year
```

	msno	is_churn	trans_count	l
3	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	27	
4	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	18	
5	noUcxTUzZqgUVjSwrf2vVUL3MK27mH9D+4ggKLa7ML4=	0	27	
8	zaFyyMnHWczQLQApdBGbR8tKjjvF9iDUDWF89g0cj1A=	0	11	
10	BTqGMXLHa5E39hsdkbNH8B9+ewExlC/OYqXbVoURgrw=	0	23	
...	...	...	...	
196381	mzqZlaVEEIeK/fCQlvWqf40NxsiTFo5erleULGIuqQ8=	0	27	
196384	J+9p9s5QOLcudsQwerQEv9XAb0yBRofuYiAg/zEC+B8=	0	28	
196385	xCZ58GQNEwUgUz9psWBxZFQ3NRTHemSqIT+HfTj1SEQ=	0	18	
196386	y0bEWP5i+HFPwux8edRMneFAAfENDusY2m22sx06qzI=	1	11	
196388	Kwe4HMBv16keDk6ri/k6I8xrdV6rbfobeo9I8yVAaRI=	0	29	

142371 rows × 30 columns

Since, membership duration is very less as compared to registration duration; it is highly likely that customers renew their membership on a monthly or quarterly basis.

Autorenew & cancel

```
df.columns
```

```
Index(['msno', 'is_churn', 'trans_count', 'logs_count', 'city_x', 'bd_x',
       'gender_x', 'registered_via_x', 'registration_init_time_x',
       'payment_method_id', 'payment_plan_days', 'plan_list_price',
       'actual_amount_paid', 'is_auto_renew', 'transaction_date',
       'membership_expire_date', 'is_cancel', 'date', 'num_25', 'num_50',
       'num_75', 'num_985', 'num_100', 'num_unq', 'total_secs', 'discount',
       'is_discount', 'amt_per_day', 'membership_duration',
       'registration_duration'],
      dtype='object')
```

```
pd.crosstab(df.is_auto_renew, df.is_cancel) # only 6355 people whose subscription got auto
```

is_cancel	0	1
is_auto_renew		
0	22523	0
1	145196	6355

```
df.describe()
```

	is_churn	trans_count	logs_count	city_x	bd_x	regi
count	174074.000000	174074.000000	174074.000000	174074.000000	174074.000000	
mean	0.079874	17.245126	15.403426	5.929013	28.855182	
std	0.271099	8.738327	10.937920	6.444552	6.002584	
min	0.000000	1.000000	0.000000	1.000000	2.000000	
25%	0.000000	10.000000	5.000000	1.000000	28.000000	
50%	0.000000	18.000000	16.000000	1.000000	28.000000	
75%	0.000000	25.000000	26.000000	13.000000	28.000000	
max	1.000000	173.000000	31.000000	22.000000	97.000000	

```
df.head()
```

	msno	is_churn	trans_count	logs_cou
3	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	27	15
4	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	18	0
5	noUcxTUzZqgUVjSwrf2vVUL3MK27mH9D+4ggKLa7ML4=	0	27	22
6	YQgllSmBodMLzkeroN78/cWo5J46fxwiOvn5eriFqtY=	1	1	25
8	zaFyyMnHWczQLQApdBGbR8tKjjvF9iDUDWF89g0cj1A=	0	11	11

Model data preparation

```
X=df.drop(['msno','is_churn'], axis=1)
y=df.is_churn
```

```
X.head()
```

	trans_count	logs_count	city_x	bd_x	gender_x	registered_via_x	registration_i

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174074 entries, 3 to 196388
Data columns (total 27 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   trans_count              174074 non-null  int64
 1   logs_count               174074 non-null  float64
 2   city_x                   174074 non-null  float64
 3   bd_x                     174074 non-null  float64
 4   gender_x                 174074 non-null  object
 5   registered_via_x         174074 non-null  float64
 6   registration_init_time_x 174074 non-null  datetime64[ns]
 7   payment_method_id        174074 non-null  int64
 8   payment_plan_days        174074 non-null  int64
 9   plan_list_price          174074 non-null  int64
 10  actual_amount_paid       174074 non-null  int64
 11  is_auto_renew            174074 non-null  int64
 12  transaction_date         174074 non-null  datetime64[ns]
 13  membership_expire_date   174074 non-null  datetime64[ns]
 14  is_cancel                174074 non-null  int64
 15  num_25                   174074 non-null  float64
 16  num_50                   174074 non-null  float64
 17  num_75                   174074 non-null  float64
 18  num_985                  174074 non-null  float64
 19  num_100                  174074 non-null  float64
 20  num_unq                  174074 non-null  float64
 21  total_secs               174074 non-null  float64
 22  discount                 174074 non-null  int64
 23  is_discount              174074 non-null  int64
 24  amt_per_day              174074 non-null  float64
 25  membership_duration      174074 non-null  int64
 26  registration_duration    174074 non-null  int64
dtypes: datetime64[ns](3), float64(12), int64(11), object(1)
memory usage: 37.2+ MB
```

```
# lets label encode gender column
X.gender_x=X.gender_x.map({'female':0,'male':1 })
```

```
X=X.drop(['registration_init_time_x','transaction_date','membership_expire_date'], axis=1)
```

```
x_col=X.columns
```

```
x_array=X.values
x_array
```

```
array([[ 1.11633525, -0.03688336,  1.09720694, ...,  0.59157946,
        -0.13561846,  1.23522514],
       [ 0.08638685, -1.40826318, -0.76483625, ..., -1.10398663,
        -0.11947775, -0.70488534],
       [ 1.11633525,  0.60309388, -0.14415519, ...,  0.59157946,
```

```
 -0.13561846, -0.45032539],
...,
[ 0.08638685, -1.40826318,  0.16618535, ...,  0.59157946,
 -0.11947775, -0.50032824],
[-0.71468413, -1.40826318,  1.25237721, ...,  0.59157946,
 -0.13561846,  0.80792808],
[ 1.34521267, -0.03688336,  0.47652588, ..., -1.10398663,
 -0.13561846,  0.11243393]])
```

```
df2=pd.DataFrame(x_array)
```

```
df2
```

	0	1	2	3	4	5	6	
0	1.116335	-0.036883	1.097207	-0.975446	-1.051898	1.089018	-0.417732	-0.14
1	0.086387	-1.408263	-0.764836	-0.142469	-1.051898	0.048375	0.601263	-0.14
2	1.116335	0.603094	-0.144155	0.857103	0.950662	-2.032911	0.346514	-0.14
3	-1.859071	0.877370	-0.144155	-0.475660	0.950662	-1.512589	-2.455721	-0.14
4	-0.714684	-0.402585	1.097207	2.689652	-1.051898	1.089018	-0.672480	-0.14
...	...	...	...	...	...	...	...	
174069	-1.744633	-0.768286	-0.764836	-0.142469	0.950662	0.048375	0.601263	-0.14
174070	1.230774	-1.042562	0.011015	0.024126	-1.051898	-2.032911	0.346514	-0.14
174071	0.086387	-1.408263	0.166185	-0.808851	-1.051898	1.089018	0.601263	-0.14
174072	-0.714684	-1.408263	1.252377	-0.475660	0.950662	1.089018	-0.162983	-0.14
174073	1.345213	-0.036883	0.476526	-0.475660	-1.051898	0.048375	0.601263	-0.14

174074 rows × 24 columns

```
df2.to_csv('kkboxinputdata.csv')
```

```
df1=df.copy()
```

```
df1.gender_x=df1.gender_x.map({'female':0,'male':1 })
```

```
df1=df1.drop(['registration_init_time_x','transaction_date','membership_expire_date'], axi
```

```
df1.head()
```

	msno	is_churn	trans_count	logs_cou
3	1aggmePpQSrzzGWj3SPRwr8A7Y3vuuNSjMorXnGZrEQ=	0	27	15
4	2xecbaQyomjOyJuv2Z+TP235ycqobBY4ys/wE6yiDb0=	0	18	0
5	noUcxTUzZqgUVjSwrf2vVUL3MK27mH9D+4ggKLa7ML4=	0	27	22
6	YQgllSmBodMLzkeroN78/cWo5J46fxwiOvn5eriFqtY=	1	1	25

```
df1.to_csv('kkboxdata.csv')
```

```
from sklearn.preprocessing import StandardScaler
```

```
st=StandardScaler()
```

```
X=st.fit_transform(X)
```

```
df.is_churn.value_counts()
```

```
0    160170
1     13904
Name: is_churn, dtype: int64
```

```
X=pd.DataFrame(X, columns=x_col)
X
```

	trans_count	logs_count	city_x	bd_x	gender_x	registered_via_x	pay
0	1.116335	-0.036883	1.097207	-0.975446	-1.051898	1.089018	
1	0.086387	-1.408263	-0.764836	-0.142469	-1.051898	0.048375	
2	1.116335	0.603094	-0.144155	0.857103	0.950662	-2.032911	
3	-1.859071	0.877370	-0.144155	-0.475660	0.950662	-1.512589	
4	-0.714684	-0.402585	1.097207	2.689652	-1.051898	1.089018	
...	...	...	...	...	...	...	
174069	-1.744633	-0.768286	-0.764836	-0.142469	0.950662	0.048375	
174070	1.230774	-1.042562	0.011015	0.024126	-1.051898	-2.032911	
174071	0.086387	-1.408263	0.166185	-0.808851	-1.051898	1.089018	
174072	-0.714684	-1.408263	1.252377	-0.475660	0.950662	1.089018	
174073	1.345213	-0.036883	0.476526	-0.475660	-1.051898	0.048375	

174074 rows × 24 columns

Lets first balance the minority class using smote to avoid biasedness

```
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=123)
X_sm , y_sm = sm.fit_resample(X,y)

print(f'''Shape of X before SMOTE:{X.shape}
Shape of X after SMOTE:{X_sm.shape}''',"\n\n")



print(f'''Target Class distributuion before SMOTE:\n{y.value_counts(normalize=True)}
Target Class distributuion after SMOTE :\n{y_sm.value_counts(normalize=True)}''')
```

```
Shape of X before SMOTE:(174074, 24)
Shape of X after SMOTE:(320340, 24)


Target Class distributuion before SMOTE:
0    0.920126
1    0.079874
Name: is_churn, dtype: float64
Target Class distributuion after SMOTE :
0    0.5
1    0.5
Name: is_churn, dtype: float64
```

Making Models

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X_sm,y_sm,random_state=369,test_size=0.3, s
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
```

```
logit=LogisticRegression()
```

```
logit.fit(X_train,y_train)
```

```
LogisticRegression()
```

```
y_pred=logit.predict(X_test)
```

```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
```

```
confusion_matrix(y_test,y_pred)
```

```
array([[43004,  5047],
       [ 3640, 44411]])
```

```
log_acc=accuracy_score(y_test,y_pred)
log_acc
```

```
0.9096064598031258
```

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.92      0.89      0.91     48051
           1       0.90      0.92      0.91     48051

    accuracy                           0.91     96102
   macro avg       0.91      0.91      0.91     96102
weighted avg       0.91      0.91      0.91     96102
```

Decision Tree Classifier

```
from sklearn.tree import DecisionTreeClassifier
```

```
dt=DecisionTreeClassifier()
```

```
dt.fit(X_train,y_train)
```

```
DecisionTreeClassifier()
```

```
y_pred3=dt.predict(X_test)
```

```
print(classification_report(y_test,y_pred3))
```

```
              precision    recall  f1-score   support

           0       0.96      0.96      0.96     48051
           1       0.96      0.96      0.96     48051

    accuracy                           0.96     96102
   macro avg       0.96      0.96      0.96     96102
weighted avg       0.96      0.96      0.96     96102
```

```
dt_acc=accuracy_score(y_test,y_pred3)
dt_acc
```

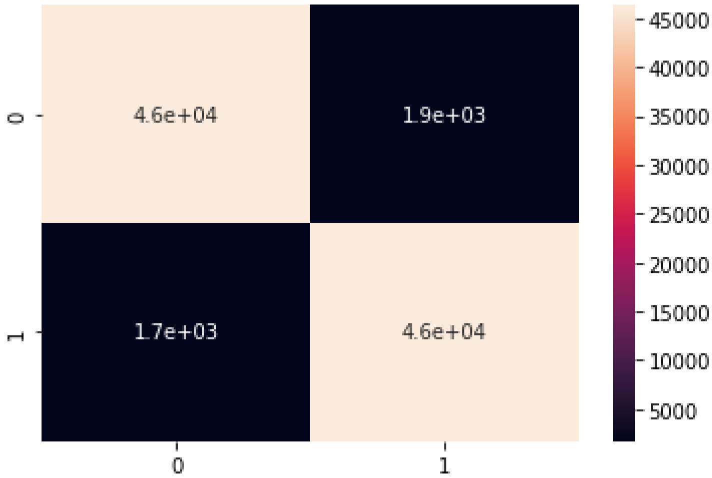
```
0.9628103473392854
```

```
confusion_matrix(y_test,y_pred3)
```

```
array([[46181,  1870],
       [ 1704, 46347]])
```

```
sns.heatmap(confusion_matrix(y_test,y_pred3), annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f152311c650>
```




```
y_pred_dttrain=dt.predict(X_train)
```

```
dt_acc=accuracy_score(y_pred_dttrain,y_train)
dt_acc # training set accuracy- As we know DT tries to overfit the data, however, testing
```

```
0.9991705241752067
```

Ensemble techniques

Random Forest Classifier

```
from sklearn.ensemble import  RandomForestClassifier
```

```
rf=RandomForestClassifier(n_estimators=50)
```

```
rf.fit(X_train,y_train)
```

```
RandomForestClassifier(n_estimators=50)
```

```
y_pred4=rf.predict(X_test)
```

```
print(confusion_matrix(y_test,y_pred4))
```

```
[[46282  1769]
 [  692 47359]]
```

```
rf_acc=accuracy_score(y_test,y_pred4)
rf_acc
```

```
0.9743917920542756
```

```
print(classification_report(y_test,y_pred4))
```

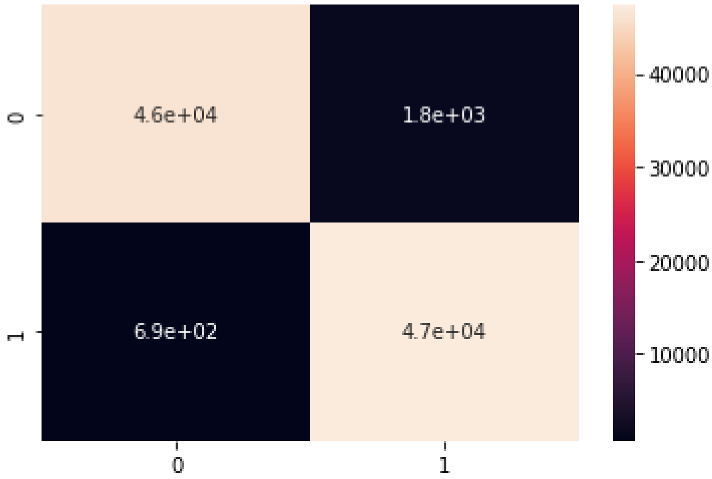
```
              precision    recall  f1-score   support

           0       0.99      0.96      0.97     48051
           1       0.96      0.99      0.97     48051

    accuracy                           0.97     96102
   macro avg       0.97      0.97      0.97     96102
weighted avg       0.97      0.97      0.97     96102
```

```
sns.heatmap(confusion_matrix(y_test,y_pred4), annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1522d8bc10>
```

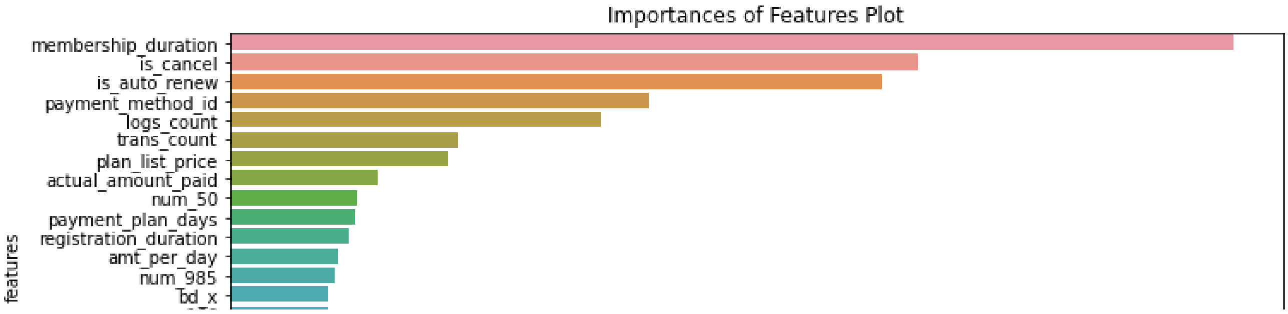



```
fi=pd.DataFrame(rf.feature_importances_, index=X.columns).sort_values(by=0, ascending=Fals
fi
```

	0
membership_duration	2.035891e-01
is_cancel	1.395293e-01
is_auto_renew	1.322047e-01
payment_method_id	8.502576e-02
logs_count	7.532261e-02
trans_count	4.623414e-02
plan_list_price	4.429923e-02
actual_amount_paid	2.981582e-02
num_50	2.585596e-02
payment_plan_days	2.541535e-02
registration_duration	2.415722e-02
amt_per_day	2.208899e-02
num_985	2.121128e-02
bd_x	2.001379e-02
num_100	1.971073e-02
city_x	1.725029e-02
num_25	1.696997e-02
num_unq	1.666487e-02
registered_via_x	1.511447e-02
num_75	1.285086e-02

```
df1_plot = pd.DataFrame({'features':x_col,
                         'importances': rf.feature_importances_})
df1_plot = df1_plot.sort_values('importances', ascending=False)
```

```
plt.figure(figsize=[11,5])
sns.barplot(x = df1_plot.importances, y = df1_plot.features)
plt.title('Importances of Features Plot')
plt.show()
```



XGBoost


```
from xgboost import XGBClassifier
```

```
xg=XGBClassifier(n_estimators=50)
```

```
xg.fit(X_train,y_train)
```

```
XGBClassifier(n_estimators=50)
```

```
y_pred5=xg.predict(X_test)
```

```
print(confusion_matrix(y_test,y_pred5))
```

```
[[45346  2705]
 [ 2403 45648]]
```

```
xg_acc=accuracy_score(y_test,y_pred5)
xg_acc
```

```
0.946848140517367
```

```
print(classification_report(y_test,y_pred5))
```

```
              precision    recall  f1-score   support

           0       0.95      0.94      0.95     48051
           1       0.94      0.95      0.95     48051

    accuracy                           0.95     96102
   macro avg       0.95      0.95      0.95     96102
weighted avg       0.95      0.95      0.95     96102
```

CrossValidation

```
from sklearn.model_selection import StratifiedKFold,cross_val_score
```

```
skf=StratifiedKFold(10)
```

```
skfscore=cross_val_score(rf,X_sm,y_sm,cv=skf) # skfscore=cross_val_score(rf,X_sm,y_sm,cv=s
```

```
skfscore.mean() # skfscore.mean() --->> 0.9747143659861397
```

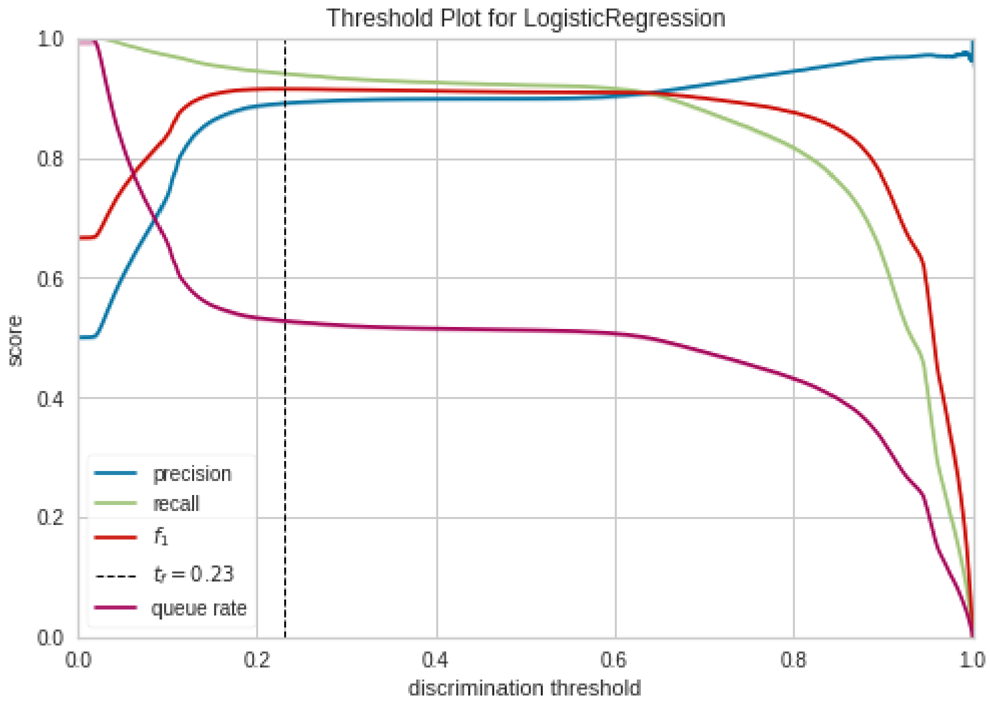
```
0.9751451582693388
```

Some Classification Visualizers

```
from yellowbrick.classifier import DiscriminationThreshold
```

```
model = LogisticRegression()
visualizer = DiscriminationThreshold(model)

visualizer.fit(X_sm, y_sm)        # Fit the data to the visualizer
visualizer.show()           # Finalize and render the figure
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1525d677d0>
```

Queue Rate: The “queue” is the spam folder or the inbox of the fraud investigation desk. This metric describes the percentage of instances that must be reviewed. If review has a high cost (e.g. fraud prevention) then this must be minimized with respect to business requirements; if it doesn’t (e.g. spam filter), this could be optimized to ensure the inbox stays clean.

In short, % of records that need to be checked

```
# This is formatted as code
```

```
#model = LogisticRegression()
# visualizer = DiscriminationThreshold(dt)

# visualizer.fit(X_sm, y_sm)        # Fit the data to the visualizer
# visualizer.show()           # Finalize and render the figure
```

```
import pickle
```

```
pickle.dump(rf, open('kkboxchurpred.pkl','wb'))
```

```
X_test.values
```

```
array([[-0.4858067 ,  1.42592177, -0.29932545, ...,  0.59157946,
        -0.13561846,  0.22971333],
       [ 0.6585804 , -0.49400997, -0.14415519, ..., -0.08664698,
        -0.11947775,  0.28244361],
       [-1.21418718,  0.73532604, -0.27202207, ...,  1.25932515,
        -0.11358948, -0.97106522],
       ...,
       [-0.02805186,  1.42592177, -0.76483625, ..., -1.10398663,
        -0.11947775, -0.73397791],
       [-1.17756652,  1.13360485, -0.76483625, ...,  0.59157946,
        -0.12657105, -0.52527114],
       [-1.63876674, -1.40141424,  0.38353188, ...,  0.2694219 ,
         2.60830269, -0.22582733]])
```