EDA_FE_model_final

December 27, 2020

Business Problem : we have to build a recommendation system that can predict whether a user will listen to a song again within one month after the user's very first observable listening event in KKbox. If the user did not listen to the song again within one month, the target variable will be 0, and 1 otherwise. This helps the company to recommend songs to users, to apply rating to songs and to determine the taste in songs of users.

ML formulation : Building a recommendation system using a collaborative filtering based algorithm with matrix factorization and word embedding.

performance metric : AUC ROC Score ROC Curve is the metric which calculates TPR and FPR at each thresholds and plots them and AUC ROC score is the area under the curve of ROC curve. This metric works best when data is balanced. while other metrics like F1-Score calculates precision and recall at a particular thresholds and considers predicted classes while AUC ROC Curve uses predicted scores. This predicted scores and thresholds helps us in determing the correct threshold that should be choosen for evaluation. while Plotting ROC Curve we make use of ordered predicted scores, we make use of each predicted score as a threshold and calculate TPR and FPR at each threshold. Then we plot ROC Curve on collected TPR and FPR values obtained by thresholding over predicted scores. The Point at which we have high TPR and low FPR this point can be used as right threshold at the time of inference. compared to f1 score and accuracy this metrics uses 0.5 as there threshold which is not right all the time. When your predictions overfit : ie y_true = [0,1,0,1,1,0,1,0,0,1] and y_pred = [1,1,1,1,1,1,1,1,1,1] (M1) as well as y_pred = [0,0,0,0,0,0,0,0,0,0] (M2) In this AUC(M1) is equal to AUC(M2) because when we apply thresholding on both model then TPR and FPR in the both the cases will be same. So AUC ROC Score doesn't make sense here. so we should apply F1-Score when we biased or overfitted or class imbalance problem when y_true and y_pred are inverted auc score varies from 0 to 0.5 this problem arises due to invertion of labels. can be solved by just inverting labels. Calculation of F1-Score : threshold = 0.5 precision = TP/(TP+FP) recall = TP/(TP+FN) F1-Score = 2xprecisionxRecall/(Precision+Recall)

Calculation of ROC Curve : 1.sort scores 2.for threshold in scores: calculate TPR and FPR list.add(TPR, FPR) 3.Plot TPR vs FPR curve 4.Calculate Area under the curve.

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

```
import numpy as np
%matplotlib inline

df = pd.read_csv('train.csv')
df.head()
```

[2]:
```
                                           msno  \
0  FGtllVqz18RPiwJj/edr2gV78zirAiY/9SmYvia+kCg=   
1  Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=   
2  Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=   
3  Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=   
4  FGtllVqz18RPiwJj/edr2gV78zirAiY/9SmYvia+kCg=   

                                        song_id source_system_tab  \
0  BBzumQNXUHKdEBOB7mAJuzok+IJA1c2Ryg/yzTF6tik=           explore   
1  bhp/MpSNoqoxOIB+/l8WPqu6jldth4DIpCm3ayXnJqM=        my library   
2  JNWfrrC7zNN7BdMpsISKa4Mw+xVJYNnxXh3/Epw7QgY=        my library   
3  2A87tzfnJTSWqD7gIZHisolhe4DMdzkbd6LzO1KHjNs=        my library   
4  3qm6XTZ6MOCU11x8FIVbAGH5l5uMkT3/ZalWG1oo2Gc=           explore   

    source_screen_name      source_type  target  
0              Explore  online-playlist       1  
1  Local playlist more   local-playlist       1  
2  Local playlist more   local-playlist       1  
3  Local playlist more   local-playlist       1  
4              Explore  online-playlist       1  
```

[5]:
```
songs = pd.read_csv('songs.csv')
songs.head()
```

[5]:
```
                                        song_id  song_length genre_ids  \
0  CXoTN1eb7AI+DntdU1vbcwGRV4SCIDxZu+YD8JP8r4E=       247640       465   
1  o0kFgae9QtnYgRkVPqLJwa05zIhRlUjfF7O1tDw0ZDU=       197328       444   
2  DwVvVurfpuz+XPuFvucclVQEyPqcpUkHR0ne1RQzPs0=       231781       465   
3  dKMBWoZyScdxSkihKG+Vf47nc18N9q4m58+b4e7dSSE=       273554       465   
4  W3bqWd3T+VeHFzHAUfARgW9AvVRaF4N5Yzm4Mr6Eo/o=       140329       726   

       artist_name                              composer      lyricist  language  
0     (Jeff Chang)                                                           3.0  
1        BLACKPINK  TEDDY|   FUTURE BOUNCE|  Bekuh BOOM         TEDDY      31.0  
2     SUPER JUNIOR                                   NaN           NaN      31.0  
3            S.H.E                                                          3.0  
4                                          Traditional   Traditional      52.0  
```

[6]:
```
members = pd.read_csv('members.csv')
members.head()
```

[6]:
```
                                           msno  city  bd gender  \
0  XQxgAYj3klVKjR3oxPPXYYFp4soD4TuBghkhMTD4oTw=     1   0    NaN
1  UizsfmJb9mV54qE9hCYyU07Va97c0lCRLEQX3ae+ztM=     1   0    NaN
2  D8nEhsIOBSoE6VthTaqDX8U6lqjJ7dLdr72mOyLya2A=     1   0    NaN
3  mCuD+tZ1hERA/o5GPqk38e041J8ZsBaLcu7nGoIIvhI=     1   0    NaN
4  q4HRBfVSssAFS9iRfxWrohxuk9kCYMKjHOEagUMV6rQ=     1   0    NaN

   registered_via  registration_init_time  expiration_date
0               7                20110820         20170920
1               7                20150628         20170622
2               4                20160411         20170712
3               9                20150906         20150907
4               4                20170126         20170613
```

1 EDA

[5]:
```python
df['msno'].unique().shape[0], df['song_id'].unique().shape[0], df.shape[0]
```

[5]:
```
(30755, 359966, 7377418)
```

[6]:
```python
len(set(df['song_id'].unique()).intersection(set(songs['song_id'].unique())))
```

[6]:
```
359914
```

[7]:
```python
len(set(df['msno'].unique()).intersection(set(members['msno'].unique())))
```

[7]:
```
30755
```

Conclusion : 1. Out Of 359966 song_ids we have only information of 359914 song_ids.
2. Out Of 30755 members we have all information of 30755 members.

[5]:
```python
df = df.merge(members, on = 'msno', how='left')
df = df.merge(songs, on = 'song_id', how = 'left')
```

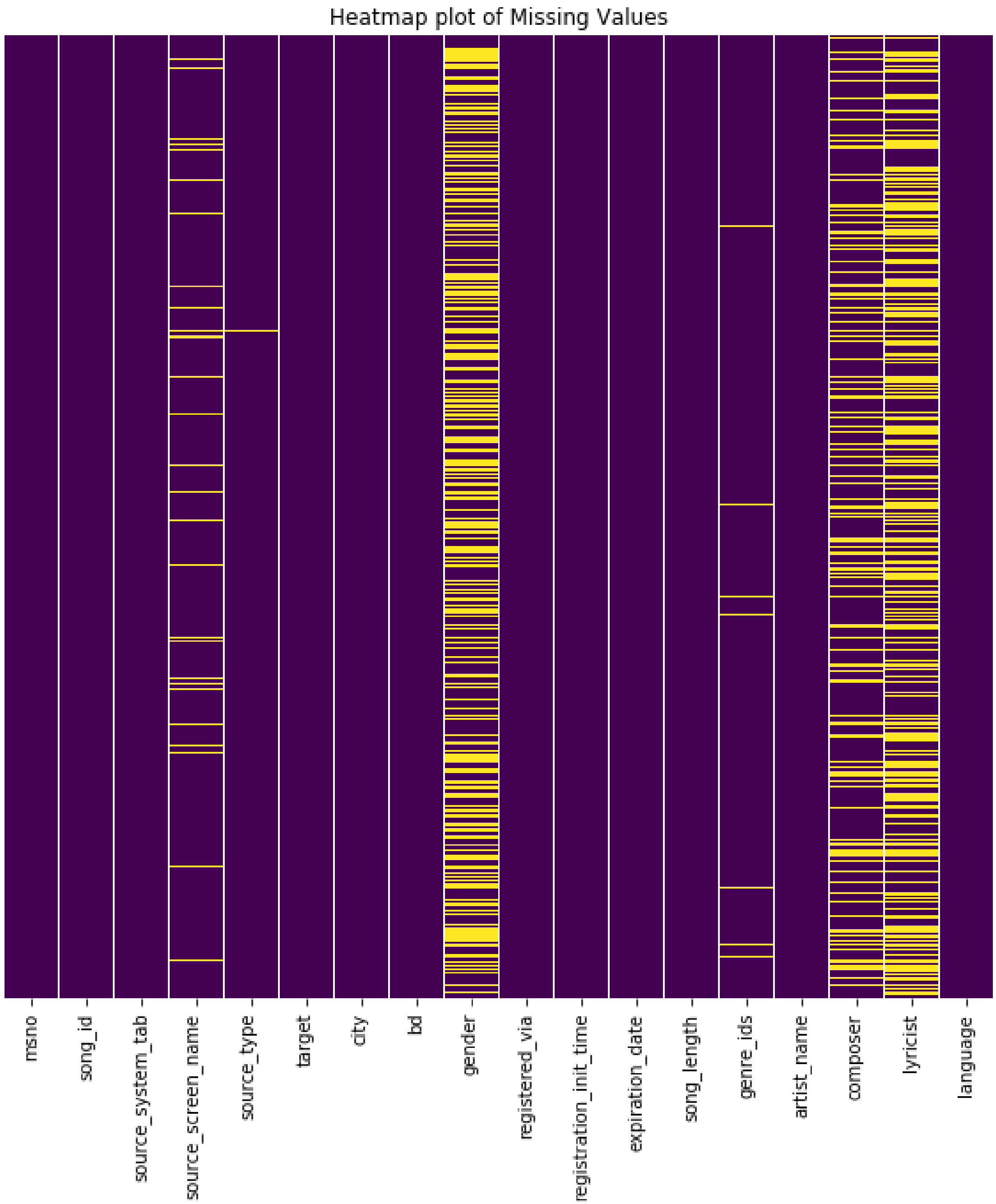
[9]:
```python
df.describe()
```

[9]:
```
             target          city            bd  registered_via  \
count  7.377418e+06  7.377418e+06  7.377418e+06    7.377418e+06
mean   5.035171e-01  7.511399e+00  1.753927e+01    6.794068e+00
std    4.999877e-01  6.641624e+00  2.155447e+01    2.275774e+00
min    0.000000e+00  1.000000e+00 -4.300000e+01    3.000000e+00
25%    0.000000e+00  1.000000e+00  0.000000e+00    4.000000e+00
50%    1.000000e+00  5.000000e+00  2.100000e+01    7.000000e+00
75%    1.000000e+00  1.300000e+01  2.900000e+01    9.000000e+00
max    1.000000e+00  2.200000e+01  1.051000e+03    1.300000e+01

       registration_init_time  expiration_date   song_length      language
count            7.377418e+06     7.377418e+06  7.377304e+06  7.377268e+06
```

```
mean          2.012810e+07    2.017157e+07  2.451210e+05  1.860933e+01
std           3.017281e+04    3.869831e+03  6.734471e+04  2.117681e+01
min           2.004033e+07    1.970010e+07  1.393000e+03 -1.000000e+00
25%           2.011070e+07    2.017091e+07  2.147260e+05  3.000000e+00
50%           2.013102e+07    2.017093e+07  2.418120e+05  3.000000e+00
75%           2.015102e+07    2.017101e+07  2.721600e+05  5.200000e+01
max           2.017013e+07    2.020102e+07  1.085171e+07  5.900000e+01
```

[6]:
```python
import re
df['artist_name_processed'] = df['artist_name'].astype(str).apply(lambda x: ' '.
 ↪join(re.sub('[^a-zA-Z ]',' ', x).lower().split()[:3]))
obj = df['artist_name_processed'].astype('category').cat
artist_map = dict(enumerate(obj.categories))
df['artist_name_processed'] = obj.codes
```

[10]:
```python
plt.figure(figsize = (10, 10))
sns.heatmap(df.isnull(), cbar = False, cmap = 'viridis', yticklabels = False)
plt.title('Heatmap plot of Missing Values')
plt.show()
```

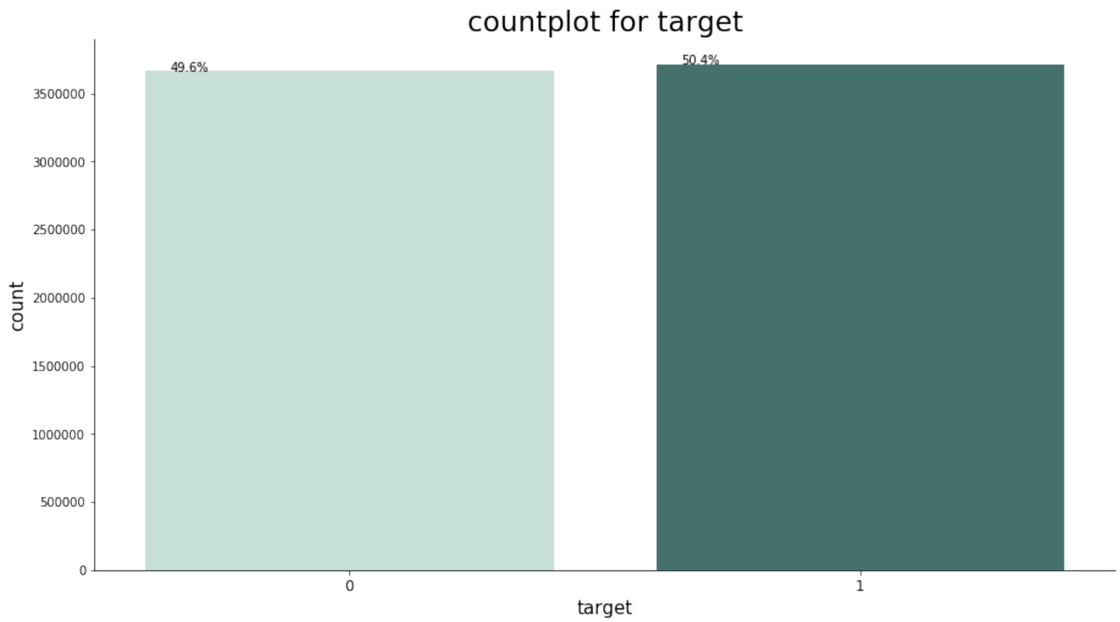


Conclusion : Gender, composer and lyricist are highly sparsed ie. they have high missing value rate. So, we need to handle them carefully.

1.1 EDA Of Categorical Variables

[209]:
```
a = pd.DataFrame(df.groupby('target').size().reset_index())
a = a.sort_values(by = 0, ascending = False)
```

```
plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'target',y = 0, data = a, palette='ch:2.5,-.10,dark=.4')
plt.xticks(fontsize = 12)
plt.xlabel('target', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('countplot for target', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.05, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```

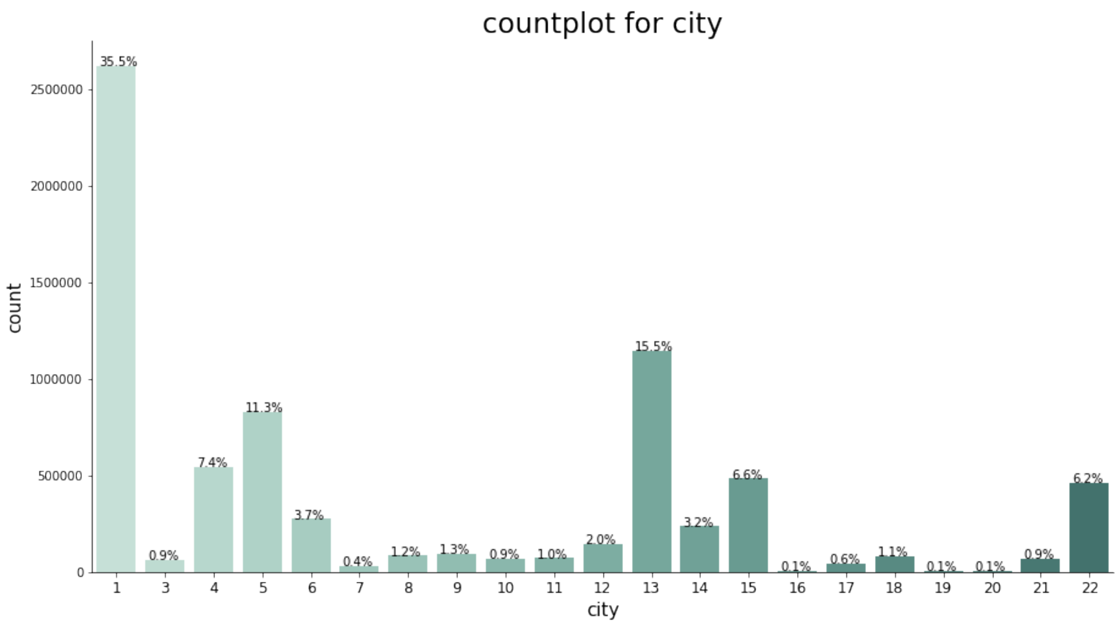


Aim :Plot for determining the distribution of Target variable.

Conclusion : Dataset is balanced for taget variable.

[123]:
```
a = pd.DataFrame(df.groupby('city').size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'city',y = 0, data = a, palette='ch:2.5,-.10,dark=.4')
plt.xticks(fontsize = 12)
plt.xlabel('city', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
```

```
plt.title('countplot for city', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.05, p.get_height()+0.5), fontsize = 10)

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```

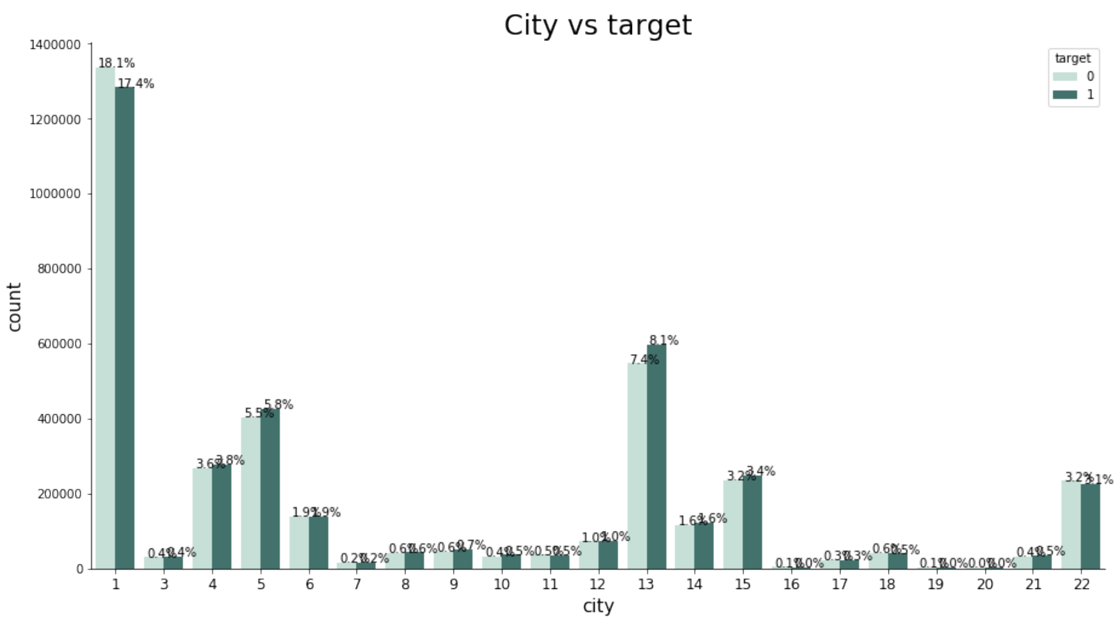


Aim for city :Plot for determining the distribution of users according to cities.

Conclusion for city : 1. There are majority of users using KKBox app from city 1 and 13. 2. City 1 and 13 must be cities with high population as there are more users in city.

[8]:
```
a = pd.DataFrame(df.groupby(['city', 'target']).size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'city',y = 0, data = a, hue = 'target', palette='ch:2.5,-.
 ↪10,dark=.4')
plt.xticks(fontsize = 12)
plt.xlabel('city', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('City vs target', fontdict = {'fontsize': 23})

for p in ax.patches:
```

```
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
↪get_x()+0.05, p.get_height()+0.5), fontsize = 10)

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```

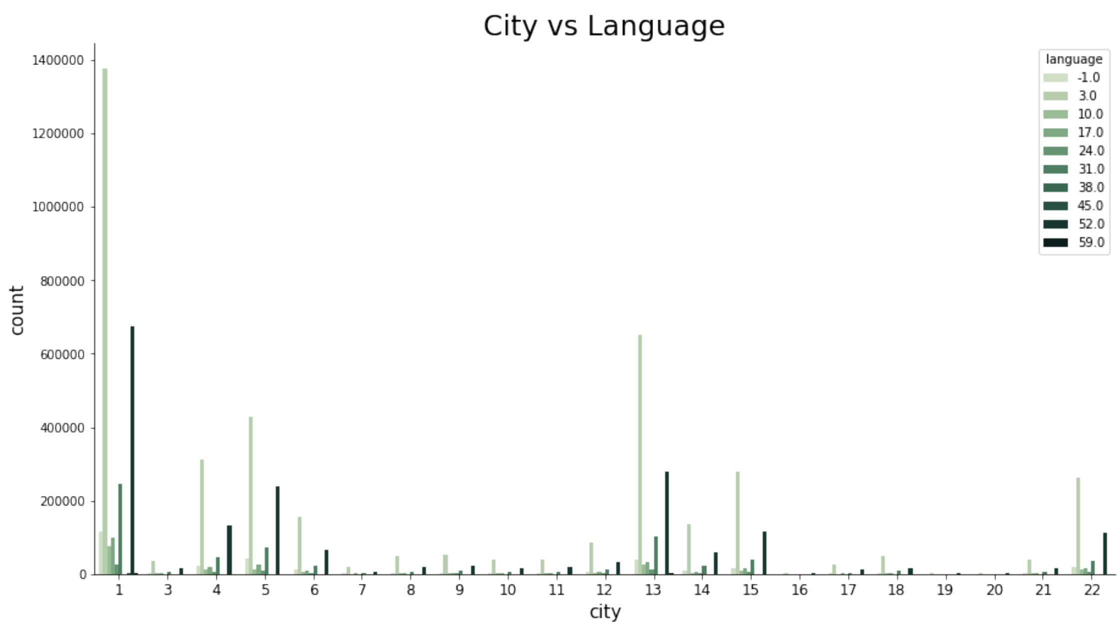


[25]:
```
a = pd.DataFrame(df.groupby(['city', 'registered_via']).size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'city',y = 0, data = a, hue = 'registered_via', palette='ch:
↪2.5,-.10,dark=.4')
plt.xticks(fontsize = 12)
plt.xlabel('city', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('City vs Registered via', fontdict = {'fontsize': 23})

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```

Aim for city vs registered via :Plot for determining the distribution of users according to cities and mode through which they have registered.

Conclusion for city vs registered via: 1. Except city 1 all cities mostly prefer to registration mode as 13 only city 1 prefer registration mode 7.

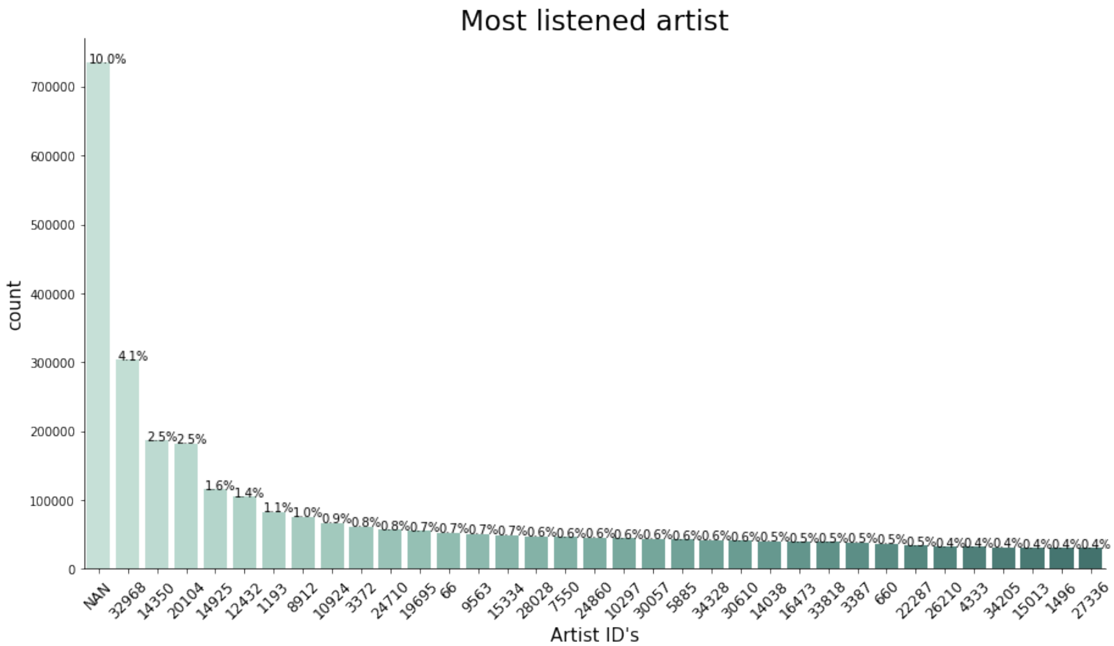
[28]:
```
a = pd.DataFrame(df.groupby(['city', 'language']).size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'city',y = 0, data = a, hue = 'language', palette='ch:2.5,-.
↪30,dark=.1')
plt.xticks(fontsize = 12)
plt.xlabel('city', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('City vs Language', fontdict = {'fontsize': 23})

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



Aim for city vs Language :Plot for determining the most prefered languages of city..

Conclusion for city vs Language: 1. Most popular two languages are 3.0 and 59.0 . 2. All cities belongs to same country.

[78]:
```
a = pd.DataFrame(df.groupby('artist_name_processed').size().reset_index())
a = a.sort_values(by = 0, ascending = False)
a = a.iloc[:35, :]
a.replace(0, 'NAN', inplace = True)
plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'artist_name_processed',y = 0, data = a, palette='ch:2.5,-.
↪10,dark=.4')
plt.xticks(rotation= 45, fontsize = 12)
plt.xlabel('Artist ID\'s', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('Most listened artist', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
↪get_x()+0.05, p.get_height()+0.5), fontsize = 10)

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)

plt.show()
```



[86]:
```
from prettytable import PrettyTable

myTable = PrettyTable(["Artist ID", "Artist Name", "Artist  ID ", "Artist ␣
↪Name"])
a = np.array(a)
for i in range(1, a.shape[0], 2):
    myTable.add_row([a[i][0], artist_map[a[i][0]], a[i+1][0],␣
↪artist_map[a[i+1][0]]])
print(myTable)
```

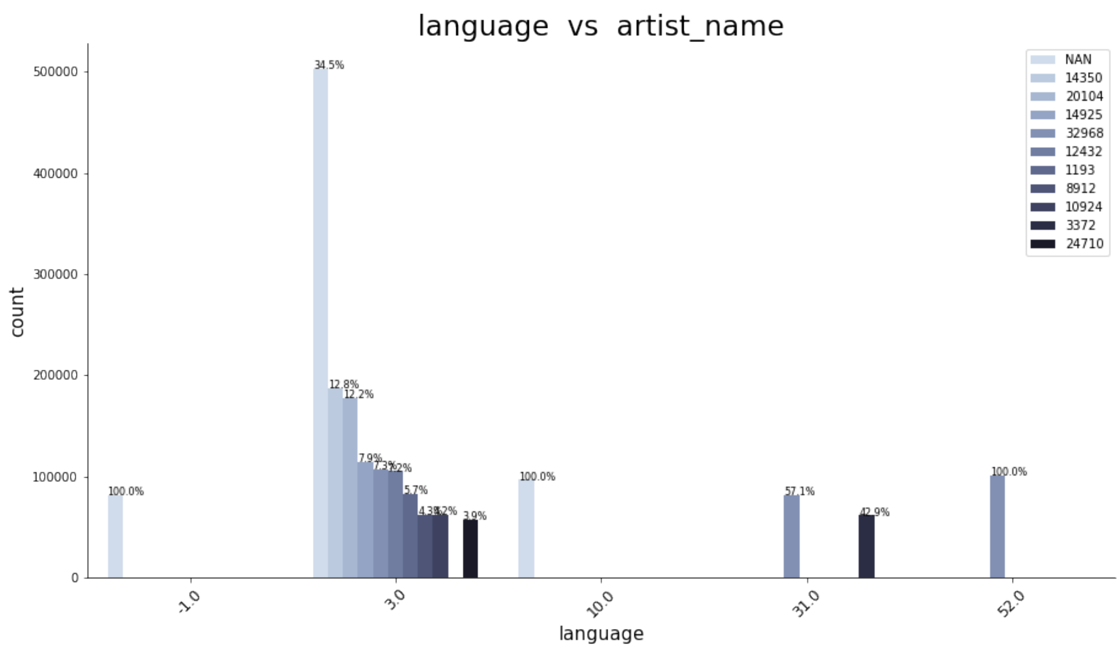
```
+-----------+------------------+-------------+--------------+
| Artist ID |    Artist Name   | Artist  ID  | Artist  Name |
+-----------+------------------+-------------+--------------+
|   32968   | various artists  |    14350    |   jay chou   |
|   20104   |      mayday      |    14925    |    jj lin    |
|   12432   |       hebe       |     1193    |     amei     |
|    8912   |    eason chan    |    10924    |    g e m     |
|    3372   |     bigbang      |    24710    |   r chord    |
|   19695   |      maroon      |      66     |    a lin     |
|    9563   |       eric       |    15334    |  jolin tsai  |
|   28028   |    sodagreen     |     7550    |    della     |
|   24860   |   rainie yang    |    10297    |  fish leong  |
|   30057   | the chainsmokers |     5885    |  claire kuo  |
|   34328   |     yoga lin     |    30610    | the last day |
|   14038   |    jam hsiao     |    16473    |   kenji wu   |
|   33818   |   william wei    |     3387    |     bii      |
```

```
|    660    |   alan walker    |    22287    | nickthereal  |
|   26210   |      s h e       |     4333    |  bruno mars  |
|   34205   |    yanzi sun     |    15013    |  jody jiang  |
|    1496   |    andrew tan    |    27336    |   shi shi    |
+-----------+------------------+-------------+--------------+
```

Aim for Artist Name :Plot for determining the most Listened artist.

Conclusion for Artist Name: 1. Most popular two Artist are jay chou and mayday. 2. There are 10% of artist names are missing. 3. 4.1% of Artists are unknown with given name as "various artists".

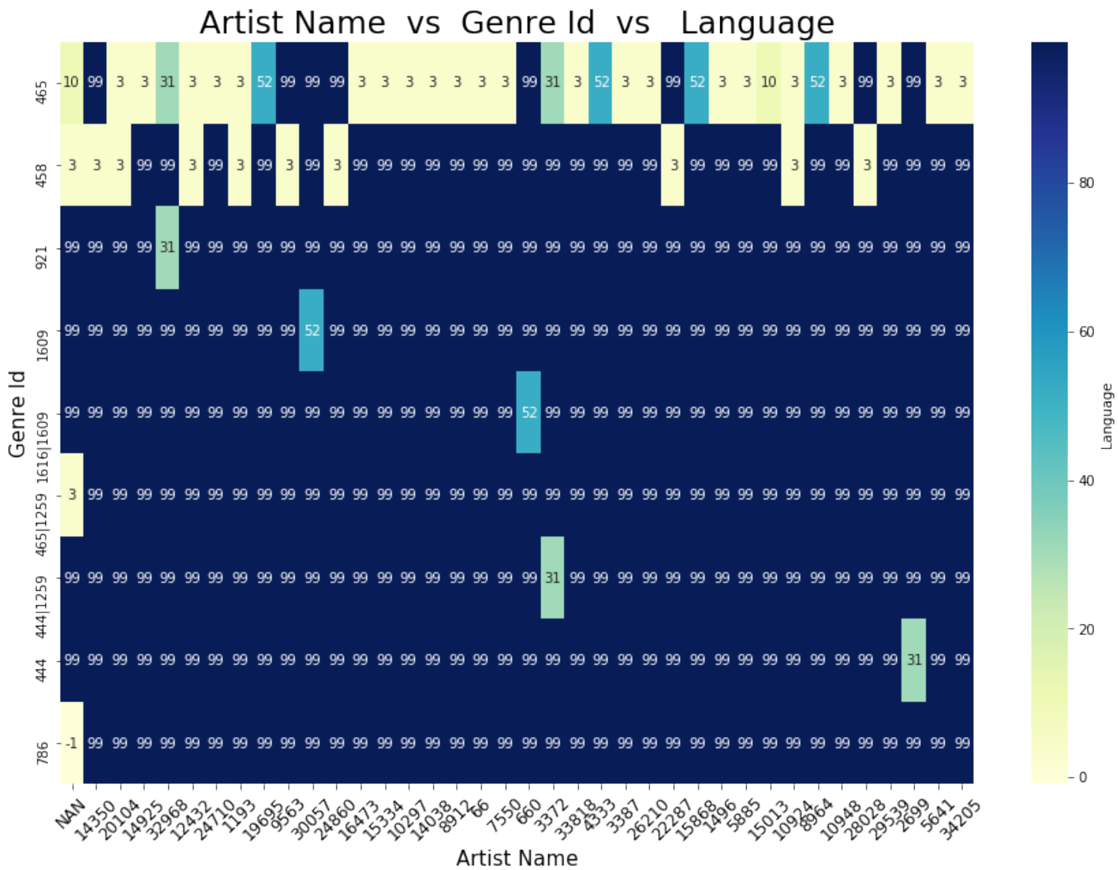
[53]:
```
a = pd.DataFrame(df.groupby(['language', 'artist_name_processed']).size().
↪reset_index())
a = a.sort_values(by = 0, ascending = False)
a = a.iloc[:15, :]
a.replace(0, 'NAN', inplace = True)
b = np.array(a.groupby('language')[0].sum().reset_index())
plt.figure(figsize = (15,8))
ax = sns.barplot(hue= 'artist_name_processed',y = 0, data = a, x = 'language',␣
↪palette='ch:30.0,-.10,dark=.10')
plt.xticks(rotation = 45, fontsize = 12)
plt.xlabel('language', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('language  vs  artist_name', fontdict = {'fontsize': 23})
plt.legend(loc = 'upper right')
count = 0
for p in ax.patches:
    if count == b.shape[0]:
            count = 0
    ax.annotate('{:.1f}%'.format( 100*p.get_height()/b[count, 1]), (p.get_x(),␣
↪p.get_height()+0.5), fontsize = 8)
    count+=1

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



Aim for Artist Name vs Language :Plot for determining the Most popular artists in Language.

Conclusion for Artist Name vs Language: 1. jay chou and mayday are two most popular singers in language 3.0 2. bigbang is the most popular singers in language 31.0 3. Maroon is the most popular artist in language 52.0 4. All the artist names in language -1.0 and 10.0 are missing.

[12]:
```
a = pd.DataFrame(df.groupby(['language', 'genre_ids', 'artist_name_processed']).size().reset_index())
a = a.sort_values(by = 0, ascending = False)
a = a.iloc[:50, :]
a.replace(0, 'NAN', inplace = True)
f = pd.DataFrame(columns = a['genre_ids'].unique(), index = a['artist_name_processed'].unique())
a = np.array(a)
for i in a:
    f[i[1]].loc[i[2]] = i[0]
f.replace(np.nan, 99, inplace = True)
plt.figure(figsize = (15, 10))
sns.heatmap(f.T, annot = True, cmap = 'YlGnBu',cbar_kws={'label': 'Language'})
plt.xticks(rotation = 45, fontsize = 12)
plt.xlabel('Artist Name', fontdict = {'fontsize':15})
plt.ylabel('Genre Id', fontdict = {'fontsize':15})
plt.title('Artist Name  vs  Genre Id  vs   Language', fontdict = {'fontsize':23})
plt.show()
```

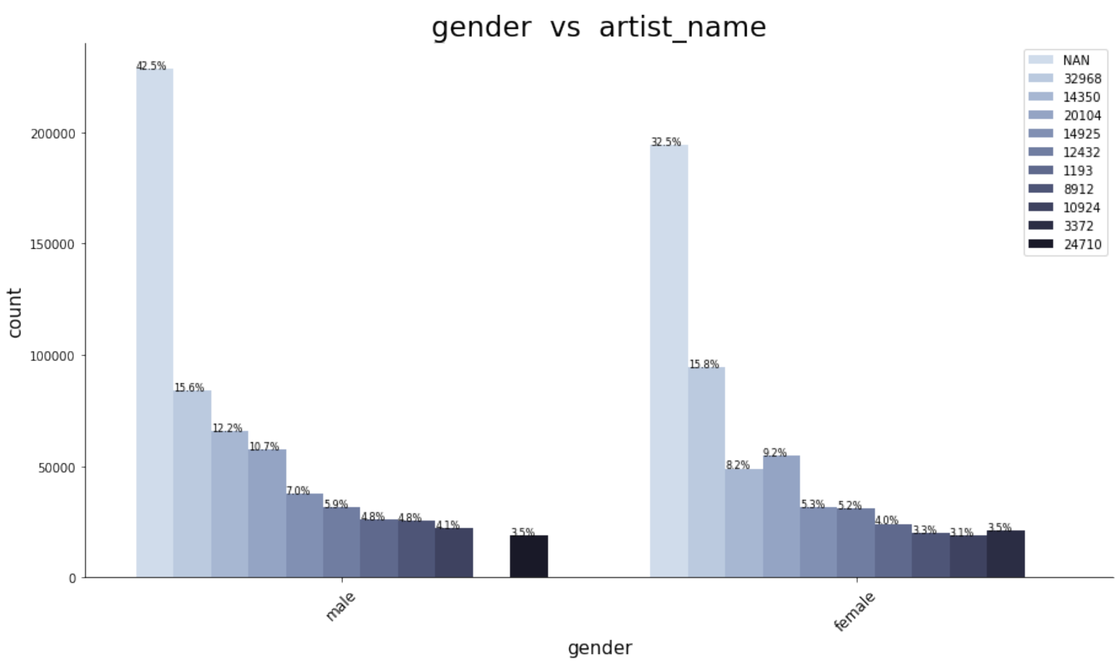


Aim for Artist Name vs Genrr ID vs Language :Plot for determining the Most popular artists of particular genre in particular Language.

Conclusion for Artist Name vs Genre ID vs Language: 1. Jay Chou sings only with genre id 458 and language 3.0 . 2. mayday sings only in 458 and 465 genre with only language 3.0 . 3. The Chainsmoker is the only artist which uses genre id 1609 with language 52.0 4. Alan Walker is the only artist which uses genre id 1616 and 1609 with languages 52.0.

[18]:
```
a = pd.DataFrame(df.groupby(['gender', 'artist_name_processed']).size().
↪reset_index())
a = a.sort_values(by = 0, ascending = False)
a = a.iloc[:20, :]
a.replace(0, 'NAN', inplace = True)
b = np.array(a.groupby('gender')[0].sum().reset_index())
plt.figure(figsize = (15,8))
ax = sns.barplot(hue= 'artist_name_processed',y = 0, data = a, x = 'gender',␣
↪palette='ch:30.0,-.10,dark=.10')
plt.xticks(rotation = 45, fontsize = 12)
plt.xlabel('gender', fontdict = {'fontsize':15})
```

```
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('gender  vs  artist_name', fontdict = {'fontsize': 23})
plt.legend(loc = 'upper right')
count = 0
for p in ax.patches:
    if count == b.shape[0]:
            count = 0
    ax.annotate('{:.1f}%'.format( 100*p.get_height()/b[count, 1]), (p.get_x(),␣
↪p.get_height()+0.5), fontsize = 8)
    count+=1

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```

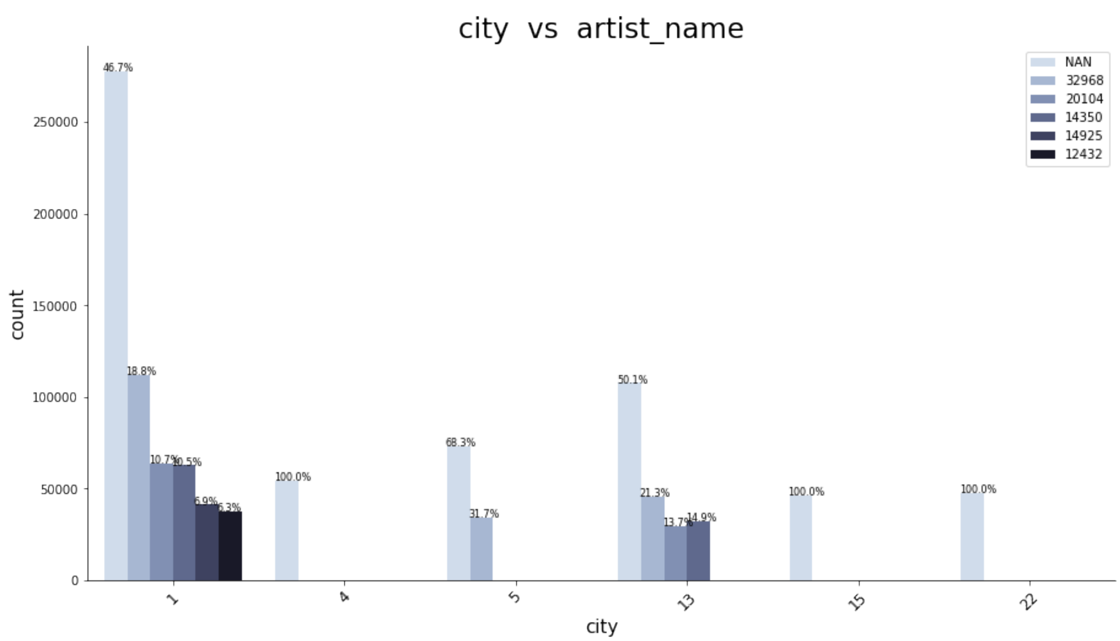


Aim for Artist Name vs Gender :Plot for determining the Most popular artists among males and females.

Conclusion for Artist Name vs Gender : 1. jay chou is more popular in males than in females. 2. Bigbang is only popular in males and not in females. 3. Sodagreen is only popular in females and not in males.

[54]:
```
a = pd.DataFrame(df.groupby(['city', 'artist_name_processed']).size().
↪reset_index())
a = a.sort_values(by = 0, ascending = False)
a = a.iloc[:15, :]
```

```python
a.replace(0, 'NAN', inplace = True)
b = np.array(a.groupby('city')[0].sum().reset_index())
plt.figure(figsize = (15,8))
ax = sns.barplot(hue= 'artist_name_processed',y = 0, data = a, x = 'city', palette='ch:30.0,-.10,dark=.10')
plt.xticks(rotation = 45, fontsize = 12)
plt.xlabel('city', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('city  vs  artist_name', fontdict = {'fontsize': 23})
plt.legend(loc = 'upper right')
count = 0
for p in ax.patches:
    if count == b.shape[0]:
            count = 0
    ax.annotate('{:.1f}%'.format( 100*p.get_height()/b[count, 1]), (p.get_x()-0.01, p.get_height()+1), fontsize = 8)
    count+=1

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



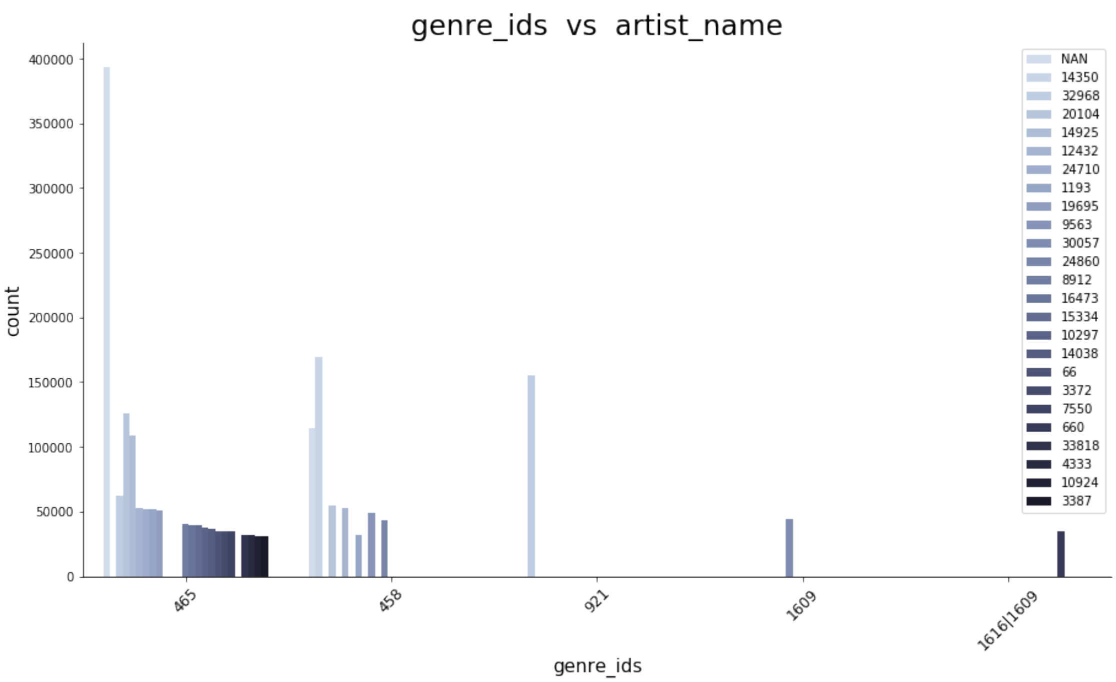
Aim for Artist Name vs City :Plot for determining the Most popular artists in City.

Conclusion for Artist Name vs City: 1. jay chou and mayday are two most popular artist in city 1 and 13. 2. All the artist names in city 4, 6, 15 and 22 are missing.

```
[37]: a = pd.DataFrame(df.groupby(['genre_ids', 'artist_name_processed']).size().
      ↪reset_index())
      a = a.sort_values(by = 0, ascending = False)
      a = a.iloc[:30, :]
      a.replace(0, 'NAN', inplace = True)
      b = np.array(a.groupby('genre_ids')[0].sum().reset_index().sort_values(by = 0,␣
      ↪ascending = False))
      plt.figure(figsize = (15,8))
      ax = sns.barplot(hue= 'artist_name_processed',y = 0, data = a, x = 'genre_ids',␣
      ↪palette='ch:30.0,-.10,dark=.10')
      plt.xticks(rotation = 45, fontsize = 12)
      plt.xlabel('genre_ids', fontdict = {'fontsize':15})
      plt.ylabel('count', fontdict = {'fontsize':15})
      plt.title('genre_ids  vs  artist_name', fontdict = {'fontsize': 23})
      plt.legend(loc = 'upper right')

      ax.spines['right'].set_visible(False)
      ax.spines['top'].set_visible(False)
      from prettytable import PrettyTable

      myTable = PrettyTable(["Artist ID", "Artist Name", "Genre ID", "Count", "Artist␣
      ↪ ID ", "Artist  Name",  "Genre  ID", "Count "])
      a = np.array(a)
      for i in range(1, a.shape[0], 2):
          try:
              myTable.add_row([a[i][1], artist_map[a[i][1]], a[i][0], a[i][2],␣
      ↪a[i+1][1], artist_map[a[i+1][1]], a[i+1][0], a[i+1][2]])
          except:
              pass
      print(myTable)

      plt.show()
```

```
+-----------+-------------+----------+--------+-------------+-----------------+
-----------+--------+
| Artist ID | Artist Name | Genre ID | Count  | Artist  ID  |   Artist  Name  |
Genre  ID | Count  |
+-----------+-------------+----------+--------+-------------+-----------------+
-----------+--------+
|   14350   |   jay chou  |   458    | 168959 |    32968    | various artists |
921     | 154734 |
|   14925   |    jj lin   |   465    | 108495 |    32968    | various artists |
465     | 61923  |
|   20104   |    mayday   |   458    | 54941  |    12432    |       hebe      |
458     | 52653  |
|   12432   |     hebe    |   465    | 52293  |    24710    |     r chord     |
465     | 51700  |
```

1193	amei	465	51292	19695	maroon	465	50546
9563	eric	458	48721	30057	the chainsmokers	1609	44149
24860	rainie yang	458	43097	8912	eason chan	465	40472
16473	kenji wu	465	39312	15334	jolin tsai	465	39065
10297	fish leong	465	37279	14038	jam hsiao	465	36853
66	a lin	465	34880	3372	bigbang	465	34565
7550	della	465	34508	660	alan walker	1616|1609	34480
33818	william wei	465	31995	4333	bruno mars	465	31817
1193	amei	458	31507	10924	g e m	465	31321

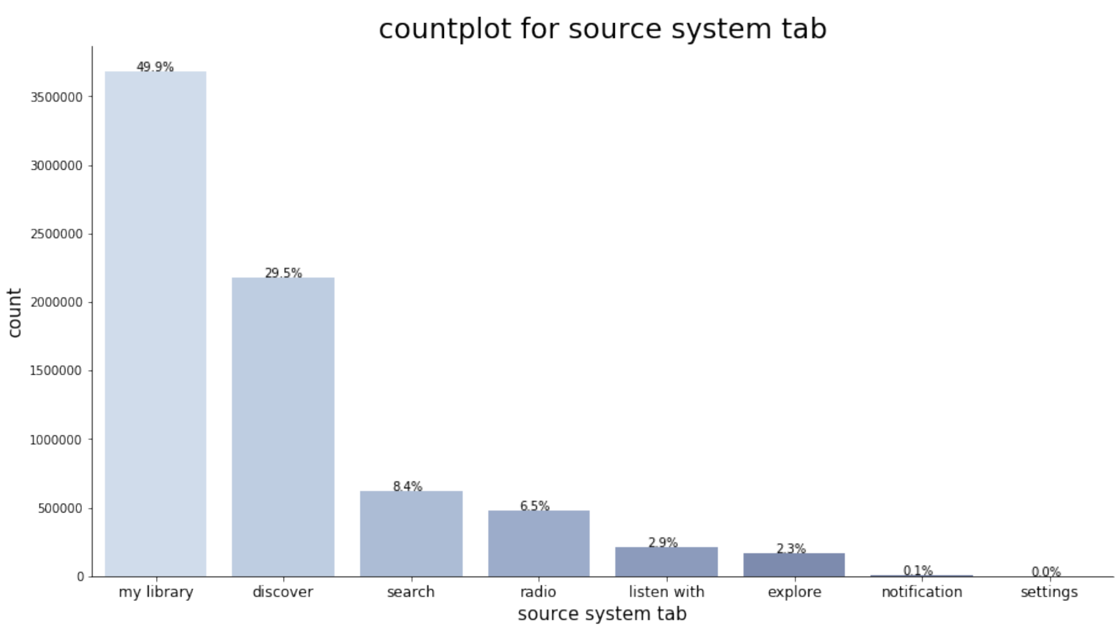


Aim for Artist Name vs genre ids :Plot for determining the Most popular artists among genre.

Conclusion for Artist Name vs genre ids: 1. mayday and jj lin are most popular artists in genre id 465. 2. jay chou and mayday are most popular artists in genre id 458. 3.

The Chainsmoker is the only popular artist in genre id 1609. 4. Alan walker is popular among genre id 1616 and 1609.

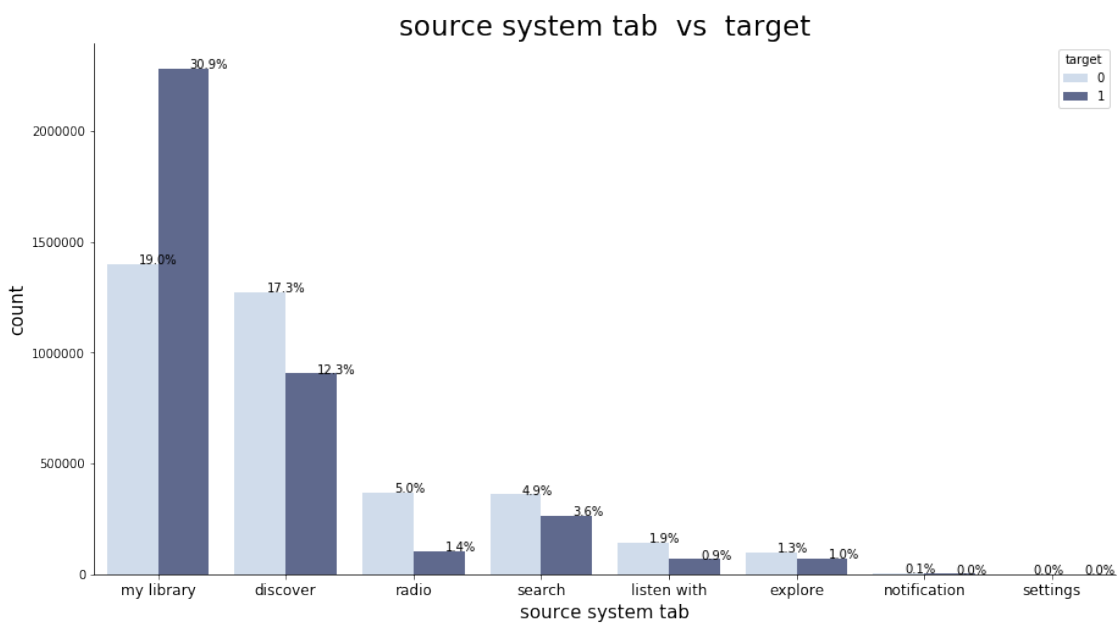
[192]:
```
a = pd.DataFrame(df.groupby('source_system_tab').size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'source_system_tab',y = 0, data = a, palette='ch:30.0,-.
↪10,dark=.4')
plt.xticks(fontsize = 12)
plt.xlabel('source system tab', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('countplot for source system tab', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
↪get_x()+0.25, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



Aim for source system tab :Plot for determining the distribution of Source system tab used by users in KKBox app while listening songs.

Conclusion for source system tab : 1.There are majority of users using KKBox app by using local storage ie my library. 2. Most of the peoples discover songs using discover, search then they try to use there my library for playing songs.

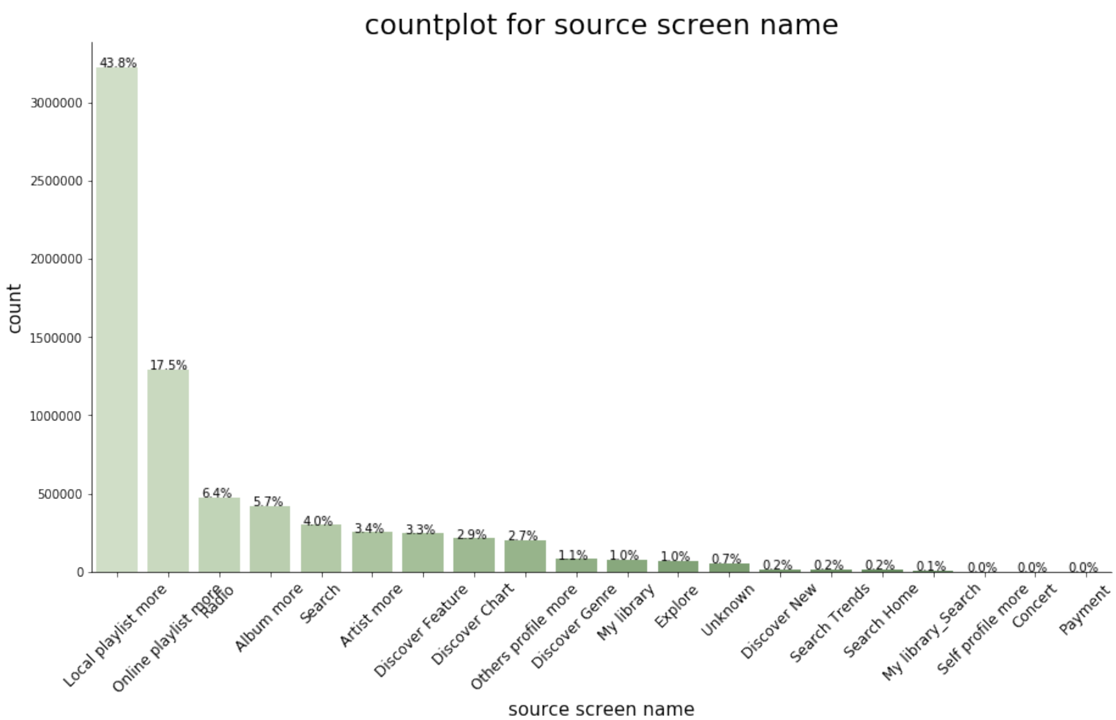
[33]:
```
a = pd.DataFrame(df.groupby(['source_system_tab', 'target']).size().
 ↪reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'source_system_tab',y = 0, data = a, hue = 'target',␣
 ↪palette='ch:30.0,-.10,dark=.4')
plt.xticks(fontsize = 12)
plt.xlabel('source system tab', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('source system tab  vs  target', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.25, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



Aim for target vs source system tab : Plot for determining the distribution of Source system tab used by users in KKBox app while listening songs with respect to variation in target variable.

Conclusion for target vs source system tab : 1. 30.9% of users listening songs repeatedly from my library. 2. 17.3% of users discovered songs where not listend more than once.

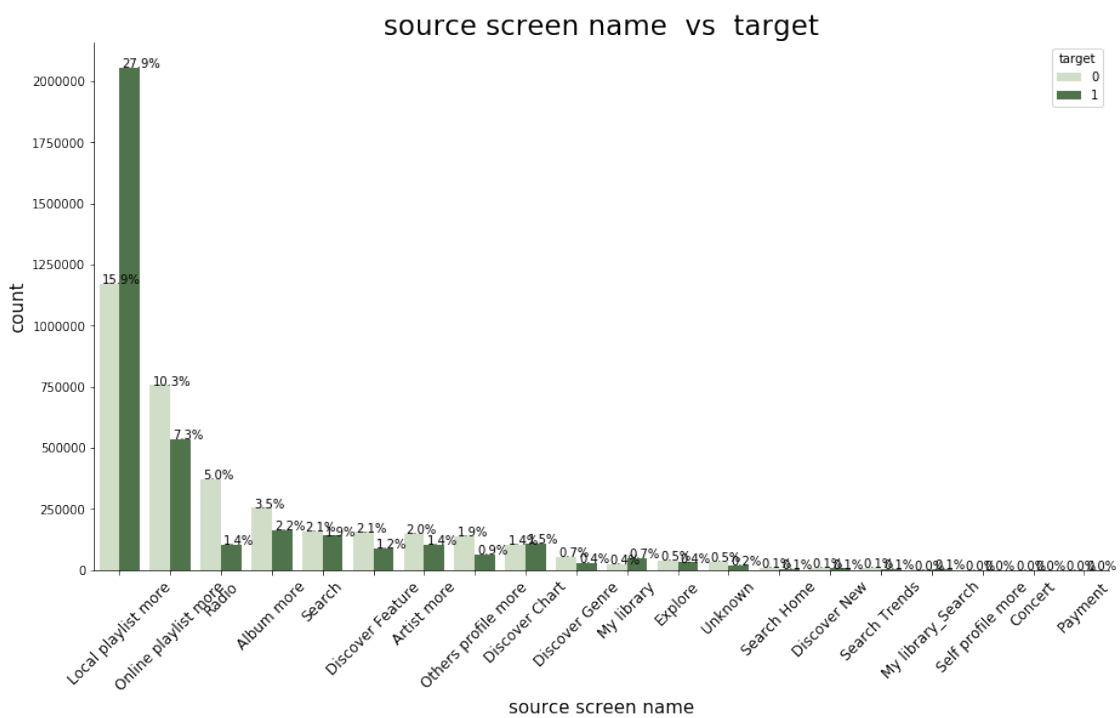
```
[137]: a = pd.DataFrame(df.groupby('source_screen_name').size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'source_screen_name',y = 0, data = a, palette='ch:23.0,-.
 ↪10,dark=.4')
plt.xticks(rotation = 45, fontsize = 12)
plt.xlabel('source screen name', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('countplot for source screen name', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.05, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



Aim for source screen name : Plot for determining the distribution of Source screen name used by users in KKBox app while listening songs.

Conclusion for source screen name : 1. 43.8% of the users are using local playlist for playing songs. 2. we can also conclude that most of the users are specific about there songs as they don't even use my library search.

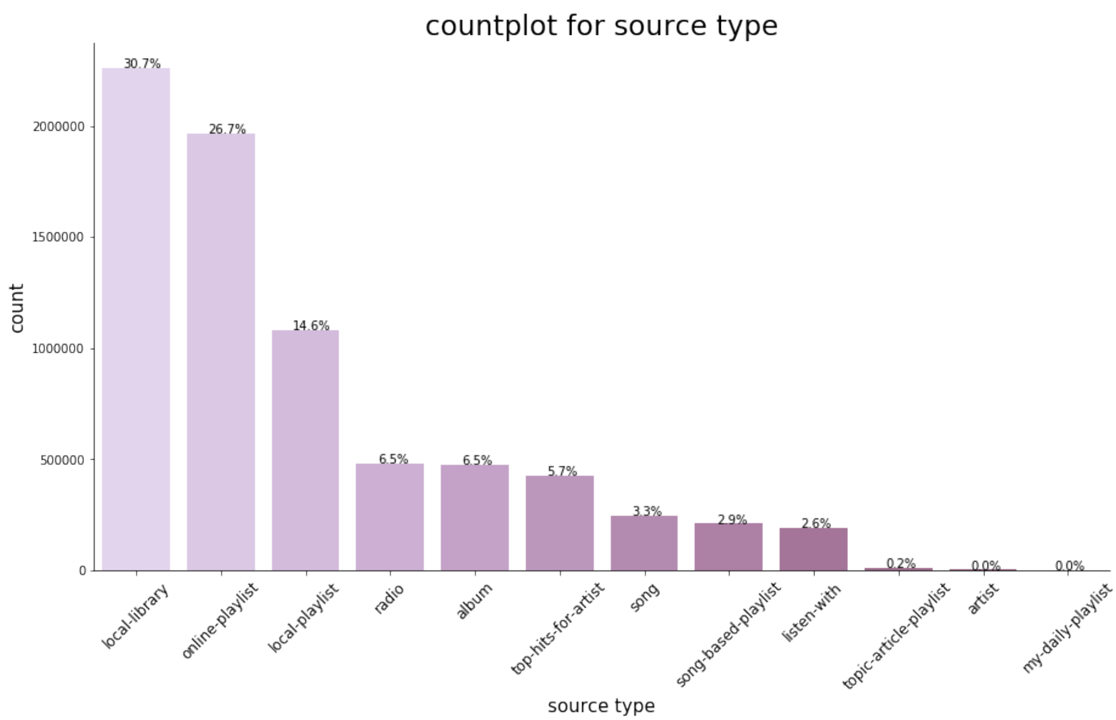
```python
[53]: a = pd.DataFrame(df.groupby(['source_screen_name', 'target']).size().
       ↪reset_index())
      a = a.sort_values(by = 0, ascending = False)

      plt.figure(figsize = (15,8))
      ax = sns.barplot(x= 'source_screen_name',y = 0, hue = 'target', data = a,␣
       ↪palette='ch:23.0,-.10,dark=.4')
      plt.xticks(rotation = 45, fontsize = 12)
      plt.xlabel('source screen name', fontdict = {'fontsize':15})
      plt.ylabel('count', fontdict = {'fontsize':15})
      plt.title('source screen name  vs  target', fontdict = {'fontsize': 23})

      for p in ax.patches:
              ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
       ↪get_x()+0.05, p.get_height()+0.5), fontsize = 10)
      ax.spines['right'].set_visible(False)
      ax.spines['top'].set_visible(False)
      plt.show()
```



Aim for source screen name : Plot for determining the distribution of Source screen name used by users in KKBox app while listening songs with respect to variation in target variable.

Conclusion for source screen name vs target : 1. 27.9% of users listening songs repeatedly from Local Playlist. 2. 5.0% of users Listening songs from radio where not listend more than once.

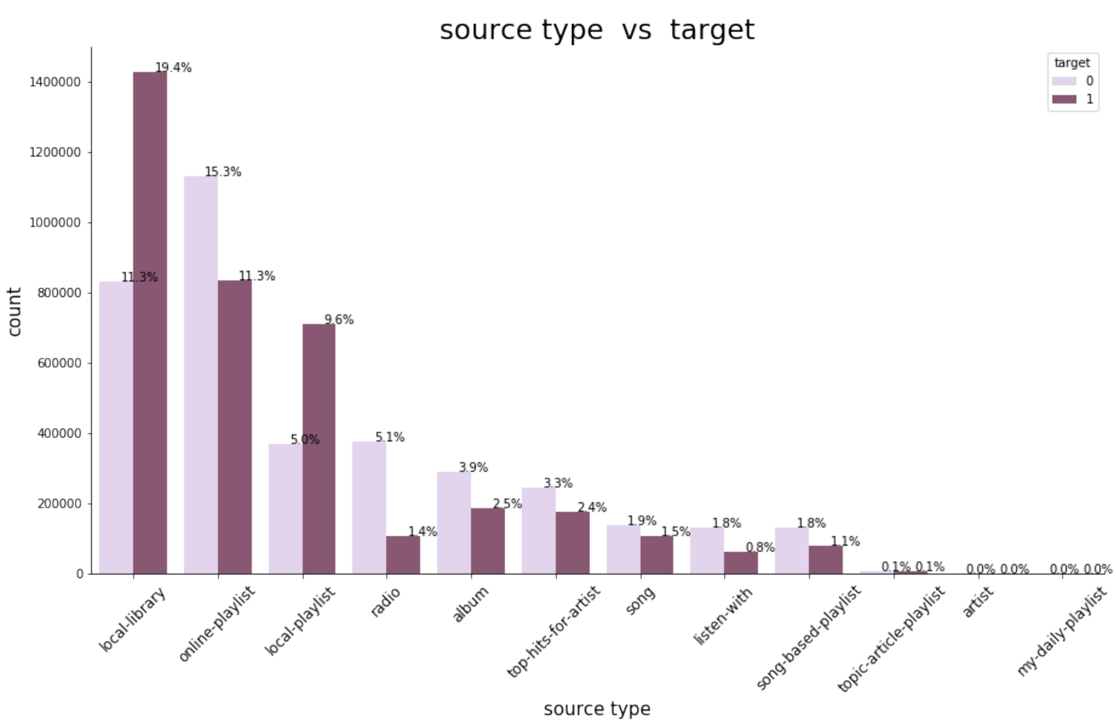
```
[200]: a = pd.DataFrame(df.groupby('source_type').size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'source_type',y = 0, data = a, palette='ch:4.0,-.30,dark=.
 ↪4')
plt.xticks(rotation = 45, fontsize = 12)
plt.xlabel('source type', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('countplot for source type', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.25, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



Aim for source type : Plot for determining the distribution of Source type used by users in KKBox app while listening songs.

Conclusion for source system type : 1. 72% of users are using app using local-library, online-playlist and local-playlist.

```
[55]: a = pd.DataFrame(df.groupby(['source_type', 'target']).size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'source_type',y = 0, data = a, hue = 'target', palette='ch:
 ↪4.0,-.30,dark=.4')
plt.xticks(rotation = 45, fontsize = 12)
plt.xlabel('source type', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('source type  vs  target', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.25, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```

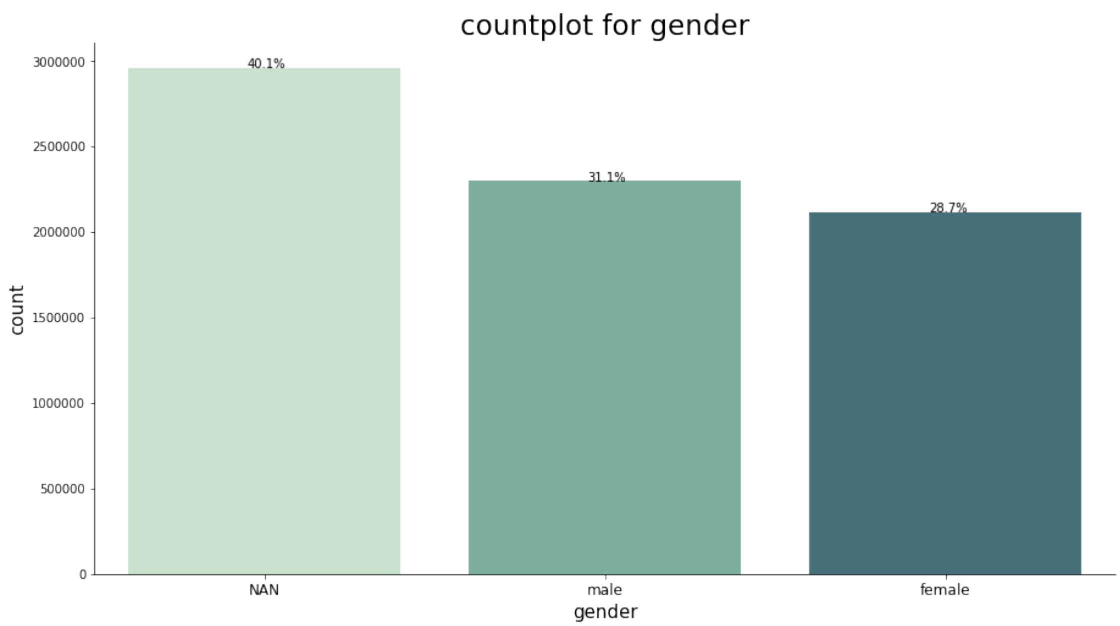


Aim for source type vs target : Plot for determining the distribution of Source type used by users in KKBox app while listening songs with respect to variation in target variable.

Conclusion for source type vs target : 1. 19.4% of users listening songs repeatedly from Local library. 2. 5.1% of users Listening songs from radio where not listend more than once.

[204]:

```
a = df['gender']
a.replace(np.nan, 'NAN',inplace = True)
a = pd.DataFrame(df.groupby('gender').size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'gender',y = 0, data = a, palette='ch:3.0,-.40,dark=.4')
plt.xticks( fontsize = 12)
plt.xlabel('gender', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('countplot for gender', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.35, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



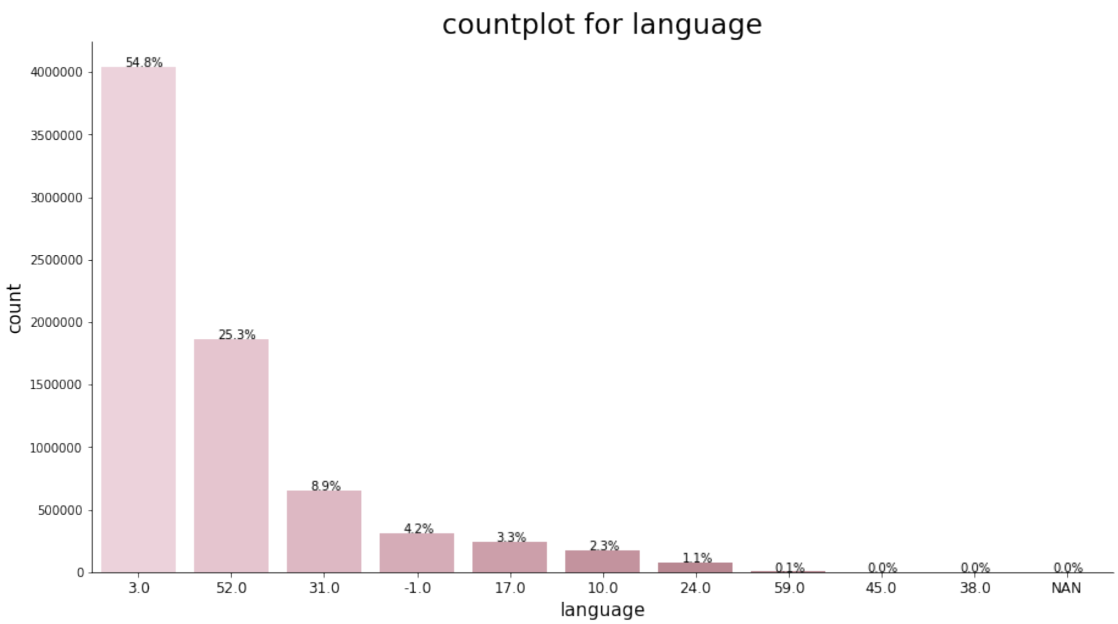
Aim for gender : Plot for determining the distribution of genders of users.

Conclusion for gender : 1.There are majority of missing values. 2. Nothing can be judged due to high missing value rate.

[292]:

```
a = df['language']
a.replace(np.nan, 'NAN',inplace = True)
a = pd.DataFrame(df.groupby('language').size().reset_index())
```

```
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'language',y = 0, data = a, palette='ch:1.0,-.1,dark=.4')
plt.xticks( fontsize = 12)
plt.xlabel('language', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('countplot for language', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.25, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```

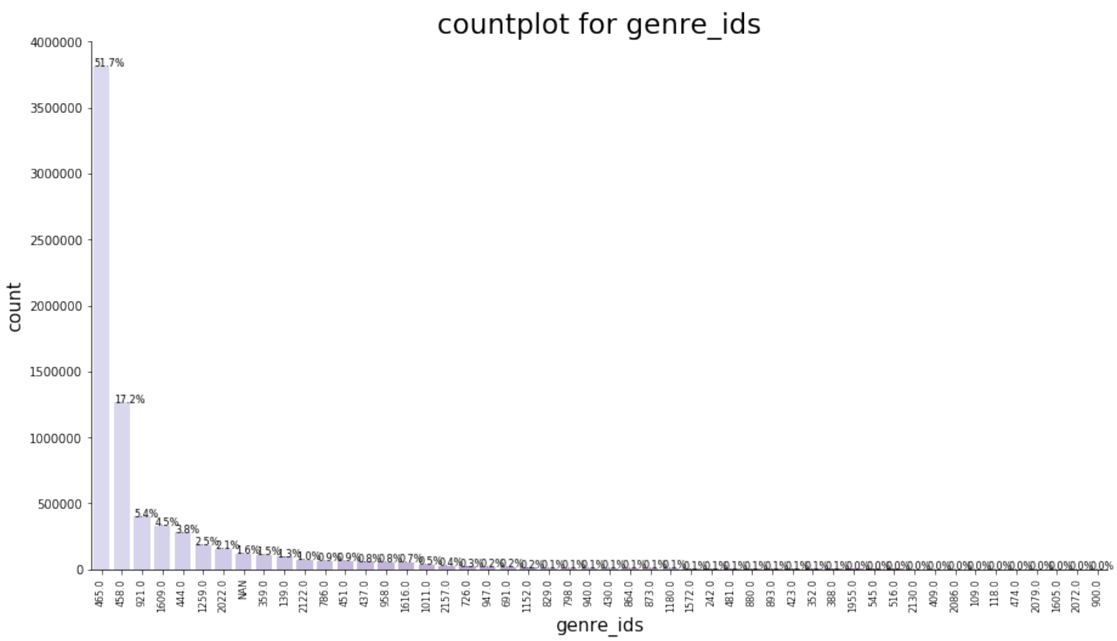


Aim for Language : Plot for determining the distribution of Language of songs most listened by users.

Conclusion for Language : 1. 54.8% of users have song language 3.0 2. It can be concluded that language 3.0 is local language of that region/country where the app is used.

[293]:
```
a = df['genre_ids']
a.replace(np.nan, 'NAN',inplace = True)
a = pd.DataFrame(df.groupby('genre_ids').size().reset_index())
a = a.sort_values(by = 0, ascending = False)
```

```
a = a[:50]

plt.figure(figsize = (15,8))
ax = sns.barplot(x= 'genre_ids',y = 0, data = a, palette='ch:1.0,-.40,dark=.4')
plt.xticks(rotation = 90,  fontsize = 8)
plt.xlabel('genre_ids', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('countplot for genre_ids', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
 ↪get_x()+0.01, p.get_height()+0.1), fontsize = 8)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```



Aim for genre ids : Plot for determining the most liked genre id by users.

Conclusion for genre ids : 1. 51.7% of users listen songs with genre id 465.

[228]:
```
a = df['registered_via']
a.replace(np.nan, 'NAN',inplace = True)
a = pd.DataFrame(df.groupby('registered_via').size().reset_index())
a = a.sort_values(by = 0, ascending = False)

plt.figure(figsize = (15,8))
```

```
ax = sns.barplot(x= 'registered_via',y = 0, data = a, palette='ch:1.0,-.
↪40,dark=.4')
plt.xticks( fontsize = 12)
plt.xlabel('registered via', fontdict = {'fontsize':15})
plt.ylabel('count', fontdict = {'fontsize':15})
plt.title('countplot for registered via', fontdict = {'fontsize': 23})

for p in ax.patches:
        ax.annotate('{:.1f}%'.format( 100*p.get_height()/df.shape[0]), (p.
↪get_x()+0.35, p.get_height()+0.5), fontsize = 10)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.show()
```

Aim for registered via : Plot for determining the distribution of mode used by users for registering in KKBox app.

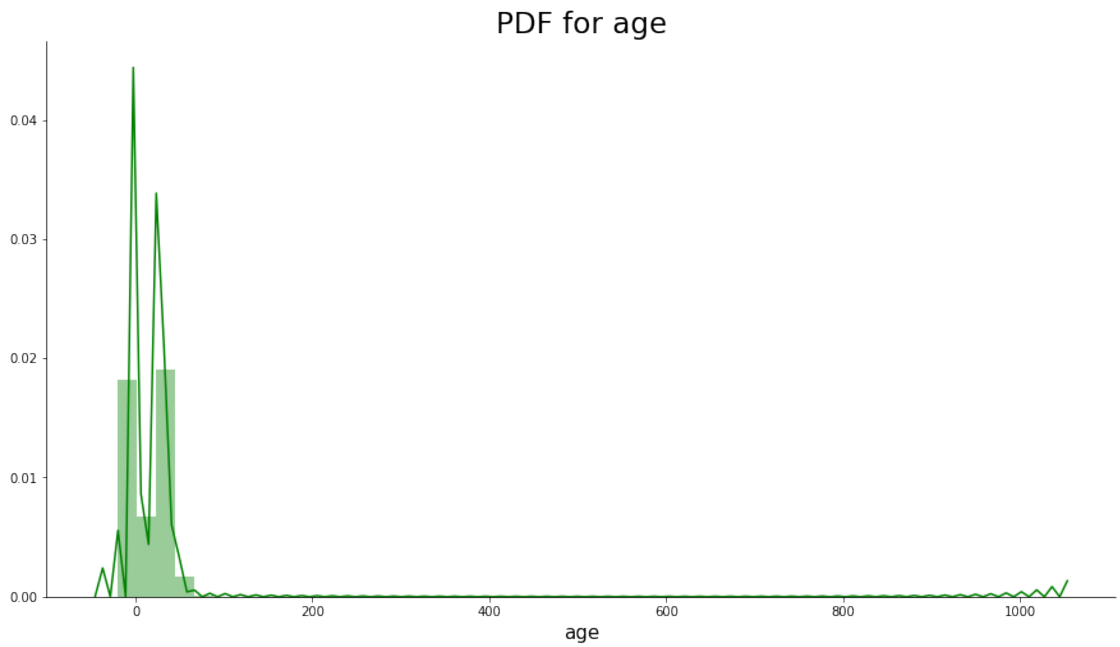
Conclusion for registered via : 1. 72.8% of users have registered via 7 and 9 registeration process.

1.2 EDA Of Continuous Variables

[297]:
```
print(df['bd'].describe())
plt.figure(figsize = (15,8))
ax = sns.distplot(a = df['bd'], color='green')
plt.xlabel('age', fontdict = {'fontsize':15})
plt.title('PDF for age', fontdict = {'fontsize': 23})
ax.spines['right'].set_visible(False)
```

```
ax.spines['top'].set_visible(False)
```

```
count    7.377418e+06
mean     1.753927e+01
std      2.155447e+01
min     -4.300000e+01
25%      0.000000e+00
50%      2.100000e+01
75%      2.900000e+01
max      1.051000e+03
Name: bd, dtype: float64
```

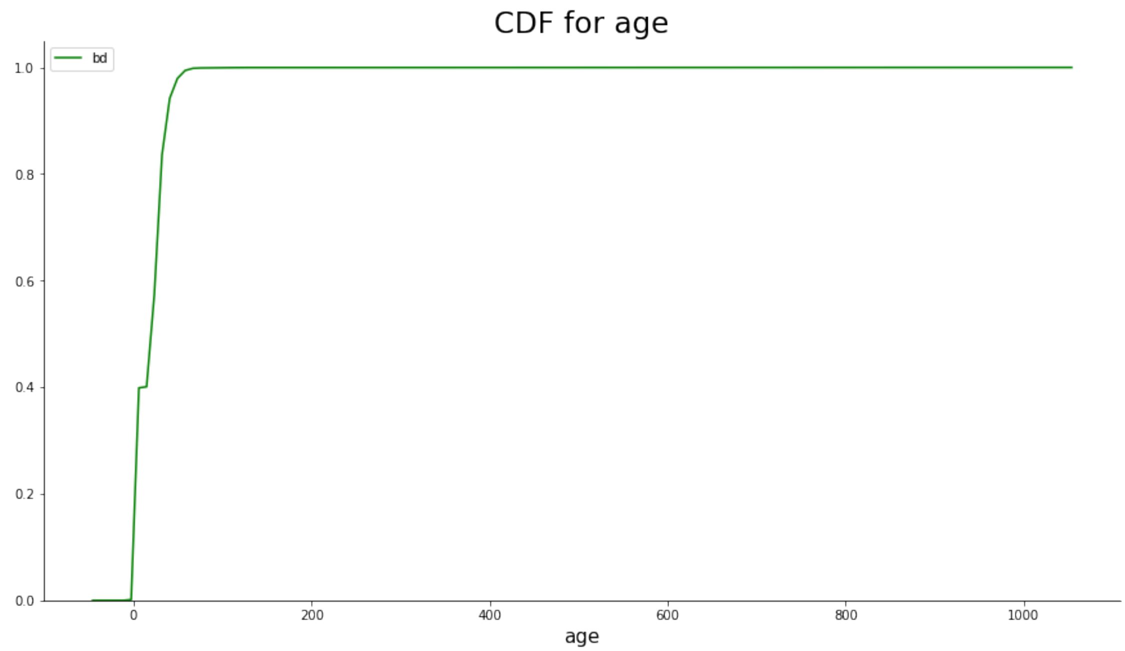


[299]:

```
print(df['bd'].describe())
plt.figure(figsize = (15,8))
ax = sns.kdeplot(data = df['bd'], color='green', cumulative = True)
plt.xlabel('age', fontdict = {'fontsize':15})
plt.title('CDF for age', fontdict = {'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

```
count    7.377418e+06
mean     1.753927e+01
std      2.155447e+01
min     -4.300000e+01
25%      0.000000e+00
50%      2.100000e+01
75%      2.900000e+01
```

```
max        1.051000e+03
Name: bd, dtype: float64
```



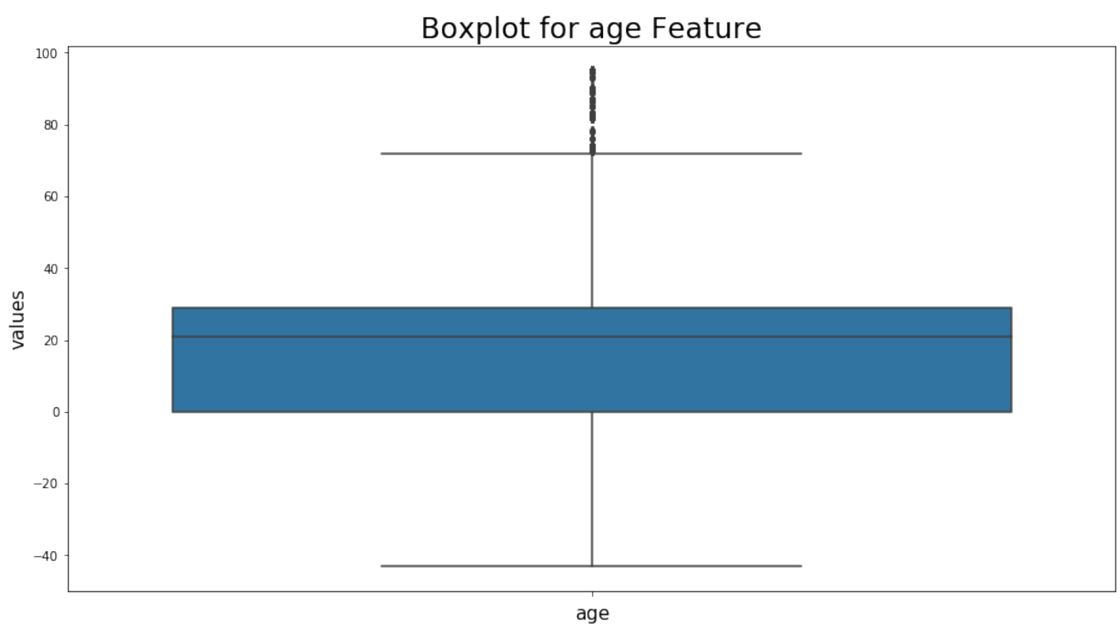
[81]:
```python
for i in range(0, 101, 10):
    print(str(i)+'th Percentile of age is '+str(np.nanpercentile(df['bd'], i)))
for i in range(90, 101, 1):
    print(str(i)+'th Percentile of age is '+str(np.nanpercentile(df['bd'], i)))
for i in [99.0, 99.1, 99.2, 99.3, 99.4, 99.5, 99.6, 99.7, 99.8, 99.9, 100]:
    print(str(i)+'th Percentile of age is '+str(np.nanpercentile(df['bd'], i)))
```

```
0th Percentile of age is -43.0
10th Percentile of age is 0.0
20th Percentile of age is 0.0
30th Percentile of age is 0.0
40th Percentile of age is 15.0
50th Percentile of age is 21.0
60th Percentile of age is 24.0
70th Percentile of age is 27.0
80th Percentile of age is 30.0
90th Percentile of age is 36.0
100th Percentile of age is 1051.0
90th Percentile of age is 36.0
91th Percentile of age is 37.0
92th Percentile of age is 38.0
93th Percentile of age is 39.0
94th Percentile of age is 40.0
95th Percentile of age is 42.0
```

```
96th Percentile of age is 44.0
97th Percentile of age is 46.0
98th Percentile of age is 50.0
99th Percentile of age is 54.0
100th Percentile of age is 1051.0
99.0th Percentile of age is 54.0
99.1th Percentile of age is 55.0
99.2th Percentile of age is 55.0
99.3th Percentile of age is 56.0
99.4th Percentile of age is 58.0
99.5th Percentile of age is 59.0
99.6th Percentile of age is 60.0
99.7th Percentile of age is 63.0
99.8th Percentile of age is 66.0
99.9th Percentile of age is 82.0
100th Percentile of age is 1051.0
```

[87]:

```
plt.figure(figsize = (15, 8))
a = df['bd'] >= 0
b = df['bd'] <= 100
a = df[a.values.tolist() and b.values.tolist()]
sns.boxplot(y = a['bd'])
plt.title('Boxplot for age Feature', fontdict = {'fontsize': 23})
plt.xlabel('age', fontdict = {'fontsize':15})
plt.ylabel('values', fontdict = {'fontsize':15})
plt.show()
```

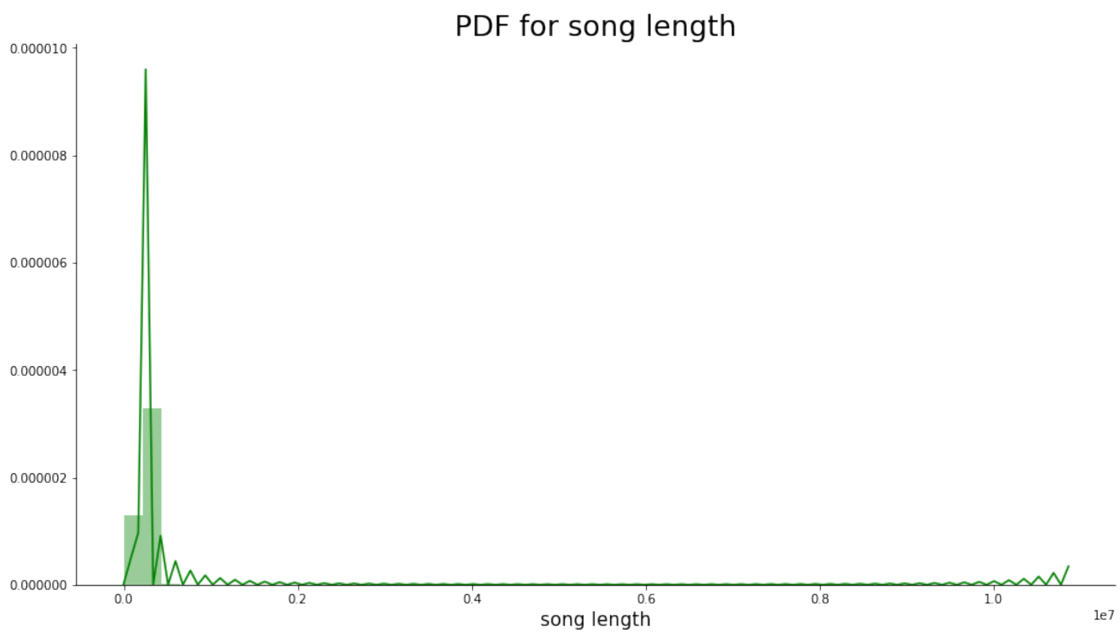


Aim for Age : Plot for determing the distribution of age feature.

Conclusion for Age : 1. Feature has outliers. 2. Majority of values are lying between 0 to 100.

[72]:
```
print(df['song_length'].describe())
plt.figure(figsize = (15,8))
ax = sns.distplot(a = df['song_length'], color='green')
plt.xlabel('song length', fontdict = {'fontsize':15})
plt.title('PDF for song length', fontdict = {'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

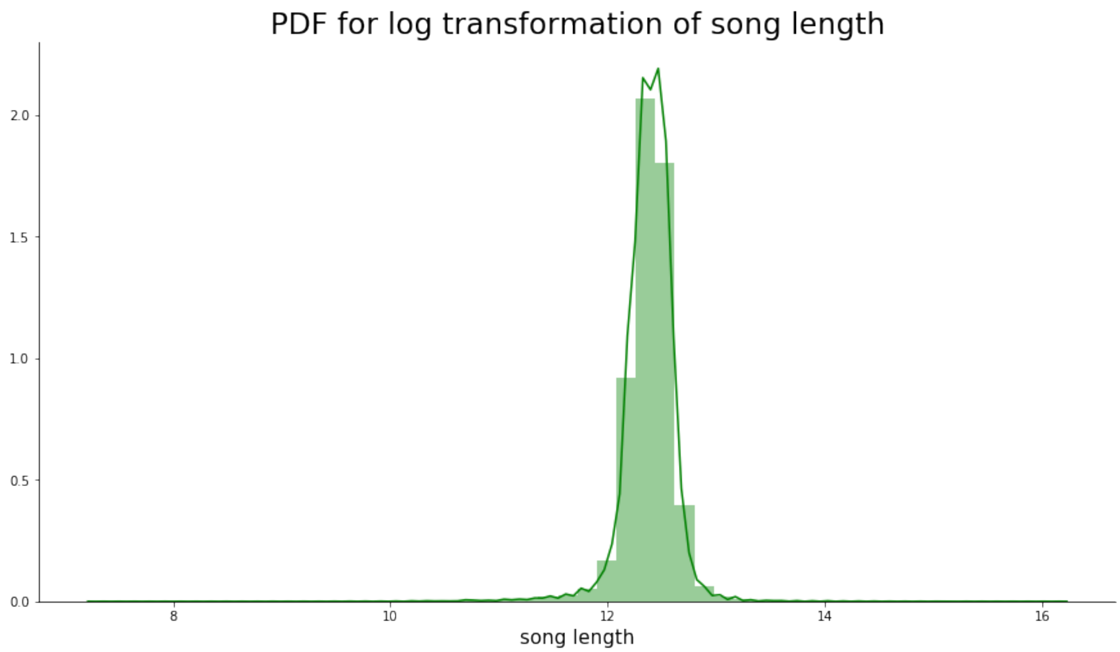
```
count    7.377304e+06
mean     2.451210e+05
std      6.734471e+04
min      1.393000e+03
25%      2.147260e+05
50%      2.418120e+05
75%      2.721600e+05
max      1.085171e+07
Name: song_length, dtype: float64
```



[67]:
```
a = np.log(df['song_length'])
print(a.describe())
plt.figure(figsize = (15,8))
ax = sns.distplot(a = np.log(df['song_length']), color='green')
plt.xlabel('song length', fontdict = {'fontsize':15})
```

```
plt.title('PDF for log transformation of song length', fontdict = {'fontsize':␣
↪23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

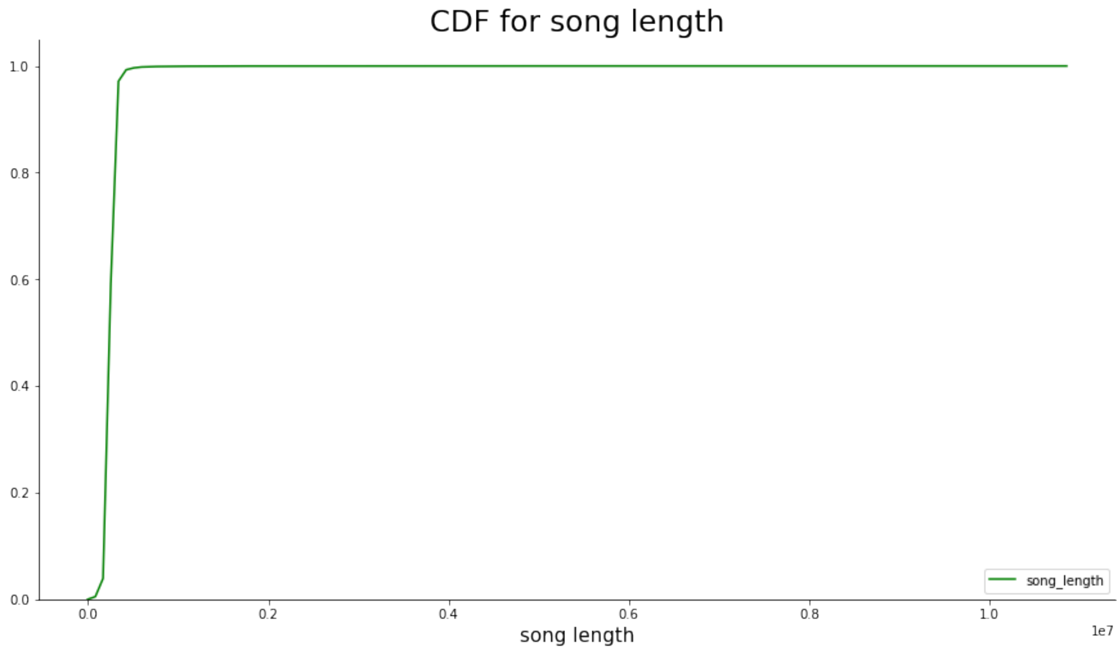
```
count    7.377304e+06
mean     1.238304e+01
std      2.356609e-01
min      7.239215e+00
25%      1.227712e+01
50%      1.239592e+01
75%      1.251415e+01
max      1.619983e+01
Name: song_length, dtype: float64
```



[18]:
```
print(df['song_length'].describe())
plt.figure(figsize = (15,8))
ax = sns.kdeplot(data = df['song_length'], color='green', cumulative = True)
plt.xlabel('song length', fontdict = {'fontsize':15})
plt.title('CDF for song length', fontdict = {'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

```
count    7.377304e+06
mean     2.451210e+05
std      6.734471e+04
min      1.393000e+03
```

```
25%      2.147260e+05
50%      2.418120e+05
75%      2.721600e+05
max      1.085171e+07
Name: song_length, dtype: float64
```

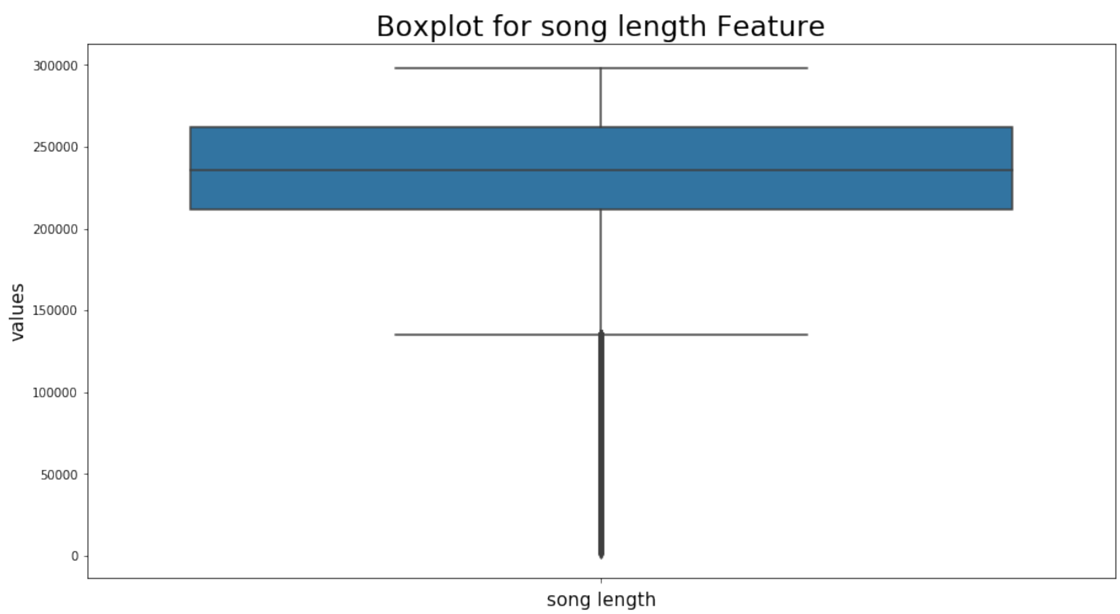


[25]:
```
for i in range(0, 101, 10):
    print(str(i)+'th Percentile of song length is '+str(np.
 ↪nanpercentile(df['song_length'], i)))
for i in range(90, 101, 1):
    print(str(i)+'th Percentile of song length is '+str(np.
 ↪nanpercentile(df['song_length'], i)))
```

```
0th Percentile of song length is 1393.0
10th Percentile of song length is 191518.0
20th Percentile of song length is 208236.0
30th Percentile of song length is 220160.0
40th Percentile of song length is 231132.0
50th Percentile of song length is 241812.0
60th Percentile of song length is 253469.0
70th Percentile of song length is 265508.0
80th Percentile of song length is 279928.0
90th Percentile of song length is 298260.0
100th Percentile of song length is 10851706.0
90th Percentile of song length is 298260.0
91th Percentile of song length is 300826.0
92th Percentile of song length is 304227.0
```

```
93th Percentile of song length is 307983.0
94th Percentile of song length is 311902.0
95th Percentile of song length is 319190.0
96th Percentile of song length is 325465.0
97th Percentile of song length is 334471.0
98th Percentile of song length is 352653.0
99th Percentile of song length is 395947.0
100th Percentile of song length is 10851706.0
```

[78]:
```python
plt.figure(figsize = (15, 8))
a = df['song_length'] >= 191518
b = df['song_length'] <= 298260
a = df[a.values.tolist() and b.values.tolist()]
sns.boxplot(y = a['song_length'])
plt.title('Boxplot for song length Feature', fontdict = {'fontsize': 23})
plt.xlabel('song length', fontdict = {'fontsize':15})
plt.ylabel('values', fontdict = {'fontsize':15})
plt.show()
```

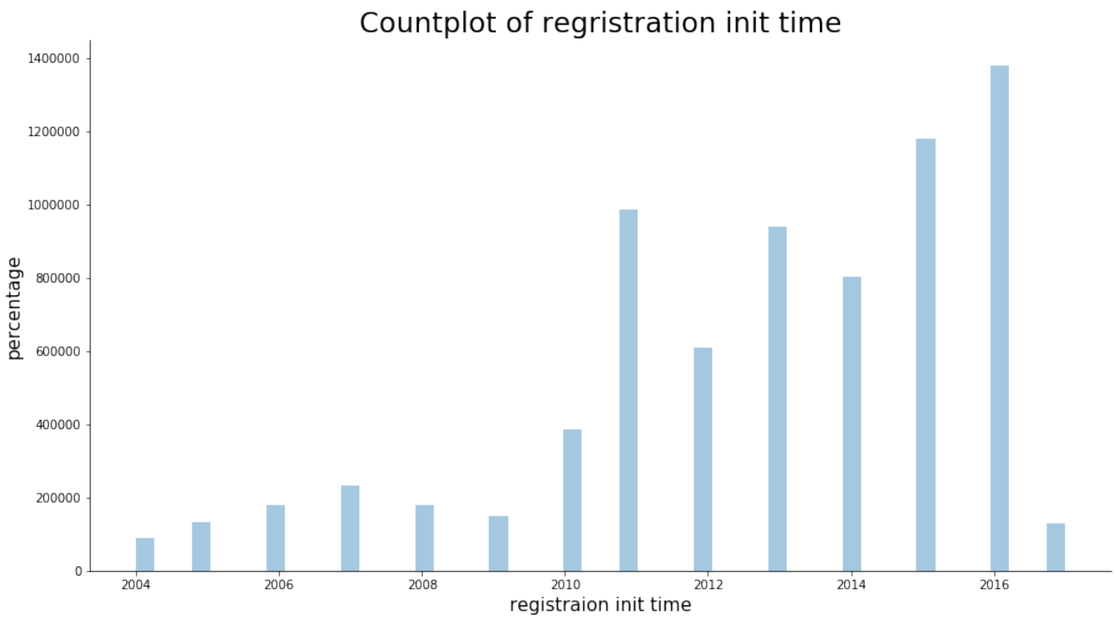


Aim for Song Length : Plots for determing the distribution of lengths of songs.

Conclusion for Song Length : 1. Feature has outliers. 2. song length are lying between 191518ms to 395947ms. 3. Applying log transformation on song length makes sense in avoiding outliers.

[118]:
```python
plt.figure(figsize = (15, 8))
ax = sns.distplot(df['registration_init_time'].astype(str).apply(lambda x:␣
↪int(x[:4])), kde = False)
```

```
plt.title('Countplot of regristration init time', fontdict = {'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.xlabel('registraion init time', fontdict = {'fontsize':15})
plt.ylabel('percentage', fontdict = {'fontsize':15})
plt.show()
```



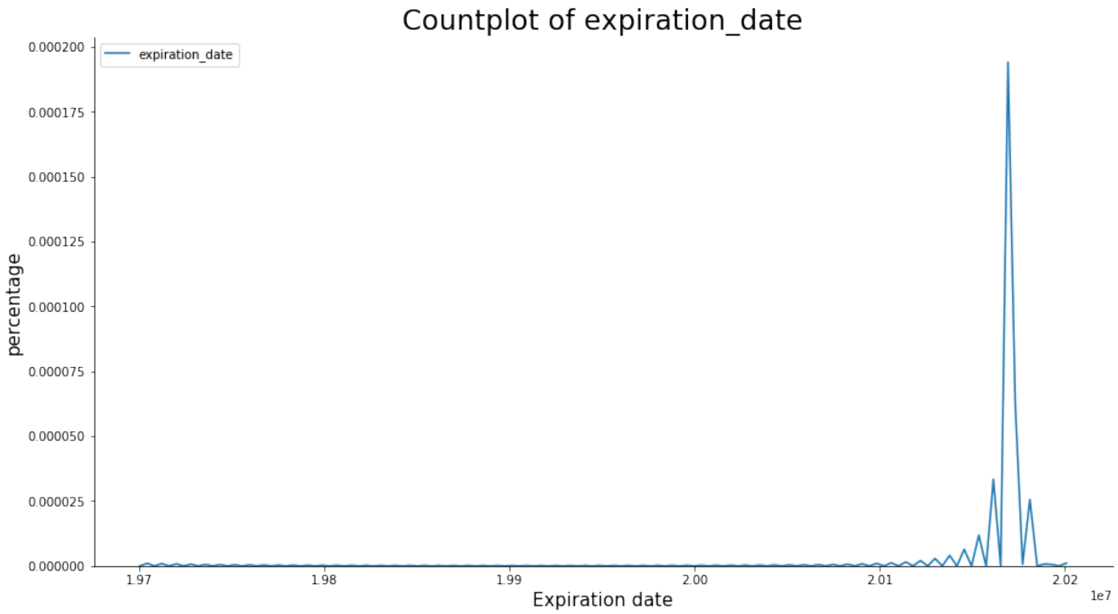
Aim for registration init time : Plot for determing the distribution of when the users registers on KKBox app.

Conclusion for registration init time : 1. Registration of users increases as time passes.

[112]:
```
print(df['expiration_date'].describe())
plt.figure(figsize = (15, 8))
ax = sns.kdeplot(df['expiration_date'])
plt.title('Countplot of expiration_date', fontdict = {'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.xlabel('Expiration date', fontdict = {'fontsize':15})
plt.ylabel('percentage', fontdict = {'fontsize':15})
plt.show()
```

```
count    7.377418e+06
mean     2.017157e+07
std      3.869831e+03
min      1.970010e+07
25%      2.017091e+07
50%      2.017093e+07
```

```
75%      2.017101e+07
max      2.020102e+07
Name: expiration_date, dtype: float64
```



Aim for expiration date : Plot for determining the distribution of expiration date of plans of users.

Conclusion for expiration date : 1. There are outliers in the features. 2. Most of plans of users expiration are in the year of 2017.

2 EDA on Feature Engineered Features

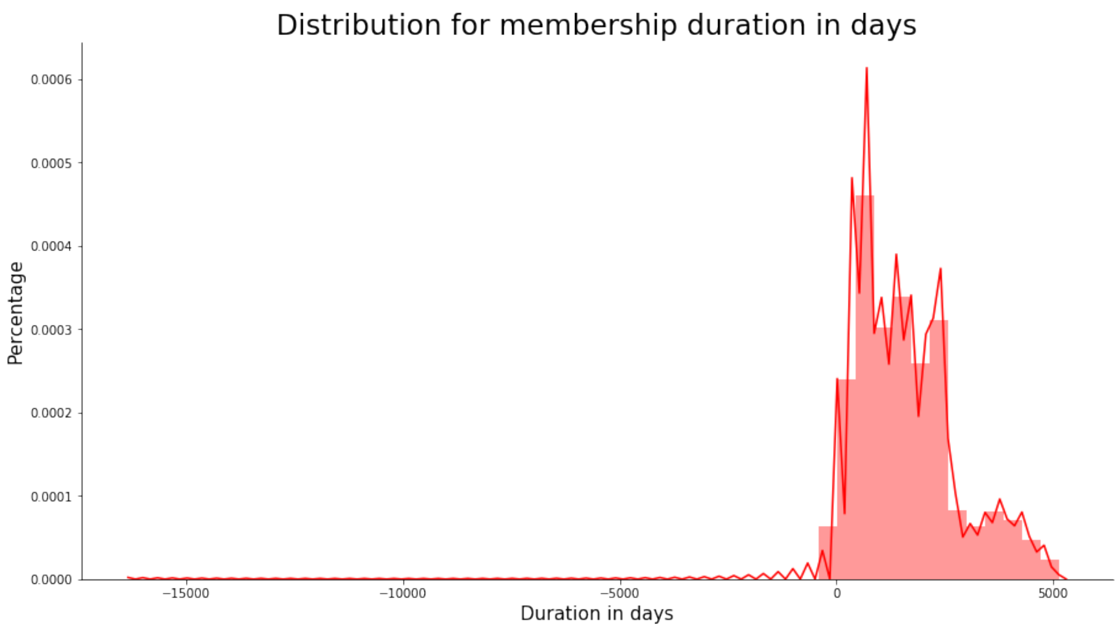
1. Duration of subscription

[20]:
```
a = pd.to_datetime(df['expiration_date'], format = '%Y%m%d') - pd.
 ↪to_datetime(df['registration_init_time'], format = '%Y%m%d')
a =list(a)
a = [i.days for i in a]
df['membership_duration'] = a
```

[23]:
```
print(df['membership_duration'].describe())
plt.figure(figsize = (15,8))
ax = sns.distplot(a = df['membership_duration'], color='red')
plt.xlabel('Duration in days', fontdict = {'fontsize':15})
plt.ylabel('Percentage', fontdict = {'fontsize': 15})
plt.title('Distribution for membership duration in days', fontdict =␣
 ↪{'fontsize': 23})
```

```
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

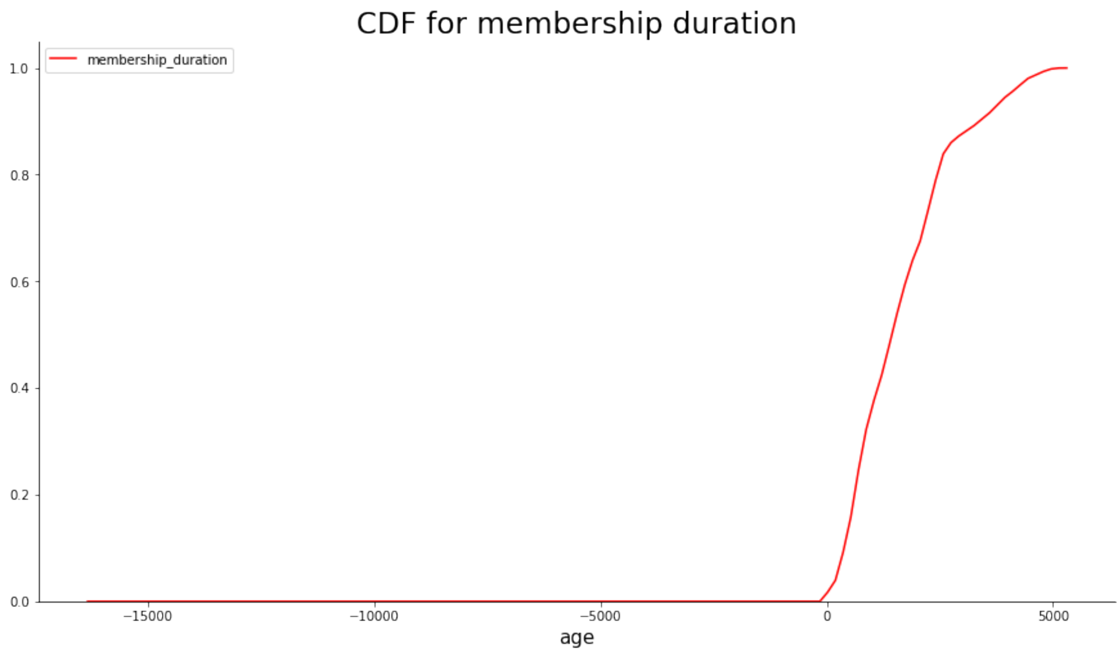
```
count    7.377418e+06
mean     1.627961e+03
std      1.128673e+03
min     -1.619100e+04
25%      7.010000e+02
50%      1.433000e+03
75%      2.286000e+03
max      5.149000e+03
Name: membership_duration, dtype: float64
```



[204]:
```
print(df['membership_duration'].describe())
plt.figure(figsize = (15,8))
ax = sns.kdeplot(data = df['membership_duration'], color='red', cumulative =␣
 ↪True)
plt.xlabel('age', fontdict = {'fontsize':15})
plt.title('CDF for membership duration', fontdict = {'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

```
count    7.377418e+06
mean     1.627961e+03
std      1.128673e+03
min     -1.619100e+04
25%      7.010000e+02
```

```
50%      1.433000e+03
75%      2.286000e+03
max      5.149000e+03
Name: membership_duration, dtype: float64
```



Aim for Duration in days : Plot for determining the distribution of duration in days of subscription.

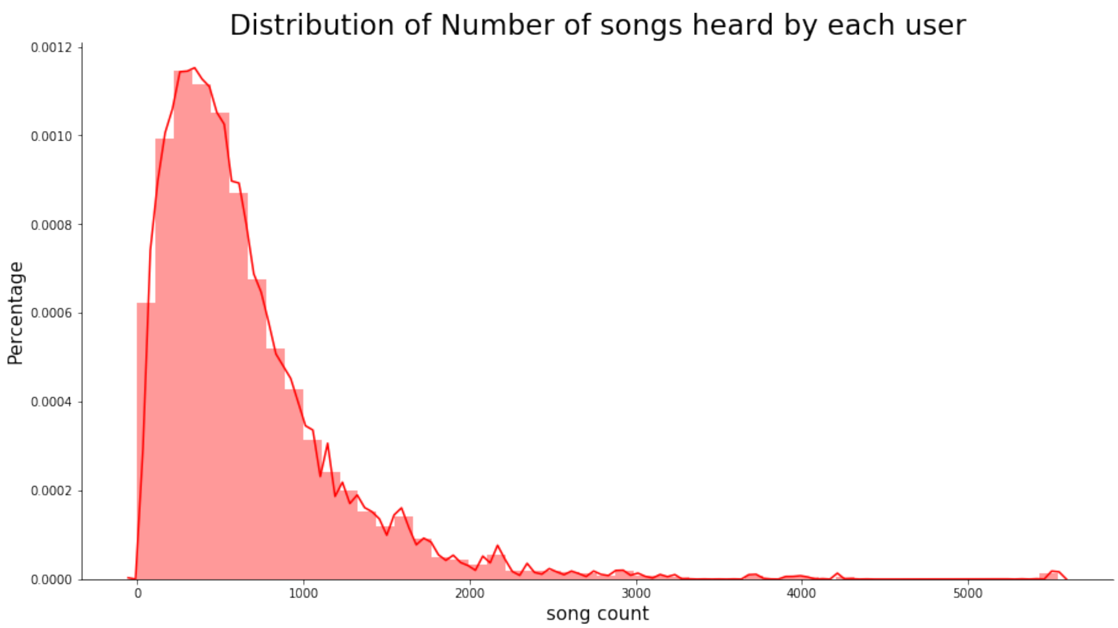
Conclusion for Duration in days : 1. There are outliers in the features. 2. Range of membership duration varies from 0 to 5000.

[190]:
```
a = pd.DataFrame(df['msno'].value_counts().reset_index())
a.rename(columns = {'index':'msno', 'msno':'song_count'}, inplace=True)
df = df.merge(a, how = 'left',on = 'msno')
```

[201]:
```
print(df['song_count'].describe())
plt.figure(figsize = (15,8))
ax = sns.distplot(a = df['song_count'], color='red')
plt.xlabel('song count', fontdict = {'fontsize':15})
plt.ylabel('Percentage', fontdict = {'fontsize': 15})
plt.title('Distribution of Number of songs heard by each user', fontdict =␣
 ↪{'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

```
count    7.371599e+06
mean     6.471541e+02
std      5.573472e+02
```

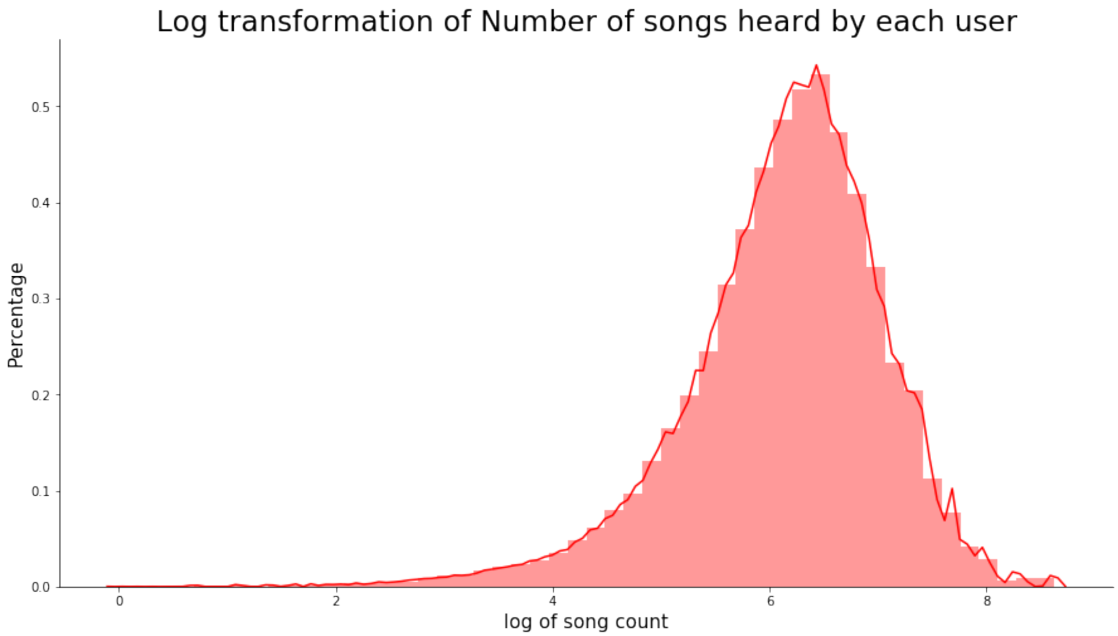
```
min      1.000000e+00
25%      2.860000e+02
50%      5.090000e+02
75%      8.360000e+02
max      5.537000e+03
Name: song_count, dtype: float64
```



[202]:

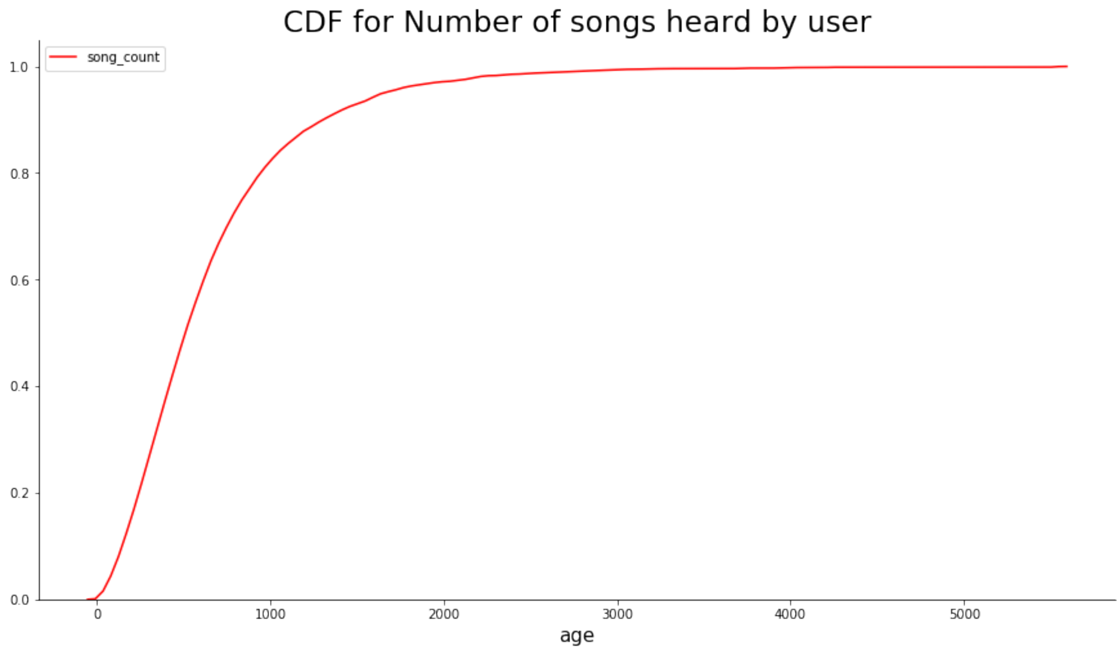
```
print(np.log(df['song_count']).describe())
plt.figure(figsize = (15,8))
ax = sns.distplot(a = np.log(df['song_count']), color='red')
plt.xlabel('log of song count', fontdict = {'fontsize':15})
plt.ylabel('Percentage', fontdict = {'fontsize': 15})
plt.title('Log transformation of Number of songs heard by each user', fontdict␣
 ↪= {'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

```
count    7.371599e+06
mean     6.128115e+00
std      9.168676e-01
min      0.000000e+00
25%      5.655992e+00
50%      6.232448e+00
75%      6.728629e+00
max      8.619208e+00
Name: song_count, dtype: float64
```



[203]:
```
print(df['song_count'].describe())
plt.figure(figsize = (15,8))
ax = sns.kdeplot(data = df['song_count'], color='red', cumulative = True)
plt.xlabel('age', fontdict = {'fontsize':15})
plt.title('CDF for Number of songs heard by user', fontdict = {'fontsize': 23})
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```

```
count    7.371599e+06
mean     6.471541e+02
std      5.573472e+02
min      1.000000e+00
25%      2.860000e+02
50%      5.090000e+02
75%      8.360000e+02
max      5.537000e+03
Name: song_count, dtype: float64
```



Aim for song count : Plot for determining the distribution of Number of songs heard by a particular user.

Conclusion for song count : 1. There are some outliers. 2. Log transformation of song count makes sense in avoiding outliers. 3. Range of song count varies from 0 to 2500.

1. Create Embedding for Users and Songs

[7]:
```
map_song_id = {key: id for id, key in enumerate(df.song_id.unique())}
map_msno = {key: id for id, key in enumerate(df.msno.unique())}
```

[8]:
```
row = []
cols = []
ids = df['song_id'].values
ms = df['msno'].values
for i in range(df.shape[0]):
    song_id = ids[i]
    msno = ms[i]
    row.append(map_song_id[song_id])
    cols.append(map_msno[msno])
row = np.array(row)
cols = np.array(cols)
```

[9]:
```
from scipy.sparse import csc_matrix
Y = csc_matrix((df.target.values, (row, cols)), dtype = np.int8)
```

```
[10]: def predict(df, emb_user, emb_song):
          df['prediction'] = np.sum(np.multiply(emb_song[df['song_id'].apply(lambda x:
       ↪ map_song_id[x])],emb_user[df['msno'].apply(lambda x: map_msno[x])]), axis=1)
          return df
```

```
[11]: lmbda = 0.0002
      def cost(df, Y,emb_user, emb_anime):
          predicted = predict(df, emb_user, emb_song)
          predicted = csc_matrix((df.prediction.values, (row, cols)), dtype = np.int8)
          return np.sum((Y-predicted).power(2))/df.shape[0]
```

```
[12]: def create_embeddings(n, K):
          return np.random.random((n, K))
```

```
[14]: def gradient(df, Y, emb_user, emb_song):
          predicted = predict(df, emb_user, emb_song)
          predicted = csc_matrix((df.prediction.values, (row, cols)), dtype = np.int8)
          delta = (Y-predicted)
          grad_user = (-2/df.shape[0])*(delta.T*emb_song) + 2*lmbda*emb_user
          grad_song = (-2/df.shape[0])*(delta*emb_user) + 2*lmbda*emb_song
          return grad_user, grad_song
```

```
[15]: emb_user = create_embeddings(30755, 30)
      emb_song = create_embeddings(359966, 30)
```

```
[16]: beta = 0.9
      grad_user, grad_song = gradient(df, Y,  emb_user, emb_song)
      v_user = grad_user
      v_song = grad_song
      for i in range(500):
          grad_user, grad_song = gradient(df, Y, emb_user, emb_song)
          v_user = beta*v_user + (1-beta)*grad_user
          v_song = beta*v_song + (1-beta)*grad_song
          emb_user = emb_user - 1*v_user
          emb_song = emb_song - 1*v_song
          print("\niteration", i+1, ":")
          print("train mse:",  cost(df, Y, emb_user, emb_song))
```

```
iteration 1 :
train mse: 43.37502700809416

iteration 2 :
train mse: 42.910836013358605

iteration 3 :
train mse: 42.45490766552742
```

```
iteration 4 :
train mse: 42.004536953172504

iteration 5 :
train mse: 41.56056075445366

iteration 6 :
train mse: 41.123853087896066

iteration 7 :
train mse: 40.69462351191162

iteration 8 :
train mse: 40.27064496006597

iteration 9 :
train mse: 39.8566118932125

iteration 10 :
train mse: 39.4504421465613

iteration 11 :
train mse: 39.05086942342158

iteration 12 :
train mse: 38.65748897514008

iteration 13 :
train mse: 38.274843990133135

iteration 14 :
train mse: 37.8969231511621

iteration 15 :
train mse: 37.52631083124204

iteration 16 :
train mse: 37.16426329645412

iteration 17 :
train mse: 36.80839136402465

iteration 18 :
train mse: 36.458558807431004

iteration 19 :
train mse: 36.11678896329312
```

```
iteration 20 :
train mse: 35.782108726928584

iteration 21 :
train mse: 35.454441242179854

iteration 22 :
train mse: 35.13069504805069

iteration 23 :
train mse: 34.814451207726066

iteration 24 :
train mse: 34.50443054738121

iteration 25 :
train mse: 34.20083801676955

iteration 26 :
train mse: 33.90267516358704

iteration 27 :
train mse: 33.608184055722475

iteration 28 :
train mse: 33.32009491667681

iteration 29 :
train mse: 33.03800082901633

iteration 30 :
train mse: 32.762038425909985

iteration 31 :
train mse: 32.48803388936346

iteration 32 :
train mse: 32.22053393206132

iteration 33 :
train mse: 31.958337591824133

iteration 34 :
train mse: 31.699166429230388

iteration 35 :
train mse: 31.444748826757547
```

```
iteration 36 :
train mse: 31.194280302403904

iteration 37 :
train mse: 30.948994485604583

iteration 38 :
train mse: 30.707528026743233

iteration 39 :
train mse: 30.469849885149518

iteration 40 :
train mse: 30.235357275404485

iteration 41 :
train mse: 30.00478622737657

iteration 42 :
train mse: 29.777944126251217

iteration 43 :
train mse: 29.55461897373851

iteration 44 :
train mse: 29.336374596098526

iteration 45 :
train mse: 29.12015301288337

iteration 46 :
train mse: 28.9073487499285

iteration 47 :
train mse: 28.698008300465013

iteration 48 :
train mse: 28.491077772738375

iteration 49 :
train mse: 28.287603738869073

iteration 50 :
train mse: 28.087751703915924

iteration 51 :
train mse: 27.891058226604486
```

```
iteration 52 :
train mse: 27.695981575125607

iteration 53 :
train mse: 27.504513096587452

iteration 54 :
train mse: 27.31509167570551

iteration 55 :
train mse: 27.12785367455118

iteration 56 :
train mse: 26.94378236396528

iteration 57 :
train mse: 26.761380201040527

iteration 58 :
train mse: 26.58213727350138

iteration 59 :
train mse: 26.405799156290183

iteration 60 :
train mse: 26.231187930519866

iteration 61 :
train mse: 26.05887913630487

iteration 62 :
train mse: 25.889261934188898

iteration 63 :
train mse: 25.72147518278075

iteration 64 :
train mse: 25.555245751291306

iteration 65 :
train mse: 25.391288117333193

iteration 66 :
train mse: 25.22984152450085

iteration 67 :
train mse: 25.07019664603524
```

```
iteration 68 :
train mse: 24.912327592119627

iteration 69 :
train mse: 24.755823107759383

iteration 70 :
train mse: 24.60112006666831

iteration 71 :
train mse: 24.44877611652207

iteration 72 :
train mse: 24.298524226226576

iteration 73 :
train mse: 24.149396441952998

iteration 74 :
train mse: 24.00169612186811

iteration 75 :
train mse: 23.856044621573563

iteration 76 :
train mse: 23.712268709730154

iteration 77 :
train mse: 23.569920668721767

iteration 78 :
train mse: 23.429129812083307

iteration 79 :
train mse: 23.290184723164664

iteration 80 :
train mse: 23.151678405642734

iteration 81 :
train mse: 23.015464217968944

iteration 82 :
train mse: 22.88034228235407

iteration 83 :
train mse: 22.747103525921943
```

```
iteration 84 :
train mse: 22.615054616669408

iteration 85 :
train mse: 22.483707307895525

iteration 86 :
train mse: 22.35514417103653

iteration 87 :
train mse: 22.22705721703718

iteration 88 :
train mse: 22.10104375270589

iteration 89 :
train mse: 21.97611115433611

iteration 90 :
train mse: 21.85168659278897

iteration 91 :
train mse: 21.729251345118307

iteration 92 :
train mse: 21.606861506288514

iteration 93 :
train mse: 21.486379652067974

iteration 94 :
train mse: 21.367260469719895

iteration 95 :
train mse: 21.249171864736415

iteration 96 :
train mse: 21.131456832187087

iteration 97 :
train mse: 21.01558621186979

iteration 98 :
train mse: 20.90053986367588

iteration 99 :
train mse: 20.786536021139103
```

```
iteration 100 :
train mse: 20.673873840414085

iteration 101 :
train mse: 20.56223559516351

iteration 102 :
train mse: 20.45135073002506

iteration 103 :
train mse: 20.342324103094064

iteration 104 :
train mse: 20.233774065669046

iteration 105 :
train mse: 20.126185340182705

iteration 106 :
train mse: 20.019500182855303

iteration 107 :
train mse: 19.913393276617917

iteration 108 :
train mse: 19.80828766920893

iteration 109 :
train mse: 19.704321349285074

iteration 110 :
train mse: 19.601417731786377

iteration 111 :
train mse: 19.49957153031047

iteration 112 :
train mse: 19.398597585225616

iteration 113 :
train mse: 19.29833201805835

iteration 114 :
train mse: 19.19898411612301

iteration 115 :
train mse: 19.100426328018827
```

```
iteration 116 :
train mse: 19.002385658505457

iteration 117 :
train mse: 18.905528194281523

iteration 118 :
train mse: 18.809259553952344

iteration 119 :
train mse: 18.71417249232726

iteration 120 :
train mse: 18.619941827886127

iteration 121 :
train mse: 18.52598090551464

iteration 122 :
train mse: 18.433082956665867

iteration 123 :
train mse: 18.340853127747405

iteration 124 :
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iteration 125 :
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iteration 128 :
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iteration 129 :
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iteration 130 :
train mse: 17.718017875630743

iteration 131 :
train mse: 17.631271130360243
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iteration 132 :
train mse: 17.54555021824709

iteration 133 :
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iteration 136 :
train mse: 17.20816768143001

iteration 137 :
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iteration 138 :
train mse: 17.044529535943333

iteration 139 :
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iteration 179 :
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iteration 371 :
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iteration 499 :
train mse: 4.624276813378339
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iteration 500 :
train mse: 4.61072125776254
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[43]:
```
from tqdm import tqdm
df_user = []
for key in map_msno:
    val = map_msno[key]
    df_user.append([key] +list(emb_user[val]))
```

[44]:
```
df_song = []
for key in map_song_id:
    val = map_song_id[key]
    df_song.append([key] +list(emb_song[val]))
```

[48]:
```
df_user = pd.DataFrame(df_user)
df_song = pd.DataFrame(df_song)

df_user = df_user.rename(columns = {0: 'msno'})
df_song = df_song.rename(columns = {0: 'song_id'})

df_user.to_csv('user_embedding.csv')
df_song.to_csv('song_embedding.csv')
```

[7]:
```
df_user = pd.read_csv('user_embedding.csv', index_col = 0)
df_song = pd.read_csv('song_embedding.csv', index_col = 0)

df = df.merge(df_user, how = 'left', on = 'msno')
df = df.merge(df_song, how = 'left', on = 'song_id')
```

2. Creating Expiration and registration year, Month, day
3. Creating Membership Duration

[ ]:
```
df['expiration_year'] = df.expiration_date.astype(str).apply(lambda x: x[:4]).
↪astype(np.uint16)
df['expiration_month'] = df.expiration_date.astype(str).apply(lambda x: x[4:6]).
↪astype(np.uint8)
df['expiration_day'] = df.expiration_date.astype(str).apply(lambda x: x[6:]).
↪astype(np.uint8)
df['registration_year'] = df.registration_init_time.astype(str).apply(lambda x:␣
↪x[:4]).astype(np.uint16)
df['registration_month'] = df.registration_init_time.astype(str).apply(lambda x:
↪ x[4:6]).astype(np.uint8)
df['registration_day'] = df.registration_init_time.astype(str).apply(lambda x:␣
↪x[6:]).astype(np.uint8)

a = list(pd.to_datetime(df['expiration_date'], format = '%Y%m%d') - pd.
↪to_datetime(df['registration_init_time'], format = '%Y%m%d'))
df['membership_duration'] = [i.days for i in a]
```

```
df.drop(columns = ['expiration_date', 'registration_init_time'], inplace =True)
```

4. Creating Number of songs heard by users

```
[ ]: a = pd.DataFrame(df['msno'].value_counts().reset_index())
a.rename(columns = {'index':'msno', 'msno':'song_count'}, inplace=True)
df = df.merge(a, how = 'left',on = 'msno')
df['song_count'] = np.log(df['song_count'])
df.rename(columns = {'song_count':'log_song_count'}, inplace=True)
```

4. Handling Outliers of age

```
[ ]: def clean(x):
    if x>=0 and x<=100:
        return x
    elif x <0:
        return 0
    elif x>100:
        return 100
df['bd'] = df.bd.apply(lambda x: clean(x)).astype(np.uint8)
```

5. Handling Most popular Genre id

```
[ ]: most_popular_genre = ['465', '458', '921', '1609', '444', '1259', '2022',␣
↪'359', '139']
def clean(x):
    b = re.findall('[0-9]+', x)
    if len(b) == 0:
        return np.nan
    if len(b) == 1:
        return int(b[0])
    if len(b)>1:
        for i in most_popular_genre:
            if i in b:
                return int(i)
        return b[0]
df['genre_ids'] = df['genre_ids'].astype(str).apply(lambda x: clean(x))
df['genre_ids'] = df['genre_ids'].astype(str).apply(lambda x: x if x in␣
↪most_popular_genre else '0').astype(np.uint16)
```

```
[ ]: df.drop(columns = ['msno', 'song_id', 'artist_name'], inplace = True)
```

```
[ ]: Y = df['target']
x = df.drop(columns = ['target'])
```

```
[ ]: from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, Y, random_state = 0,␣
↪stratify = Y, test_size = 0.2)
```

```
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train,␣
↪random_state = 0, stratify = y_train, test_size = 0.2)
```

6. Applying One Hot Encoding on categorical Feature

```
[ ]: categorical_features = ['source_system_tab', 'source_screen_name',␣
↪'source_type', 'city', 'registered_via', 'language', 'gender']
x_train_ohe = pd.get_dummies(x_train[categorical_features])
x_val_ohe = pd.get_dummies(x_val[categorical_features])
x_test_ohe = pd.get_dummies(x_test[categorical_features])
```

```
[ ]: x_train = pd.concat([x_train, x_train_ohe], axis = 1)
x_val = pd.concat([x_val, x_val_ohe], axis = 1)
x_test = pd.concat([x_test, x_test_ohe], axis = 1)
x_train.drop(columns = ['city', 'registered_via', 'language',␣
↪'source_system_tab', 'source_screen_name', 'source_type', 'gender'], inplace␣
↪= True)
x_val.drop(columns = ['city', 'registered_via', 'language',␣
↪'source_system_tab', 'source_screen_name', 'source_type', 'gender'], inplace␣
↪= True)
x_test.drop(columns = ['city', 'registered_via', 'language',␣
↪'source_system_tab', 'source_screen_name', 'source_type', 'gender'], inplace␣
↪= True)
```

```
[ ]: x_train.drop(columns = ['composer', 'lyricist'], inplace = True)
x_val.drop(columns = ['composer', 'lyricist'], inplace = True)
x_test.drop(columns = ['composer', 'lyricist'], inplace = True)
```

```
[ ]: from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(x_train['song_length'])
x_train['song_length'] = scaler.transform(x_train['song_length'].values.
↪reshape(-1, 1))
x_val['song_length'] = scaler.transform(x_val['song_length'].values.reshape(-1,␣
↪1))
x_test['song_length'] = scaler.transform(x_test['song_length'].values.
↪reshape(-1, 1))
```

7. Changing data type of feature to reduce space

```
[ ]: import numpy as np
x_train['bd'] = x_train['bd'].astype(np.uint8)
x_val['bd'] = x_val['bd'].astype(np.uint8)
x_test['bd'] = x_test['bd'].astype(np.uint8)
```

```
[ ]: x_train['genre_ids'] = x_train['genre_ids'].astype(np.uint16)
x_val['genre_ids'] = x_val['genre_ids'].astype(np.uint16)
x_test['genre_ids'] = x_test['genre_ids'].astype(np.uint16)
```

8. Changing missing values to median

```
[ ]: median = x_train['song_length'].median()
     x_train['song_length'].fillna(median, inplace = True)
     x_test['song_length'].fillna(median, inplace = True)
     x_val['song_length'].fillna(median, inplace = True)
```

```
[ ]: x_train.to_csv('x_train.csv'), y_train.to_csv('y_train.csv')
     x_test.to_csv('x_test.csv'), y_test.to_csv('y_test.csv')
     x_val.to_csv('x_val.csv'), y_val.to_csv('y_val.csv')
```

3 Feature Engineering Conclusion

1.Creating 30 Features of user embedding which helps in determining the user. 2.Creating 30 Features of song embedding which helps in determing the song.3.Creating 1 feature of Number of days of membership. 4.Creating 1 feature of Number of songs heard by user. 5. Creating 6 features of Expiration and registration year, month and day of users.6. Applying log Transformation of song count feature as it follows normal distribution.7. keeping most popular genre id among all.8. Applying one hot encoding to all categorical features.9. Treating missing values as a new category and dropping it in applying one hot encoding for categorical features.10. filling missing values as median value in continuous features.

4 Modeling

```
[10]: def plot_confusion_matrix(test_y, predict_y):
          C = confusion_matrix(test_y, predict_y)
          print("Percentage of misclassified points ",round((len(test_y)-np.trace(C))/
       ↪len(test_y)*100, 3), '%')
          A =(((C.T)/(C.sum(axis=1))).T)
          B =(C/C.sum(axis=0))
          labels = [1,2]
          cmap=sns.light_palette("green")
          # representing A in heatmap format
          print("-"*50, "Confusion matrix", "-"*50)
          plt.figure(figsize=(10,5))
          sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels,␣
       ↪yticklabels=labels)
          plt.xlabel('Predicted Class')
          plt.ylabel('Original Class')
          plt.show()

          print("-"*50, "Precision matrix", "-"*50)
          plt.figure(figsize=(10,5))
          sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels,␣
       ↪yticklabels=labels)
```

```
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of columns in precision matrix",B.sum(axis=0))

    # representing B in heatmap format
    print("-"*50, "Recall matrix"    , "-"*50)
    plt.figure(figsize=(10,5))
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels,␣
 ↪yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print("Sum of rows in precision matrix",A.sum(axis=1))
```

[2]:
```
import dask.dataframe as pd
x_train = pd.read_csv('E:/x_train.csv')
x_test = pd.read_csv('x_test.csv')
x_val = pd.read_csv('x_val.csv')
y_train = pd.read_csv('y_train.csv')
y_test = pd.read_csv('y_test.csv')
y_val = pd.read_csv('y_val.csv')
```

[3]:
```
x_train = x_train.drop(columns = ['Unnamed: 0'])
x_test = x_test.drop(columns = ['Unnamed: 0'])
x_val = x_val.drop(columns = ['Unnamed: 0'])
y_train = y_train.drop(columns = ['Unnamed: 0'])
y_test = y_test.drop(columns = ['Unnamed: 0'])
y_val = y_val.drop(columns = ['Unnamed: 0'])
```

[7]:
```
import warnings
import numpy as np
warnings.filterwarnings("ignore")
```

1. Logistic Regression

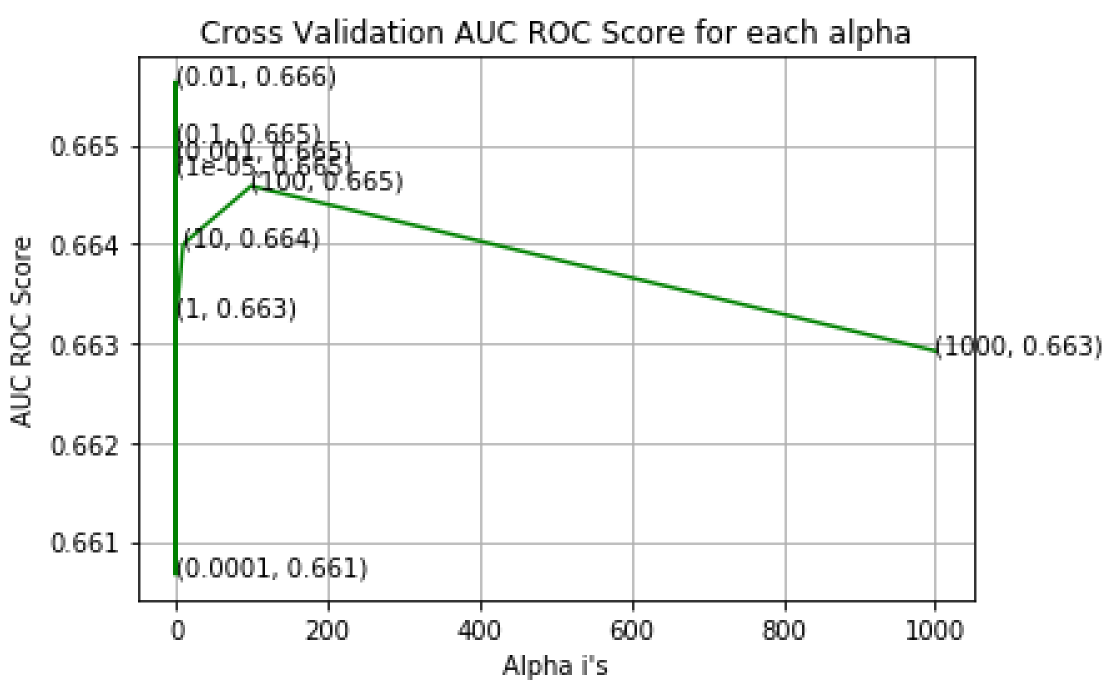
[5]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

alphas = [10 ** x for x in range(-5, 4)]
cv_logs = []
for i in alphas:
    regressor = LogisticRegression(penalty='l2',C=i,class_weight='balanced')
    regressor.fit(x_train, y_train)
    sig_clf = CalibratedClassifierCV(regressor, method="sigmoid")
    sig_clf.fit(x_train, y_train)
```

```
    y_pred = sig_clf.predict_proba(x_val)
    score = roc_auc_score(y_val, y_pred[:, 1])
    print ('AUC ROC Score for c = ',i,'is',score)
    cv_logs.append(score)

fig, ax = plt.subplots()
ax.plot(alphas, cv_logs,c='g')
for i, txt in enumerate(np.round(cv_logs,3)):
    ax.annotate((alphas[i],np.round(txt,3)), (alphas[i],cv_logs[i]))
plt.grid()
plt.title("Cross Validation AUC ROC Score for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("AUC ROC Score")
plt.show()
```

```
AUC ROC Score for c =  1e-05 is 0.6647200724158513
AUC ROC Score for c =  0.0001 is 0.66066237329238
AUC ROC Score for c =  0.001 is 0.6648746192677282
AUC ROC Score for c =  0.01 is 0.6656384442856027
AUC ROC Score for c =  0.1 is 0.6650492350905566
AUC ROC Score for c =  1 is 0.6632797240083415
AUC ROC Score for c =  10 is 0.6639936211617927
AUC ROC Score for c =  100 is 0.6645825333981991
AUC ROC Score for c =  1000 is 0.6629217742893395
```



[5]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

regressor = LogisticRegression(penalty='l2',C=0.01,class_weight='balanced')
regressor.fit(x_train, y_train)
sig_clf = CalibratedClassifierCV(regressor, method="sigmoid")
sig_clf.fit(x_train, y_train)

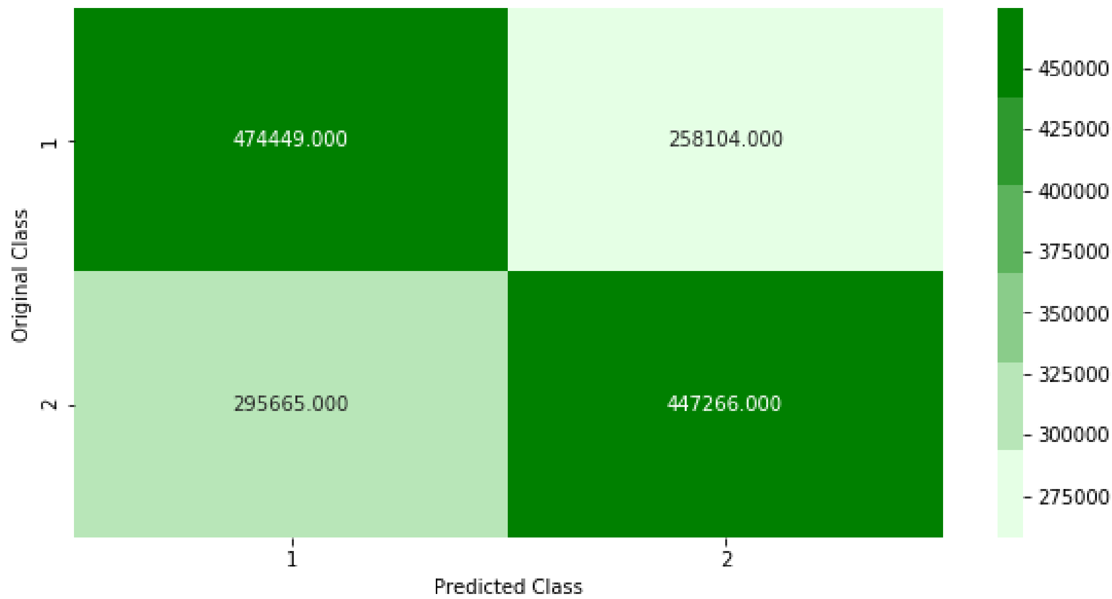
y_pred = sig_clf.predict_proba(x_train)
score = roc_auc_score(y_train, y_pred[:, 1])
print ('Train AUC ROC Score for c = ',0.01,'is',score)
y_pred = sig_clf.predict_proba(x_val)
score = roc_auc_score(y_val, y_pred[:, 1])
print ('validation AUC ROC Score for c = ',0.01,'is',score)
y_pred = sig_clf.predict_proba(x_test)
score = roc_auc_score(y_test, y_pred[:, 1])
print ('Test AUC ROC Score for c = ',0.01,'is',score)
```

```
Train AUC ROC Score for c =  0.01 is 0.6652841982097703
validation AUC ROC Score for c =  0.01 is 0.6647462700597071
Test AUC ROC Score for c =  0.01 is 0.6650204873576647
```

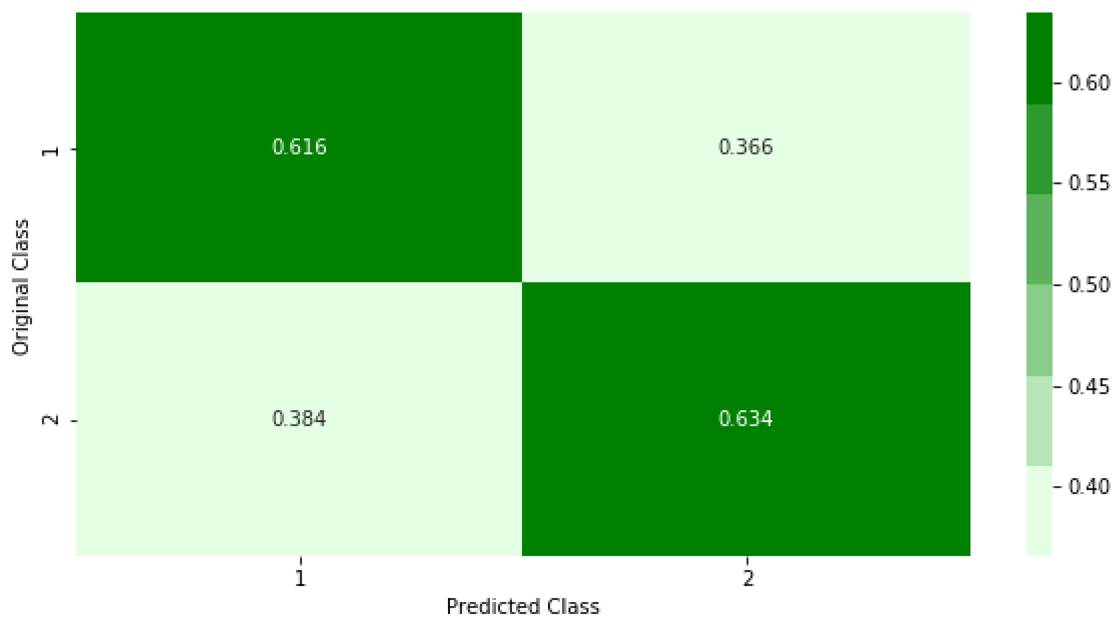
[6]:

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
plot_confusion_matrix(y_test, sig_clf.predict(x_test))
```

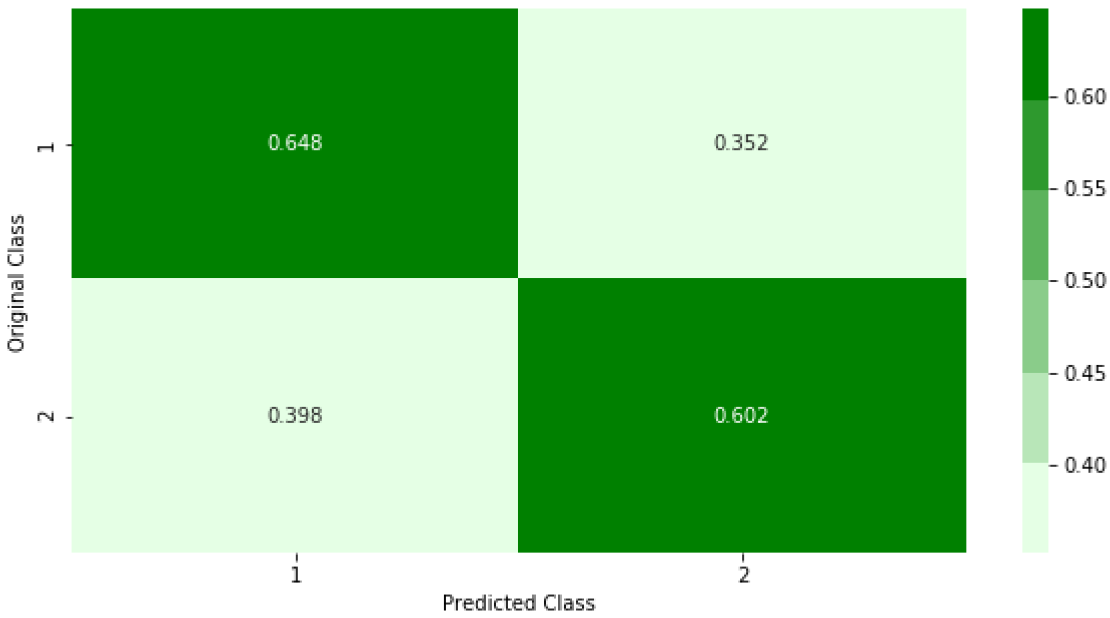
```
Percentage of misclassified points  37.531 %
-------------------------------------------------- Confusion matrix
--------------------------------------------------
```



-- Precision matrix



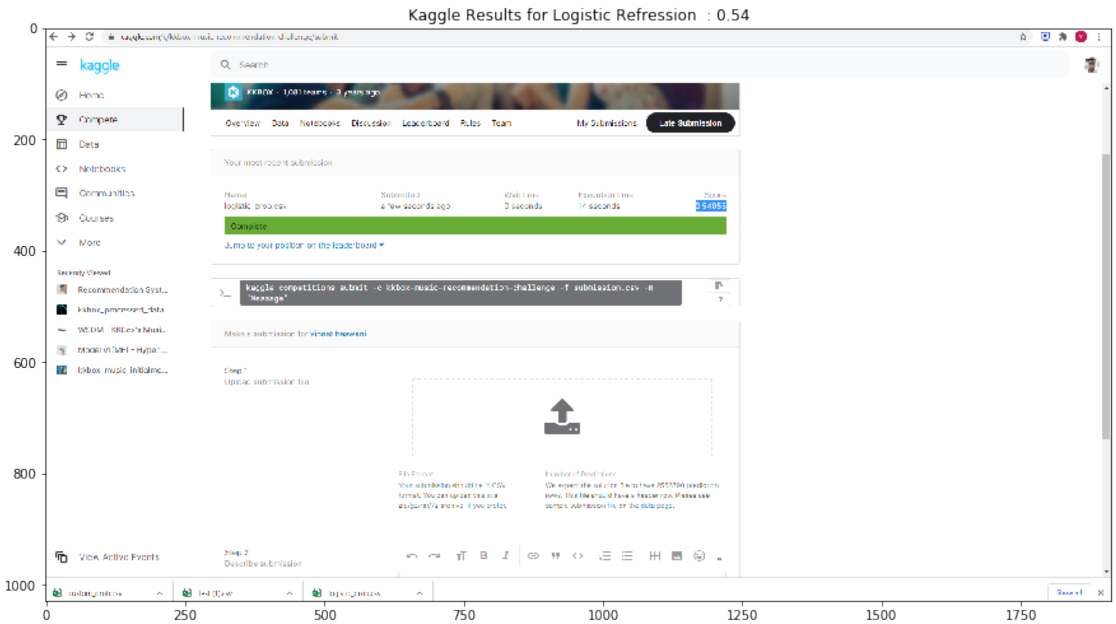
Sum of columns in precision matrix [1. 1.]
-- Recall matrix




```
Sum of rows in precision matrix [1. 1.]
```

[16]:
```
import matplotlib.pyplot as plt
import cv2
plt.figure(figsize = (15, 20))
plt.title('Kaggle Results for Logistic Refression  : 0.54')
plt.imshow(cv2.cvtColor(cv2.imread('logistic Regression prob.png'), cv2.
 ↪COLOR_BGR2RGB))
```

[16]:
```
<matplotlib.image.AxesImage at 0x1d7531dc208>
```



2. SGDClassifier with log loss

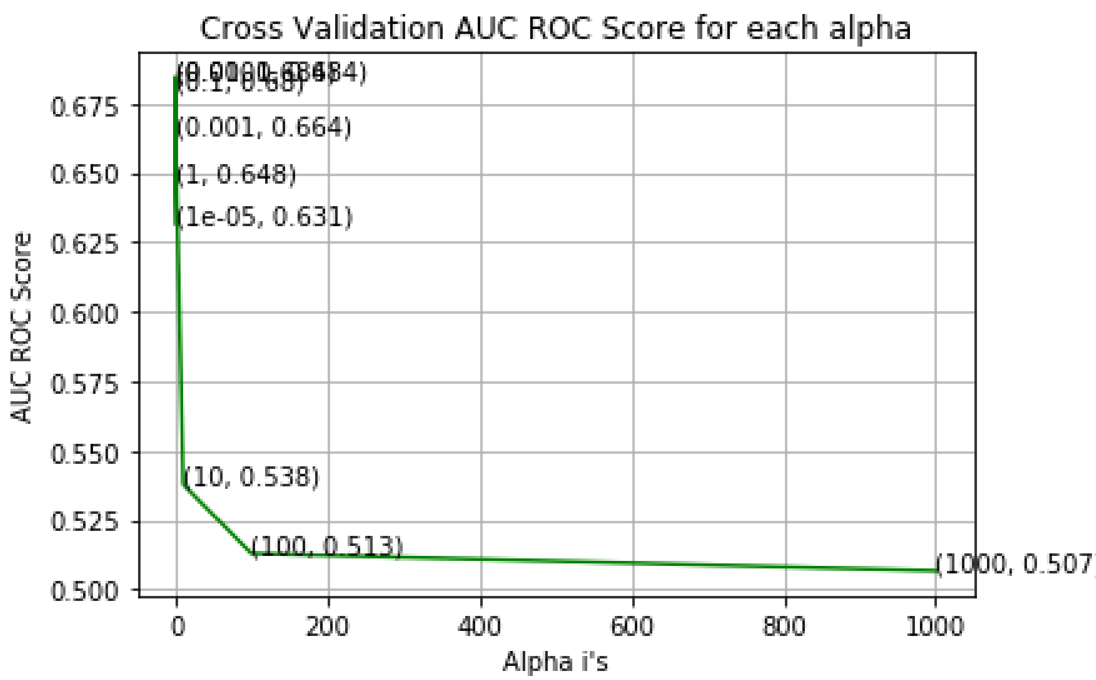
[6]:
```
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

alphas = [10 ** x for x in range(-5, 4)]
cv_logs = []
for i in alphas:
    regressor = SGDClassifier(penalty='l2',alpha=i,class_weight='balanced')
    regressor.fit(x_train, y_train)
    sig_clf = CalibratedClassifierCV(regressor, method="sigmoid")
    sig_clf.fit(x_train, y_train)
    y_pred = sig_clf.predict_proba(x_val)
    score = roc_auc_score(y_val, y_pred[:, 1])
    print ('AUC ROC Score for c = ',i,'is',score)
    cv_logs.append(score)

fig, ax = plt.subplots()
ax.plot(alphas, cv_logs,c='g')
for i, txt in enumerate(np.round(cv_logs,3)):
    ax.annotate((alphas[i],np.round(txt,3)), (alphas[i],cv_logs[i]))
plt.grid()
plt.title("Cross Validation AUC ROC Score for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("AUC ROC Score")
```

```
plt.show()
```

```
AUC ROC Score for c =  1e-05 is 0.6314927694977276
AUC ROC Score for c =  0.0001 is 0.6843973579421669
AUC ROC Score for c =  0.001 is 0.6641265100237393
AUC ROC Score for c =  0.01 is 0.6843594993560639
AUC ROC Score for c =  0.1 is 0.6802011765466669
AUC ROC Score for c =  1 is 0.647585506803966
AUC ROC Score for c =  10 is 0.5380404000104143
AUC ROC Score for c =  100 is 0.5129237882688955
AUC ROC Score for c =  1000 is 0.5067033561296438
```

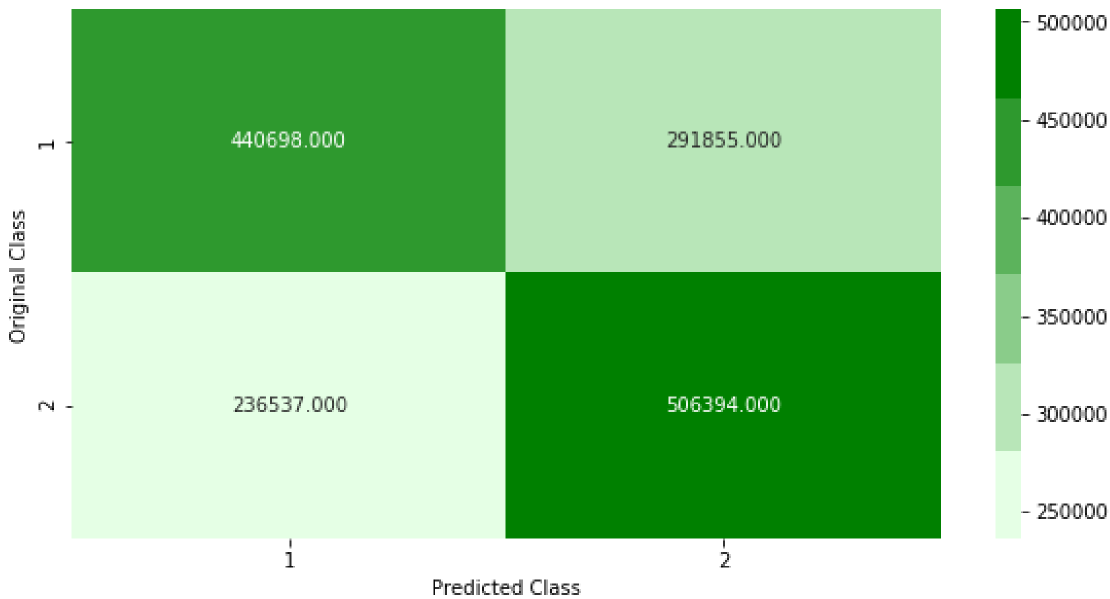


[7]:
```
regressor = SGDClassifier(penalty='l2',alpha=0.01,class_weight='balanced')
regressor.fit(x_train, y_train)
sig_clf = CalibratedClassifierCV(regressor, method="sigmoid")
sig_clf.fit(x_train, y_train)
y_pred = sig_clf.predict_proba(x_val)
score = roc_auc_score(y_val, y_pred[:, 1])
print ('validation AUC ROC Score for c = ',0.01,'is',score)
y_pred = sig_clf.predict_proba(x_test)
score = roc_auc_score(y_test, y_pred[:, 1])
print ('Test AUC ROC Score for c = ',0.01,'is',score)
```

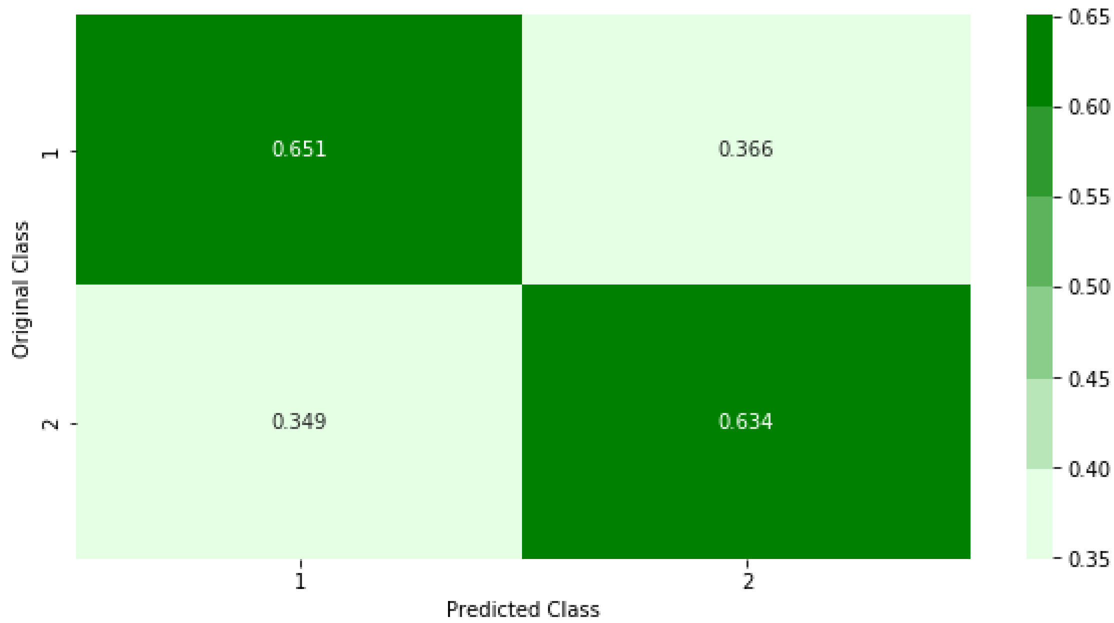
```
validation AUC ROC Score for c =  0.01 is 0.6843594993560639
Test AUC ROC Score for c =  0.01 is 0.6846739588359931
```

[20]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
plot_confusion_matrix(y_test, sig_clf.predict(x_test))
```

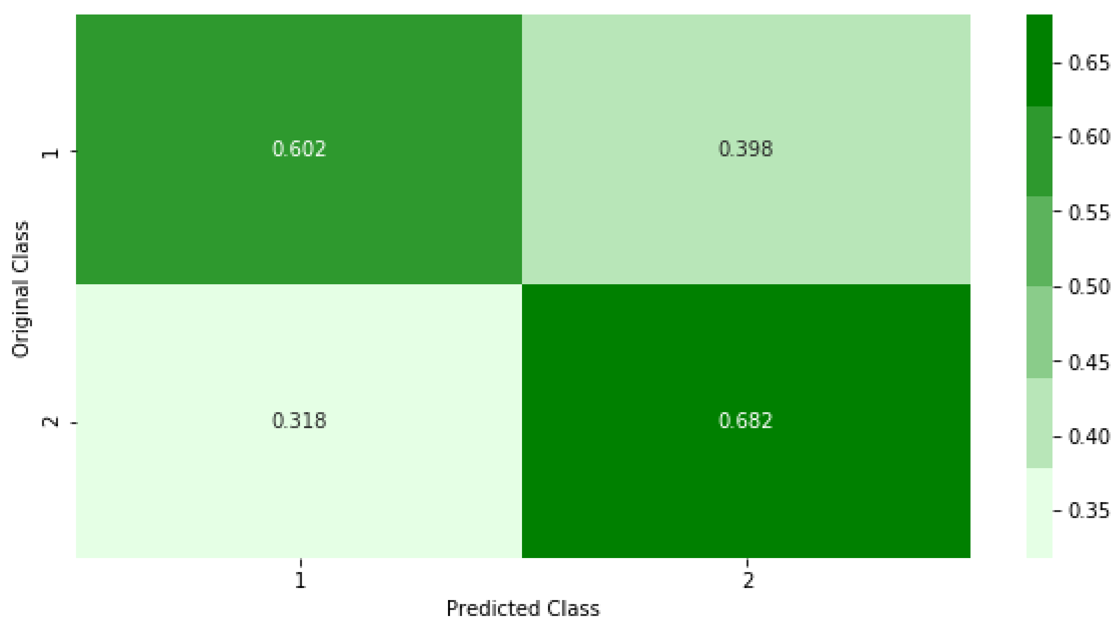
```
Percentage of misclassified points  35.811 %
-------------------------------------------------- Confusion matrix
--------------------------------------------------
```




```
-------------------------------------------------- Precision matrix
--------------------------------------------------
```



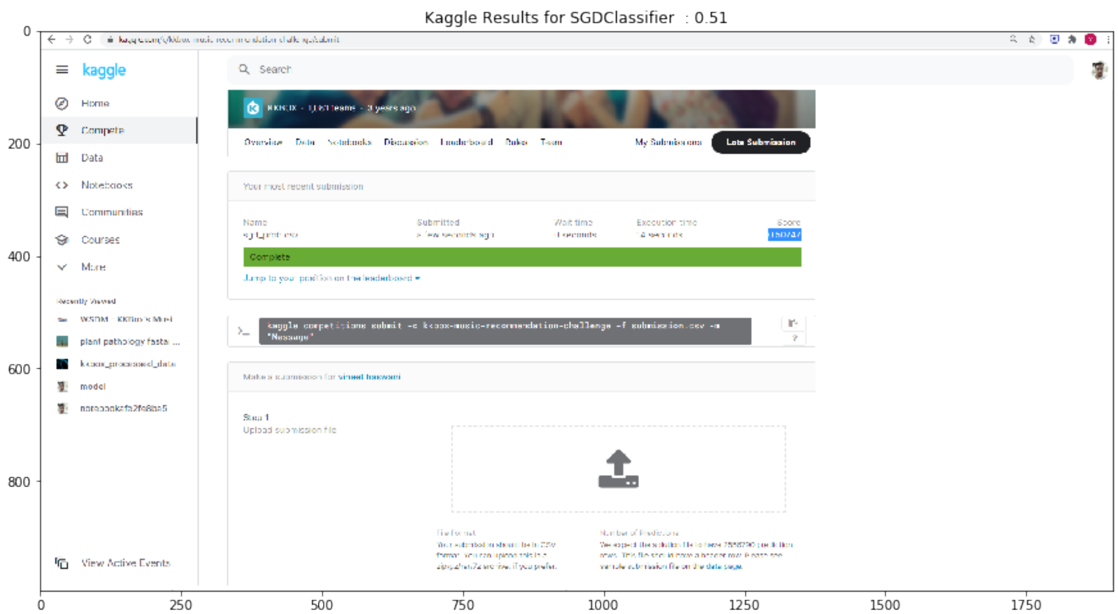

```
Sum of columns in precision matrix [1. 1.]
--------------------------------------------------- Recall matrix
---------------------------------------------------
```




```
Sum of rows in precision matrix [1. 1.]
```

```
[18]: import matplotlib.pyplot as plt
      import cv2
      plt.figure(figsize = (15, 20))
      plt.title('Kaggle Results for SGDClassifier  : 0.51')
      plt.imshow(cv2.cvtColor(cv2.imread('sgd_prob.png'), cv2.COLOR_BGR2RGB))
```

```
[18]: <matplotlib.image.AxesImage at 0x1d7577b0388>
```



3. Decision Tree

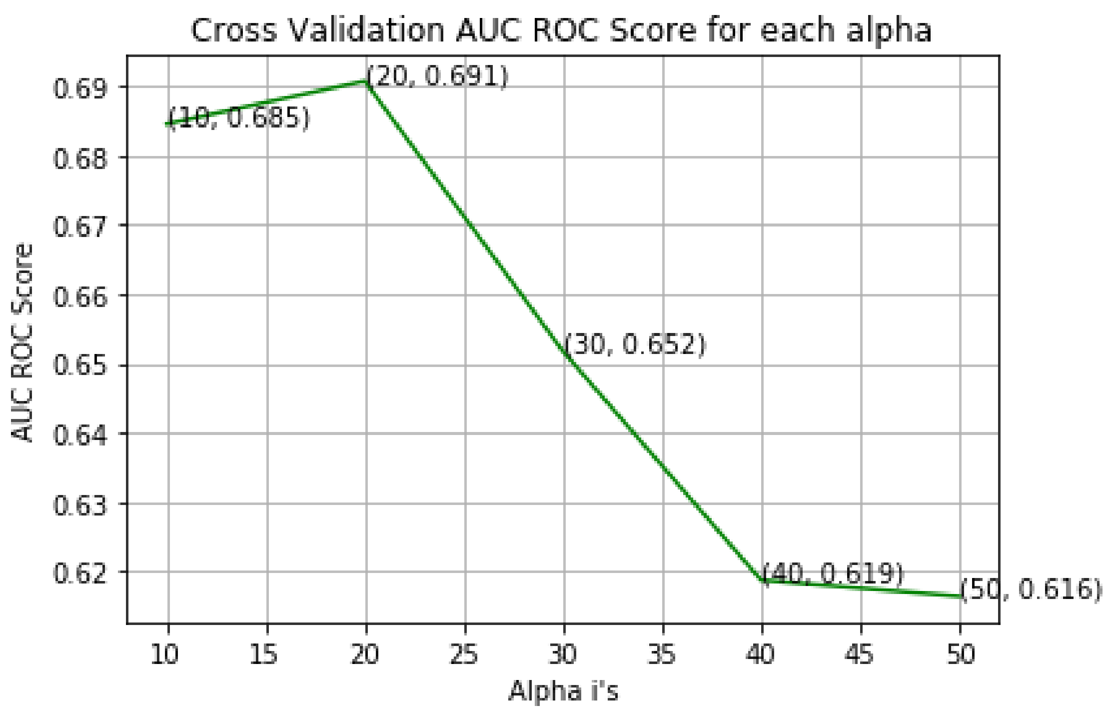
```
[6]: from sklearn.tree import DecisionTreeClassifier
     from sklearn.calibration import CalibratedClassifierCV
     from sklearn.metrics import roc_auc_score
     import matplotlib.pyplot as plt

     depth=[10, 20, 30, 40, 50]
     cv_logs=[]
     for i in depth:
         classifier=DecisionTreeClassifier(max_depth=i,random_state=42)
         classifier.fit(x_train, y_train)
         y_pred = classifier.predict_proba(x_val)
         score = roc_auc_score(y_val, y_pred[:, 1])
         print ('AUC ROC Score for depth = ',i,'is',score)
         cv_logs.append(score)

     fig, ax = plt.subplots()
     ax.plot(alphas, cv_logs,c='g')
```

```
for i, txt in enumerate(np.round(cv_logs,3)):
    ax.annotate((alphas[i],np.round(txt,3)), (alphas[i],cv_logs[i]))
plt.grid()
plt.title("Cross Validation AUC ROC Score for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("AUC ROC Score")
plt.show()
```

```
AUC ROC Score for depth =  10 is 0.6845244398493214
AUC ROC Score for depth =  20 is 0.6907042320141951
AUC ROC Score for depth =  30 is 0.6517873490908819
AUC ROC Score for depth =  40 is 0.6187848824044917
AUC ROC Score for depth =  50 is 0.6164559012685721
```

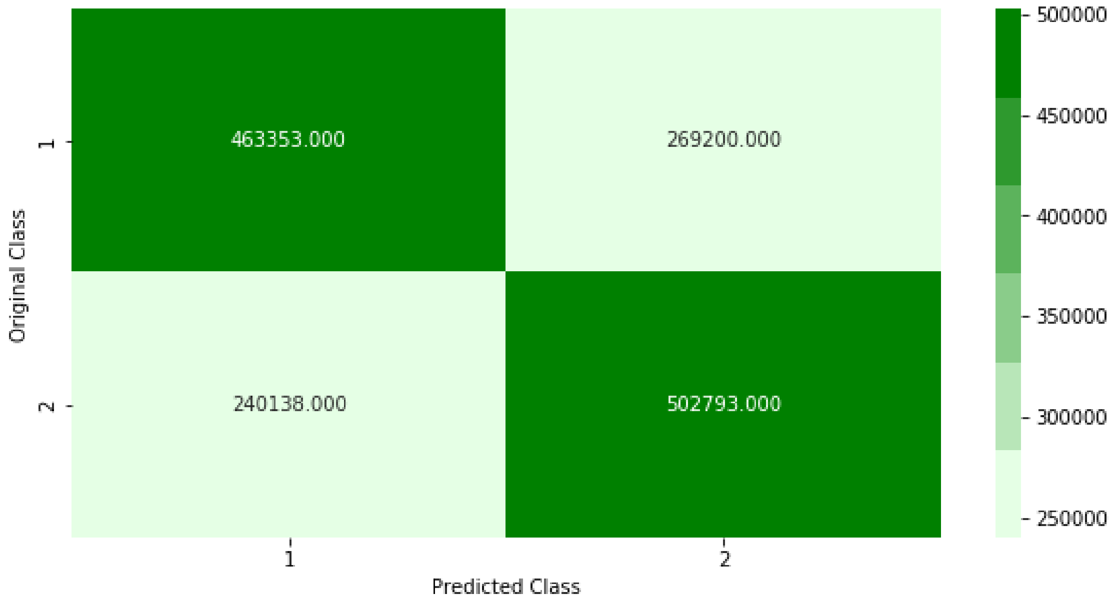


[13]:
```
classifier=DecisionTreeClassifier(max_depth=20,random_state=42)
classifier.fit(x_train, y_train)
y_pred = classifier.predict_proba(x_val)
score = roc_auc_score(y_val, y_pred[:, 1])
print ('validation AUC ROC Score for depth = ',20,'is',score)
y_pred = classifier.predict_proba(x_test)
score = roc_auc_score(y_test, y_pred[:, 1])
print ('Test AUC ROC Score for depth = ',20,'is',score)
```

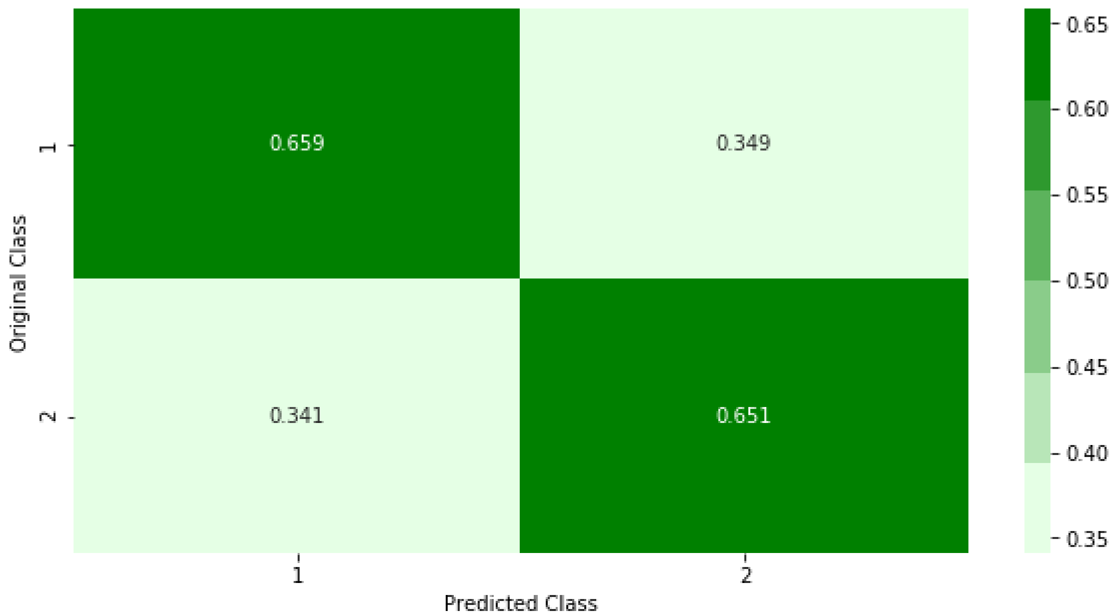
```
validation AUC ROC Score for depth =  20 is 0.6907042320141951
Test AUC ROC Score for depth =  20 is 0.6924008796996413
```

[24]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
plot_confusion_matrix(y_test, classifier.predict(x_test))
```

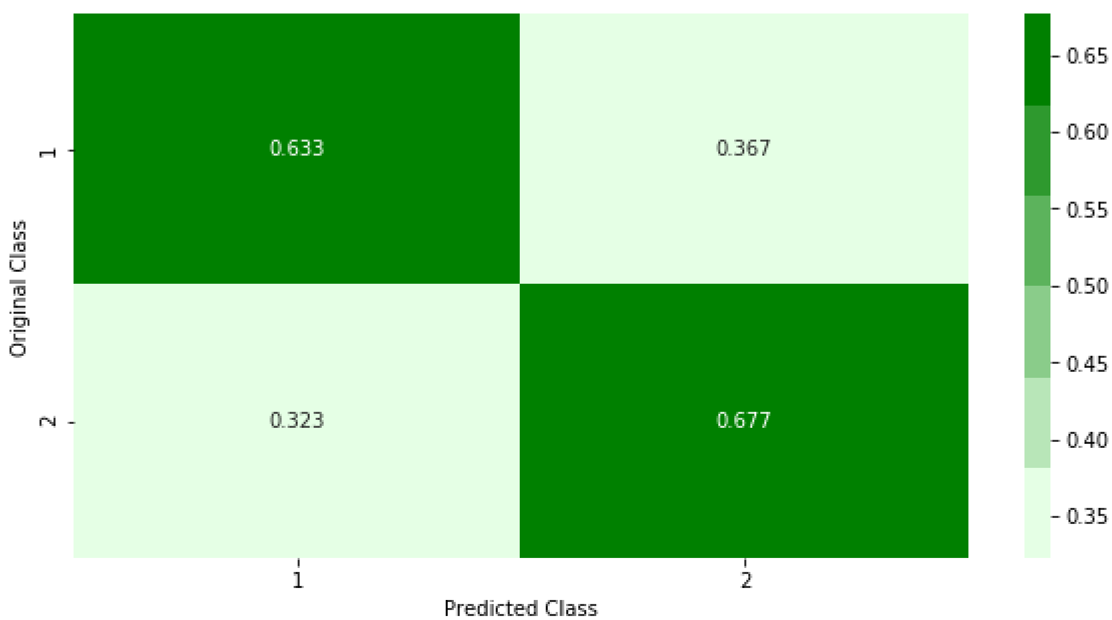
```
Percentage of misclassified points  34.52 %
-------------------------------------------------- Confusion matrix
--------------------------------------------------
```




```
-------------------------------------------------- Precision matrix
--------------------------------------------------
```



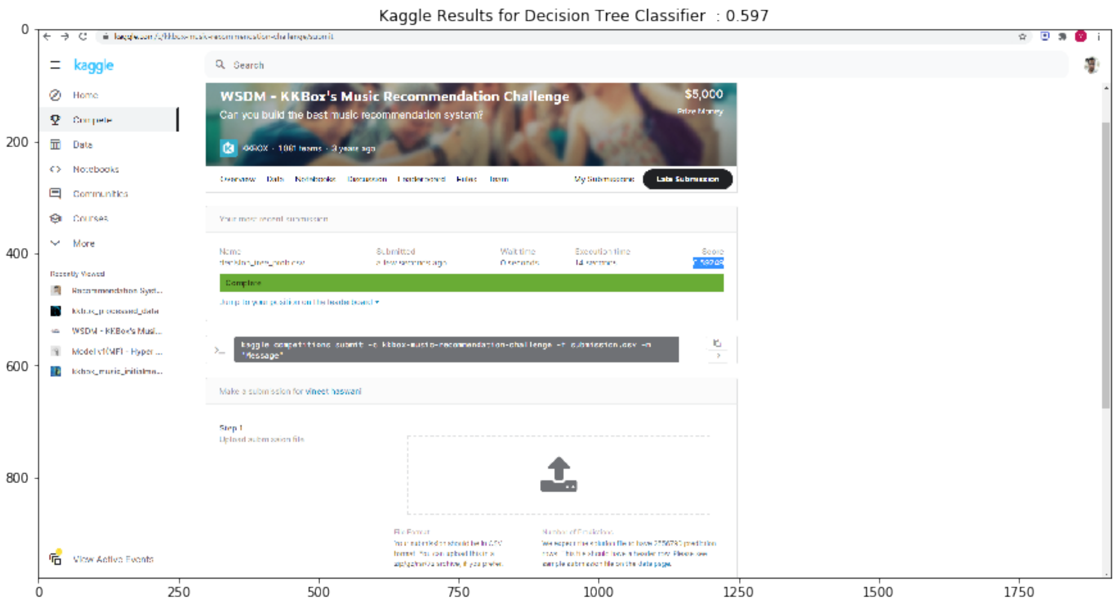

```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix
--------------------------------------------------
```




```
Sum of rows in precision matrix [1. 1.]
```

```
[20]: import matplotlib.pyplot as plt
      import cv2
      plt.figure(figsize = (15, 20))
      plt.title('Kaggle Results for Decision Tree Classifier  : 0.597')
      plt.imshow(cv2.cvtColor(cv2.imread('Decision Tree prob.png'), cv2.
       ↪COLOR_BGR2RGB))
```

```
[20]: <matplotlib.image.AxesImage at 0x1d7575283c8>
```



4. Random Forest

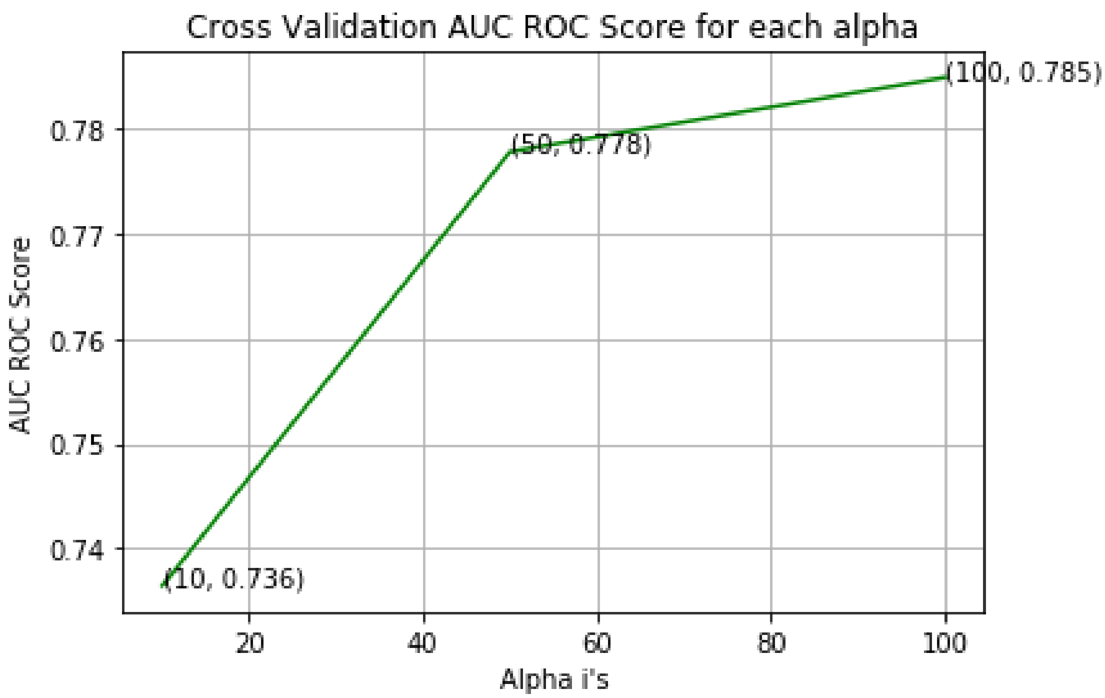
```
[9]: from sklearn.ensemble import RandomForestClassifier
     from sklearn.calibration import CalibratedClassifierCV
     from sklearn.metrics import roc_auc_score
     import matplotlib.pyplot as plt

     alphas=[10,50,100]
     cv_logs=[]
     for i in alphas:
         classifier=RandomForestClassifier(n_estimators=i,random_state=42,n_jobs=-1)
         classifier.fit(x_train, y_train)
         y_pred = classifier.predict_proba(x_val)
         score = roc_auc_score(y_val, y_pred[:, 1])
         print ('AUC ROC Score for c = ',i,'is',score)
         cv_logs.append(score)

     fig, ax = plt.subplots()
```

```
ax.plot(alphas, cv_logs,c='g')
for i, txt in enumerate(np.round(cv_logs,3)):
    ax.annotate((alphas[i],np.round(txt,3)), (alphas[i],cv_logs[i]))
plt.grid()
plt.title("Cross Validation AUC ROC Score for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("AUC ROC Score")
plt.show()
```

```
AUC ROC Score for c =  10 is 0.736468057712352
AUC ROC Score for c =  50 is 0.7777900131752978
AUC ROC Score for c =  100 is 0.7848667134629947
```



[1]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

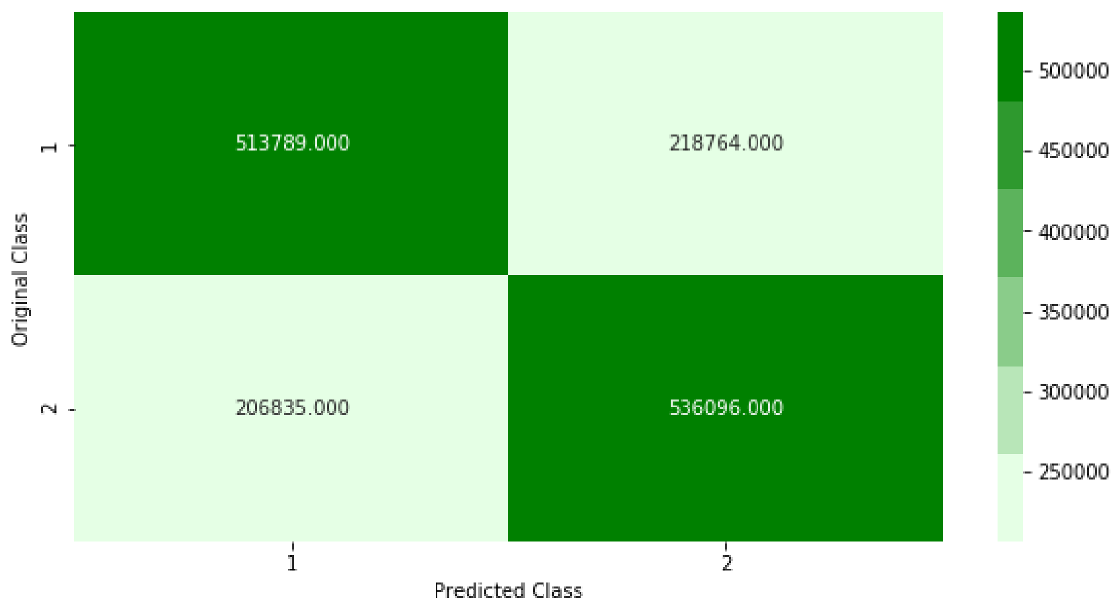
classifier=RandomForestClassifier(n_estimators=100,random_state=42, n_jobs = 6)
classifier.fit(x_train, y_train)
y_pred = classifier.predict_proba(x_val)
score = roc_auc_score(y_val, y_pred[:, 1])
print ('validation AUC ROC Score for c = ',100,'is',score)
y_pred = classifier.predict_proba(x_test)
```

```
score = roc_auc_score(y_test, y_pred[:, 1])
print ('Test AUC ROC Score for c = ',100,'is',score)
```

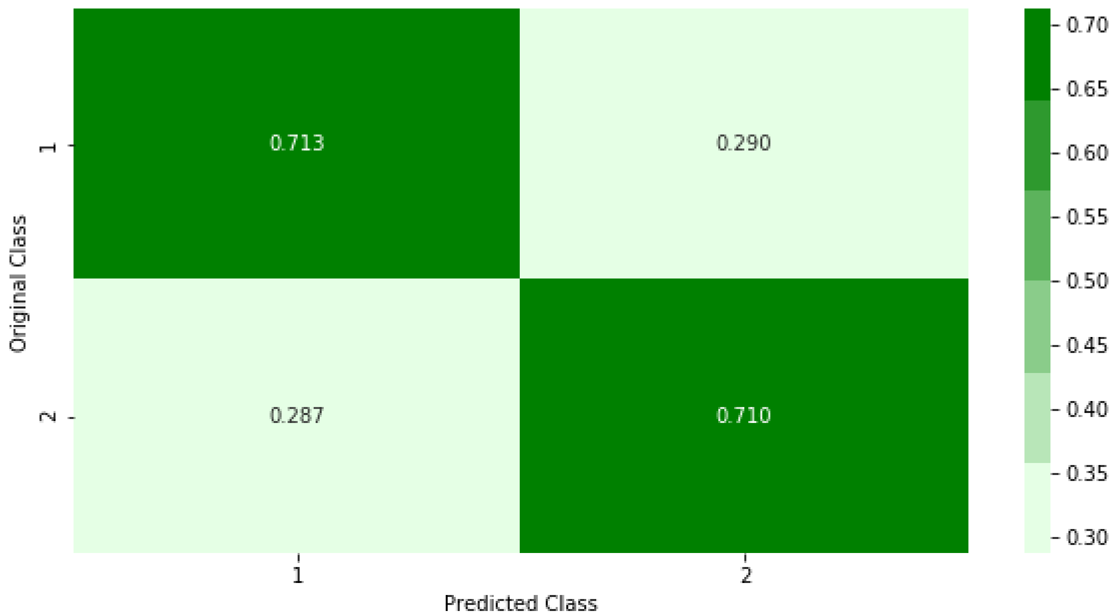
```
validation AUC ROC Score for c =  100 is 0.7848667134629947
Test AUC ROC Score for c =  100 is 0.7856958254261837
```

[22]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
plot_confusion_matrix(y_test, classifier.predict(x_test))
```

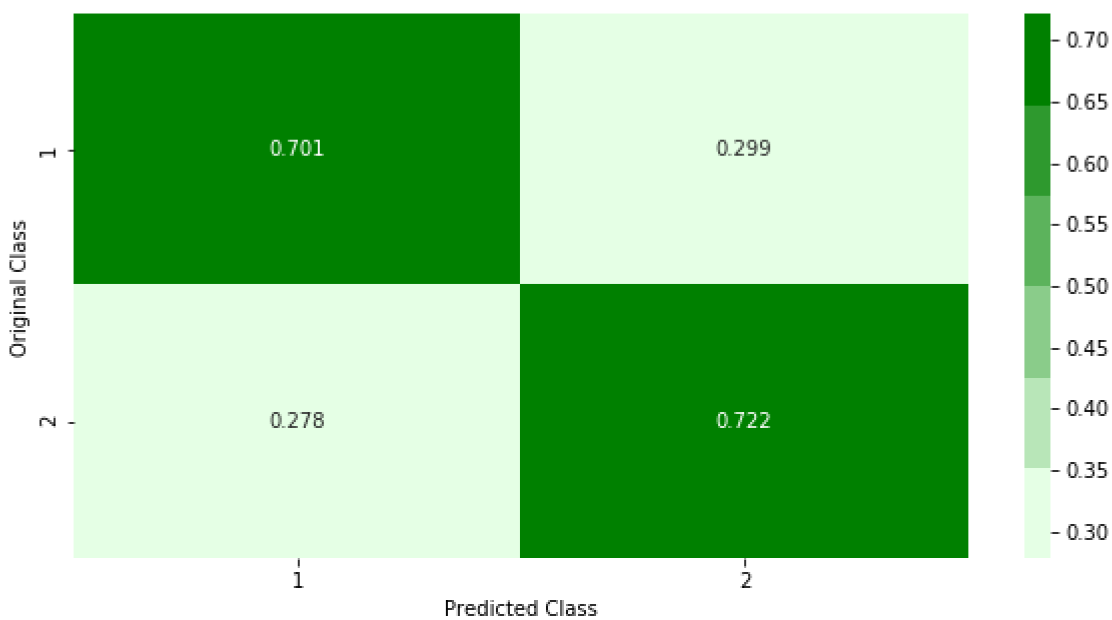
```
Percentage of misclassified points  28.845 %
-------------------------------------------------- Confusion matrix
--------------------------------------------------
```




```
-------------------------------------------------- Precision matrix
--------------------------------------------------
```



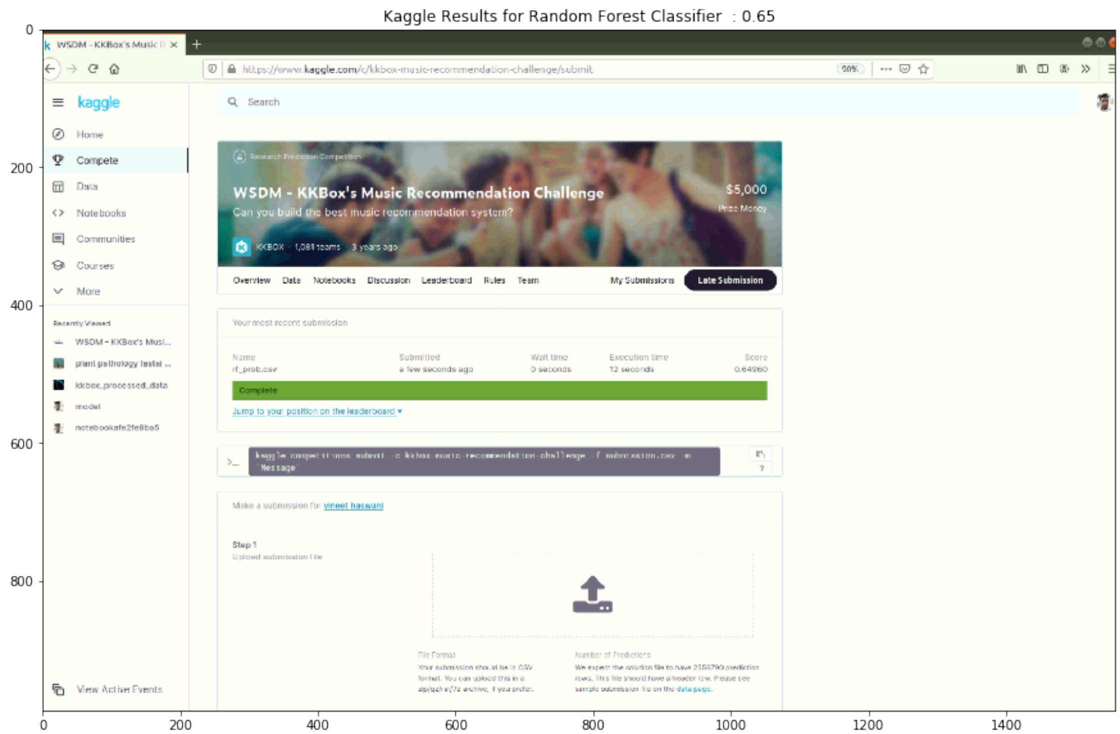

```
Sum of columns in precision matrix [1. 1.]
--------------------------------------------------- Recall matrix
---------------------------------------------------
```




```
Sum of rows in precision matrix [1. 1.]
```

```
[28]: import matplotlib.pyplot as plt
      import cv2
      plt.figure(figsize = (15, 20))
      plt.title('Kaggle Results for Random Forest Classifier  : 0.65')
      plt.imshow(cv2.cvtColor(cv2.imread('Random Forest prob.png'), cv2.
       ↪COLOR_BGR2RGB))
```

```
[28]: <matplotlib.image.AxesImage at 0x1d757fa4cc8>
```



5. AdaBoost

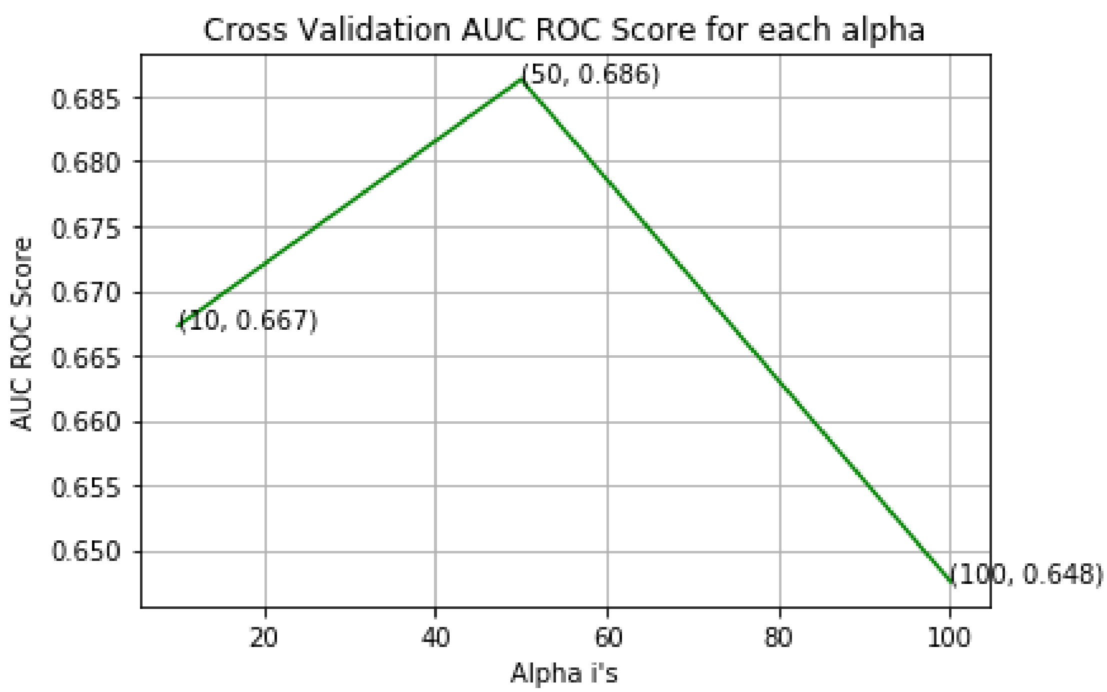
```
[5]: from sklearn.ensemble import AdaBoostClassifier
     from sklearn.calibration import CalibratedClassifierCV
     from sklearn.metrics import roc_auc_score
     import matplotlib.pyplot as plt

     alphas=[10,50,100]
     cv_logs=[]
     for i in alphas:
         classifier=AdaBoostClassifier(n_estimators=i,random_state=42,n_jobs=-1)
         classifier.fit(x_train, y_train)
         y_pred = classifier.predict_proba(x_val)
         score = roc_auc_score(y_val, y_pred[:, 1])
         print ('AUC ROC Score for c = ',i,'is',score)
```

```
    cv_logs.append(score)

fig, ax = plt.subplots()
ax.plot(alphas, cv_logs,c='g')
for i, txt in enumerate(np.round(cv_logs,3)):
    ax.annotate((alphas[i],np.round(txt,3)), (alphas[i],cv_logs[i]))
plt.grid()
plt.title("Cross Validation AUC ROC Score for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("AUC ROC Score")
plt.show()
```

```
AUC ROC Score for c =  10 is 0.6672817891319418
AUC ROC Score for c =  50 is 0.6863191808701756
AUC ROC Score for c =  100 is 0.6902886908284588
```



[8]:
```
classifier=AdaBoostClassifier(n_estimators=50,random_state=42)
classifier.fit(x_train, y_train)
y_pred = classifier.predict_proba(x_train)

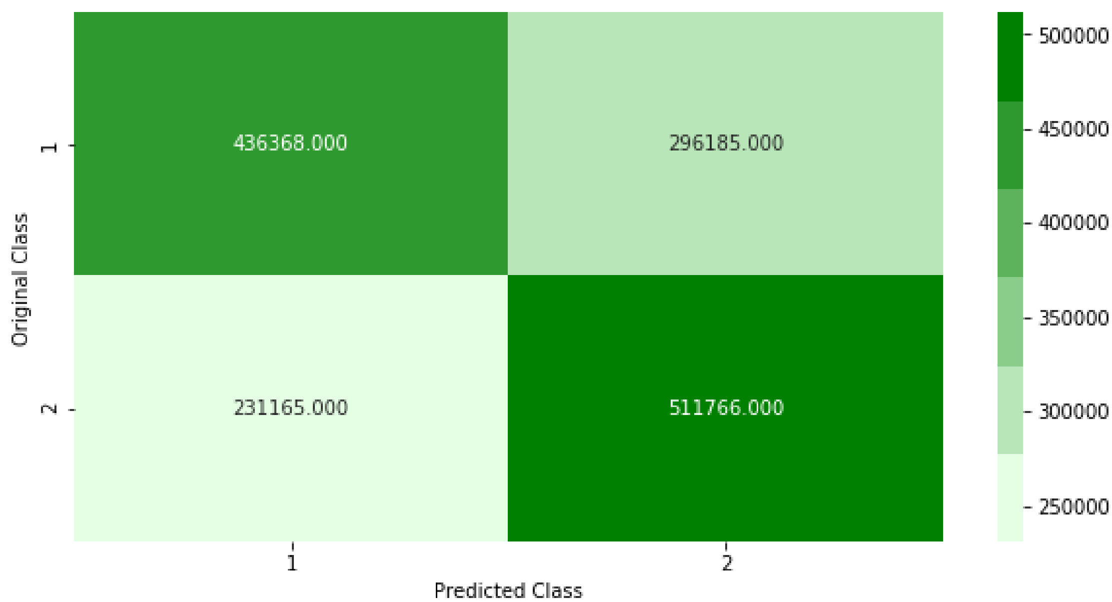
score = roc_auc_score(y_train, y_pred[:, 1])
print ('Train AUC ROC Score for c = ',50,'is',score)
y_pred = classifier.predict_proba(x_val)
score = roc_auc_score(y_val, y_pred[:, 1])
print ('validation AUC ROC Score for c = ',50,'is',score)
```

```
y_pred = classifier.predict_proba(x_test)
score = roc_auc_score(y_test, y_pred[:, 1])
print ('Test AUC ROC Score for c = ',50,'is',score)
```

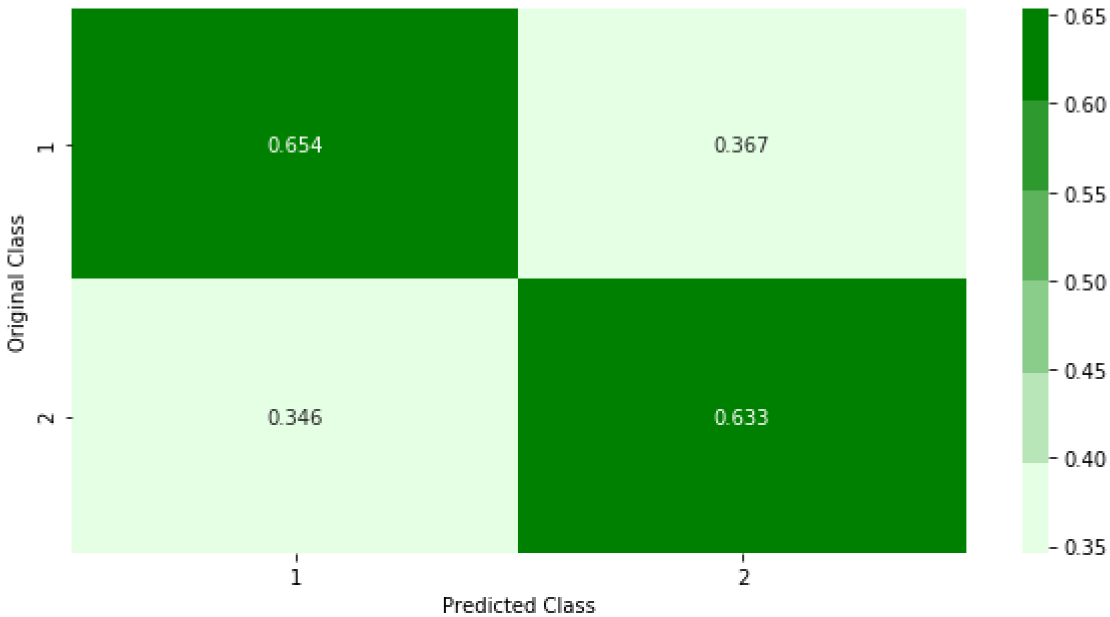
```
Train AUC ROC Score for c =  50 is 0.6865621097439154
validation AUC ROC Score for c =  50 is 0.6863191808701756
Test AUC ROC Score for c =  50 is 0.6863646809616059
```

[18]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
plot_confusion_matrix(y_test, classifier.predict(x_test))
```

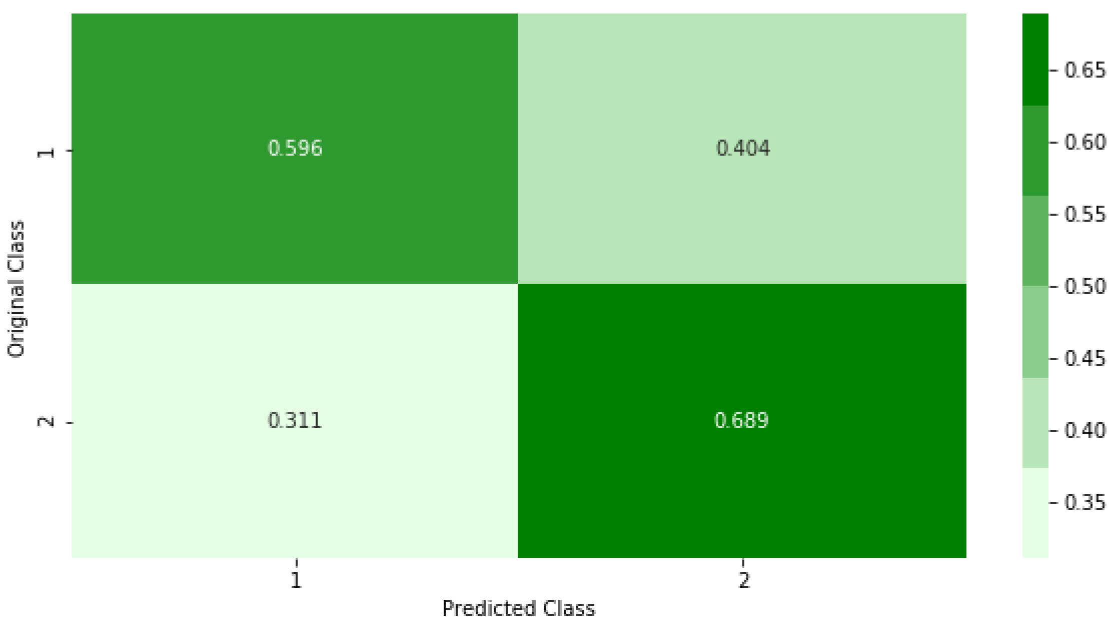
```
Percentage of misclassified points  35.741 %
-------------------------------------------------- Confusion matrix
--------------------------------------------------
```




```
-------------------------------------------------- Precision matrix
--------------------------------------------------
```



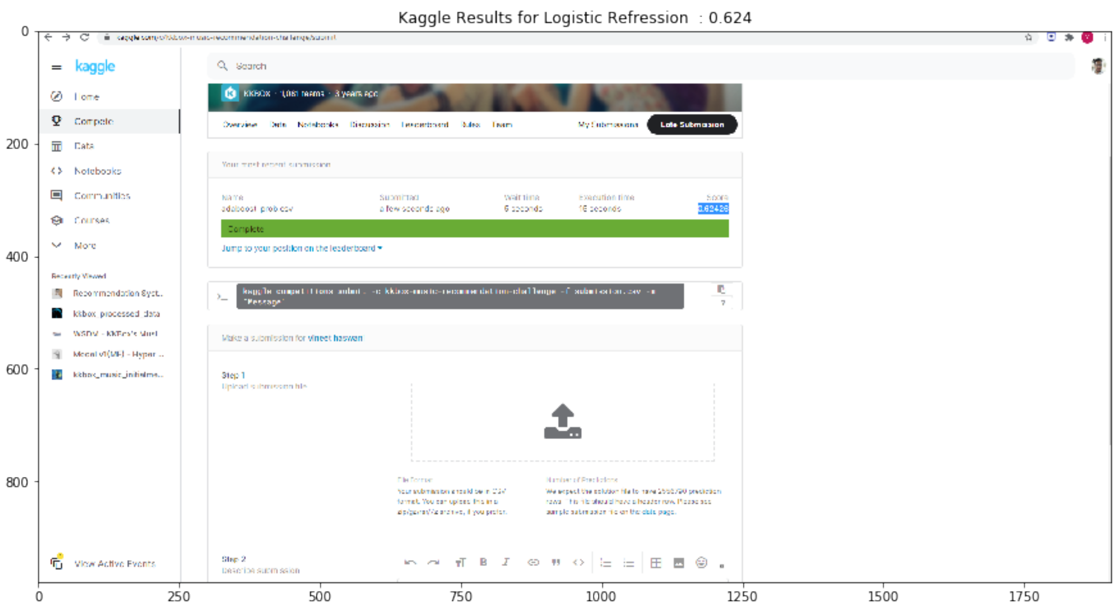
Sum of columns in precision matrix [1. 1.]
--- Recall matrix



Sum of rows in precision matrix [1. 1.]

[4]:
```python
import matplotlib.pyplot as plt
import cv2
plt.figure(figsize = (15, 20))
plt.title('Kaggle Results for Logistic Refression  : 0.624')
plt.imshow(cv2.cvtColor(cv2.imread('Adaboost prob.png'), cv2.COLOR_BGR2RGB))
```

[4]:
```
<matplotlib.image.AxesImage at 0x158a4dd6508>
```

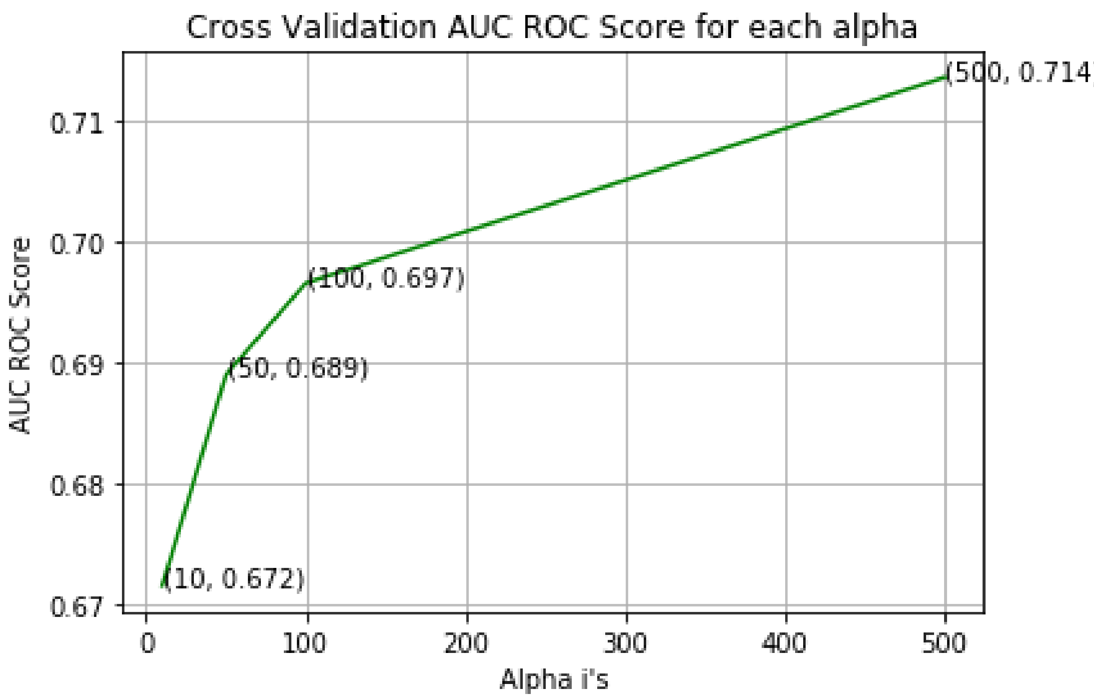


6. XGBoost

[21]:
```python
from xgboost import XGBClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

alpha=[10,50,100,500]
cv_logs=[]
for i in alpha:
    classifier=XGBClassifier(n_estimators=i,nthread=-1)
    classifier.fit(x_train, y_train)
    y_pred = classifier.predict_proba(x_val)
    score = roc_auc_score(y_val, y_pred[:, 1])
    print ('AUC ROC Score for c = ',i,'is',score)
    cv_logs.append(score)

fig, ax = plt.subplots()
ax.plot(alphas, cv_logs,c='g')
```

```
for i, txt in enumerate(np.round(cv_logs,3)):
    ax.annotate((alphas[i],np.round(txt,3)), (alphas[i],cv_logs[i]))
plt.grid()
plt.title("Cross Validation AUC ROC Score for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("AUC ROC Score")
plt.show()
```

```
AUC ROC Score for c =  10 is 0.6715350819922914
AUC ROC Score for c =  50 is 0.6890097897657351
AUC ROC Score for c =  100 is 0.6965871653598837
AUC ROC Score for c =  500 is 0.7135917108237587
```



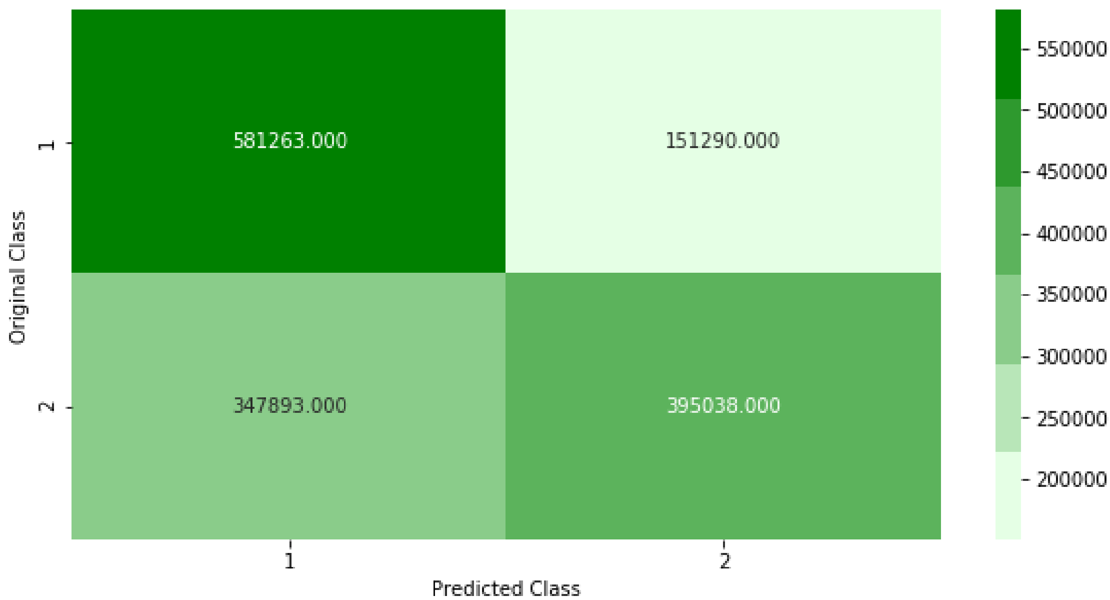
[23]:
```
from xgboost import XGBClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt

classifier=XGBClassifier(n_estimators=500,nthread=-1)
classifier.fit(x_train, y_train)

y_pred = sig_clf.predict_proba(x_val)
score = roc_auc_score(y_val, y_pred[:, 1])
print ('validation AUC ROC Score for c = ',0.01,'is',score)
```

```
y_pred = sig_clf.predict_proba(x_test)
score = roc_auc_score(y_test, y_pred[:, 1])
print ('Test AUC ROC Score for c = ',0.01,'is',score)
```

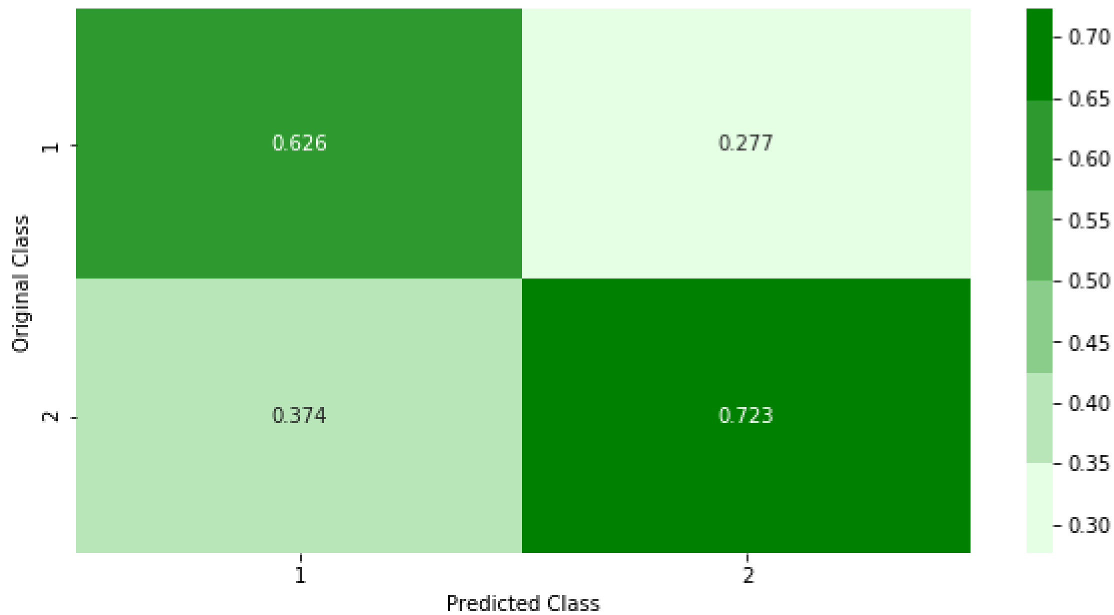
```
validation AUC ROC Score for c =  500 is 0.7135917108237587
Test AUC ROC Score for c =  500 is 0.7123181532419605
```

[11]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
plot_confusion_matrix(y_test, classifier.predict(x_test))
```

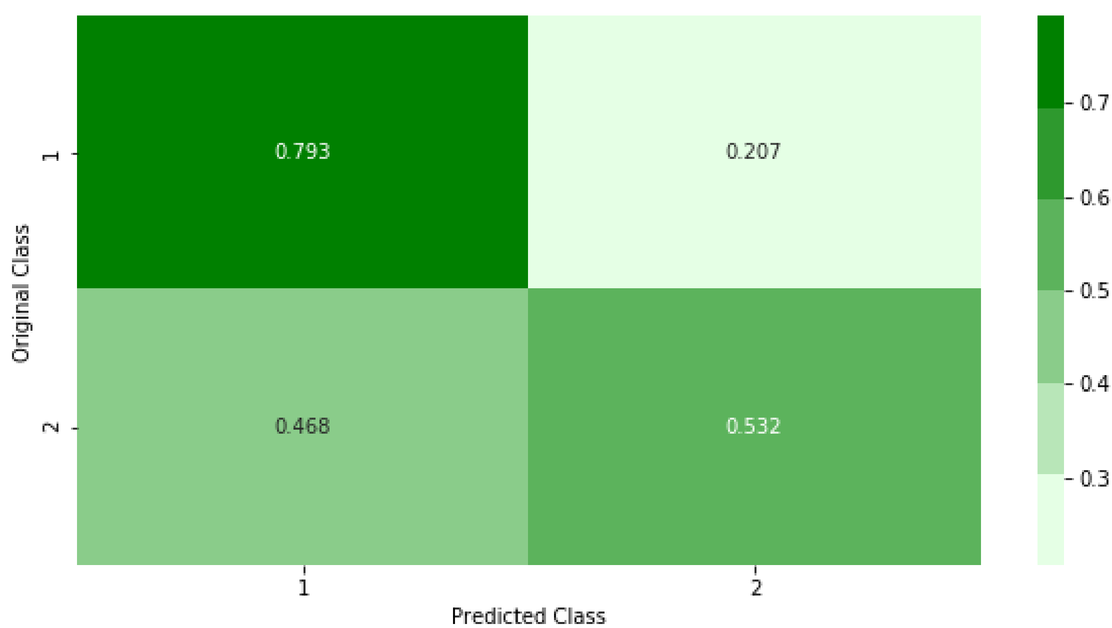
```
Percentage of misclassified points  33.832 %
-------------------------------------------------- Confusion matrix
--------------------------------------------------
```




```
-------------------------------------------------- Precision matrix
--------------------------------------------------
```



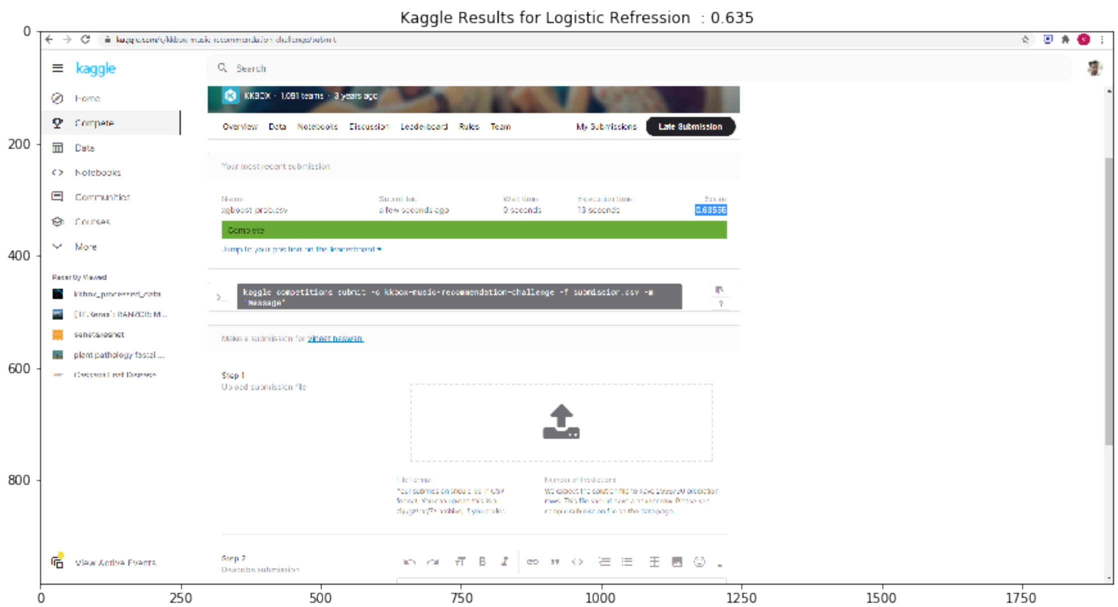

```
Sum of columns in precision matrix [1. 1.]
-------------------------------------------------- Recall matrix
--------------------------------------------------
```




```
Sum of rows in precision matrix [1. 1.]
```

[24]:
```python
import matplotlib.pyplot as plt
import cv2
plt.figure(figsize = (15, 20))
plt.title('Kaggle Results for Logistic Refression  : 0.635')
plt.imshow(cv2.cvtColor(cv2.imread('xgboost_prob.png'), cv2.COLOR_BGR2RGB))
```

[24]: <matplotlib.image.AxesImage at 0x1d75939a7c8>



7. Custom Ensemble Model

[ ]:
```python
import numpy as np
def generating_samples(input_data, target_data):
    selected_rows = np.sort(np.random.choice(input_data.shape[0], int(input_data.shape[0]*0.6), replace = True))

    sampled_input_data = input_data.iloc[selected_rows, :]
    sampled_target_data = target_data.iloc[selected_rows, :]

    return sampled_input_data , sampled_target_data, selected_rows
```

[1]:
```python
from scipy.stats import mode
from tqdm import tqdm
from sklearn.metrics import roc_auc_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

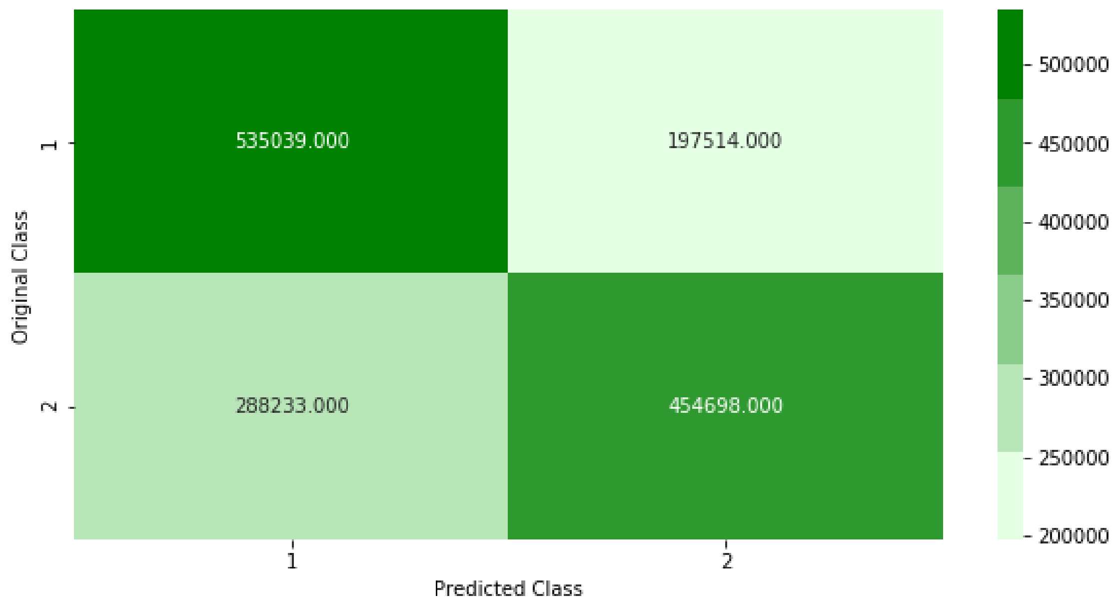
```python
def custom_model(x_train, y_train, x_test, y_test, n_estimators = 10, alpha =␣
↪100, max_depth = 40):
    # x_train, x_test, y_train, y_test = train_test_split(x_train, y_train,␣
↪test_size = 0.5, random_state = 0, stratify = y_train)
    d1_x_train, d2_x_train, d1_y_train, d2_y_train = train_test_split(x_train,␣
↪y_train, test_size = 0.5, random_state = 0, stratify = y_train)
    predictions = []
    base_models = []
    for i in tqdm(range(n_estimators)):
        ## generating samples
        x, y, rows = generating_samples(d1_x_train, d1_y_train)
        ## training base model
        base_model = DecisionTreeClassifier(max_depth=max_depth,random_state=42)
        base_model.fit(x, y)
        pred = base_model.predict_proba(d2_x_train)[:, 1].reshape(-1, 1)
        predictions.append(pred)
        base_models.append(base_model)
    predictions = np.array(predictions).T
    predictions = predictions.reshape(-1, n_estimators)

    ## training meta model
    meta_model =␣
↪LogisticRegression(penalty='l2',C=alpha,class_weight='balanced')
    meta_model.fit(predictions, d2_y_train)
    y_pred = meta_model.predict_proba(predictions)

    score = roc_auc_score(d2_y_train, y_pred[:, 1])
    print('AUC Score of Model on train set is :', score )

    ### Calculate AUC ROC Score on test set
    predictions = []
    for base_model in base_models:
        pred = base_model.predict_proba(x_test)[:, 1].reshape(-1, 1)
        predictions.append(pred)
    predictions = np.array(predictions).T
    predictions = predictions.reshape(-1, n_estimators)
    y_pred = meta_model.predict_proba(predictions)
    score = roc_auc_score(y_test, y_pred[:, 1])
    print('AUC Score of Model on test set is :', score )
    return base_models, meta_model, y_pred

base_models, meta_model, y_pred = custom_model(x_train, y_train, x_test,␣
↪y_test, n_estimators = 100, alpha = 100, max_depth = 10)
```

```
AUC Score of Model on train set is : 0.6959068940143411
AUC Score of Model on test set is : 0.6961223438481663
```

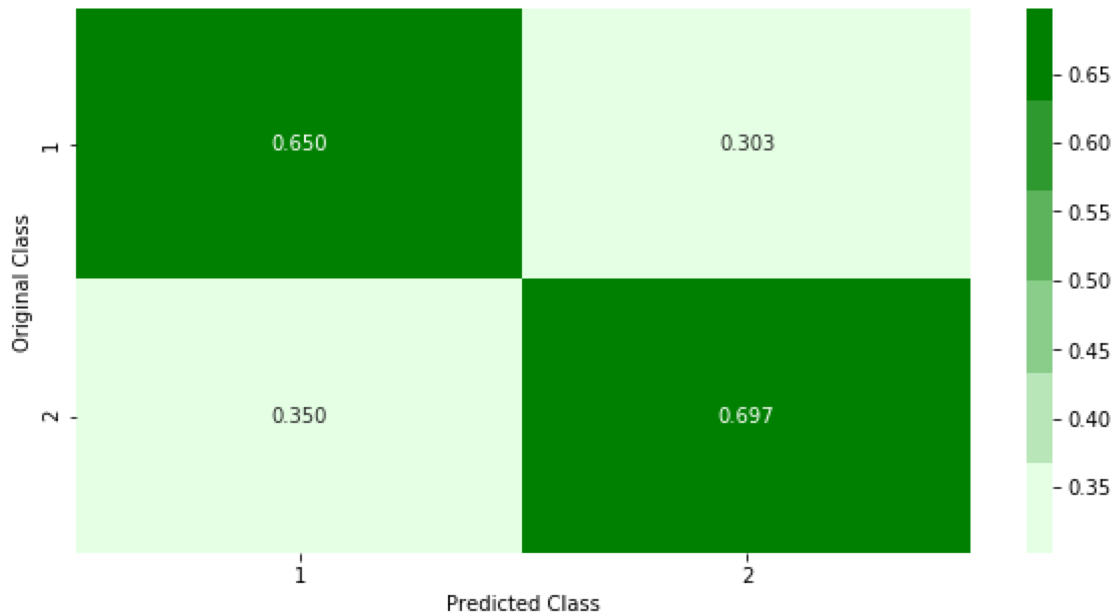
[11]:

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
plot_confusion_matrix(y_test, y_pred[:, 1] >0.5)
```

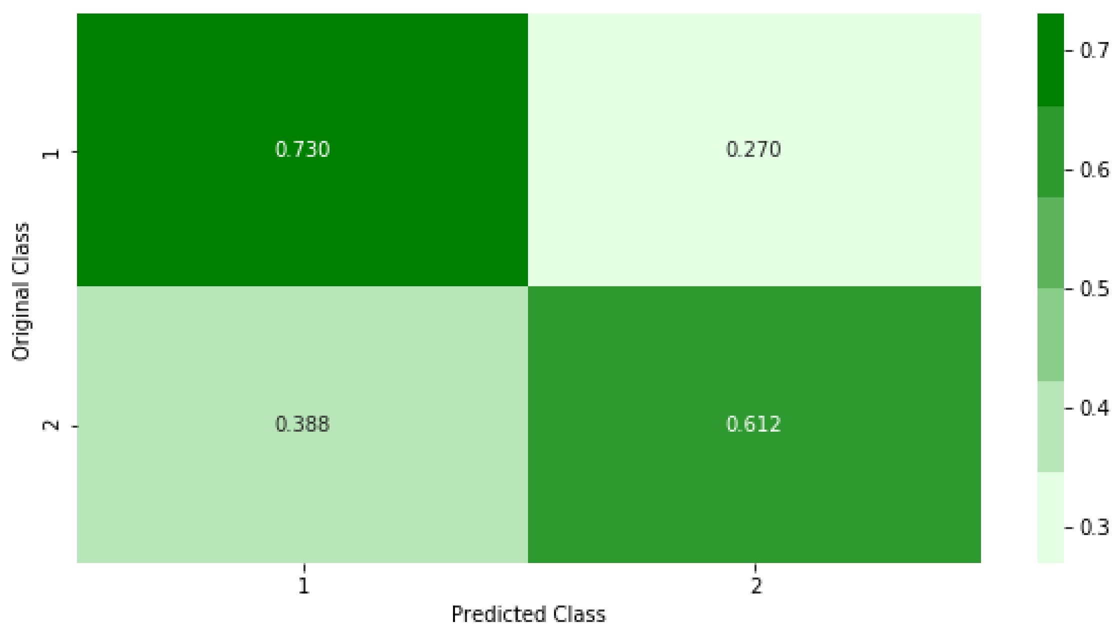
```
Percentage of misclassified points  32.921 %
-------------------------------------------------- Confusion matrix
--------------------------------------------------
```




```
-------------------------------------------------- Precision matrix
--------------------------------------------------
```



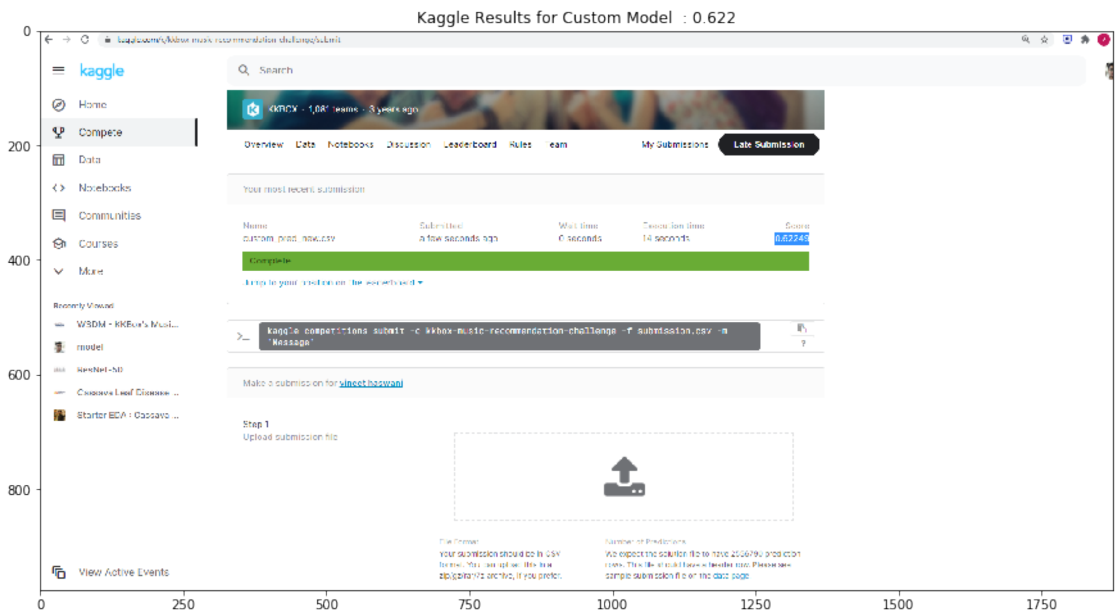
Sum of columns in precision matrix [1. 1.]
-- Recall matrix



Sum of rows in precision matrix [1. 1.]

```
[5]: import matplotlib.pyplot as plt
     import cv2
     plt.figure(figsize = (15, 20))
     plt.title('Kaggle Results for Custom Model  : 0.622')
     plt.imshow(cv2.cvtColor(cv2.imread('custom_prob.png'), cv2.COLOR_BGR2RGB))
```

```
[5]: <matplotlib.image.AxesImage at 0x158a4d9ad08>
```



5 Conclusion for Modeling :

```
[6]: from prettytable import PrettyTable

     myTable = PrettyTable(["Model Name", "HyperParameter", "AUC Score on Test"])
     myTable.add_row(["Logistic Regression", "alpha : 0.01", "66.50 %"])
     myTable.add_row(["SGDClassifier with log loss", "alpha : 0.01", "68.46 %"])
     myTable.add_row(["Decision Tree Classifier", "max_depth :20", "69.24 %"])
     myTable.add_row(["Random Forest Classifier", "n_estimators : 100", "78.56 %"])
     myTable.add_row(["AdaBoost Regression", "n_estimators : 50", "68.63 %"])
     myTable.add_row(["XGBoost Classifier", "n_estimators : 500", "71.23 %"])
     myTable.add_row(["Custom Model", "alpha :100 max_depth :40", "69.61 %"])

     print(myTable)
```

```
+------------------------------+--------------------------+-------------------+
|          Model Name          |      HyperParameter      | AUC Score on Test |
+------------------------------+--------------------------+-------------------+
|     Logistic Regression      |       alpha : 0.01       |      66.50 %      |
```

SGDClassifier with log loss	alpha : 0.01	68.46 %
Decision Tree Classifier	max_depth :20	69.24 %
Random Forest Classifier	n_estimators : 100	78.56 %
AdaBoost Regression	n_estimators : 50	68.63 %
XGBoost Classifier	n_estimators : 500	71.23 %
Custom Model	alpha :100 max_depth :40	69.61 %

Best Model is Random Forest classifier with number of trees as 100 with AUC Score of 78.56%. Further it can be improved by applying Calibration on top of classifier but it is very expensive to apply need more than 35 GB of ram for computation