KKBOX's Music Recommendation Challange

1. Introduction

- People are fond of listening music every time whether it's a commute time, work time or focus time. Muisc helps anybody to connect with what you are doing.
- Different people have different flavours of music. Music has served its users with various platforms like waves of Victrola, culture of Cassette, Walkman era, i-pods, FM-Radios and now latest musical apps.
- Intenet made life easy in terms of selecting music of users' choice, but still algorithms are needed to recommend favourite music to users without selecting manually.

-> Problem Description

- WSDM (International Conference on Web Search and Data Mining) has given a challenge to the Kaggle community to build better music recommendation system using a donated dataset from KKBOX.
- Given set of features we have to predict wether the user would like to listen the recommneded song or not.

-> Source/Useful links

- Kaggle has given train and test datasets along with information related to user and songs to explore more about song recommendation.
- https://www.kaggle.com/c/kkbox-music-recommendation-challenge (https://www.kaggle.com/c/kkbox-music-recommendation-challenge)
- https://isrc.ifpi.org/en/isrc-standard/code-syntax (https://isrc.ifpi.org/en/isrc-standard/code-syntax)
- https://www.kaggle.com/c/kkbox-music-recommendation-challenge/discussion/45942 (https://www.kaggle.com/c/kkbox-music-recommendation-challenge/discussion/45942)
- https://www.kaggle.com/asmitavikas/feature-engineered-0-68310 (https://www.kaggle.com/asmitavikas/feature-engineered-0-68310)
- https://www.kaggle.com/rohandx1996/recommendation-system-with-83-accuracy-lgbm (https://www.kaggle.com/rohandx1996/recommendation-system-with-83-accuracy-lgbm)

-> Real-world/Business objectives and constraints

- Song recommendation should not take hours or days. Few minutes/seconds would be sufficient to predict the chances of listening.
- Minimize the bad recommendations as it leads to bad customer experiences.
- Prediction should be intepretable.

-> Machine Learning problem formulation

- In this task, we have to predict the chances of a user listening to a song repetitively after the first observable listening event within a time window was triggered. If there are recurring listening event(s) triggered within a month after the user's very first observable listening event, its target is marked 1, and 0 otherwise in the training set.
- KKBOX has provided a training data set consists of information of the first observable listening event for each unique user-song pair within a specific time duration.

-> Data overview

- Source : [https://www.kaggle.com/c/kkbox-music-recommendation-challenge/data (https://www.kaggle.com/c/kkbox-music-recommendation-challenge/data)](https://www.kaggle.com/c/kkbox-music-recommendation-challenge/data)
- Total 5 data files are given
- train.csv : this file includes
    - user_id (msno),
    - song_id,
    - source_system_tab (where the event was triggered),
    - source_type (an entry point a user first plays music),
    - source_screen_name (name of the layout user sees),
    - target (1 means there are recurring listening event(s) triggered within a month after the user's very first observable listening event, target=0 otherwise).
- test.csv : Contains fields same as above except target, which we have to predict.
- songs.csv: It includes fields like
    - song_id,
    - song_length,
    - genre_id,
    - artist_name,
    - composer,
    - lyricist
    - lanugage.
- members.csv: It contains attributes like
    - msno (user_id),
    - city,
    - bd (may contains outliers),
    - gender,
    - register_via (register method),
    - register_init_time (date),
    - expirartion_date (date).
- song_extra_info.csv : This file contains
    - song_id,
    - song_name
    - ISRC (International Standard Recording Code) used to identify songs.

-> Example data point

- train:
  - msno : Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=
  - song_id : bhp/MpSNoqoxOIB+/l8WPqu6jldth4DIpCm3ayXnJqM=
  - source_system_tab : my library
  - source_screen_name : Local playlist more
  - source_type : local-playlist
  - target : 1
- test:
  - id : 1
  - msno : V8ruy7SGk7tDm3zA51DPpn6qutt+vmKMBKa21dp54uM=
  - song_id : y/rsZ9DC7FwK5F2PK2D5mj+aOBUJAjuu3dZ14NgE0vM=
  - source_system_tab : my library
  - source_screen_name : local playlist more
  - source_type : local-library
- songs:
  - song_id : o0kFgae9QtnYgRkVPqLJwa05zIhRlUjfF7O1tDw0ZDU=
  - song_length : 197328
  - genre_ids : 444
  - artist_name : BLACKPINK
  - composer : TEDDY| FUTURE BOUNCE| Bekuh BOOM
  - lyricist : TEDDY
  - language : 31
- songs_extra_info:
  - song_id : ClazTFnk6r0Bnuie44bocdNMM3rdlrq0bCGAsGUWcHE=
  - name : Let Me Love You
  - isrc : QMZSY1600015
- members:
  - msno : UizsfmJb9mV54qE9hCYyU07Va97c0lCRLEQX3ae+ztM=
  - city : 1
  - bd : 0
  - gender : NaN
  - registered_via : 7
  - registration_init_time : 20150628
  - expiration_date : 20170622

- We are given two classes 0/1 hence we can map this problem as a binary classification problem.

-> Performance metric

- There is no clear instructions about performance metric so we will consider AUC.

2. EDA

In [ ]:

```
# Importing basic libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import missingno as msno
import gc
import lightgbm as lgb
from xgboost import XGBClassifier
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.p
y:19: FutureWarning: pandas.util.testing is deprecated. Use the fun
ctions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

- Reading files from respective paths

In [ ]:

```
data_path = 'Data/'
train = pd.read_csv(data_path+'train.csv')
test = pd.read_csv(data_path+'test.csv')
songs = pd.read_csv(data_path+'songs.csv')
members = pd.read_csv(data_path+'members.csv')
song_extra_info = pd.read_csv(data_path+'song_extra_info.csv')
```

- Printing shapes and features for each file.

In [ ]:

```
print('Shape of train file is : ', train.shape)
print('Shape of test file is : ', test.shape)
print('Shape of songs file is : ', songs.shape)
print('Shape of members file is : ', members.shape)
print('Shape of songs_extra_info file is : ', song_extra_info.shape)
```

```
Shape of train file is :  (7377418, 6)
Shape of test file is :  (2556790, 6)
Shape of songs file is :  (2296320, 7)
Shape of members file is :  (34403, 7)
Shape of songs_extra_info file is :  (2295971, 3)
```

In [ ]:

```
print('Features of train : ', train.columns)
print('Features of test :', test.columns)
print('Features of songs : ', songs.columns)
print('Features of members : ', members.columns)
print('Features of songs_extra_info : ', song_extra_info.columns)
```

```
Features of train :  Index(['msno', 'song_id', 'source_system_tab',
'source_screen_name',
       'source_type', 'target'],
      dtype='object')
Features of test : Index(['id', 'msno', 'song_id', 'source_system_t
ab', 'source_screen_name',
       'source_type'],
      dtype='object')
Features of songs :  Index(['song_id', 'song_length', 'genre_ids',
'artist_name', 'composer',
       'lyricist', 'language'],
      dtype='object')
Features of members :  Index(['msno', 'city', 'bd', 'gender', 'regi
stered_via',
       'registration_init_time', 'expiration_date'],
      dtype='object')
Features of songs_extra_info :  Index(['song_id', 'name', 'isrc'],
dtype='object')
```

Train data analysis

- We will analyze each and every feature from the files with respect to target.

In [ ]:

```
# information about train data usinf pandas
train.info()
```

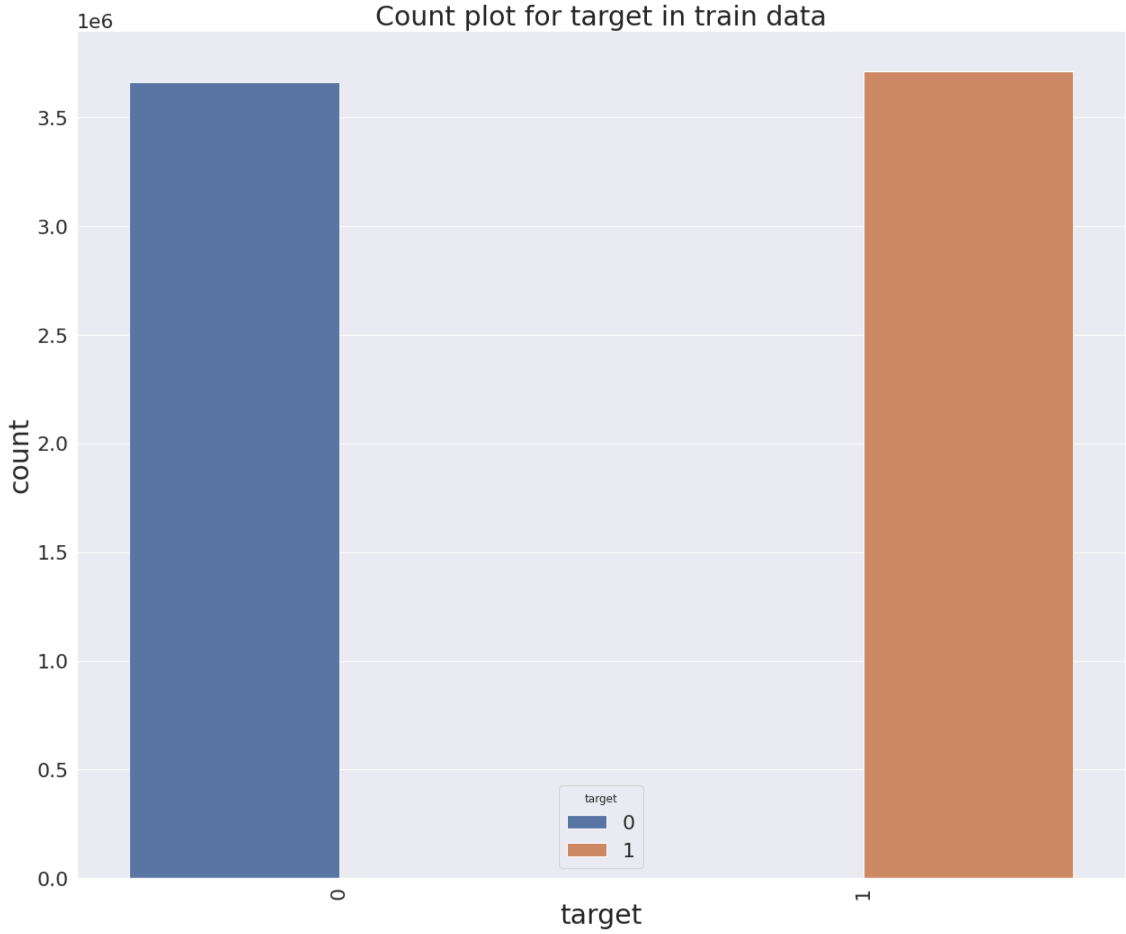
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7377418 entries, 0 to 7377417
Data columns (total 6 columns):
 #   Column              Dtype
---  ------              -----
 0   msno                object
 1   song_id             object
 2   source_system_tab   object
 3   source_screen_name  object
 4   source_type         object
 5   target              int64
dtypes: int64(1), object(5)
memory usage: 337.7+ MB
```

In [ ]:

```
# source : https://www.kaggle.com/rohandx1996/recommendation-system-with-83-accu
racy-lgbm
def count_plot(data, x, hue, type):
  '''Function to plot histograms with respect to argument type (category/targe
t)'''
  plt.figure(figsize=(18,15))
  sns.set(font_scale=2)
  sns.countplot(x=x, hue=hue, data=data)
  plt.xlabel(x,fontsize=30)
  plt.ylabel('count',fontsize=30)
  plt.xticks(rotation='90')
  plt.title('Count plot for {0} in {1} data'.format(x, type),fontsize=30)
  plt.tight_layout()
```

In [ ]:

```
count_plot(train, 'target', 'target', 'train')
```



In [ ]:

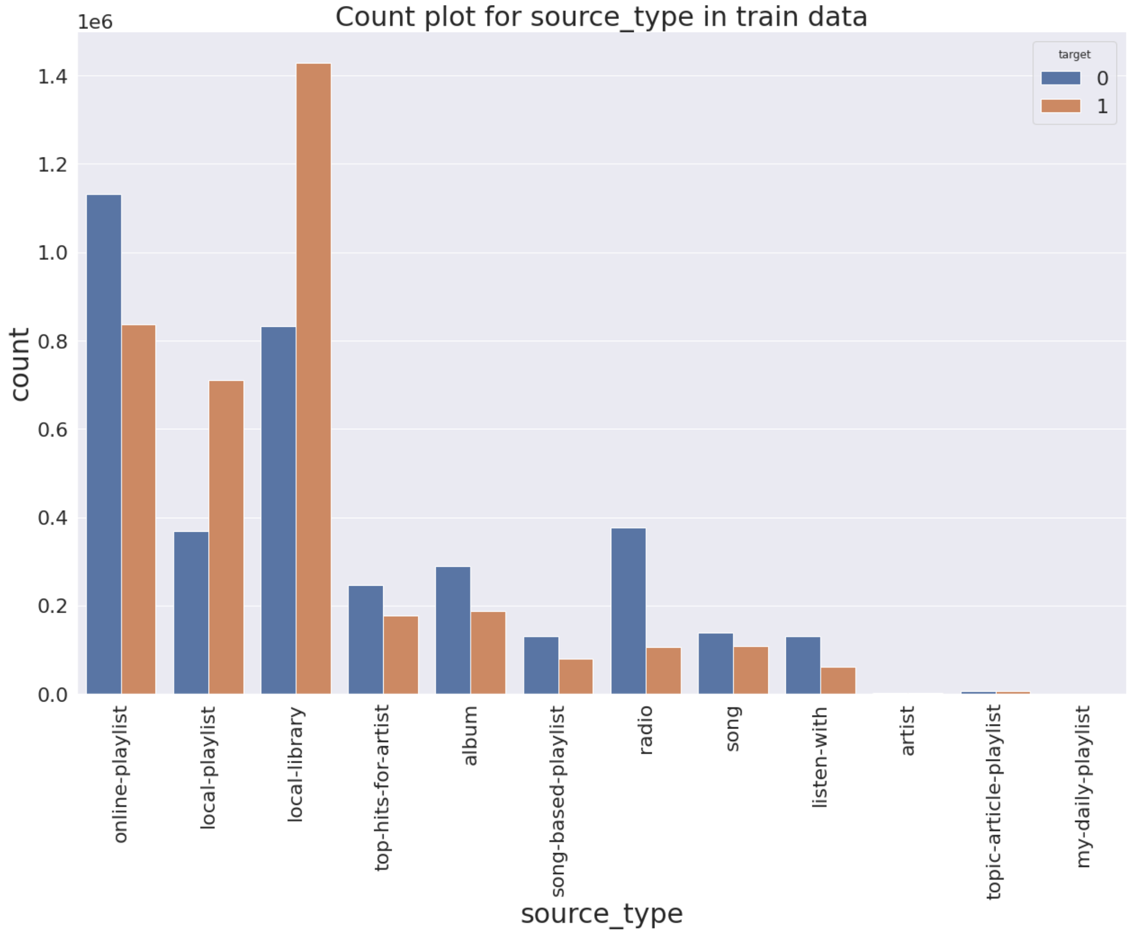
```
print('Data for label 1 : {:.4f}%'.format(train['target'].value_counts()[0]/trai
n.shape[0] * 100))
print('Data for label 0 : {:.4f}%'.format(train['target'].value_counts()[1]/trai
n.shape[0] * 100))
```

```
Data for label 1 : 49.6483%
Data for label 0 : 50.3517%
```

- From the above plots we can say that the data is almost balanced.
- Label-1 data is around 49.6% and label-0 data is around 50.4%.

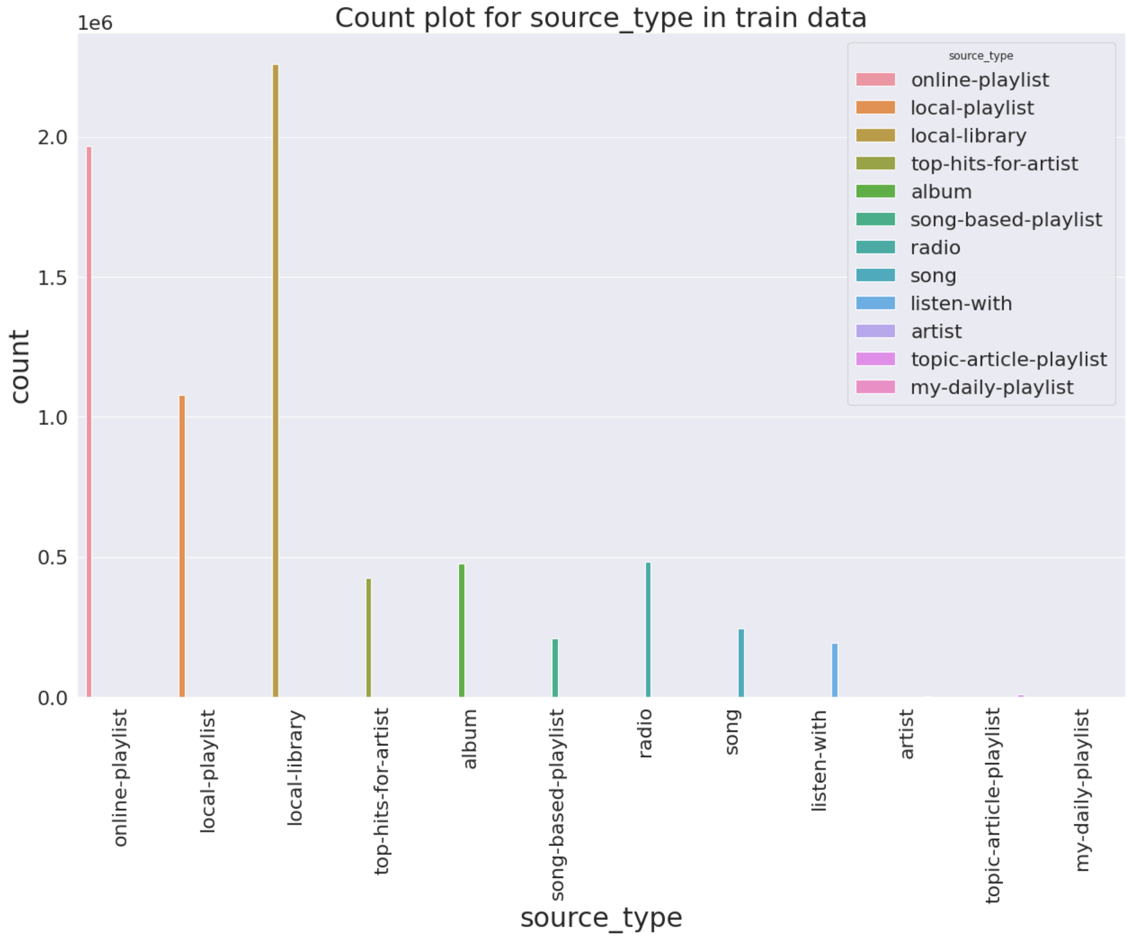
In [ ]:

```
count_plot(train, 'source_type', 'target', 'train')
```



In [ ]:

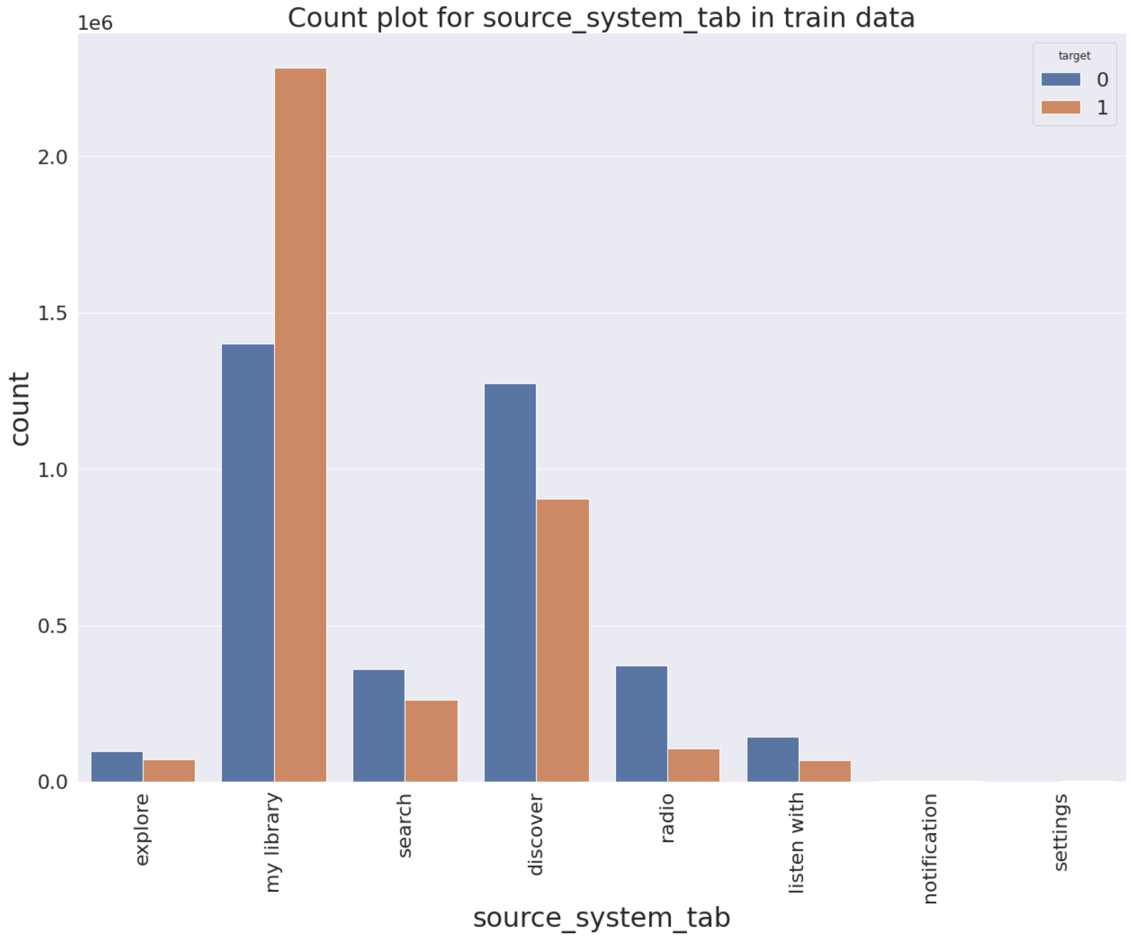
```
count_plot(train, 'source_type', 'source_type', 'train')
```



- source_type is the entry point, a user first plays music on mobile apps.
- From the above plots we can say that, most of the users starts playing songs via their local-library, online-playlist or local-playlist.
- People don't start listening music with artist or daily-playlist.

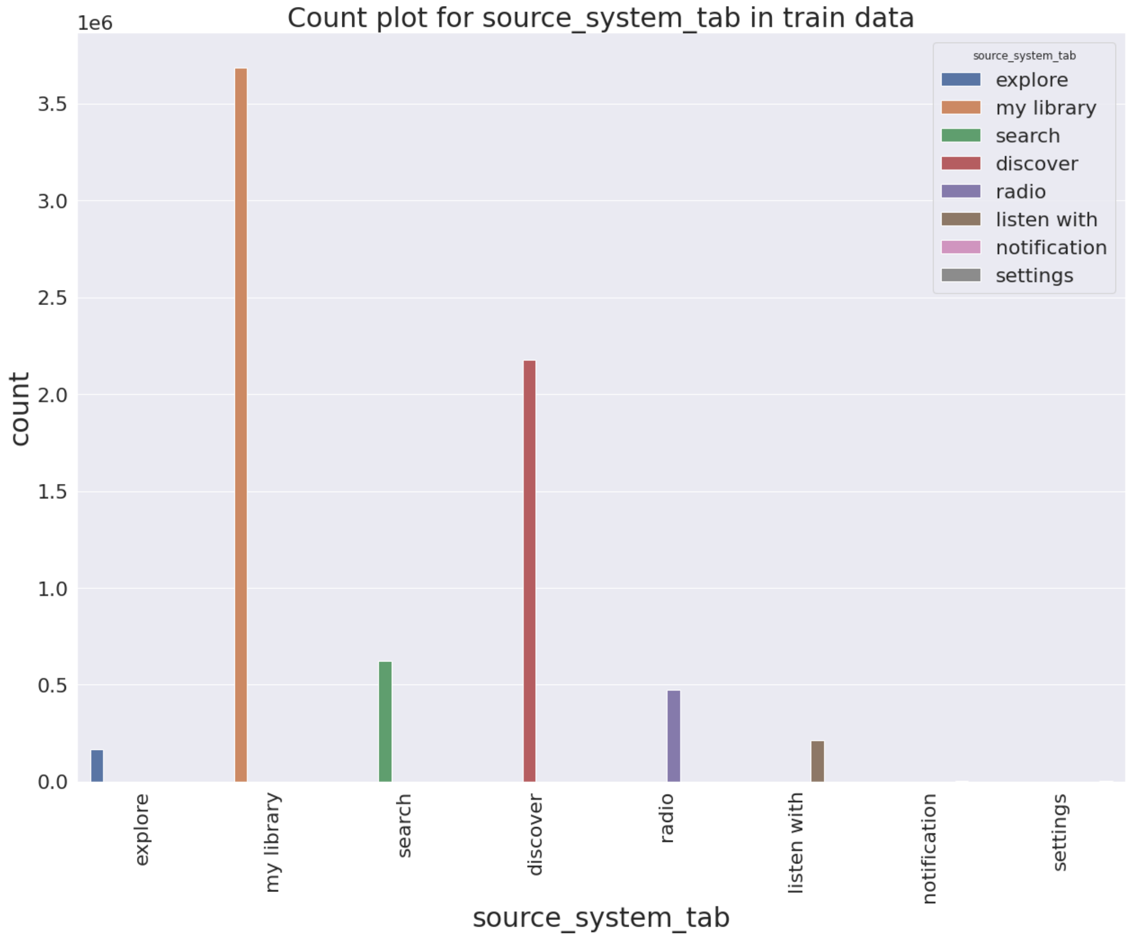
In [ ]:

```
count_plot(train, 'source_system_tab', 'target', 'train')
```



In [ ]:

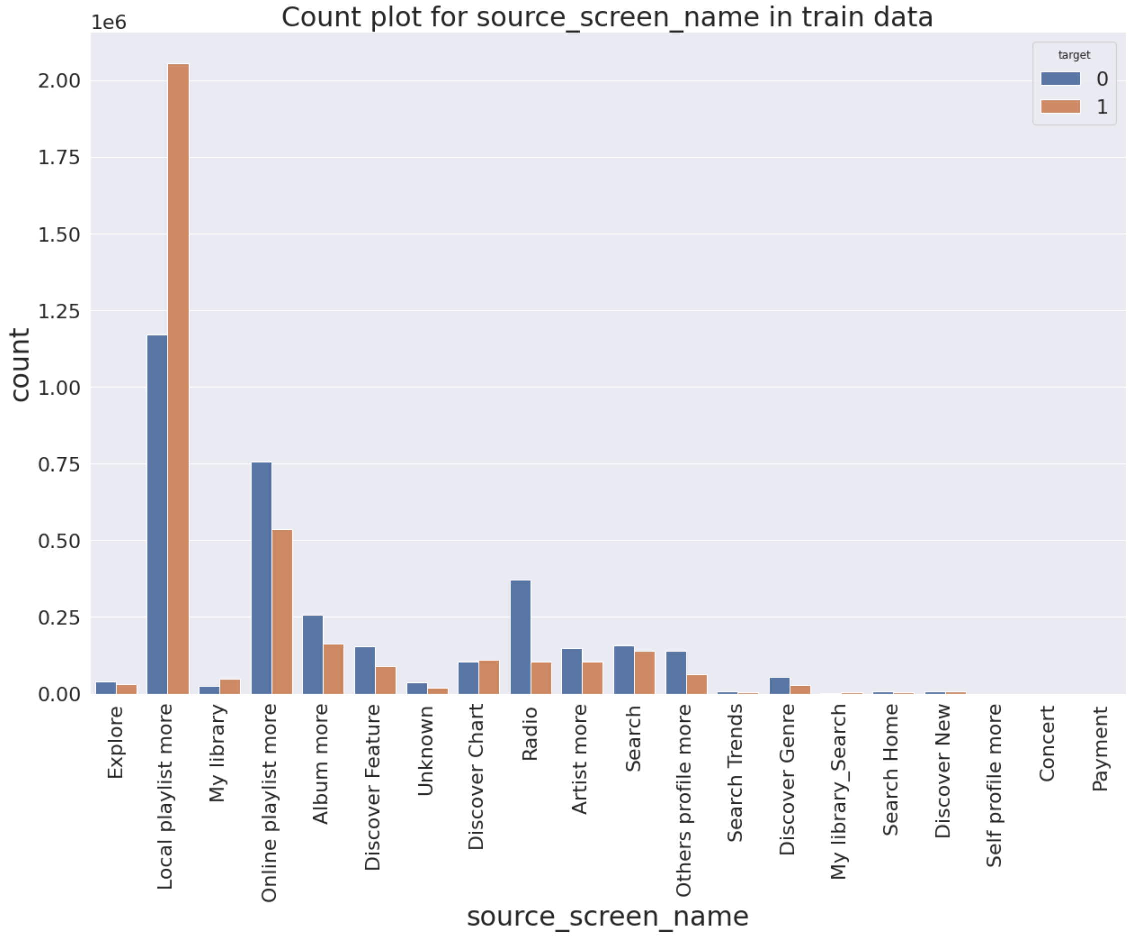
```
count_plot(train, 'source_system_tab', 'source_system_tab', 'train')
```



- source_system_tab indicates the name of the tab where the event was triggered. System tabs are used to categorize KKBOX mobile apps functions.
- It can be depicted from the above plot that people repeat songs from their library or discover tabs.
- From notifications or settings tab people are not interested to repeat songs.

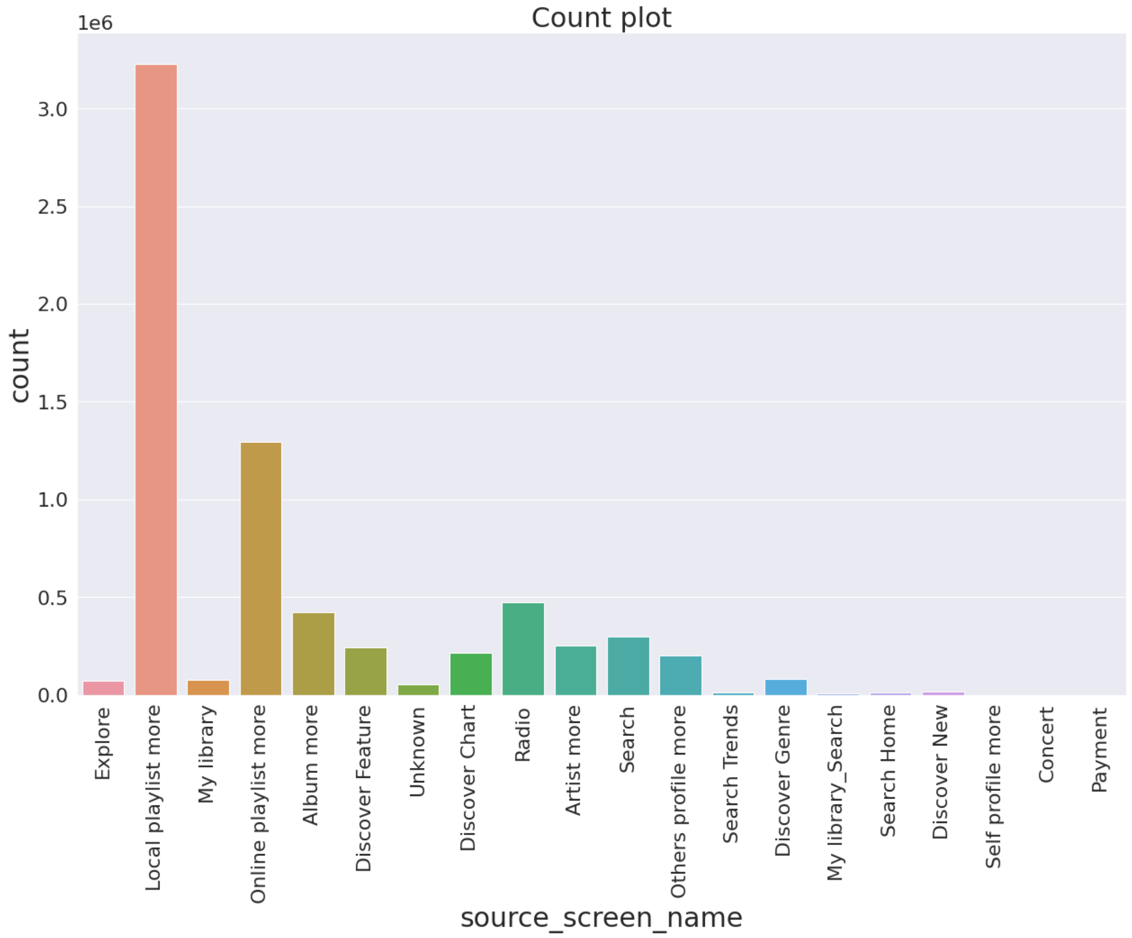
In [ ]:

```
count_plot(train, 'source_screen_name', 'target', 'train')
```



In [ ]:

```
count_plot_function(train, 'source_screen_name')
```



- source_screen_name is the name of the layout a user sees.
- Most of the users prefer local_playlist or online_playlist_more as their favourite layouts.

Members data Analysis

In [ ]:

```
members.info()
```

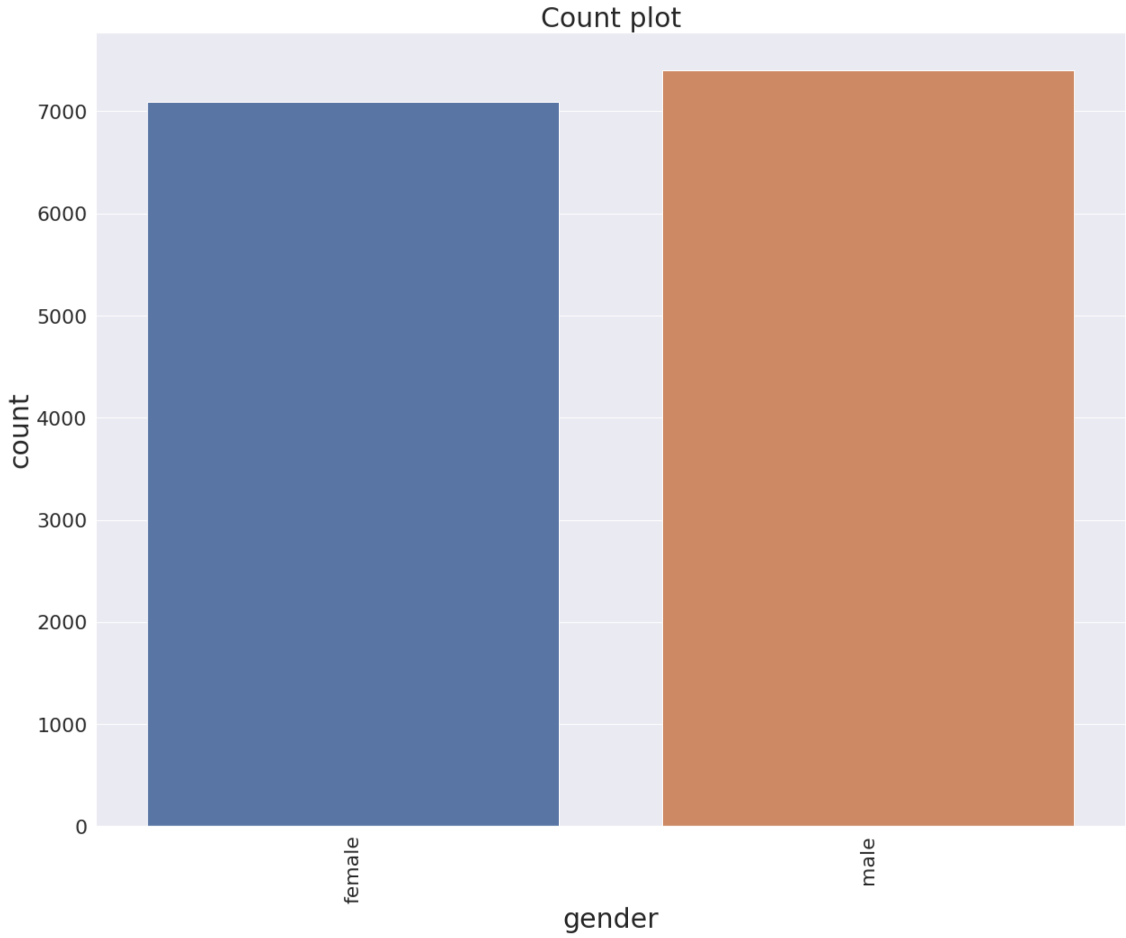
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34403 entries, 0 to 34402
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   msno                    34403 non-null  object
 1   city                    34403 non-null  int64 
 2   bd                      34403 non-null  int64 
 3   gender                  14501 non-null  object
 4   registered_via          34403 non-null  int64 
 5   registration_init_time  34403 non-null  int64 
 6   expiration_date         34403 non-null  int64 
dtypes: int64(5), object(2)
memory usage: 1.8+ MB
```

In [ ]:

```
#source : https://seaborn.pydata.org/generated/seaborn.countplot.html
def count_plot_function(data, x):
  '''Function to plot histograms for categories'''
  plt.figure(figsize=(18,15))
  sns.set(font_scale=2)
  sns.countplot(x=x, data=data)
  plt.xlabel(x,fontsize=30)
  plt.ylabel('count',fontsize=30)
  plt.xticks(rotation='90')
  plt.title('Count plot',fontsize=30)
  plt.tight_layout()
```

In [ ]:

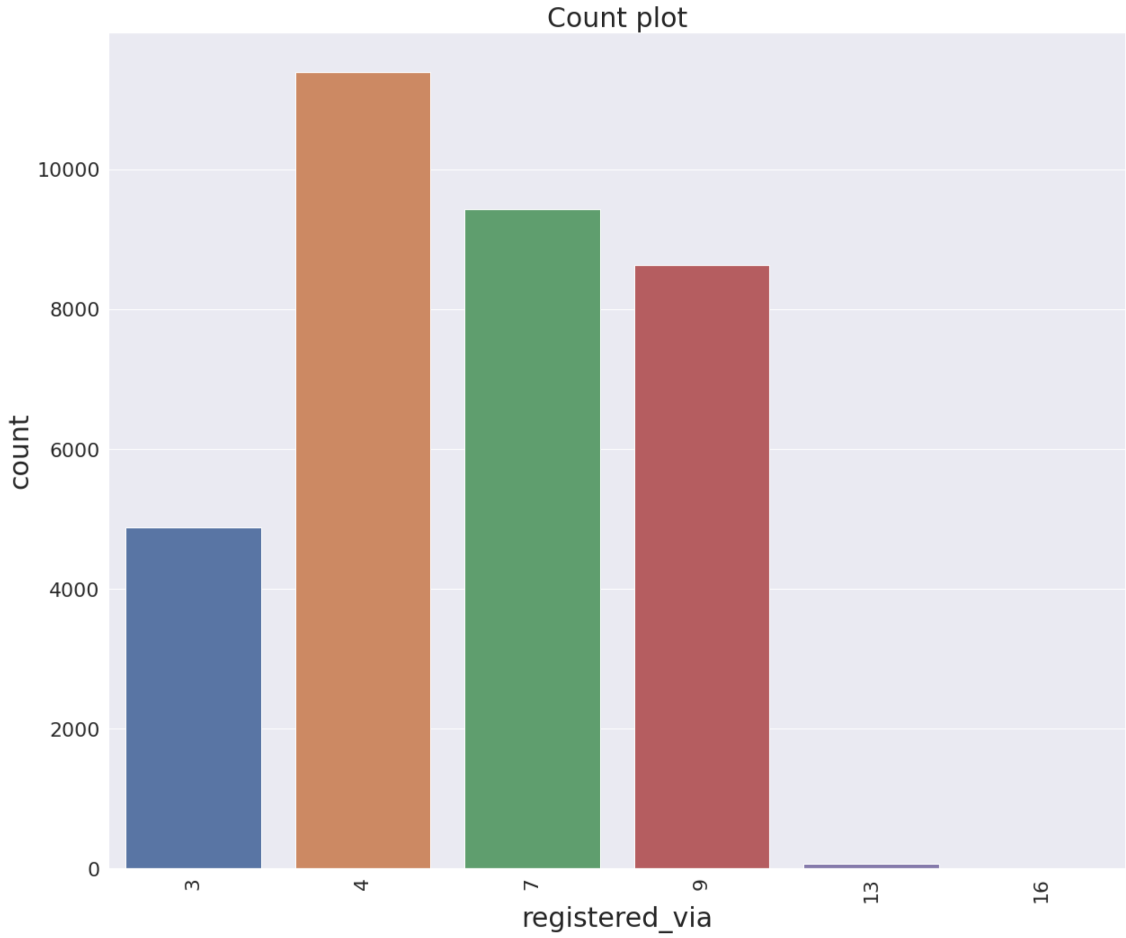
```
count_plot_function(members, 'gender')
```



- Both male and female users prefer to listen songs equally.

In [ ]:

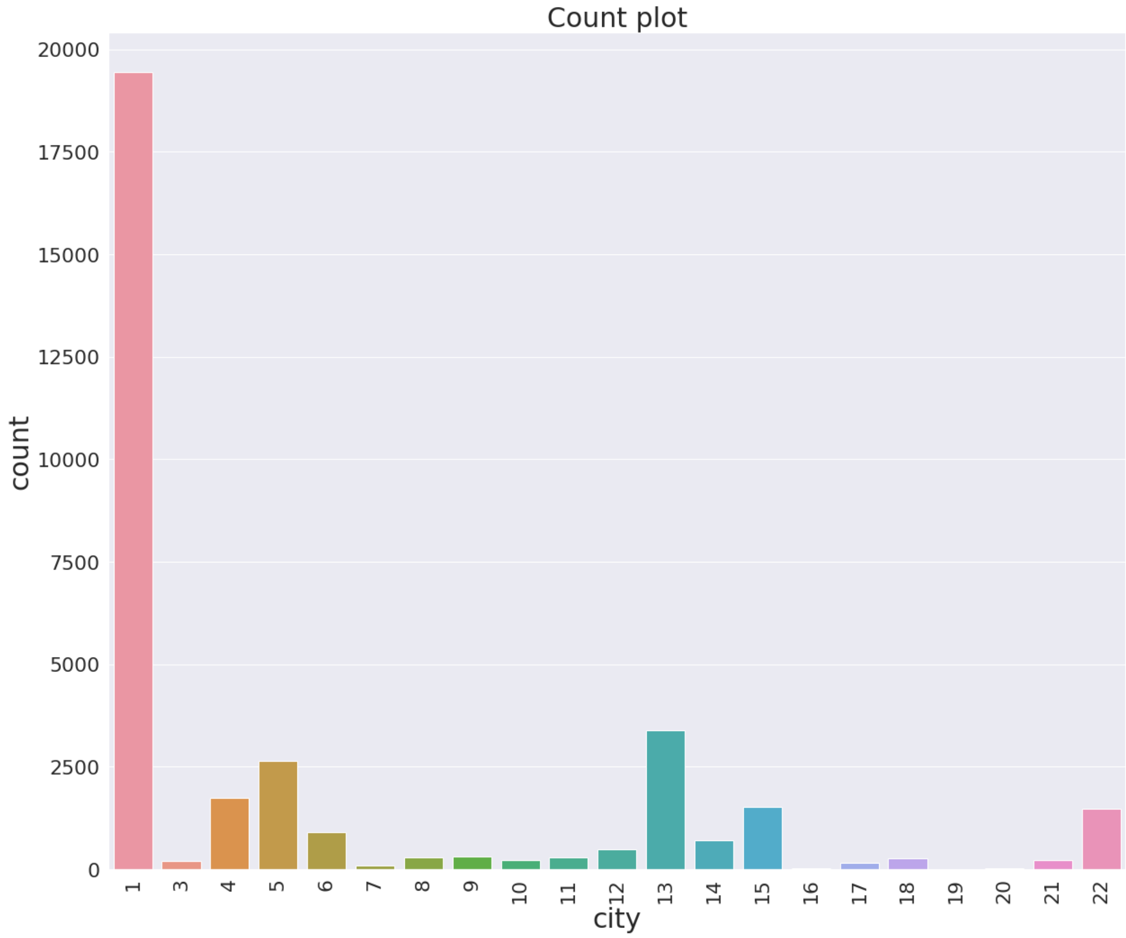
```
count_plot_function(members, 'registered_via')
```



- Most of the registrations happened via method '4', '7' and '9'.
- Few uses have registered theirselves via '13' and '16' methods.

In [ ]:

```
count_plot_function(members, 'city')
```



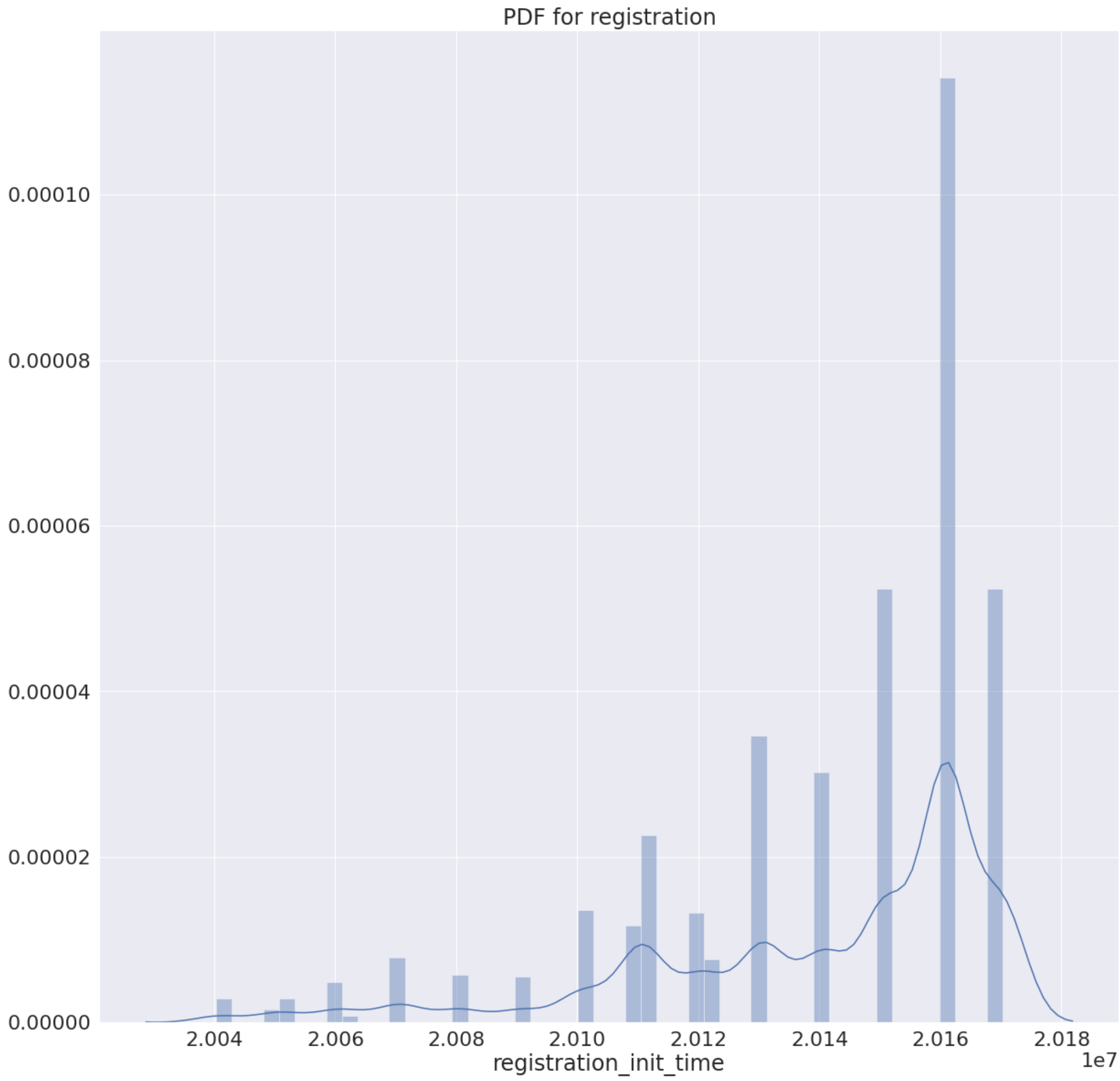
- Most of the people who used to listen songs are from '1'- labelled city.
- Some cities have very few people who prefer listening music via this music app.

In [ ]:

```
# https://seaborn.pydata.org/generated/seaborn.distplot.html
plt.figure(figsize = (20, 20))
sns.distplot(members.registration_init_time)
sns.set(font_scale=2)
plt.title('PDF for registration')
```

Out[ ]:

```
Text(0.5, 1.0, 'PDF for registration')
```



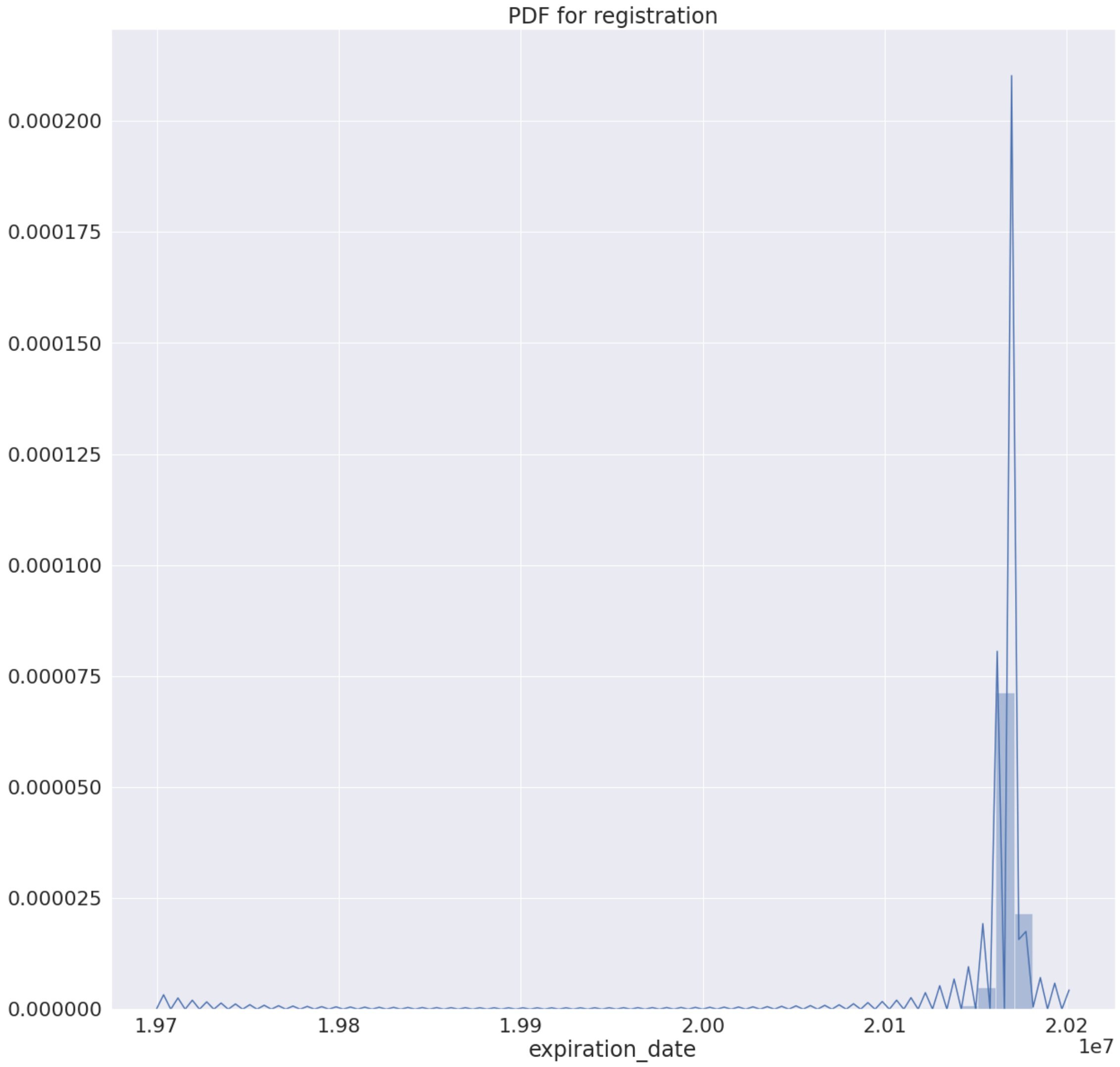
- We can see that initially people were not fond of listening music but after certain amount time people started to listen music and registered themselves to this music app.

In [ ]:

```
plt.figure(figsize = (20, 20))
sns.distplot(members['expiration_date'])
sns.set(font_scale=2)
plt.title('PDF for registration')
```

Out[ ]:

```
Text(0.5, 1.0, 'PDF for registration')
```



- We have seen that after certain time people start registering themselves for the music app, their expiration period also starts increasing after certain time period.

In [ ]:

```
members.bd.unique()
```

Out[ ]:

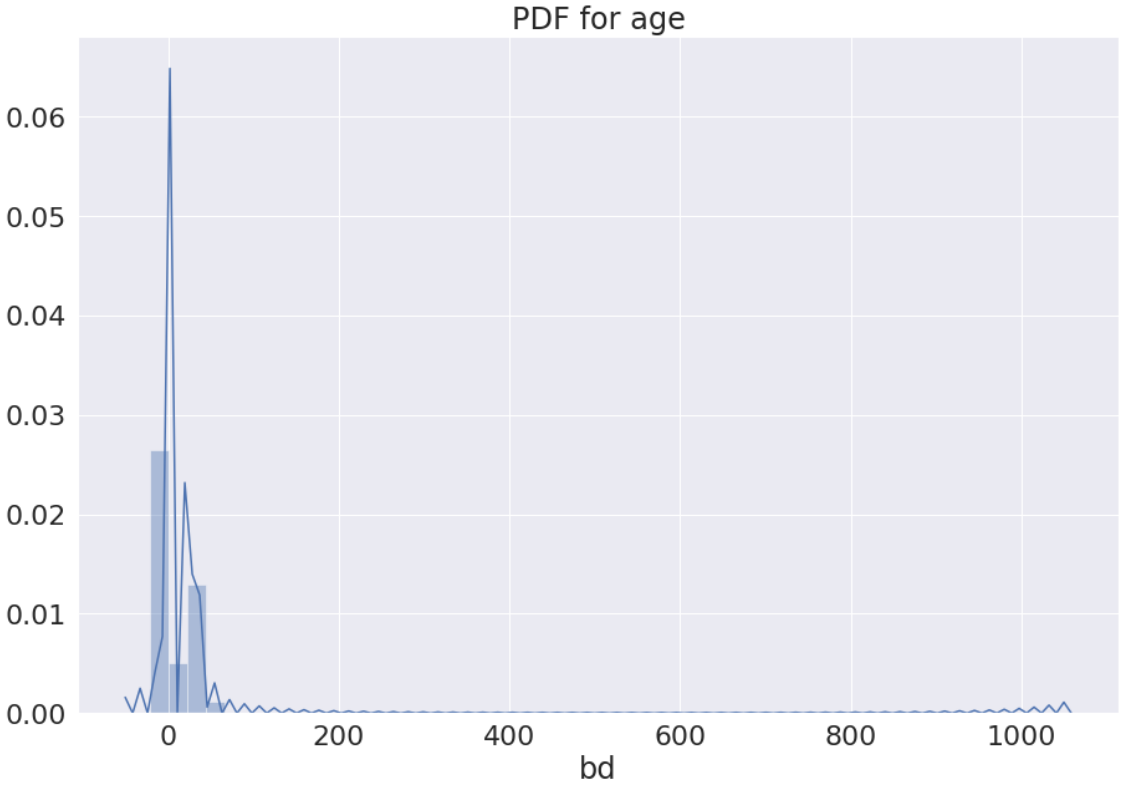
```
array([   0,   43,   28,   33,   20,   30,   29,   26,   25,   21,
22,
         16,   23,   37,   18,   19,   51,   24,   17,   45,   36,
57,
         27,   34,   32,   15,   48,   50,   54,   47,   35,   46,
31,
         14,   41,   59,    2,   40,   38,   55,   39,   73,   49,
44,
        103,   52,   70,   42,   65,   56,  101,   58,   53,   64,
63,
         76,   66,   97,    3,   72,   67,   62,   61,  105,   60,
13,
         90,   12,   68,  131,   74,   89,  931,  -38,  144,   85,
112,
         96,   11,  102,   83, 1051,   87,    7,   95,  -43,  111,
93,
          5,   78, 1030,  106,  107,   82,   10])
```

In [ ]:

```
def plot_pdf_cdf(x, flag):
  '''Function to plot pdf and cdf'''
  plt.figure(figsize = (15, 10))
  kwargs = {'cumulative': True}
  if flag:
    sns.distplot(x, hist_kws=kwargs, kde_kws=kwargs)
    plt.title('CDF for age')
  else:
    sns.distplot(x)
    plt.title('PDF for age')
  sns.set(font_scale=2)
```

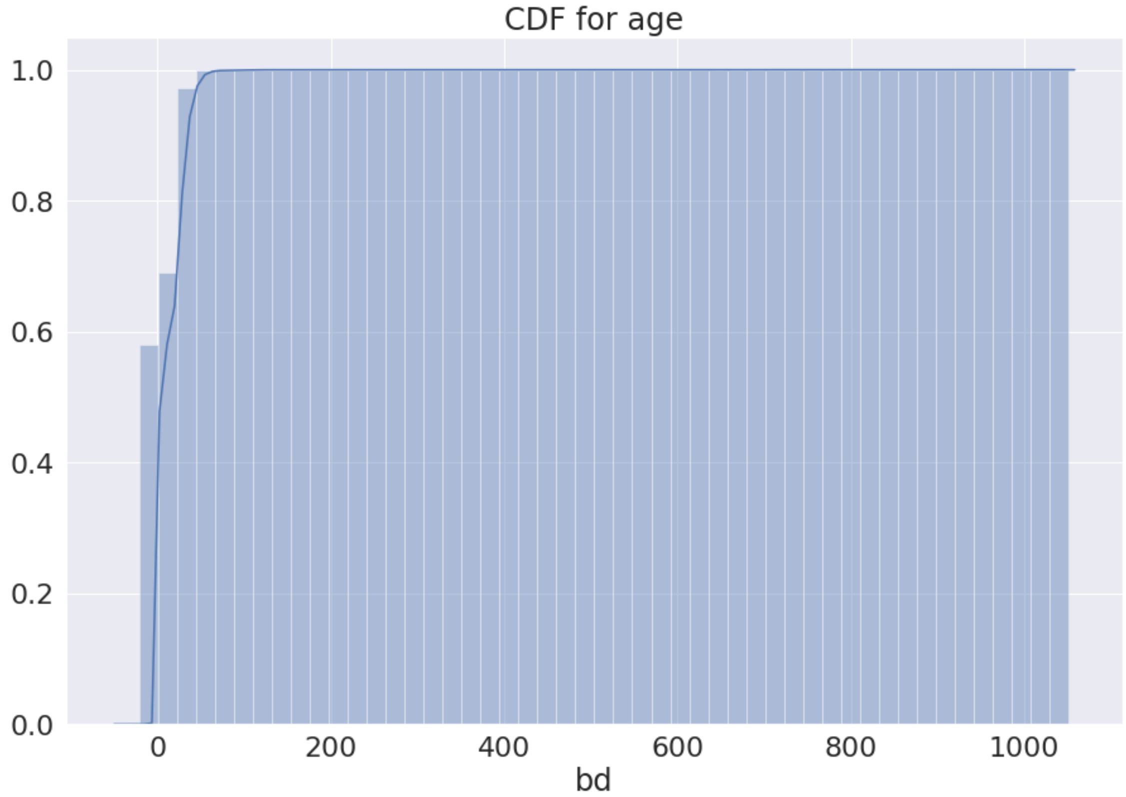
In [ ]:

```
plot_pdf_cdf(members['bd'], False)
```



In [ ]:

```
plot_pdf_cdf(members['bd'], True)
```



In [ ]:

```
np.percentile(members['bd'].values, 98)
```

Out[ ]:

```
47.0
```

- 98th percentile user is of 47 age.
- Means most of the user are below 50.
- We can also observe via above CDF that almost 99% values are below 50.
- There are also some outliers like 1030, -38, -43, 1051, etc. As age cannot be negative value or more than 1000 for humans.

Songs data analysis

- We have two files which contains information about songs so let's merge two files: songs and song_extra_info on 'song_id' and analyze features in details.

In [ ]:

```
songs_all_info = songs.merge(song_extra_info, on='song_id')
```

In [ ]:

```
# source : https://www.kaggle.com/asmitavikas/feature-engineered-0-68310

def isrc_to_year(isrc):
    if type(isrc) == str:
        if int(isrc[5:7]) > 17:
            return 1900 + int(isrc[5:7])
        else:
            return 2000 + int(isrc[5:7])
    else:
        return np.nan

songs_all_info['song_year'] = songs_all_info['isrc'].apply(isrc_to_year)
```

In [ ]:

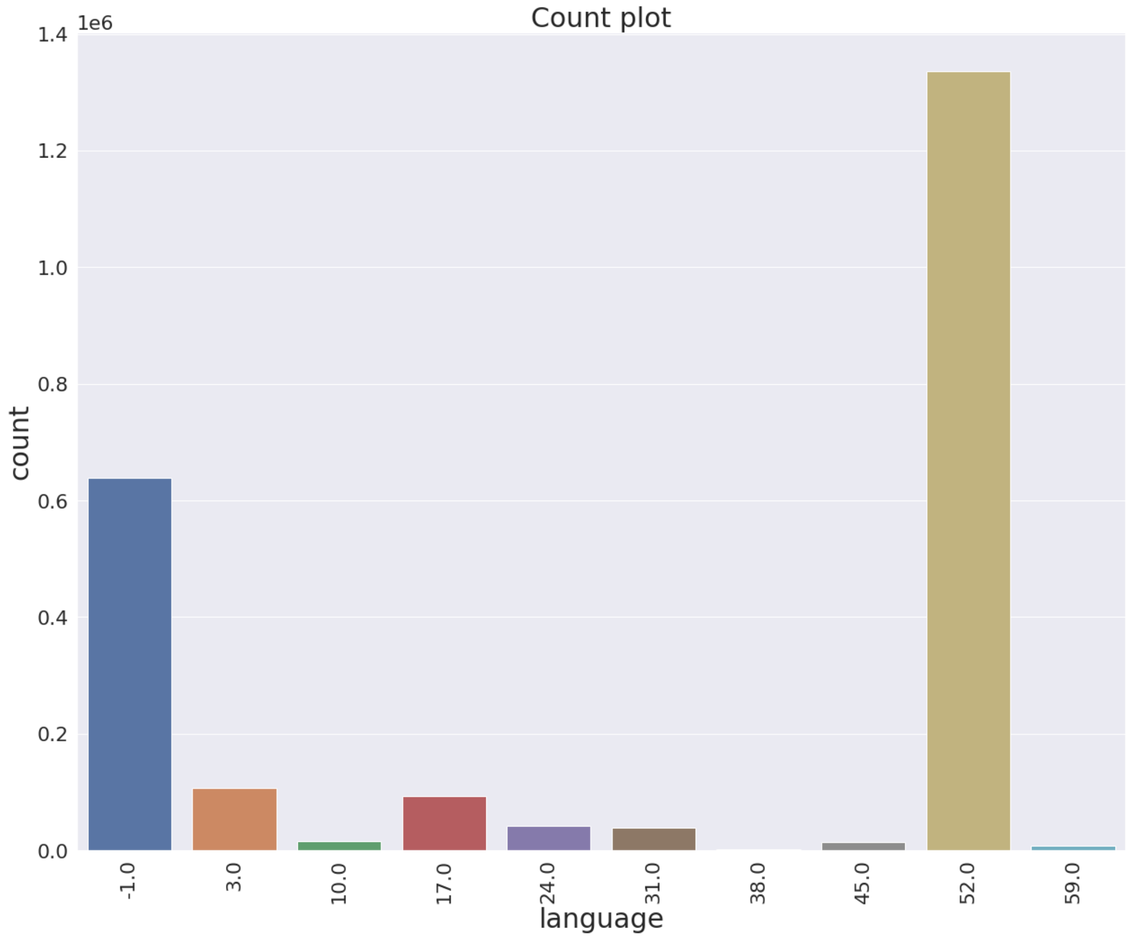
```
songs_all_info['language'].unique()
```

Out[ ]:

```
array([ 3., 31., 52., 17., 10., -1., 24., 59., 45., 38., nan])
```

In [ ]:

```
count_plot_function(songs_all_info, 'language')
```



- Users prefer to listen songs from '52' and '-1' language.

Merging of data and analysis

Missing values

- We will check % of missing values in each column of dataframe.

In [ ]:

```
def check_missing_values(df):
  '''Function to check missing values in df'''
  for col in df.columns:
    nan_count = df[col].isnull().sum()
    total = df.shape[0]
    percentage = nan_count/total * 100
    print(col, 'has {:.2f}% missing values'.format(percentage))
```

In [ ]:

```
print('Missing values analysis for train data')
check_missing_values(train)
```

```
Missing values analysis for train data
msno has 0.00% missing values
song_id has 0.00% missing values
source_system_tab has 0.34% missing values
source_screen_name has 5.62% missing values
source_type has 0.29% missing values
target has 0.00% missing values
```

In [ ]:

```
print('Missing values analysis for memebrs data')
check_missing_values(members)
```

```
Missing values analysis for memebrs data
msno has 0.00% missing values
city has 0.00% missing values
bd has 0.00% missing values
gender has 57.85% missing values
registered_via has 0.00% missing values
registration_init_time has 0.00% missing values
expiration_date has 0.00% missing values
```

In [ ]:

```
print('Missing values analysis for songs data')
check_missing_values(songs)
```

```
Missing values analysis for songs data
song_id has 0.00% missing values
song_length has 0.00% missing values
genre_ids has 4.10% missing values
artist_name has 0.00% missing values
composer has 46.66% missing values
lyricist has 84.71% missing values
language has 0.00% missing values
```

In [ ]:

```
print('Missing values analysis for songs_all_info data')
check_missing_values(songs_all_info)
```

```
Missing values analysis for songs_all_info data
song_id has 0.00% missing values
song_length has 0.00% missing values
genre_ids has 4.10% missing values
artist_name has 0.00% missing values
composer has 46.66% missing values
lyricist has 84.71% missing values
language has 0.00% missing values
name has 0.00% missing values
isrc has 5.95% missing values
song_year has 5.95% missing values
```

- We can see that train data has over all missing values below 6%.
- In members data 'gender' feature has 57.85% missing values.
- Songs has 'composer' and 'lyricist' features which contains 47% and 85% missing values respectively.

In [ ]:

```
train_members = pd.merge(train, members, on='msno', how='left')
train_merged = pd.merge(train_members, songs_all_info, on='song_id', how='left')
```

In [ ]:

```
test_members = pd.merge(test, members, on='msno', how='left')
test_merged = pd.merge(test_members, songs_all_info, on='song_id', how='left')
```

In [ ]:

```
del train_members
del test_members
```

In [ ]:

```
check_missing_values(train_merged)
```

```
msno has 0.00% missing values
song_id has 0.00% missing values
source_system_tab has 0.34% missing values
source_screen_name has 5.62% missing values
source_type has 0.29% missing values
target has 0.00% missing values
city has 0.00% missing values
bd has 0.00% missing values
gender has 40.14% missing values
registered_via has 0.00% missing values
registration_init_time has 0.00% missing values
expiration_date has 0.00% missing values
song_length has 0.02% missing values
genre_ids has 1.63% missing values
artist_name has 0.02% missing values
composer has 22.73% missing values
lyricist has 43.10% missing values
language has 0.02% missing values
name has 0.02% missing values
isrc has 7.83% missing values
song_year has 7.83% missing values
```

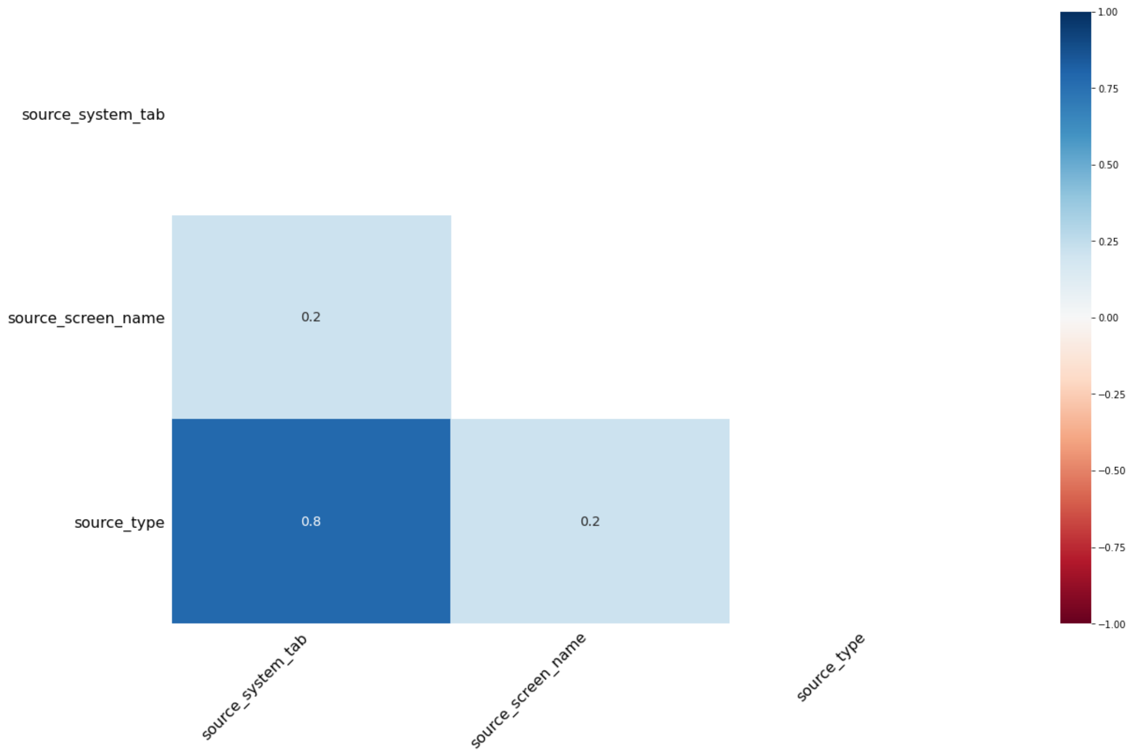
- After merging we can say that, 'gender' feature has 40%, 'composer' has 23% and 'lyricist' has 43% missing values.
- Other fetaures are having less than 8% missing values.

In [ ]:

```
msno.heatmap(train)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7080d67358>
```



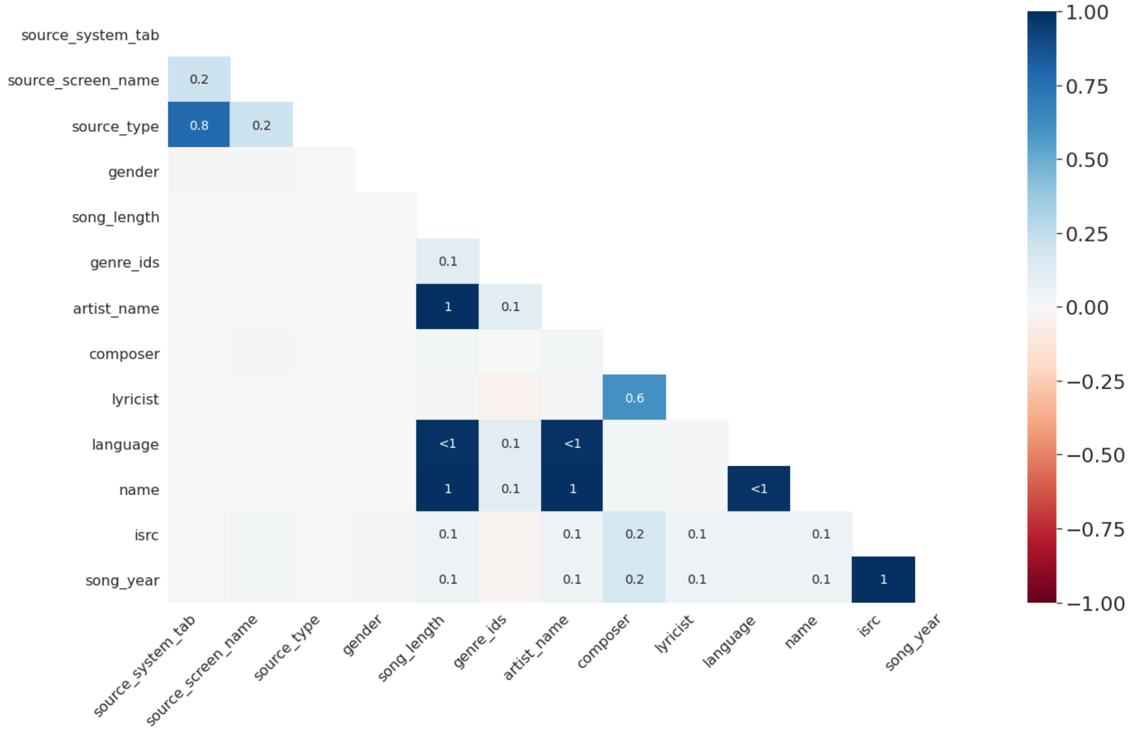
- From the above heatmap we can say that no missing values in msno, song_id or target.
- source_type and source_system_tab are having positive strongly corelation.
- In simple lanugauge from the point, where user starts to play the songs and over some tabs it repats the song.

In [ ]:

```
msno.heatmap(train_merged)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f94b3a4b4e0>
```



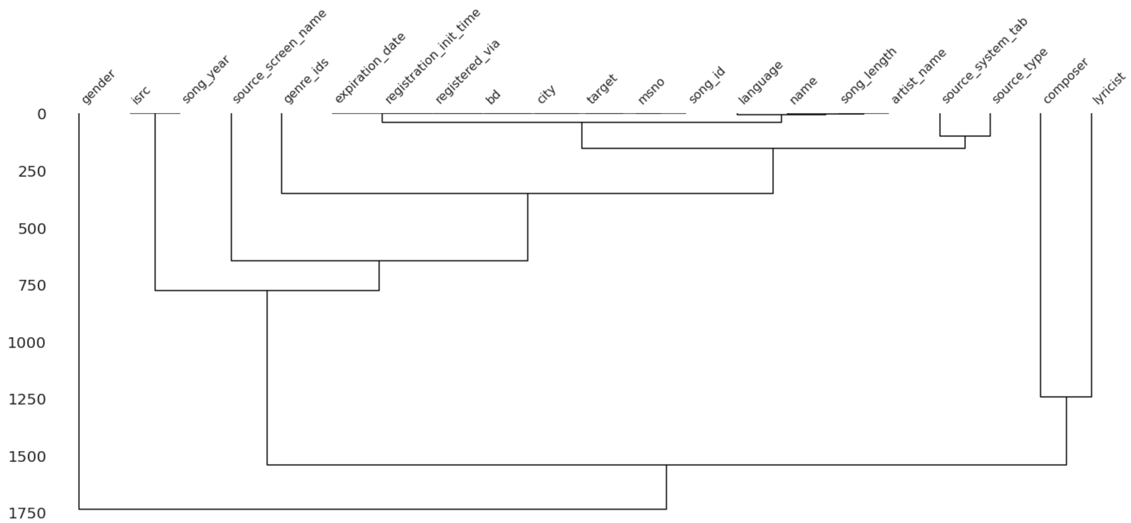
- From the above heatmap we can say that, song length is depends on artist and the language in which it is made.
- lyrist and composer are also corelated, like some composers have their biases on lyrist and vice versa.
- song_length is also correlated with artist, composer, lyricist, genre_id, language, name, song_year, isrc.

In [ ]:

```
msno.dendrogram(train_merged)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f951b51aef0>
```



- A strong nullity correlation here we can see:
- source_system_tab -> source_type
- composer -> lyricst
- lanugage -> song_length, artist_name, name
- isrc -> song_year

2. Feature Engineering

- We have train, test, members, songs and songs_extra_info files.
- We will extract individual independent features from members, songs and songs_extra.
- We will extract dependent features on train and val data after splitting to avoid data leakage problem.

In [ ]:

```
del train, test, members, songs, song_extra_info
```

In [ ]:

```
import time
import numpy as np
import pandas as pd
import lightgbm as lgb
import gc
```

In [ ]:

```
data_path = '/content/drive/My Drive/CS-1/Data/'
```

In [ ]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/a
uth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.go
ogleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoo
b&response_type=code&scope=email%20https%3a%2f%2fwww.googleapis.co
m%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdr
ive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readon
ly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
··········
Mounted at /content/drive
```

In [ ]:

```
members = pd.read_csv(data_path + 'members.csv')
songs = pd.read_csv(data_path + 'songs.csv')
songs_extra = pd.read_csv(data_path + 'song_extra_info.csv')
train = pd.read_csv(data_path + 'train.csv')
test = pd.read_csv(data_path + 'test.csv')
```

Splitting data

In [ ]:

```
# https://www.kaggle.com/kamilkk/i-have-to-say-this
# As the data is oredered in chronological order so, we will take 80% train and
 20% val data from train data
tr_index = train.shape[0] * 8 // 10
```

In [ ]:

```
train_data = train.iloc[:tr_index]
val_data = train.iloc[tr_index:]
print(train_data.shape, val_data.shape, test.shape)
```

```
(5901934, 6) (1475484, 6) (2556790, 6)
```

Merge data with members, songs and songs_extra

In [ ]:

```
# merge with members
train_members = pd.merge(train_data, members, on='msno', how='left')
val_members = pd.merge(val_data, members, on='msno', how='left')
test_members = pd.merge(test, members, on='msno', how='left')
```

In [ ]:

```
# merge songs and songs_extra
songs_all = pd.merge(songs, songs_extra, on='song_id', how='left')
```

In [ ]:

```
# merge with members
train_all = pd.merge(train_members, songs_all, on='song_id', how='left')
val_all = pd.merge(val_members, songs_all, on='song_id', how='left')
test_all = pd.merge(test_members, songs_all, on='song_id', how='left')
```

In [ ]:

```
del train_members
del val_members
del test_members
del songs_all
```

In [ ]:

```
del train_data
del val_data
```

In [ ]:

```
del train, test
```

F.E. for Memebrs

- Members dataframe has registration and expiration dates, from which we can extract features like membership time, individual day, month and year.
- From analysis of 'bd' feature we noticed some oputliers like negetive and higher values of ages, which we can remove.

In [ ]:

```
def filter_age(x):
  # 98th percentile is 47
  '''Function to fix age value between 0 to 75'''
  if x >= 0 and x <= 75:
    return x
  else:
    return np.nan

train_all['bd'] = train_all['bd'].apply(filter_age)
val_all['bd'] = val_all['bd'].apply(filter_age)
test_all['bd'] = test_all['bd'].apply(filter_age)
```

- I have borrowed some ideas for F.E. from the kaggle kernel https://www.kaggle.com/asmitavikas/feature-engineered-0-68310 (https://www.kaggle.com/asmitavikas/feature-engineered-0-68310)

In [ ]:

```
# source: https://www.kaggle.com/asmitavikas/feature-engineered-0-68310
def extract_date_fatures(data):
  '''Function to extract features like day, month, year from dates.'''
  # convert into date format
  data['expiration_date'] = pd.to_datetime(data['expiration_date'], format='%Y%m
%d')
  data['registration_init_time'] = pd.to_datetime(data['registration_init_time'
], format='%Y%m%d')

  # get membership period from registration and expiration dates
  data['membership_days'] = data['expiration_date'].subtract(data['registration_
init_time']).dt.days.astype(int)

  # extract year, month and day from dates
  data['registration_year'] = data['registration_init_time'].dt.year
  data['registration_month'] = data['registration_init_time'].dt.month
  data['registration_day'] = data['registration_init_time'].dt.day

  data['expiration_year'] = data['expiration_date'].dt.year
  data['expiration_month'] = data['expiration_date'].dt.month
  data['expiration_day'] = data['expiration_date'].dt.day

  return data

train_all = extract_date_fatures(train_all)
val_all = extract_date_fatures(val_all)
test_all = extract_date_fatures(test_all)
```

F.E for Songs

- We have seen that songs has 'lyricist' and 'composer' features which have more than 25% of missing values. So let's just ignore these two features for now and fill missing values in the remaining features.

In [ ]:

```
train_all.tail(3)
```

Out[ ]:

	msno	
5901931	+fzJ5Uou/rxl1pXlebOEBHFKC4LBwDfgnc2R7287CVs=	b8Ec5KHbhiJc+Aeg4hg
5901932	+fzJ5Uou/rxl1pXlebOEBHFKC4LBwDfgnc2R7287CVs=	fwaxN4NL0q27tHQq4VI
5901933	+fzJ5Uou/rxl1pXlebOEBHFKC4LBwDfgnc2R7287CVs=	yqZjiUmLn/+h6g047I0LI

In [ ]:

```
train_all.isnull().any()
```

Out[ ]:

```
msno                       False
song_id                    False
source_system_tab           True
source_screen_name          True
source_type                 True
target                     False
city                       False
bd                          True
gender                      True
registered_via             False
registration_init_time     False
expiration_date            False
song_length                 True
genre_ids                   True
artist_name                 True
composer                    True
lyricist                    True
language                    True
name                        True
isrc                        True
membership_days            False
registration_year          False
registration_month         False
registration_day           False
expiration_year            False
expiration_month           False
expiration_day             False
dtype: bool
```

In [ ]:

```
train_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5901934 entries, 0 to 5901933
Data columns (total 27 columns):
 #   Column                  Dtype
---  ------                  -----
 0   msno                    object
 1   song_id                 object
 2   source_system_tab       object
 3   source_screen_name      object
 4   source_type             object
 5   target                  int64
 6   city                    int64
 7   bd                      float64
 8   gender                  object
 9   registered_via          int64
 10  registration_init_time  datetime64[ns]
 11  expiration_date         datetime64[ns]
 12  song_length             float64
 13  genre_ids               object
 14  artist_name             object
 15  composer                object
 16  lyricist                object
 17  language                float64
 18  name                    object
 19  isrc                    object
 20  membership_days         int64
 21  registration_year       int64
 22  registration_month      int64
 23  registration_day        int64
 24  expiration_year         int64
 25  expiration_month        int64
 26  expiration_day          int64
dtypes: datetime64[ns](2), float64(3), int64(10), object(12)
memory usage: 1.2+ GB
```

In [ ]:

```
# Filling missing values
def filling_missing_values(data):
  data['source_system_tab'].fillna('no_system_tab', inplace=True)
  data['source_screen_name'].fillna('no_screen_name', inplace=True)
  data['source_type'].fillna('np_source_type', inplace=True)
  data['bd'].fillna(0, inplace=True)
  data['gender'].fillna('gender_missing', inplace=True)
  data['song_length'].fillna(0, inplace=True)
  data['genre_ids'].fillna(0, inplace=True)
  data['lyricist'].fillna('no_lyricist', inplace=True)
  data['artist_name'].fillna('no_artist_name', inplace=True)
  data['composer'].fillna('no_composer', inplace=True)
  data['language'].fillna('no_language', inplace=True)
  data['name'].fillna('no_name', inplace=True)
  return data

train_all = filling_missing_values(train_all)
val_all = filling_missing_values(val_all)
test_all = filling_missing_values(test_all)
```

F.E. for Genre

- Some genre_ids have more than one values which are seperated by '|'.
- We can extract features from genre_ids like total_count of genres.
- We can also seperate genre_ids in-to individual columns. To achieve this we will consider more than 2 genre_ids_count.
- I have borrowed this F.E idea from first place soultion.
- https://github.com/lystdo/Codes-for-WSDM-CUP-Music-Rec-1st-place-solution/blob/master/input/training/script/id_process.py (https://github.com/lystdo/Codes-for-WSDM-CUP-Music-Rec-1st-place-solution/blob/master/input/training/script/id_process.py)

In [ ]:

```
# source : https://github.com/lystdo/Codes-for-WSDM-CUP-Music-Rec-1st-place-solu
tion/blob/master/input/training/script/id_process.py
def generate_genre_ids(data):
  '''Function to sepearate each genre_id and count total number of genre_ids'''
  genre_ids_matrix = np.zeros((data.shape[0], 4))

  for i in range(data.shape[0]):
    ids = str(data['genre_ids'].values[i]).split('|')
    if len(ids) > 2:
        genre_ids_matrix[i, 0] = (ids[0])
        genre_ids_matrix[i, 1] = (ids[1])
        genre_ids_matrix[i, 2] = (ids[2])
    elif len(ids) > 1:
        genre_ids_matrix[i, 0] = (ids[0])
        genre_ids_matrix[i, 1] = (ids[1])
    elif len(ids) == 1:
        genre_ids_matrix[i, 0] = (ids[0])
    genre_ids_matrix[i, 3] = len(ids)

  data['first_genre_id'] = genre_ids_matrix[:, 0] # keeps first genre_id
  data['second_genre_id'] = genre_ids_matrix[:, 1] # keeps second genre_id
  data['third_genre_id'] = genre_ids_matrix[:, 2] # keeps third genre_id
  data['genre_ids_count'] = genre_ids_matrix[:, 3] # keeps count of genre_ids
  return data
```

In [ ]:

```
train_all = generate_genre_ids(train_all)
val_all = generate_genre_ids(val_all)
test_all = generate_genre_ids(test_all)
```

- We will drop 'composer' and 'lyricist' as they contains higher missing values.

In [ ]:

```
train_all = train_all.drop(['composer', 'lyricist'], axis=1)
val_all = val_all.drop(['composer', 'lyricist'], axis=1)
test_all = test_all.drop(['composer', 'lyricist'], axis=1)
```

F.E for Artist

- Some songs has 'feat' included in their artist names. We will add another column with boolean value based on 'feat' presents or not.
- If more than one artists are present in the song then their names are seperated by & and ,
- We will add extra features like is_featured, artist_count, first_artist_name.

In [ ]:

```
def calculate_is_featured(data):
  '''Function to check 'feat' in artist field.'''
  data['is_featured'] = data['artist_name'].apply(lambda x: 1 if ' feat' in str(
x) else 0).astype(np.int8)
  return data
```

In [ ]:

```
train_all = calculate_is_featured(train_all)
val_all = calculate_is_featured(val_all)
test_all = calculate_is_featured(test_all)
```

In [ ]:

```
# source : https://github.com/lystdo/Codes-for-WSDM-CUP-Music-Rec-1st-place-solu
tion/blob/master/input/training/script/id_process.py
def artist_count(x):
  '''Function to count total number of artists for each song'''
  return x.count('and') + x.count(',') + x.count(' feat') + x.count('&') + 1

def get_first_artist(x):
  '''Function to extract first artist name from more than one artists'''
  if x.count('and') > 0:
    x = x.split('and')[0]
  if x.count(',') > 0:
    x = x.split(',')[0]
  if x.count(' feat') > 0:
    x = x.split(' feat')[0]
  if x.count('&') > 0:
    x = x.split('&')[0]
  return x.strip()
```

In [ ]:

```
def calculate_artist_features(data):
  '''Function to execute above both functions'''
  # get artist count
  data['artist_count'] = data['artist_name'].apply(artist_count).astype(np.int8)
  # get first artist name
  data['first_artist_name'] = data['artist_name'].apply(get_first_artist)
  return data
```

In [ ]:

```
train_all = calculate_artist_features(train_all)
val_all = calculate_artist_features(val_all)
test_all = calculate_artist_features(test_all)
```

F.E. for Lyricist

In [ ]:

```
def lyricist_count(x):
    '''Function to count lyricists'''
    if x == 'no_lyricist':
        return 0
    else:
        return sum(map(x.count, ['|', '/', '\\', ';'])) + 1
    return sum(map(x.count, ['|', '/', '\\', ';']))

def get_first_lyricist(x):
    '''Function to get lyricist first name'''
    try:
        if x.count('|') > 0:
            x = x.split('|')[0]
        if x.count('/') > 0:
            x = x.split('/')[0]
        if x.count('\\') > 0:
            x = x.split('\\')[0]
        if x.count(';') > 0:
            x = x.split(';')[0]
        return x.strip()
    except:
        return x

def calculate_lyricist_features(data):
  '''Function to extract features for lyricist'''
  data['lyricist_count'] = data['lyricist'].apply(lyricist_count).astype(np.int8
)
  data['first_lyricist'] = data['lyricist'].apply(get_first_lyricist)
  return data

train_all = calculate_lyricist_features(train_all)
val_all = calculate_lyricist_features(val_all)
test_all = calculate_lyricist_features(test_all)
```

F.E. Composer

In [ ]:

```
def composer_count(x):
    '''Function to get composer count'''
    if x == 'no_composer':
        return 0
    else:
        return sum(map(x.count, ['|', '/', '\\', ';'])) + 1

def get_first_composer(x):
    '''Function to get first composer name'''
    try:
        if x.count('|') > 0:
            x = x.split('|')[0]
        if x.count('/') > 0:
            x = x.split('/')[0]
        if x.count('\\') > 0:
            x = x.split('\\')[0]
        if x.count(';') > 0:
            x = x.split(';')[0]
        return x.strip()
    except:
        return x

def calculate_composer_features(data):
  '''Function to extrract composer features'''
  data['composer_count'] = data['composer'].apply(composer_count).astype(np.int8
)
  data['first_composer'] = data['composer'].apply(get_first_composer)
  return data

train_all = calculate_composer_features(train_all)
val_all = calculate_composer_features(val_all)
test_all = calculate_composer_features(test_all)
```

F.E. for Extra

- We will add boolean feature for songs, if song comes from '17' or '45' lanuage then we will set boolean feature.
- We will calculate mean length of song from train songs and will set the song's size as an extra boolean feature either smaller than mean or not.

In [ ]:

```
# source : https://www.kaggle.com/asmitavikas/feature-engineered-0-68310

def song_lang_boolean(x):
  '''Function to add language boolean feature'''
  if 17.0 == str(x) or 45.0 == str(x):
    return 1
  else:
    return 0

mean_song_length = np.mean(train_all['song_length'])
def smaller_song(x):
  '''Function to add song_size boolean feature'''
  if x < mean_song_length:
    return 1
  else:
    return 0
```

In [ ]:

```
def calculate_language_features(data):
  data['song_lang_boolean'] = data['language'].apply(song_lang_boolean).astype(n
p.int8)
  data['song_size_boolean'] = data['song_length'].apply(smaller_song).astype(np.
int8)
  return data
```

In [ ]:

```
train_all = calculate_language_features(train_all)
val_all = calculate_language_features(val_all)
test_all = calculate_language_features(test_all)
```

F.E for songs_extra

- songs_extra file has feature like 'isrc' which is International Standard Recording Code. For each song its isrc is unique which contains information like countr_code, registraion_code, year of reference and designation code.
- https://isrc.ifpi.org/en/isrc-standard/code-syntax (https://isrc.ifpi.org/en/isrc-standard/code-syntax)
- We can extract features like country_code, registration_code and song_year from 'isrc' feature.

In [ ]:

```
# source : https://www.kaggle.com/asmitavikas/feature-engineered-0-68310
def calcualte_songs_features(data):
  '''Function to extract features from isrc.'''
  isrc = data['isrc']
  data['country_code'] = isrc.str.slice(0, 2)
  data['registration_code'] = isrc.str.slice(2, 5)
  data['song_year'] = isrc.str.slice(5, 7).astype(float)
  data['song_year'] = data['song_year'].apply(lambda x: 2000+x if x < 18 else 19
00+x)
  data['isrc_missing'] = (data['country_code'] == 0) * 1.0
  return data
```

In [ ]:

```
train_all = calcualte_songs_features(train_all)
val_all = calcualte_songs_features(val_all)
test_all = calcualte_songs_features(test_all)
```

In [ ]:

```
def filling_missing_isrc_values(data):
  '''Function to fill missing isrc values'''
  data['isrc'].fillna('no_isrc', inplace=True)
  data['country_code'].fillna('no_country_code', inplace=True)
  data['registration_code'].fillna('no_registration_code', inplace=True)
  data['song_year'].fillna('no_song_year', inplace=True)
  return data

train_all = filling_missing_isrc_values(train_all)
val_all = filling_missing_isrc_values(val_all)
test_all = filling_missing_isrc_values(test_all)
```

In [ ]:

```
val_all.columns
```

Out[ ]:

```
Index(['msno', 'song_id', 'source_system_tab', 'source_screen_nam
e',
       'source_type', 'target', 'city', 'bd', 'gender', 'registered
_via',
       'registration_init_time', 'expiration_date', 'song_length',
'genre_ids',
       'artist_name', 'composer', 'lyricist', 'language', 'name',
'isrc',
       'membership_days', 'registration_year', 'registration_mont
h',
       'registration_day', 'expiration_year', 'expiration_month',
       'expiration_day', 'first_genre_id', 'second_genre_id', 'thir
d_genre_id',
       'genre_ids_count', 'is_featured', 'artist_count', 'first_art
ist_name',
       'lyricist_count', 'first_lyricist', 'composer_count', 'first
_composer',
       'song_lang_boolean', 'song_size_boolean', 'country_code',
       'registration_code', 'song_year', 'isrc_missing'],
      dtype='object')
```

In [ ]:

```
train_all = train_all.drop(['genre_ids', 'artist_name', 'composer', 'lyricist',
'isrc', 'registration_init_time', 'expiration_date'], axis=1)
val_all = val_all.drop(['genre_ids', 'artist_name' , 'composer', 'lyricist', 'is
rc', 'registration_init_time', 'expiration_date'], axis=1)
test_all = test_all.drop(['genre_ids', 'artist_name' , 'composer', 'lyricist',
'isrc', 'registration_init_time', 'expiration_date'], axis=1)
```

Group by features

- As some users have preferences over their favourite songs, artists or language.
- Like indian people over 40 ages are fond of hindi soothing or bollywood classics rather than english pop or rock music.
- Using group by we can extract some features based on user's choices like song_count (for each song how many times he/she listens), artist_count (for each artist how many number of users or songs are present in our dataset.)
- We will extract theese types of group by features according to train, val and test data seperately to avoid data leakage issues.

In [ ]:

```
def calculate_groupby_features(data):
  '''Function to calculate group by features on dataframe '''
  # song count for each user
  member_song_count = data.groupby('msno').count()['song_id'].to_dict()
  data['member_song_count'] = data['msno'].apply(lambda x: member_song_count[x])

  # song count for each artist
  artist_song_count = data.groupby('first_artist_name').count()['song_id'].to_di
ct()
  data['artist_song_count'] = data['first_artist_name'].apply(lambda x: artist_s
ong_count[x])

  # song count for each composer
  composer_song_count = data.groupby('first_composer').count()['song_id'].to_dic
t()
  data['composer_song_count'] = data['first_composer'].apply(lambda x: composer_
song_count[x])

  # song count for each lyricist
  lyricist_song_count = data.groupby('first_lyricist').count()['song_id'].to_dic
t()
  data['lyricist_song_count'] = data['first_lyricist'].apply(lambda x: lyricist_
song_count[x])

  # song count for each genre_id
  first_genre_id_song_count = data.groupby('first_genre_id').count()['song_id'].
to_dict()
  data['genre_song_count'] = data['first_genre_id'].apply(lambda x: first_genre_
id_song_count[x])

  # song count for each lanugage
  lang_song_count = data.groupby('language').count()['song_id'].to_dict()
  data['lang_song_count'] = data['language'].apply(lambda x: lang_song_count[x])

  # user count for each song
  song_member_count = data.groupby('song_id').count()['msno'].to_dict()
  data['song_member_count'] = data['song_id'].apply(lambda x: song_member_count[
x])

  # We can add group by  wrt 'age'
  age_song_count = data.groupby('bd').count()['song_id'].to_dict()
  data['age_song_count'] = data['bd'].apply(lambda x: age_song_count[x])

  return data
```

In [ ]:

```
train_all = calculate_groupby_features(train_all)
val_all = calculate_groupby_features(val_all)
test_all = calculate_groupby_features(test_all)
```

In [ ]:

```
save_path = '/content/drive/My Drive/CS-1/'

train_all.to_csv(save_path + 'train_all_new.csv', index=False)
val_all.to_csv(save_path + 'val_all_new.csv', index=False)
test_all.to_csv(save_path + 'test_all_new.csv', index=False)
```

3. Summary

-> EDA

- We have analyzed each and every feature from train and validation dataset with the help of different plots like barplot, PDF and CDF.
- We have also analyzed missing values and their percentages in features.

-> Feature Engineering

- From songs, songs_extra_info and members we have combined all information related to user and songs and extracted various features.
- We have extracted features like membership days, information of year, month and day from registration and expiration dates.
- We have also extracted groupby features for songs and users with respect to artist, lyricist, composer, language, age etc.
- We have extracted features like song year, country code, registration code from isrc code for each and every song. Along with that we have extracted counts like artist count, genre count, lyricist count, composer count etc.