Music Recommendation System

¶

What is Recommendation system and how it is used for recommending the particular song to user

A recommender system, or a recommendation system is a subclass of information filtering system that seeks to predict the "rating" or "preference" a user would give to an item.

Recommender systems are used in a variety of areas, with commonly recognised examples taking the form of playlist generators for video and music services, product recommenders for online stores, or content recommenders for social media platforms and open web content recommenders. These systems can operate using a single input, like music, or multiple inputs within and across platforms like news, books, and search queries.

By using music recommender system, the music provider can predict and then offer the appropriate songs to their users based on the characteristics of the music that has been heard previously.

Our research would like to develop a music recommender system that can give recommendations based on similarity of features on audio files.

Let us check the Information about the data

The Dataset that we are going to deal for this project is :

- kaggle_visible_evaluation_triplets - It contains User_Id of the listener,Song_Id of the song and frequency that is how many times the song has been played.
- Unique_tracks - It contains information about Track_id , Song_id, Artist_name and Release of the song.

Importing the necessary libraries for analysing the data

In [59]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
import os
import random
from datetime import datetime
import warnings
warnings.filterwarnings("ignore")
```

Reading the kaggle_triplets dataset

In [60]:

```
song_df = pd.read_table('kaggle_visible_evaluation_triplets.txt',sep="\t",names=["user_id",
```

Checking the head and tail section of the dataset

In [61]:

```
song_df.head()
```

Out[61]:

	user_id	song_id	Freq
0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOBONKR12A58A7A7E0	1
1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOEGIYH12A6D4FC0E3	1
2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOFLJQZ12A6D4FADA6	1
3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOHTKMO12AB01843B0	1
4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SODQZCY12A6D4F9D11	1

In [62]:

```
song_df.tail()
```

Out[62]:

	user_id	song_id	Freq
1450928	5e650759ebf89012044c6d52121eeada8b0ec814	SOVLNXV12A6D4F706E	1
1450929	5e650759ebf89012044c6d52121eeada8b0ec814	SOVDSJC12A58A7A271	2
1450930	5e650759ebf89012044c6d52121eeada8b0ec814	SOBRHVR12A8C133F35	2
1450931	5e650759ebf89012044c6d52121eeada8b0ec814	SOMGVYU12A8C1314FF	2
1450932	5e650759ebf89012044c6d52121eeada8b0ec814	SOTCMDJ12A6D4F8528	3

Checking the information about the kaggle_triplets data

In [63]:

```
## Checking the for the columns in the dataset

song_df.columns
song_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1450933 entries, 0 to 1450932
Data columns (total 3 columns):
 #   Column   Non-Null Count    Dtype 
---  ------   --------------    ----- 
 0   user_id  1450933 non-null  object
 1   song_id  1450933 non-null  object
 2   Freq     1450933 non-null  int64 
dtypes: int64(1), object(2)
memory usage: 33.2+ MB
```

Reading the unique_tracks dataset to merge the two given datasets

In [64]:

```
song_df2 = pd.read_table('unique_tracks.txt',sep='<SEP>',names=["Track_id","song_id","Artis
```

In [65]:

```
song_df2.head()
```

Out[65]:

	Track_id	song_id	Artist_name	song_name
0	TRMMMYQ128F932D901	SOQMMHC12AB0180CB8	Faster Pussy cat	Silent Night
1	TRMMMKD128F425225D	SOVFVAK12A8C1350D9	Karkkiautomaatti	Tanssi vaan
2	TRMMMRX128F93187D9	SOGTUKN12AB017F4F1	Hudson Mohawke	No One Could Ever
3	TRMMMCH128F425532C	SOBNYVR12A8C13558C	Yerba Brava	Si Vos Querés
4	TRMMMWA128F426B589	SOHSBXH12A8C13B0DF	Der Mystic	Tangle Of Aspens

In [66]:

```
song_df2.tail()
```

Out[66]:

	Track_id	song_id	Artist_name	song_name
999995	TRYYYUS12903CD2DF0	SOTXAME12AB018F136	Kiko Navarro	O Samba Da Vida
999996	TRYYYJO128F426DA37	SOXQYIQ12A8C137FBB	Kuldeep Manak	Jago Chhadeo
999997	TRYYYMG128F4260ECA	SOHODZI12A8C137BB3	Gabriel Le Mar	Novemba
999998	TRYYYDJ128F9310A21	SOLXGOR12A81C21EB7	Elude	Faraday
999999	TRYYYVU12903CD01E3	SOWXJXQ12AB0189F43	Texta	Fernweh feat. Sektion Kuchikäschtli

Drop the Track_id column as it is not much useful we know song or track have the similar features so better drop those column

In [67]:

```
df2=song_df2.drop('Track_id',axis=1)
```

In [68]:

```
df2.head()
```

Out[68]:

	song_id	Artist_name	song_name
0	SOQMMHC12AB0180CB8	Faster Pussy cat	Silent Night
1	SOVFVAK12A8C1350D9	Karkkiautomaatti	Tanssi vaan
2	SOGTUKN12AB017F4F1	Hudson Mohawke	No One Could Ever
3	SOBNYVR12A8C13558C	Yerba Brava	Si Vos Querés
4	SOHSBXH12A8C13B0DF	Der Mystic	Tangle Of Aspens

Checking for the information about the data

In [69]:

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
 #   Column       Non-Null Count    Dtype 
---  ------       --------------    ----- 
 0   song_id      1000000 non-null  object
 1   Artist_name  1000000 non-null  object
 2   song_name    999985 non-null   object
dtypes: object(3)
memory usage: 22.9+ MB
```

Let us merge the two datasets together to perform some analysis on the given merged data

As we are merging the two datasets and we have a chance to encounter duplicates as we have same columns in two datasets called song_id so better drop those duplicates before merging the data

In [70]:

```
df = pd.merge(song_df,df2.drop_duplicates(['song_id']),on='song_id',how='left')
```

Checking the head of the dataset after merging

In [71]:

```
df.head()
```

Out[71]:

	user_id	song_id	Freq	Artist_name	s
0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOBONKR12A58A7A7E0	1	Dwight Yoakam	
1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOEGIYH12A6D4FC0E3	1	Barry Tuckwell/Academy of St Martin-in-the-Fie...	f
2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOFLJQZ12A6D4FADA6	1	Cartola	
3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOHTKMO12AB01843B0	1	Lonnie Gordon	E
4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SODQZCY12A6D4F9D11	1	Miguel Calo	

Checking the shape of the data, columns, info and data types of given merged dataset

In [72]:

```
print("the shape of merged data is :",df.shape)
print("Checking for the column names:",df.columns)
print("Checking the length of the data :",len(df))
print("finding the Information about the data :",df.info())
```

```
the shape of merged data is : (1450933, 5)
Checking for the column names: Index(['user_id', 'song_id', 'Freq', 'Artist_
name', 'song_name'], dtype='object')
Checking the length of the data : 1450933
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1450933 entries, 0 to 1450932
Data columns (total 5 columns):
 #   Column       Non-Null Count    Dtype 
---  ------       --------------    ----- 
 0   user_id      1450933 non-null  object
 1   song_id      1450933 non-null  object
 2   Freq         1450933 non-null  int64 
 3   Artist_name  1450933 non-null  object
 4   song_name    1450932 non-null  object
dtypes: int64(1), object(4)
memory usage: 66.4+ MB
finding the Information about the data : None
```

Let us check wheather our dataset is clean or not to proceed for Analysis part

Checking for the null values within the dataframe

In [73]:

```
df.isnull().sum()
```

Out[73]:

```
user_id        0
song_id        0
Freq           0
Artist_name    0
song_name      1
dtype: int64
```

In [74]:

```
df['song_name'].isnull().sum()
```

Out[74]:

```
1
```

In [75]:

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

In [76]:

```
df.isnull().sum()
```

Out[76]:

```
index          0
user_id        0
song_id        0
Freq           0
Artist_name    0
song_name      0
dtype: int64
```

In [78]:

```
df.head()
```

Out[78]:

	index	user_id	song_id	Freq	Artist_n
0	0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOBONKR12A58A7A7E0	1	Dwight Yoa
1	1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOEGIYH12A6D4FC0E3	1	E Tuckwell/Acac of St Martin-in
2	2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOFLJQZ12A6D4FADA6	1	Ca
3	3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOHTKMO12AB01843B0	1	Lonnie Gc
4	4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SODQZCY12A6D4F9D11	1	Miguel

Applying basic statistics to know about our data indepth

In [79]:

```
df.describe()
```

Out[79]:

	index	Freq
count	1.450932e+06	1.450932e+06
mean	7.254664e+05	3.187151e+00
std	4.188483e+05	7.051666e+00
min	0.000000e+00	1.000000e+00
25%	3.627338e+05	1.000000e+00
50%	7.254665e+05	1.000000e+00
75%	1.088199e+06	3.000000e+00
max	1.450932e+06	9.230000e+02

In [80]:

```
df.describe(include = 'object')
```

Out[80]:

	user_id	song_id	Artist_name	song_
count	1450932	1450932	1450932	145
unique	110000	163205	28360	13
top	7d90be8dfdbde170f036ce8a4b915440137cb11c	SOFRQTD12A81C233C0	Coldplay	kosı
freq	53	5043	12279	

Checking for the skewness and kurtosis that is present within the data

In [81]:

```
print("Skewness Present in the data is almost : ",df.skew())
print("Kurtosis Present in the data is almost : ",df.kurt())
```

```
Skewness Present in the data is almost :  index    -0.000001
Freq     17.243840
dtype: float64
Kurtosis Present in the data is almost :  index     -1.199999
Freq     785.298304
dtype: float64
```

Checking for the unique values of each columns in the dataset

In [82]:

```
print("Number of Unique User id: {} \nNumber of Unique Song id: {} \nNumber of Unique Freq:
```

```
Number of Unique User id: 110000
Number of Unique Song id: 163205
Number of Unique Freq: 299
Number of Unique Artist names: 28360
Number of Unique Song names: 137622
```

Performing the some data preprocessing and EDA to find the insights in the data

Checking the value_counts for the given User_id column

In [83]:

```
df['user_id'].value_counts()
```

Out[83]:

```
7d90be8dfdbde170f036ce8a4b915440137cb11c    53
d30e18323f15426c3cdc8585252ed34459916f51    52
016a24e91a72c159a5048ab1b9b2ba5ce761b526    52
03ad93fdb01506ce205f4708decf8e4b1ae90fff    52
0f8308935bcbb9a1e04ebb7c4d41c037e5f23b90    52
                                            ..
0818903f259c72534e01c37911432a22392bb419     5
d6e56e1514fda1abe7b9729a12c1f6180ae1ee7f     5
230e320c2e679ea5fbbfed7ae4dad7ad9e1f4f21     5
a1c14d5d7395a6bbb49d080f45b44c5e5cc28a8e     5
1a6f41f40adc550d5c6acefb7172c42e804126b4     5
Name: user_id, Length: 110000, dtype: int64
```

Checking the number of unique songs that the user listened

In [84]:

```
print(len(pd.unique(df['user_id'])))
```

```
110000
```

These value counts show the number of unique songs that the user listened to. We have 110,000 users. Let us see how many among these have listened to more than 10 songs

Checking the number of users who listened more then 10 unique songs

In [85]:

```
v = df['user_id'].value_counts()
count = 0
for i in v:
    if i == 9:
        print(count)
        break
    count = count + 1
```

```
61841
```

Hence, we can see that around 62,000 users have listened to 10 or more unique songs.

Checking for the Song ID count

We intend to find number of times a song was played. For this, we need to take the frequency column under consideration as well. One way of doing this is by using the Song_ID as a key in dictionary and add the frequency of each of the occurences of that song.

In [86]:

```
df.shape
```

Out[86]:

```
(1450932, 6)
```

In [87]:

```
artist_song_count = {}
songs = {}
for i in range(1450932):
    if df['song_id'][i] in songs:
        songs[df['song_id'][i]] = songs[df['song_id'][i]] + df['Freq'][i]
    else:
        songs[df['song_id'][i]] = df['Freq'][i]
        if df['Artist_name'][i] in artist_song_count:
            artist_song_count[df['Artist_name'][i]] = artist_song_count[df['Artist_name'][i
        else:
            artist_song_count[df['Artist_name'][i]] = 1
```

We have song play count stored in a dictionary called songs. A song's playcount can be found out by accessing the dictionary with song id as the key

Importing the operator library

In [88]:

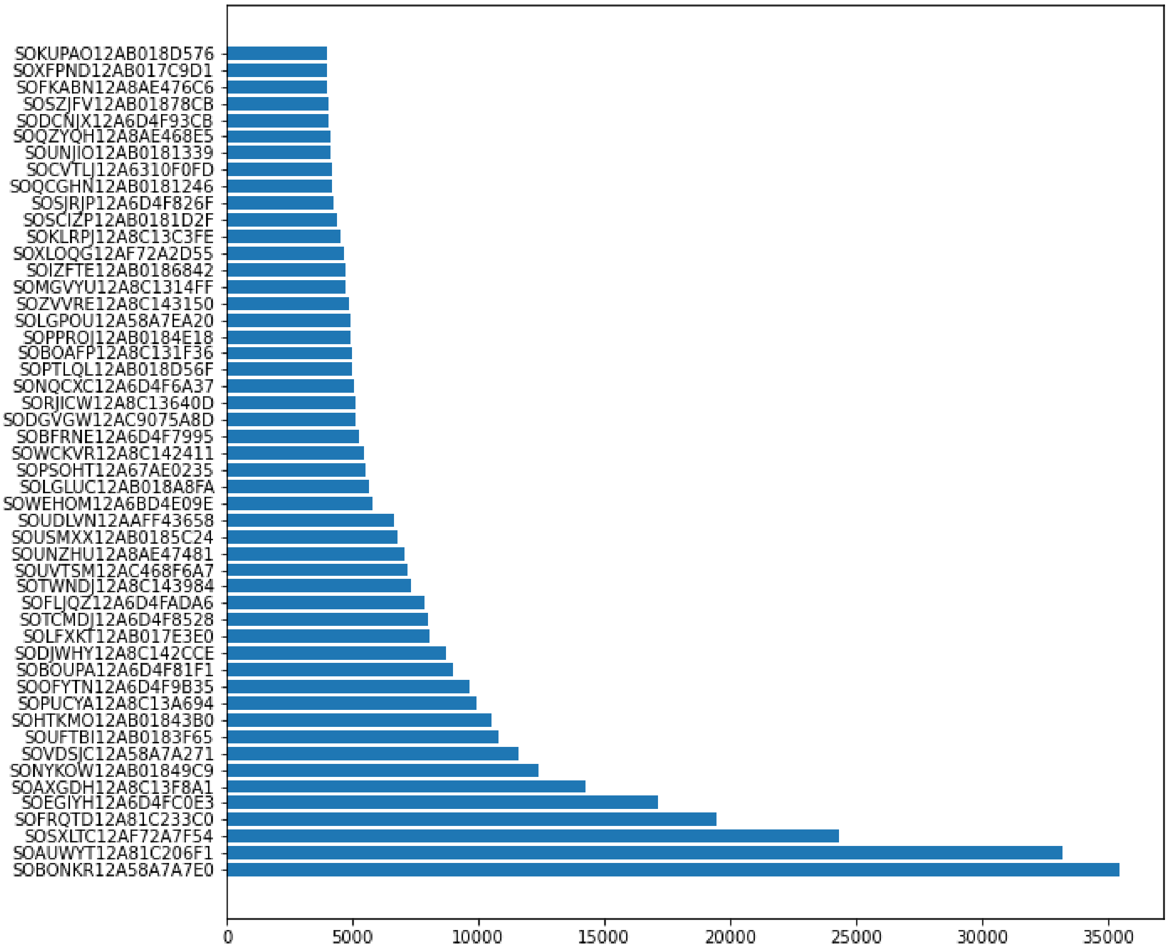
```
import operator
```

In [89]:

```
### Creating a songs_sorted variable

songs_sorted = dict(sorted(songs.items(), key=operator.itemgetter(1),reverse=True))
```

In [90]:

```
D = {}
for i in range(50):
    D[list(songs_sorted.keys())[i]]= list(songs_sorted.values())[i]
plt.figure(figsize=(10,10))
plt.barh(*zip(*D.items()))
plt.show()
```



Since the number of songs are very high, we did a countplot of the top 50 songs by playcount. From the countplot, we can observe that just 10 songs have a playcount of above 10,000. The remaining 40 songs have close playcounts between 5000 and 10,000. We can do a similar analysis for the next 50 songs.

Since the SongIDs are a bit difficult to read, lets replot with song name: and Artist name on the y-axis

In [91]:

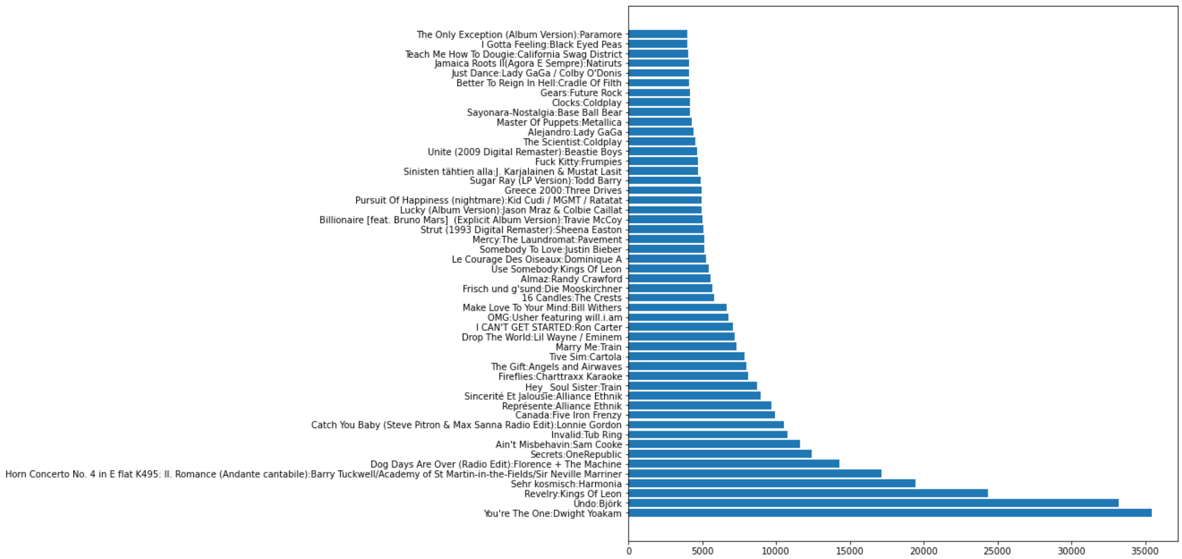
```
song_artist = {}
for i in range(1450932):
    if df['song_name'][i] + ':' + df['Artist_name'][i] in song_artist:
        song_artist[df['song_name'][i] + ':' + df['Artist_name'][i]] = song_artist[df['song
    else:
        song_artist[df['song_name'][i] + ':' + df['Artist_name'][i]] = df['Freq'][i]
```

In [92]:

```
### Sorting the songs according to the artist names

s_art_sorted = dict(sorted(song_artist.items(), key=operator.itemgetter(1),reverse=True))
```

In [93]:

```
D1 = {}
for i in range(50):
    D1[list(s_art_sorted.keys())[i]]= list(s_art_sorted.values())[i]
plt.figure(figsize=(11,11))
plt.barh(*zip(*D1.items()))
plt.show()
```



When we plot the bargraph by considering the columns like song_name and the artist_name we can see that the "You're The One:Dwight Yoakam" and "Undo:Bjork" has got the most listened count compare to other artist songs since we can say that those songs has been liked many users based on there listened count

Let us check the Artist_name based on there song value counts

In [94]:

```
## Checking the value count of artists

df['Artist_name'].value_counts()
```

Out[94]:

```
Coldplay                                    12279
Kings Of Leon                                8514
Florence + The Machine                       8213
Justin Bieber                                7669
Jack Johnson                                 6784
                                            ...
Glenn Tipton                                    1
Thomas Di Leva                                  1
Sidney Polak feat. EastWestRockers              1
Norma Winstone_ Glauco Venier_ Klaus Gesing     1
Lee Coombs                                      1
Name: Artist_name, Length: 28360, dtype: int64
```

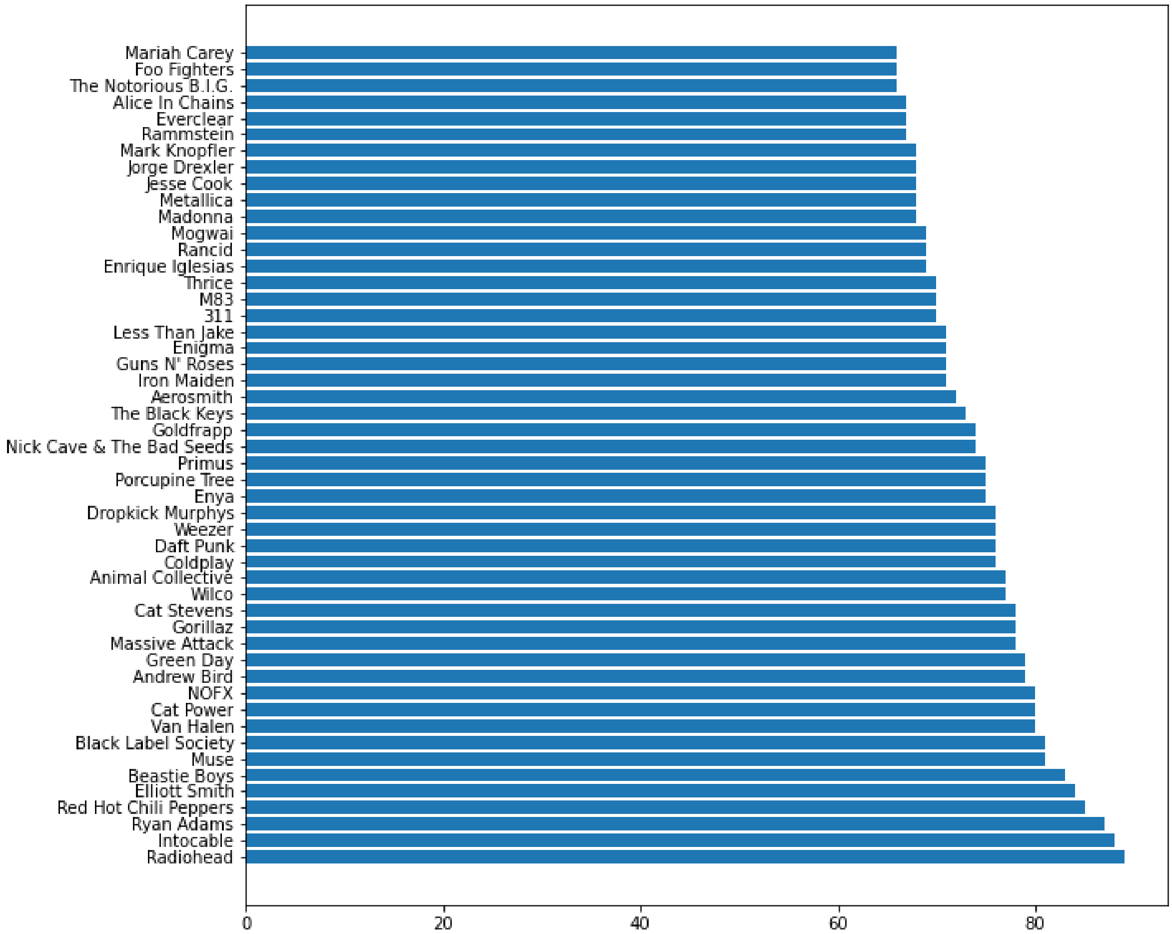
This data for number of songs by an artist is misguiding as songs are repeated.To find out the number of songs each artist releases, we access the dictionary 'songs' which has all the unique songs and find the artist name corresponding to that song and store this in a new dictionary. The dictionary artist_song_count does just that.

In [95]:

```
artist_song_count_sorted = dict(sorted(artist_song_count.items(), key=operator.itemgetter(1
```

In [96]:

```
D2 = {}
for i in range(50):
    D2[list(artist_song_count_sorted.keys())[i]]= list(artist_song_count_sorted.values())[i
plt.figure(figsize=(10,10))
plt.barh(*zip(*D2.items()))
plt.show()
```



The bar plot above shows the top 50 users with highest song counts. Almost 45 of these artists have more than 70 songs

Checking the Artist_name based on their songs listened count

In [97]:

```
(df.groupby(by=["Artist_name"]).sum()).sort_values(by = 'Freq', ascending = False)
```

Out[97]:

Artist_name	index	Freq
Kings Of Leon	6080546825	35857
Dwight Yoakam	3051126379	35688
Björk	3722575301	35210
Coldplay	8781618883	32135
Florence + The Machine	5989627100	28224
...	...	...
Mau - Telepopmusik	844649	1
Simon Says Feat. Aisjah	324543	1
Cyndi Lauper with Jeff Beck	1284749	1
Cycle Sphere	1419293	1
Özlem Tekin	1083377	1

28360 rows × 2 columns

Comparing the raw value_counts of artist name earlier gave us a wrong picture as that approach did not take the frequency of the song into consideration. After we correct that, we get **Kings of Leon** as the artist with most play counts followed by **Dwight Yoakam, Bjork** and **Coldplay**

Checking the top 20 songs of different artist_names based on listen count

In [98]:

```
DF = (df.groupby(by=["Artist_name"]).sum()).sort_values(by = 'Freq', ascending = False)[:20
DF.head(20)
```

Out[98]:

Artist_name	index	Freq
Kings Of Leon	6080546825	35857
Dwight Yoakam	3051126379	35688
Björk	3722575301	35210
Coldplay	8781618883	32135
Florence + The Machine	5989627100	28224
Justin Bieber	5481781317	26133
Alliance Ethnik	2898490819	21603
Train	4714475281	21356
OneRepublic	4316851496	20802
Harmonia	3636502263	19461
Jack Johnson	4990697217	18333
Linkin Park	4042140333	18256
Eminem	4601826516	17681
The Black Keys	4790698414	17366
Barry Tuckwell/Academy of St Martin-in-the-Fields/Sir Neville Marriner	2335048442	17124
Muse	4312112854	17031
Taylor Swift	4003011952	16547
Metallica	3647901088	16105
John Mayer	3782340975	14979
Radiohead	3905981993	14010

We can clearly see that Artists named **Kings of leon**,**Dwight Yoakam**,**Björk**,**Coldplay** has the most listened count to there songs

Let us check artist and his songs based on their song counts

In [99]:

```
song_artist_df = pd.DataFrame.from_dict(song_artist, orient='index',columns=['Song_count'])
song_artist_df.head()
```

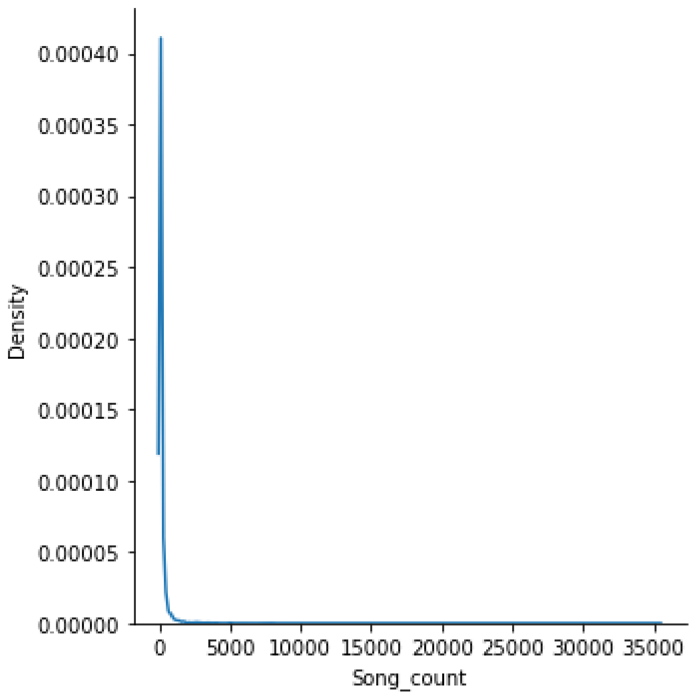
Out[99]:

	Song_count
You're The One:Dwight Yoakam	35432
Horn Concerto No. 4 in E flat K495: II. Romance (Andante cantabile):Barry Tuckwell/Academy of St Martin-in-the-Fields/Sir Neville Marriner	17115
Tive Sim:Cartola	7895
Catch You Baby (Steve Pitron & Max Sanna Radio Edit):Lonnie Gordon	10515
El Cuatrero:Miguel Calo	732

Checking the distribution plot based on songs_count

In [100]:

```
sns.displot(song_artist_df['Song_count'], kind = 'kde')
plt.show()
```



These distribution plot shows that very few songs have high playcounts

Analysing the songs of Top Popular Artists

1. Analysing the songs of King of leon

In [101]:

```
df_kol = df.loc[df['Artist_name'] == 'Kings Of Leon']
df_kol.head()
```

Out[101]:

	index	user_id	song_id	Freq	Artist_n
109	109	fdf6afb5daefb42774617cf223475c6013969724	SOPWKOX12A8C139D43	1	King
135	135	18ce1da0e1017e31baaa5f80afa64ee3c7fab379	SOSXLTC12AF72A7F54	9	King
184	184	eda9bc7bcd72d18b9cf964990eb13a5b1789e78f	SOWCKVR12A8C142411	1	King
329	329	248378ac27e1745d6a9d59392b7dc5b02a6186a6	SOSXLTC12AF72A7F54	2	King
370	370	c732f882aa8d6db3bfaf8037d6418f27d3e07fc8	SOWCKVR12A8C142411	1	King

In [102]:

```
### Checking the shape of df_kol dataframe

df_kol.shape
```

Out[102]:

(8514, 6)

In [103]:

```
df_kol = df_kol.reset_index()
```

In [104]:

```
df_kol.head()
```

Out[104]:

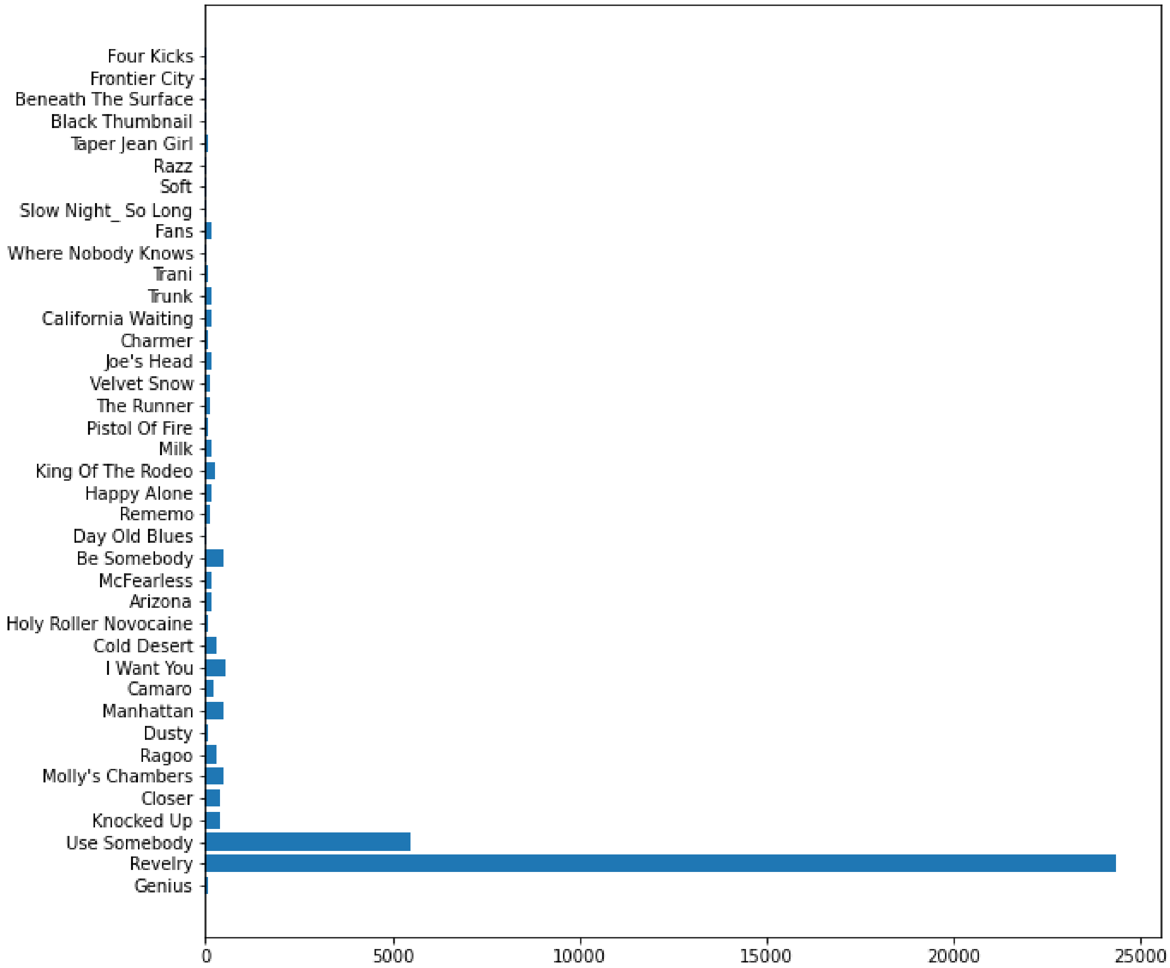
	level_0	index	user_id	song_id	Freq	A
0	109	109	fdf6afb5daefb42774617cf223475c6013969724	SOPWKOX12A8C139D43	1	
1	135	135	18ce1da0e1017e31baaa5f80afa64ee3c7fab379	SOSXLTC12AF72A7F54	9	
2	184	184	eda9bc7bcd72d18b9cf964990eb13a5b1789e78f	SOWCKVR12A8C142411	1	
3	329	329	248378ac27e1745d6a9d59392b7dc5b02a6186a6	SOSXLTC12AF72A7F54	2	
4	370	370	c732f882aa8d6db3bfaf8037d6418f27d3e07fc8	SOWCKVR12A8C142411	1	

In [105]:

```
kol_songs = {}
for i in range(8514):
    if df_kol['song_name'][i] in kol_songs:
        kol_songs[df_kol['song_name'][i]] = kol_songs[df_kol['song_name'][i]] + df_kol['Fre
    else:
        kol_songs[df_kol['song_name'][i]] = df_kol['Freq'][i]
```

In [106]:

```
plt.figure(figsize=(10,10))
plt.barh(*zip(*kol_songs.items()))
plt.show()
```



When we look on the bar plot above the songs like **Revelry and Use Somebody** heavily contributed to King of Leon's high playcount and which made him popular singer with those two songs

2. Analysing the songs of Dwight Yoakam

In [107]:

```
df_dy = df.loc[df['Artist_name'] == 'Dwight Yoakam']
```

In [108]:

```
df_dy.shape
```

Out[108]:

```
(4246, 6)
```

In [109]:

```
df_dy.columns
```

Out[109]:

```
Index(['index', 'user_id', 'song_id', 'Freq', 'Artist_name', 'song_name'], d
type='object')
```

In [110]:

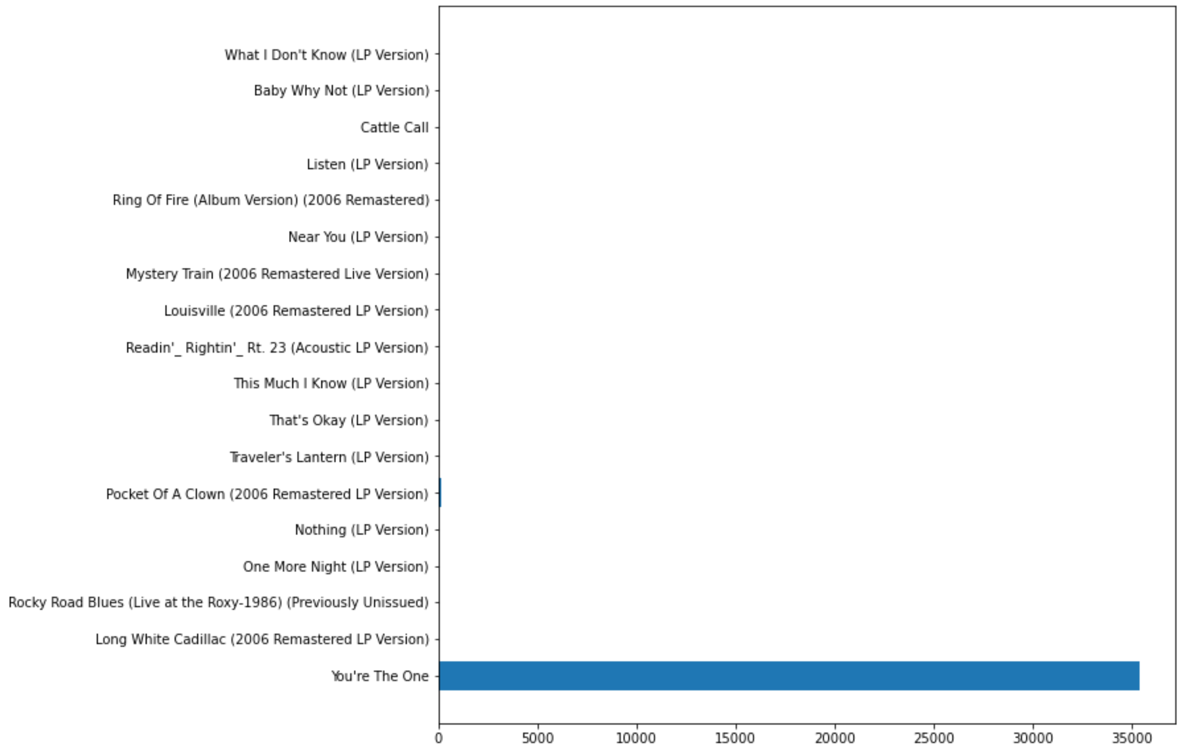
```
df_dy = df_dy.reset_index()
```

In [111]:

```
songs_dy = {}
for i in range(4246):
    if df_dy['song_name'][i] in songs_dy:
        songs_dy[df_dy.loc[i,'song_name']] = songs_dy[df_dy.loc[i,'song_name']] + df_dy.loc
    else:
        songs_dy[df_dy.loc[i,'song_name']] = df_dy.loc[i,'Freq']
```

In [112]:

```
plt.figure(figsize=(10,10))
plt.barh(*zip(*songs_dy.items()))
plt.show()
```



We can boldly conclude that the song **'You're The One'** contributes to Dwight Yoakams high song playcount on its own and which made him popular singer with only this one song

3. Analysing the songs of Coldplay

In [113]:

```
df_cp = df.loc[df['Artist_name'] == 'Coldplay']
```

In [114]:

```
df_cp.shape
```

Out[114]:

```
(12279, 6)
```

In [115]:

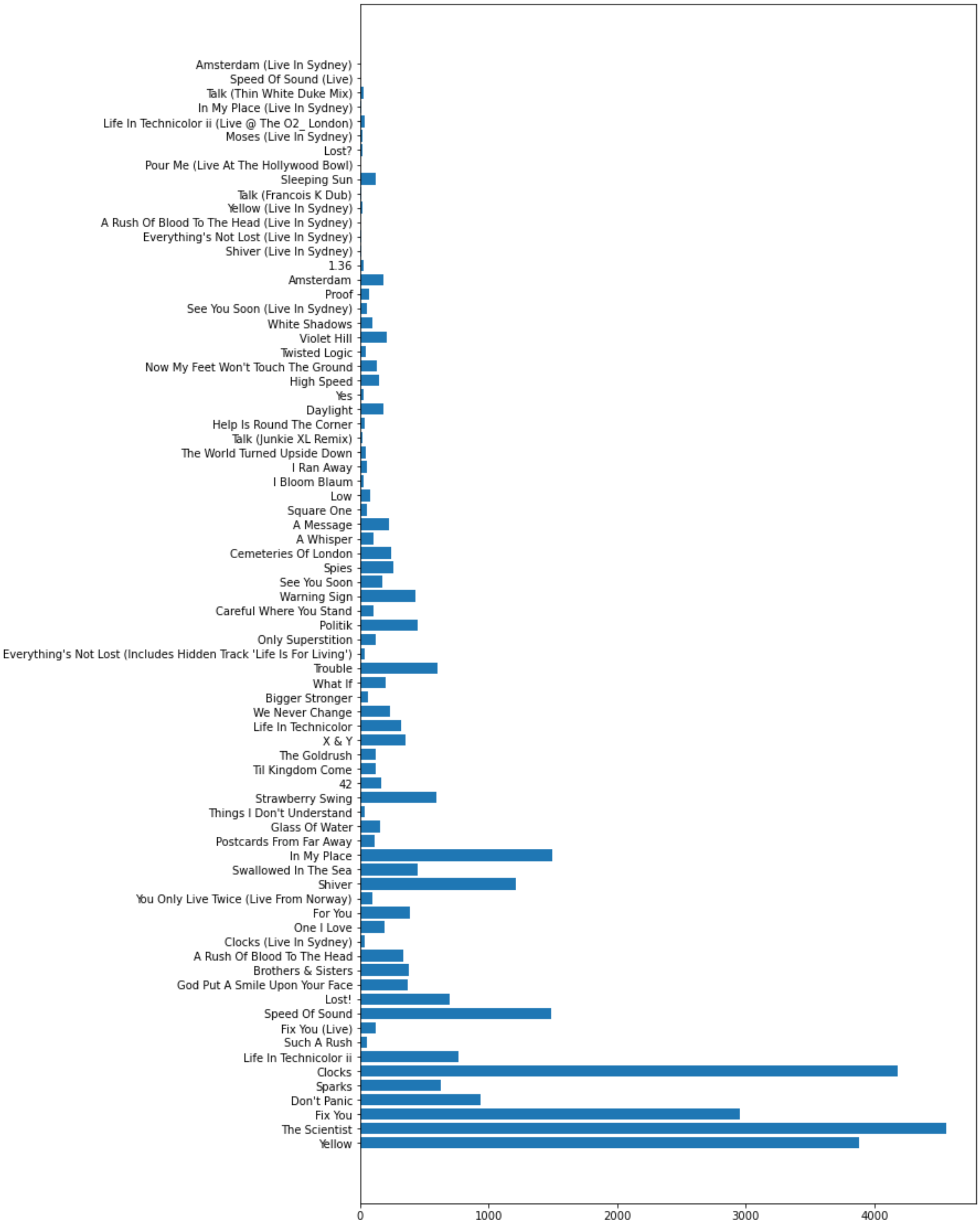
```
df_cp = df_cp.reset_index()
```

In [116]:

```
songs_cp = {}
for i in range(12279):
    if df_cp['song_name'][i] in songs_cp:
        songs_cp[df_cp.loc[i,'song_name']] = songs_cp[df_cp.loc[i,'song_name']] + df_cp.loc
    else:
        songs_cp[df_cp.loc[i,'song_name']] = df_cp.loc[i,'Freq']
```

In [117]:

```
plt.figure(figsize=(10,20))
plt.barh(*zip(*songs_cp.items()))
plt.show()
```



Coldplay has a number of songs contributing to their high song playcount. Major contributors are the songs **The Scientist,Clocks,Yellow** and **Fix you**. The songs **In my place,Shiver** and **Speed of sound** also contibute significantly.

And we can see that most of the songs of him got popular when compare to other artists so we can say that he has highest **fan base** compare to other artists

Until now we have did some **Exploratory data analysis** across different columns in dataset with respect to song_id, artist_name etc.

Now let us take our Original data and do the further prediction in building the recommendation systems

In [118]:

```
df = pd.merge(song_df,df2.drop_duplicates(['song_id']),on='song_id',how='left')
```

In [119]:

```
df.head()
```

Out[119]:

	user_id	song_id	Freq	Artist_name	s
0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOBONKR12A58A7A7E0	1	Dwight Yoakam	
1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOEGIYH12A6D4FC0E3	1	Barry Tuckwell/Academy of St Martin-in-the-Fie...	f
2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOFLJQZ12A6D4FADA6	1	Cartola	
3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOHTKMO12AB01843B0	1	Lonnie Gordon	E
4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SODQZCY12A6D4F9D11	1	Miguel Calo	

In [120]:

```
### Creating a song column which combine both song_name and Artist_name

df['song'] = df['song_name']+' - '+df['Artist_name']
```

In [121]:

```
df.head()
```

Out[121]:

	user_id	song_id	Freq	Artist_name	s
0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOBONKR12A58A7A7E0	1	Dwight Yoakam	
1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOEGIYH12A6D4FC0E3	1	Barry Tuckwell/Academy of St Martin-in-the-Fie...	f
2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOFLJQZ12A6D4FADA6	1	Cartola	
3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOHTKMO12AB01843B0	1	Lonnie Gordon	E
4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SODQZCY12A6D4F9D11	1	Miguel Calo	

In [122]:

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

In [123]:

```
df.head()
```

Out[123]:

	index	user_id	song_id	Freq	Artist_n
0	0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOBONKR12A58A7A7E0	1	Dwight Yoa
1	1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOEGIYH12A6D4FC0E3	1	E Tuckwell/Acad of St Martin-in
2	2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOFLJQZ12A6D4FADA6	1	Ca
3	3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOHTKMO12AB01843B0	1	Lonnie Gc
4	4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SODQZCY12A6D4F9D11	1	Miguel

In [124]:

```
df.shape
```

Out[124]:

(1450932, 7)

Upto now we have understood the **Some Data Preprocesing and also did some Exploratory Data Analysis**

To find the insights about the data let us built some popular **Recomendation models to predict the Songs to New and Existing users**

Building a Recommendation model by using Popularity based Filtering to predict the songs to new users

In [126]:

```
### Top 10 popular songs. We recommend these to a new user

for i in list(D1.keys())[:10]:
    print(i)
```

```
You're The One:Dwight Yoakam
Undo:Björk
Revelry:Kings Of Leon
Sehr kosmisch:Harmonia
Horn Concerto No. 4 in E flat K495: II. Romance (Andante cantabile):Barry Tu
ckwell/Academy of St Martin-in-the-Fields/Sir Neville Marriner
Dog Days Are Over (Radio Edit):Florence + The Machine
Secrets:OneRepublic
Ain't Misbehavin:Sam Cooke
Invalid:Tub Ring
Catch You Baby (Steve Pitron & Max Sanna Radio Edit):Lonnie Gordon
```

Till now we have the songs sorted by popularity. Now, we recommend these songs in a batch of 10 songs to the user. We only recommend songs which the user did not previously listen to.

In [127]:

```
### Creating a User dictionary

users = {}
for i in range(1450932):
    if df['user_id'][i] in users:
        if df['song_id'][i] not in users[df['user_id'][i]]:
            users[df['user_id'][i]].append(df['song_id'][i])
    else:
        users[df['user_id'][i]] = []
        (users[df['user_id'][i]]).append(df['song_id'][i])
```

In [135]:

```
popular_songs = list(s_art_sorted.keys())[:65]
```

In [136]:

```
popular_songs_ids = list(songs_sorted.keys())[:65]
```

In [137]:

```
# Recommend a song to a user

def recommend(User):
    k = 0
    recommended_songs = []
    while k < 10:
        if popular_songs_ids[k] not in users[User]:
            k = k + 1
            recommended_songs.append(popular_songs[k])
    return recommended_songs
```

In [138]:

```
# This is most generally used to recommend for a new user

print(list(songs_sorted.values())[:10])
```

```
[35432, 33179, 24359, 19454, 17115, 14279, 12392, 11610, 10794, 10515]
```

Predicting the popular top 10 songs to the existing user

In [139]:

```
result = recommend(df['user_id'][6])
for i in result:
    print(i)
```

```
Undo:Björk
Revelry:Kings Of Leon
Sehr kosmisch:Harmonia
Horn Concerto No. 4 in E flat K495: II. Romance (Andante cantabile):Barry Tu
ckwell/Academy of St Martin-in-the-Fields/Sir Neville Marriner
Dog Days Are Over (Radio Edit):Florence + The Machine
Secrets:OneRepublic
Ain't Misbehavin:Sam Cooke
Invalid:Tub Ring
Catch You Baby (Steve Pitron & Max Sanna Radio Edit):Lonnie Gordon
Canada:Five Iron Frenzy
```

Trimming the songs into top 50k samples for predicting the best results in quick time

In [141]:

```
df = df.head(50000)
```

Building the Recommendation model using Item based Collaborative filtering

In [142]:

```
import recommender as recommender

ir = recommender.item_similarity_recommender_py()
ir.create(df, 'user_id', 'song')
```

In [143]:

```
user_items = ir.get_user_items(df['user_id'][5])
```

Displaying the User listened songs history

In [144]:

```
for user_item in user_items:
    print(user_item)
```

```
You're The One - Dwight Yoakam
Horn Concerto No. 4 in E flat K495: II. Romance (Andante cantabile) - Barry
Tuckwell/Academy of St Martin-in-the-Fields/Sir Neville Marriner
Tive Sim - Cartola
Catch You Baby (Steve Pitron & Max Sanna Radio Edit) - Lonnie Gordon
El Cuatrero - Miguel Calo
Unite (2009 Digital Remaster) - Beastie Boys
```

Suggesting the top 10 recommended songs to that user based on his previous songs history

In [145]:

```
ir.recommend(df['user_id'][5])
```

```
No. of unique songs for the user: 6
no. of unique songs in the training set: 25834
Non zero values in cooccurence_matrix :4732
```

Out[145]:

	user_id	song	score	rank
0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	Undo - Björk	0.067280	1
1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	Revelry - Kings Of Leon	0.063660	2
2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	La Magia De Tus Besos - Grupo Niche	0.055556	3
3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	Everybody's Fool - Evanescence	0.055556	4
4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	Histoire de geek - Smash hit combo	0.055556	5
5	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	Cuenta Conmigo - Jerry Rivera	0.055556	6
6	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	Heaven's Missing An Angel - 98º	0.055556	7
7	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	That's The Way Love Goes - David Frizzell	0.055556	8
8	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	Rattlechaser - Xploding Plastix	0.055556	9
9	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	Fly With Me - 98º	0.055556	10

Suggesting the related songs based on the Artist_name using item wise similarity

In [146]:

```
ir.get_similar_items(['Représente - Alliance Ethnik', 'Secrets - OneRepublic'])
```

```
no. of unique songs in the training set: 25834
Non zero values in cooccurence_matrix :1822
```

Out[146]:

	user_id	song	score	rank
0		Dog Days Are Over (Radio Edit) - Florence + Th...	0.070349	1
1		You're The One - Dwight Yoakam	0.066960	2
2		Horn Concerto No. 4 in E flat K495: II. Romanc...	0.063751	3
3		Catch You Baby (Steve Pitron & Max Sanna Radio...	0.059145	4
4		Revelry - Kings Of Leon	0.054947	5
5		Undo - Björk	0.054057	6
6		OMG - Usher featuring will.i.am	0.052382	7
7		Billionaire [feat. Bruno Mars] (Explicit Albu...	0.052007	8
8		Sehr kosmisch - Harmonia	0.051036	9
9		Pursuit Of Happiness (nightmare) - Kid Cudi / ...	0.049951	10

Building the Collaborative filtering using the KNN algorithm method

In [149]:

```
### Importing the necessary files for implementing the KNN algorithm

from scipy.sparse import csr_matrix
import knn_recommender as knn_recommender
```

Preparing the data for further prediction using KNN algorithm

Let us check how many songs a user listen an average?

In [150]:

```
song_user = df.groupby('user_id')['song_id'].count()
```

In [151]:

```
print(f"A user listens to an average of {np.mean(song_user)} songs")
```

```
A user listens to an average of 13.27668613913967 songs
```

Checking the songs listen count of user with min and max of songs

In [152]:

```
print(f"A user listens to an average of {np.median(song_user)} songs, with minimum {np.min(
```

```
A user listens to an average of 11.0 songs, with minimum 5 and maximum 48 so
ngs
```

In [153]:

```
# Checking the for the Unique songs in the sample dataset

unique_songs = df['song_id'].unique().shape[0]
print(f"There are {unique_songs} unique songs in the dataset")
```

```
There are 25922 unique songs in the dataset
```

In [154]:

```
# Checking for the Unique users in the sample dataset

unique_users = df['user_id'].unique().shape[0]
print(f"There are {unique_users} unique users in the dataset")
```

```
There are 3766 unique users in the dataset
```

Check how many values will it be if all the songs have been listened by all the users

In [155]:

```
values_matrix = unique_users * unique_songs
```

In [156]:

```
# Substract the total values with the actual shape of the DataFrame songs

zero_values_matrix = values_matrix - df.shape[0]
```

In [157]:

```
print(f"The matrix of users x songs has {zero_values_matrix} values that are zero")
```

```
The matrix of users x songs has 97572252 values that are zero
```

Get the users who have listened to at least 16 songs

In [158]:

```
song_ten_id = song_user[song_user > 16].index.to_list()
```

In [159]:

```
## Filtering the dataset to keep only those users who have listened more than 16 songs

df_song_id_more_ten = df[df['user_id'].isin(song_ten_id)].reset_index(drop=True)
```

We need now to work with a scipy-sparse matrix to avoid overflow and wasted memory. For that purpose, we'll use the csr_matrix function from scipy.sparse.

In [160]:

```
# convert the dataframe into a pivot table

df_songs_features = df_song_id_more_ten.pivot(index='song_id', columns='user_id', values='F

# obtain a sparse matrix

mat_songs_features = csr_matrix(df_songs_features.values)
```

In [161]:

```
df_songs_features.head()
```

Out[161]:

user_id	0011d5f4fb02ff276763d385c3f2ded2b00ad94a	003998bc33cddeba02428a43:
song_id		
SOAACPJ12A81C21360	0.0	
SOAACSG12AB018DC80	0.0	
SOAAFAC12A67ADF7EB	0.0	
SOAAFYH12A8C13717A	0.0	
SOAAGYY12A6D4F705E	0.0	

5 rows × 1032 columns

In [162]:

```
df_unique_songs = df.drop_duplicates(subset=['song_id']).reset_index(drop=True)[['song_id',
```

In [163]:

```
decode_id_song = {
    song: i for i, song in
    enumerate(list(df_unique_songs.set_index('song_id').loc[df_songs_features.index].song_n
}
```

Creating a Model and making recommendations

So, we know that we want to use the model to predict songs. For that, we'll use the Recommender class wrote in the knn_recommender file.

In [164]:

```
from knn_recommender import Recommender
model = Recommender(metric='cosine', algorithm='brute', k=20, data=mat_songs_features, deco
```

In [165]:

```
## Taking a song to recommend songs similar to it

song = "Représente"
```

In [166]:

```
### Recommending a new songs based on given old song ''represente''

new_recommendations = model.make_recommendation(new_song=song, n_recommendations=10)
```

```
Starting the recommendation process for Représente ...
... Done
```

In [167]:

```
print(f"The recommendations for {song} song are:")
new_recommendations
```

```
The recommendations for Représente song are:
```

Out[167]:

```
['Bigger Boys and Stolen Sweethearts',
 'Only Superstition',
 'La Poupée',
 'Mundian To Back Me',
 'U Make Me Wanna',
 'Mony Mony',
 'Number One (Explicit Album Version) (Feat. Kanye West)',
 'Peace Sign / Index Down [feat. Busta Rhymes] (Explicit Album Version)',
 'Damien III',
 'The Gift']
```

Building a content based filtering model for recommending the songs

Importing necessary libraries for content based filtering

In [169]:

```
from typing import List, Dict
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
```

Here we are using the **TfidfVectorizer and cosine_similarity** for extracting the **keyword** from our data

In [170]:

```
df.head()
```

Out[170]:

	index	user_id	song_id	Freq	Artist_n
0	0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOBONKR12A58A7A7E0	1	Dwight Yoa
1	1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOEGIYH12A6D4FC0E3	1	E Tuckwell/Acac of St Martin-in
2	2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOFLJQZ12A6D4FADA6	1	Ca
3	3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOHTKMO12AB01843B0	1	Lonnie Gc
4	4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SODQZCY12A6D4F9D11	1	Miguel

In [171]:

```
df.shape
```

Out[171]:

```
(50000, 7)
```

In [172]:

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

In [173]:

```
df.head()
```

Out[173]:

	user_id	song_id	Freq	Artist_name	s
0	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOBONKR12A58A7A7E0	1	Dwight Yoakam	
1	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOEGIYH12A6D4FC0E3	1	Barry Tuckwell/Academy of St Martin-in-the-Fie...	f
2	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOFLJQZ12A6D4FADA6	1	Cartola	
3	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SOHTKMO12AB01843B0	1	Lonnie Gordon	E
4	fd50c4007b68a3737fe052d5a4f78ce8aa117f3d	SODQZCY12A6D4F9D11	1	Miguel Calo	

Here we are considering only **5000 songs** to run the **content based filtering smoothly**, and also we are dropping the **freq column** has it is numerical and can't be used while extracting the **keyword**

In [174]:

```
df = df.sample(n=5000).drop('Freq',axis=1).reset_index(drop=True)
```

Here we use **TF-IDF** vectorizer that calculates the TF-IDF score for each song, word-by-word. We can replace this with description of the song if available

In [175]:

```
tfidf = TfidfVectorizer(analyzer='word', stop_words='english')
```

In [176]:

```
lyrics_matrix = tfidf.fit_transform(df['song'])
```

We now need to calculate the similarity of one song to another. to calculate those we are going to use cosine similarity.

We want to calculate the cosine similarity of each item with every other item in the dataset. So we just pass the lyrics_matrix as argument.

In [177]:

```
cosine_similarities = cosine_similarity(lyrics_matrix)
```

Once we get the similarities, we'll store in a dictionary the names of the 50 most similar songs for each song in our dataset.

In [178]:

```
similarities = {}

for i in range(len(cosine_similarities)):

    # Now we'll sort each element in cosine_similarities and get the indexes of the songs.

    similar_indices = cosine_similarities[i].argsort()[:-50:-1]

    # After that, we'll store in similarities each name of the 50 most similar songs.
    # Except the first one that is the same song.

    similarities[df['song'].iloc[i]] = [(cosine_similarities[i][x], df['song'][x], df['Arti
```

Now We can use that similarity scores to access the most similar items and give a recommendation. For that, to do that task we'll define our Content based recommender class.

In [179]:

```
class ContentBasedRecommender:
    def __init__(self, matrix):
        self.matrix_similar = matrix

    def _print_message(self, song, recom_song):
        rec_items = len(recom_song)

        print(f'The {rec_items} recommended songs for {song} are:')
        for i in range(rec_items):
            print(f"Number {i+1}:")
            print(f"{recom_song[i][1]} by {recom_song[i][2]} with {round(recom_song[i][0],
            print("--------------------")

    def recommend(self, recommendation):
        # Get song to find recommendations for
        song = recommendation['song']
        # Get number of songs to recommend
        number_songs = recommendation['number_songs']
        # Get the number of songs most similars from matrix similarities
        recom_song = self.matrix_similar[song][:number_songs]
        # print each item
        self._print_message(song=song, recom_song=recom_song)
```

In [180]:

```
recommedations = ContentBasedRecommender(similarities)
```

In [181]:

```
recommendation = {
    "song": df['song'].iloc[10],
    "number_songs": 10
}
```

Recommending the Top 10 songs to the existed user based on keyword similarity

In [182]:

```
recommedations.recommend(recommendation)
```

```
The 10 recommended songs for When I Come To You - Jonny Lang are:
Number 1:
Red Light - Jonny Lang by Jonny Lang with 0.674 similarity score
--------------------
Number 2:
My Love Remains - Jonny Lang by Jonny Lang with 0.659 similarity score
--------------------
Number 3:
Uncle Jonny - The Killers by The Killers with 0.361 similarity score
--------------------
Number 4:
Come As You Are - Nirvana by Nirvana with 0.305 similarity score
--------------------
Number 5:
Here I Come - Fergie by Fergie with 0.286 similarity score
--------------------
Number 6:
Auld Lang Syne (Album Version) - Relient K by Relient K with 0.28 similarity
score
--------------------
Number 7:
I'd Come For You (Album Version) - Nickelback by Nickelback with 0.279 simil
arity score
--------------------
Number 8:
I'd Come For You (Album Version) - Nickelback by Nickelback with 0.279 simil
arity score
--------------------
Number 9:
Come With Me (Album Version) - DAY26 by DAY26 with 0.247 similarity score
--------------------
Number 10:
How Come - Ray LaMontagne by Ray LaMontagne with 0.238 similarity score
--------------------
```

Hybrid Recommendation system

Hybrid recommendation system is the most used recommendation system approach used in music and movie recommendation projects, it combines the collaborative filtering, content-based filtering, and other approaches.

Hybrid approaches can be implemented in several ways: by making content-based and collaborative-based predictions separately and then combining them or by adding content-based capabilities to a collaborative-based approach (and vice versa), or by unifying the approaches into one model.

Hybrid methods can also be used to overcome some of the common problems in recommender systems such as cold start and the sparsity problem. **NetFlix** is the good example which use the hybrid recommendation systems effectively

This model combines the recommendations generated from **content-based, collaborative filtering and popularity model.** The hybrid model overcomes the shortcomings of individual models and improves the diversity of the recommendations

Importing the Necessary modules from the surprise library

In [183]:

```
from surprise import SVD, BaselineOnly, SVDpp, NMF, SlopeOne, CoClustering, Reader
from surprise import Dataset
from surprise.model_selection import cross_validate
from surprise.prediction_algorithms import KNNBaseline, KNNBasic, KNNWithMeans, KNNWithZSco
from surprise import accuracy
from surprise.model_selection import train_test_split
from surprise import dump
```

In [184]:

```
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.metrics.pairwise import linear_kernel, cosine_similarity
```

In [185]:

```
reader = Reader()
data = Dataset.load_from_df(song_df[['user_id','song_id','Freq']],reader)
```

In [186]:

```
trainset, testset = train_test_split(data, test_size=0.25)
```

Matrix Factorization based on SVD(Singluar value Decomposition) approach

In [189]:

```
### Evaluating the SVD(Single Value Decomposition) model from surprise library

algo = SVD()

### Train the algorithm on trainset and predict the Frequency on testset

algo.fit(trainset)
predictions = algo.test(testset)

### Let us check the RMSE value of SVD

accuracy.rmse(predictions)
accuracy.mae(predictions)
```

```
RMSE: 7.1096
MAE:  4.0355
```

Out[189]:

```
4.035535995751783
```

Evaluating the Model by using Baselineonly approach

In [190]:

```
#### Evaluating the Baselineonly model from surprise library

algo = BaselineOnly()

### Train the algorithm on trainset and predict the Frequency on testset

algo.fit(trainset)
predictions = algo.test(testset)

### Let us check the RMSE value of Baselineonly

accuracy.rmse(predictions)
accuracy.mae(predictions)
```

```
Estimating biases using als...
RMSE: 6.6644
MAE:  2.5732
```

Out[190]:

```
2.573236105769552
```

Matrix Factorization based on SVDpp approach

In [191]:

```
### Evaluating the SVDpp from surprise library

algo = SVDpp()

### Train the algorithm on trainset and predict the Frequency on testset

algo.fit(trainset)
predictions = algo.test(testset)

### Let us check the RMSE value of SVDpp model

accuracy.rmse(predictions)
accuracy.mae(predictions)
```

```
RMSE: 7.1096
MAE:  4.0355
```

Out[191]:

```
4.03551911522511
```

Collaborative filtering algorithm based on Non-negative Matrix Factorization.

In [192]:

```
### Checking the collaborative based on NMF

algo = NMF()

# Train the algorithm on the trainset, and predict Frequency for the testset

algo.fit(trainset)
predictions = algo.test(testset)

accuracy.rmse(predictions)
accuracy.mae(predictions)
```

```
RMSE: 6.7670
MAE:  2.3266
```

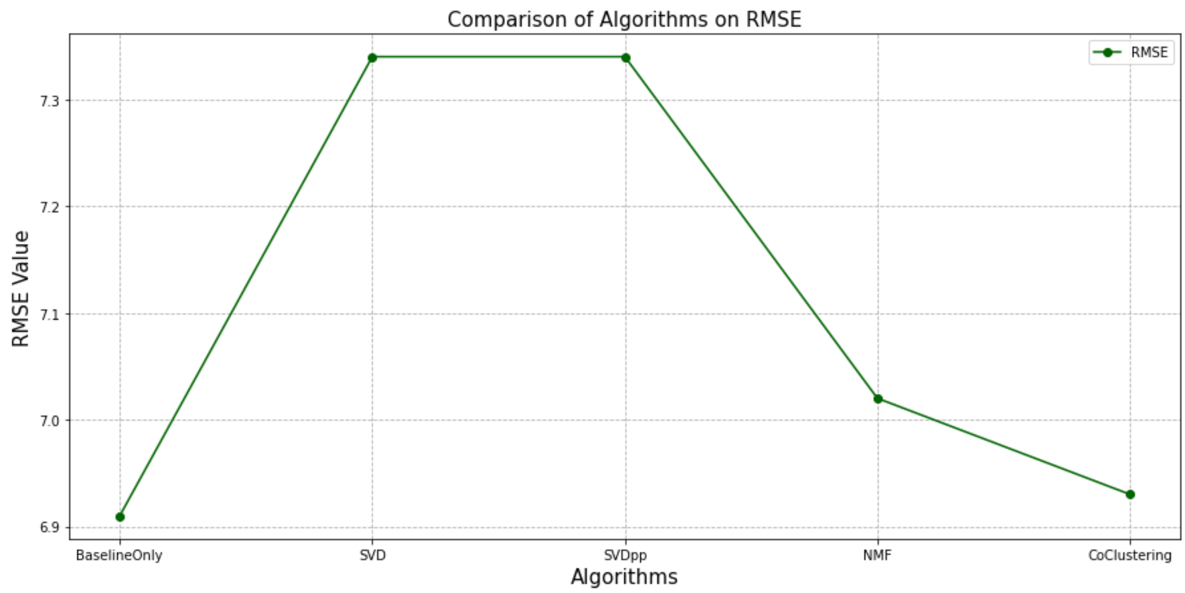
Out[192]:

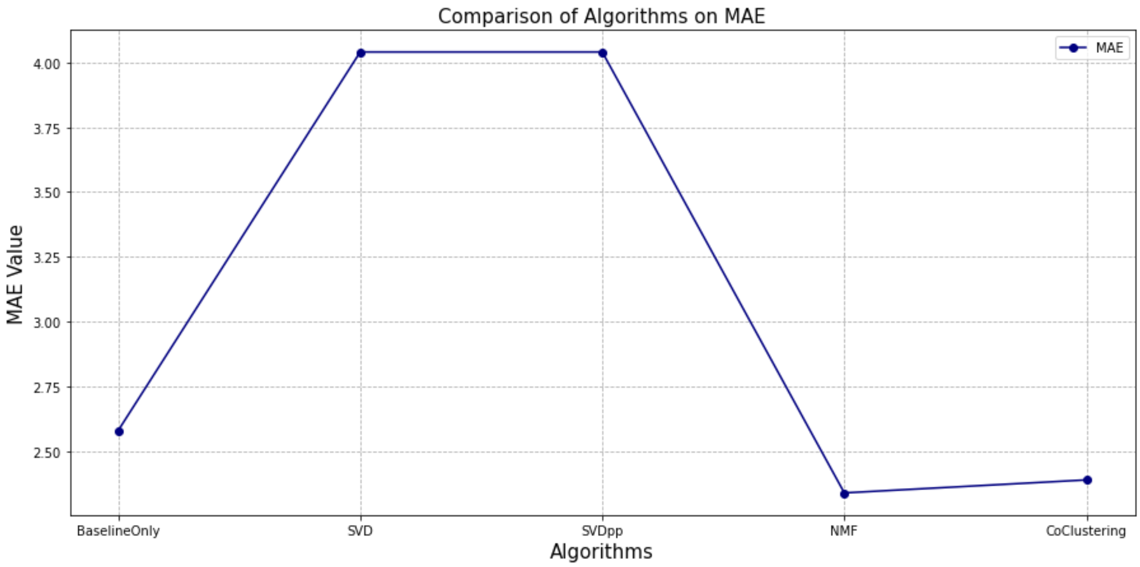
```
2.3266039924660804
```

Comparing the all algorithms on RMSE and MAE and showing there results by plotting a graph

In [193]:

```
x_algo = ['BaselineOnly', 'SVD', 'SVDpp', 'NMF', 'CoClustering']


rmse = [6.91,7.34,7.34,7.02,6.93]
mae = [2.58,4.04,4.04,2.34,2.39]
fit_time = [4.586215, 55.877482,3256.132195,55.372593,19.347667]
test_time = [2.908219,2.632710,73.504739,2.918873,2.986175]

plt.figure(figsize=(15,7))

# plt.subplot(1, 2, 1)
plt.title('Comparison of Algorithms on RMSE', loc='center', fontsize=15)
plt.plot(x_algo, rmse, label='RMSE', color='darkgreen', marker='o')
plt.xlabel('Algorithms', fontsize=15)
plt.ylabel('RMSE Value', fontsize=15)
plt.legend()
plt.grid(ls='dashed')
plt.show()

# plt.subplot(1, 2, 2)
plt.figure(figsize=(15,7))
plt.title('Comparison of Algorithms on MAE', loc='center', fontsize=15)
plt.plot(x_algo, mae, label='MAE', color='navy', marker='o')
plt.xlabel('Algorithms', fontsize=15)
plt.ylabel('MAE Value', fontsize=15)
plt.legend()
plt.grid(ls='dashed')

plt.show()
```





Comparision of algorithms by on RMSE and MAE and by fit_time and train_time

In [194]:

```
x_algo = ['BaselineOnly','SVD', 'SVDpp', 'NMF','CoClustering']

rmse = [6.91,7.34,7.34,7.02,6.93]
mae = [2.58,4.04,4.04,2.34,2.39 ]
fit_time = [4.586215,55.877482,3256.132195,55.372593,19.347667]
test_time = [2.908219,2.632710,73.504739,2.918873,2.986175]

plt.figure(figsize=(15,6))
plt.title('Comparison of Algorithms on RMSE and MAE', loc='center', fontsize=15)
plt.plot(x_algo, rmse, label='RMSE', color='darkgreen', marker='o')
plt.plot(x_algo, mae, label='MAE', color='navy', marker='o')
plt.xlabel('Algorithms', fontsize=15)
plt.ylabel('Value', fontsize=15)
plt.legend()
plt.grid(ls='dashed')
plt.show()

plt.figure(figsize=(15,6))
plt.title('Comparison of Algorithms on fit and train time', loc='center', fontsize=15)
plt.plot(x_algo, fit_time, label='Fit Time', color='navy', marker='o')
plt.plot(x_algo, test_time, label='Test Time', color='red', marker='o')
plt.xlabel('Algorithms', fontsize=15)
plt.ylabel('Time (s)', fontsize=15)
plt.legend()
plt.grid(ls='dashed')
plt.show()
```