Recommender System

In [1]:

```
from __future__ import print_function

import numpy as np
import pandas as pd
import collections
from mpl_toolkits.mplot3d import Axes3D
from IPython import display
from matplotlib import pyplot as plt
from IPython.display import display
import seaborn as sns
import sklearn
import sklearn.manifold
import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()
tf.logging.set_verbosity(tf.logging.ERROR)
```

```
WARNING:tensorflow:From C:\Users\user\anaconda3\lib\site-packages\tensorflow\python\compat
\v2_compat.py:96: disable_resource_variables (from tensorflow.python.ops.variable_scope) i
s deprecated and will be removed in a future version.
Instructions for updating:
non-resource variables are not supported in the long term
```

In [2]:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error
from collections import Counter, defaultdict
from operator import itemgetter
import tensorflow as tf
from tensorflow import keras
from pylab import rcParams
from pylab import savefig
import lightfm
from lightfm import LightFM
from lightfm.data import Dataset
from lightfm import cross_validation
from lightfm.evaluation import precision_at_k
from lightfm.evaluation import recall_at_k
from lightfm.cross_validation import random_train_test_split
from scipy.sparse import csr_matrix
import scipy
import recmetrics

from sklearn.model_selection import train_test_split
from collections import Counter, defaultdict
from sklearn.metrics import accuracy_score
import matplotlib.ticker as ticker
from math import sqrt
from sklearn.metrics import mean_squared_error
```

```
C:\Users\user\anaconda3\lib\site-packages\lightfm\_lightfm_fast.py:9: UserWarning: LightFM
was compiled without OpenMP support. Only a single thread will be used.
  warnings.warn(
```

In [3]:

```
# Install Altair and activate its colab renderer.
#print("Installing Altair...")
#!pip install git+git://github.com/altair-viz/altair.git
#import altair as alt
#alt.data_transformers.enable('default', max_rows=None)
```

```
#alt.renderers.enable('colab')
#print("Done installing Altair.")

# Install spreadsheets and import authentication module.
#USER_RATINGS = False
#!pip install --upgrade -q gspread
#from google.colab import auth
#import gspread
#from oauth2client.client import GoogleCredentials
```

In [4]:

```
import matplotlib.pyplot as plt
import os
import warnings
from keras.layers import Input, Embedding, Flatten, Dot, Dense, Concatenate
from keras.models import Model
```

Firstly, I converted my data files from .dat to .csv format. I did this via excel using the data tab and it's "get external data" option and extracted it from text. All the delimiting was done by default and I had my files in a delimited format.

To start I read in all of my files and fixed the index for user ID's and artist ID's. This would save us a lot of problems later on when we try to join these dataframes together so doing it initially made the most sense.

In [5]:

```
df = pd.read_csv("data/hetrec2011-lastfm-2k/artists.csv")
df
```

Out[5]:

	id	name	url	pictureURL
0	1	MALICE MIZER	http://www.last.fm/music/MALICE+MIZER	http://userserve-ak.last.fm/serve/252/10808.jpg
1	2	Diary of Dreams	http://www.last.fm/music/Diary+of+Dreams	http://userserve-ak.last.fm/serve/252/3052066.jpg
2	3	Carpathian Forest	http://www.last.fm/music/Carpathian+Forest	http://userserve-ak.last.fm/serve/252/40222717...
3	4	Moi dix Mois	http://www.last.fm/music/Moi+dix+Mois	http://userserve-ak.last.fm/serve/252/54697835...
4	5	Bella Morte	http://www.last.fm/music/Bella+Morte	http://userserve-ak.last.fm/serve/252/14789013...
...	...	...	...	...
17627	18741	Diamanda GalÃ¡s	http://www.last.fm/music/Diamanda+Gal%C3%A1s	http://userserve-ak.last.fm/serve/252/16352971...
17628	18742	Aya RL	http://www.last.fm/music/Aya+RL	http://userserve-ak.last.fm/serve/252/207445.jpg
17629	18743	Coptic Rain	http://www.last.fm/music/Coptic+Rain	http://userserve-ak.last.fm/serve/252/344868.jpg
17630	18744	Oz Alchemist	http://www.last.fm/music/Oz+Alchemist	http://userserve-ak.last.fm/serve/252/29297695...
17631	18745	Grzegorz Tomczak	http://www.last.fm/music/Grzegorz+Tomczak	http://userserve-ak.last.fm/serve/252/59486303...

17632 rows × 4 columns

In [6]:

```
df['id'] = pd.to_numeric(df['id'])
```

```
lst = []
m = np.array(df['id'])
for i in range(0,17632):
    #print(i)
    if i not in df.id.values:
        lst.append(i)

len(lst)
```

Out[6]:

```
965
```

Just taking a quick look at the data I could see the last few artist ID's were 18743... and I later found out this would prove problematic. This for loop above demonstrates that in the range of 0 to 17632 (the number of unique artist ID's as per our readME) that there are 965 missing values for this range. This is something we will rectify in all our files.

In [7]:

```
newart = []
for i in range(0, 17632):
    newart.append(i)
```

In [8]:

```
newart = np.array(newart)
df['artID'] = newart.tolist()
```

In [9]:

```
df.drop(columns=['id'], inplace=True)
df.head()
```

Out[9]:

	name	url	pictureURL	artID
0	MALICE MIZER	http://www.last.fm/music/MALICE+MIZER	http://userserve-ak.last.fm/serve/252/10808.jpg	0
1	Diary of Dreams	http://www.last.fm/music/Diary+of+Dreams	http://userserve-ak.last.fm/serve/252/3052066.jpg	1
2	Carpathian Forest	http://www.last.fm/music/Carpathian+Forest	http://userserve-ak.last.fm/serve/252/40222717...	2
3	Moi dix Mois	http://www.last.fm/music/Moi+dix+Mois	http://userserve-ak.last.fm/serve/252/54697835...	3
4	Bella Morte	http://www.last.fm/music/Bella+Morte	http://userserve-ak.last.fm/serve/252/14789013...	4

Our artist ID's are fixed for this file now. There appears to be some unclean names such as "Diamanda GalÃ¡s" among others just taking an initial look at the data here.

Faulty ID values in one file!

I had to alter my approach slightly hence why df4 is read in secondly. I found in this dataframe that there were users that did not appear in other dataframes so I had to remove these users from this dataframe and reindex accordingly. I noticed this due to some very strange tags associated with "AC/DC" which we will see later and have been fixed now. All the rough work related to this can be found in another file "recommender-past.ipynb" on the github repository for this assignment.

In [10]:

```
df4 = pd.read_csv("data/hetrec2011-lastfm-2k/user_taggedartists-timestamps.csv")
df4
```

Out[10]:

	userID	artistID	tagID	day	month	year
0	2	52	13	1	4	2009

	userID	artistID	tagID	day	month	year
1	2	52	15	1	4	2009
2	2	52	18	1	4	2009
3	2	52	21	1	4	2009
4	2	52	41	1	4	2009
...	...	...	...	...	...	...
186474	2100	16437	4	1	7	2010
186475	2100	16437	292	1	5	2010
186476	2100	16437	2087	1	7	2010
186477	2100	16437	2801	1	5	2010
186478	2100	16437	3335	1	7	2010

186479 rows × 6 columns

In [11]:

```
vals = (df4['artistID'].unique()).tolist()
vals.sort()
values = []
for i in range(len(vals)):
    if vals[i] in m:
        values.append(vals[i])
```

In [12]:

```
missing = []
for i in range(len(vals)):
    if vals[i] not in values:
        missing.append(vals[i])
```

In [13]:

```
list3 = values + missing
print(len(list3))
```

```
12523
```

In [14]:

```
df4 = df4[~df4.artistID.isin(missing)]
```

In [250…

```
# from earlier
keys = m
values = newart
dictionary = dict(zip(keys, values))
#print(dictionary) # {'a': 1, 'b': 2, 'c': 3}
```

In [16]:

```
a_subset = {key: value for key, value in dictionary.items() if key in list3}
```

In [17]:

```
s = df4['artistID']

df4['artistID'] = s.map(a_subset)
```

```
C:\Users\user\AppData\Local\Temp/ipykernel_28620/3743877304.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df4['artistID'] = s.map(a_subset)
```

In [18]:

```
df1 = pd.read_csv("data/hetrec2011-lastfm-2k/tags.csv")
df1
```

Out[18]:

	tagID	tagValue
0	1	metal
1	2	alternative metal
2	3	goth rock
3	4	black metal
4	5	death metal
...	...	...
11941	12644	suomi
11942	12645	symbiosis
11943	12646	sverige
11944	12647	eire
11945	12648	electro latino

11946 rows × 2 columns

This file is exclusively dealing with tags. We can disregard changing the index for now.

In [19]:

```
df2 = pd.read_csv("data/hetrec2011-lastfm-2k/user_artists.csv")
df2
```

Out[19]:

	userID	artistID	weight
0	2	51	13883
1	2	52	11690
2	2	53	11351
3	2	54	10300
4	2	55	8983
...	...	...	...
92829	2100	18726	337
92830	2100	18727	297
92831	2100	18728	281
92832	2100	18729	280
92833	2100	18730	263

92834 rows × 3 columns

Due to the fact values are repeated here we can't simply do what we did before to fix the ID values. We also have the presence of userID's which has a similar index problem. We will implement a dictionary to fix these values and map the old values to our new values.

In [20]:
```
df2['artistID'].min()
```
Out[20]:
```
1
```
In [21]:
```
# Since the ids start at 2, we get them to start at 0. We also need to have the max value
df2["userID"] = df2["userID"].apply(lambda x: str(x-2))
df2["artistID"] = df2["artistID"].apply(lambda x: str(x-1))
```
In [22]:
```
df2['userID'] = df2['userID'].astype(int)
xyz =  np.array(df2['userID'])
#zzz = np.array(played['userID'])
vals = []
for i in range(len(xyz)):
    v = xyz[i]
    if v not in vals:
        vals.append(v)
    else:
        continue
```
In [23]:
```
vals[-1]
```
Out[23]:
```
2098
```
In [24]:
```
unique_list = list(set(vals))
unique_list.sort()
unique_list[-1]
```
Out[24]:
```
2098
```
In [25]:
```
usenew = []
for i in range(0, 1892):
    usenew.append(i)

usenew[-1]
```
Out[25]:
```
1891
```
In [26]:
```
keys = unique_list
values = usenew
dictionary = dict(zip(keys, values))
#print(dictionary) # {'a': 1, 'b': 2, 'c': 3}
```
In [27]:
```
s = df2['userID']

df2['userID'] = s.map(dictionary)
```
In [28]:
```
df2.head()
```
Out[28]:

	userID	artistID	weight

	userID	artistID	weight
0	0	50	13883
1	0	51	11690
2	0	52	11351
3	0	53	10300
4	0	54	8983

In [29]:

```
df2['artistID'] = df2['artistID'].astype(int)
xyz =  np.array(df2['artistID'])
#zzz = np.array(played['userID'])
vals = []
for i in range(len(xyz)):
    v = xyz[i]
    if v not in vals:
        vals.append(v)
    else:
        continue
```

In [30]:

```
unique_list = list(set(vals))
unique_list.sort()
unique_list[0]
```

Out[30]:

```
0
```

In [31]:

```
usenew = []
for i in range(0, 17632):
    usenew.append(i)

usenew[-1]
```

Out[31]:

```
17631
```

In [32]:

```
keys = unique_list
values = usenew
diction = dict(zip(keys, values))
#print(diction) # {'a': 1, 'b': 2, 'c': 3}
```

In [33]:

```
s = df2['artistID']

df2['artistID'] = s.map(diction)
```

In [34]:

```
df2['weight'].max()
```

Out[34]:

```
352698
```

In [35]:

```
df2
```

Out[35]:

	userID	artistID	weight
0	0	45	13883

	userID	artistID	weight
1	0	46	11690
2	0	47	11351
3	0	48	10300
4	0	49	8983
...	...	...	...
92829	1891	17615	337
92830	1891	17616	297
92831	1891	17617	281
92832	1891	17618	280
92833	1891	17619	263

92834 rows × 3 columns

Our dataframe "df2" is now adjusted correctly.

In [36]:
```
df3 = pd.read_csv("data/hetrec2011-lastfm-2k/user_friends.csv")
df3
```

Out[36]:

	userID	friendID
0	2	275
1	2	428
2	2	515
3	2	761
4	2	831
...	...	...
25429	2099	1801
25430	2099	2006
25431	2099	2016
25432	2100	586
25433	2100	607

25434 rows × 2 columns

In [37]:
```
# Since the ids start at 2, we get them to start at 0. We also need to have the max value
df3["userID"] = df3["userID"].apply(lambda x: str(x-2))
df3["friendID"] = df3["friendID"].apply(lambda x: str(x-2))

df3['userID'] = pd.to_numeric(df3['userID'])
df3['friendID'] = pd.to_numeric(df3['friendID'])
```

In [38]:
```
df3['friendID'].max()
```

2098

Out[38]:

In [39]:
```
df3['friendID'].nunique()
```

Out[39]: 1892

In [40]:
```
xyz =  np.array(df3['userID'])
#zzz = np.array(df2['userID'])
vals = []
for i in range(len(xyz)):
    if xyz[i] not in vals:
        vals.append(xyz[i])
```

In [41]:
```
unique_list = list(set(vals))
unique_list.sort()
unique_list[-1]
```

Out[41]: 2098

In [42]:
```
usenew = []
for i in range(0, 1892):
    usenew.append(i)

usenew[-1]
```

Out[42]: 1891

In [43]:
```
keys = unique_list
values = usenew
dictionary = dict(zip(keys, values))
#print(dictionary) # {'a': 1, 'b': 2, 'c': 3}
```

In [44]:
```
s = df3['userID']

df3['userID'] = s.map(dictionary)
```

In [45]:
```
o = df3['friendID']

df3['friendID'] = o.map(dictionary)
```

In [46]:
```
df3['friendID'].max()
```

Out[46]: 1891

In [47]:
```
df3.isnull().values.any()
```

Out[47]: False

In [48]:
```
df4
```

Out[48]:

	userID	artistID	tagID	day	month	year

	userID	artistID	tagID	day	month	year
0	2	46	13	1	4	2009
1	2	46	15	1	4	2009
2	2	46	18	1	4	2009
3	2	46	21	1	4	2009
4	2	46	41	1	4	2009
...	...	...	...	...	...	...
186474	2100	15609	4	1	7	2010
186475	2100	15609	292	1	5	2010
186476	2100	15609	2087	1	7	2010
186477	2100	15609	2801	1	5	2010
186478	2100	15609	3335	1	7	2010

184941 rows × 6 columns

In [49]:

```
# Since the ids start at 2, we get them to start at 0. We also need to have the max value
df4["userID"] = df4["userID"].apply(lambda x: str(x-2))
df4['userID'] = df4['userID'].astype(int)
```

```
C:\Users\user\AppData\Local\Temp/ipykernel_28620/3309841126.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  df4["userID"] = df4["userID"].apply(lambda x: str(x-2))
C:\Users\user\AppData\Local\Temp/ipykernel_28620/3309841126.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  df4['userID'] = df4['userID'].astype(int)
```

In [50]:

```
s = df4['userID']

df4['userID'] = s.map(dictionary)
#print(dictionary)
```

```
C:\Users\user\AppData\Local\Temp/ipykernel_28620/432615126.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  df4['userID'] = s.map(dictionary)
```

In [51]:

```
df4
```

Out[51]:

	userID	artistID	tagID	day	month	year
0	0	46	13	1	4	2009

	userID	artistID	tagID	day	month	year
1	0	46	15	1	4	2009
2	0	46	18	1	4	2009
3	0	46	21	1	4	2009
4	0	46	41	1	4	2009
...	...	...	...	...	...	...
186474	1891	15609	4	1	7	2010
186475	1891	15609	292	1	5	2010
186476	1891	15609	2087	1	7	2010
186477	1891	15609	2801	1	5	2010
186478	1891	15609	3335	1	7	2010

184941 rows × 6 columns

In [52]:

```
df4.drop(columns=['day', 'month', 'year'], inplace=True)
```

```
C:\Users\user\anaconda3\lib\site-packages\pandas\core\frame.py:4906: SettingWithCopyWarnin
g:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

In [53]:

```
tags = pd.merge(df1, df4, how="inner", left_on="tagID", right_on="tagID")
tags.isnull().values.any()
tags['artistID'].max()
```

Out[53]:

```
17630
```

All of our dataframes have the correct index for artist ID's and user ID's now. This will help us avoid any errors with our recommender model now.

Methodology

Now that all our data files are read in and in the appropriate format we will begin our end to end process. These are as follows:

1. Data cleaning and processing

2. Visualization of trends in the data

3. Fitting our Model

4. Evaluating our Model

Cleaning and Processing

Initial analysis and cleaning

In [54]:
```
df['name'].value_counts()
```

Out[54]:
```
MALICE MIZER                     1
BEAT!BEAT!BEAT!                  1
ãƒˆã‚¯ãƒžãƒ«ã‚·ãƒ¥ãƒ¼ã‚´               1
Thao with The Get Down Stay Down    1
ãƒªã‚¢ãƒ»ãƒ‡ã‚£ã‚¾ãƒ³               1
                                ..
Innerpartysystem                 1
Helia                            1
Devil Sold His Soul              1
Nevea Tears                      1
Grzegorz Tomczak                 1
Name: name, Length: 17632, dtype: int64
```

Let's check all our dataframes for null values to start.

In [55]:
```
dfs = [df, df1, df2, df3, df4]
na = []
for i in range(len(dfs)):
    if dfs[i].isnull().values.any() > 0:
        na.append(dfs[i])
```

In [56]:
```
na
```

Out[56]:
```
[                      name                                         url  \
 0             MALICE MIZER         http://www.last.fm/music/MALICE+MIZER
 1          Diary of Dreams       http://www.last.fm/music/Diary+of+Dreams
 2        Carpathian Forest     http://www.last.fm/music/Carpathian+Forest
 3             Moi dix Mois         http://www.last.fm/music/Moi+dix+Mois
 4              Bella Morte          http://www.last.fm/music/Bella+Morte
 ...                   ...                                           ...
 17627     Diamanda GalÃ¡s   http://www.last.fm/music/Diamanda+Gal%C3%A1s
 17628              Aya RL                http://www.last.fm/music/Aya+RL
 17629         Coptic Rain           http://www.last.fm/music/Coptic+Rain
 17630        Oz Alchemist          http://www.last.fm/music/Oz+Alchemist
 17631    Grzegorz Tomczak      http://www.last.fm/music/Grzegorz+Tomczak

                                              pictureURL  artID
 0         http://userserve-ak.last.fm/serve/252/10808.jpg      0
 1       http://userserve-ak.last.fm/serve/252/3052066.jpg      1
 2       http://userserve-ak.last.fm/serve/252/40222717...      2
 3       http://userserve-ak.last.fm/serve/252/54697835...      3
 4       http://userserve-ak.last.fm/serve/252/14789013...      4
 ...                                                   ...    ...
 17627   http://userserve-ak.last.fm/serve/252/16352971...  17627
 17628    http://userserve-ak.last.fm/serve/252/207445.jpg  17628
 17629    http://userserve-ak.last.fm/serve/252/344868.jpg  17629
 17630   http://userserve-ak.last.fm/serve/252/29297695...  17630
 17631   http://userserve-ak.last.fm/serve/252/59486303...  17631

 [17632 rows x 4 columns]]
```

The only dataframe with nulls is our artists dataframe. Let's investigate this further to see if there is any important missing values such as ID's etc.

In [57]:
```
df.dtypes
```

Out[57]:
```
name          object
url           object
pictureURL    object
artID          int64
dtype: object
```

In [58]:

```
features_with_na = [features for features in df.columns if df[features].isnull().sum() > (
for feature in features_with_na:
    print(feature, np.round(df[feature].isnull().mean(), 4), '% missing values')
    print(features_with_na)
```

```
pictureURL 0.0252 % missing values
['pictureURL']
```

This is a positive result as there are very few null values in the dataframe and the small amount that exist are in a column of lesser important that we will not need to impute missing values for.

In [59]:

```
played = pd.merge(df, df2, how="inner", left_on="artID", right_on="artistID")
played.rename(columns={"weight": "played"}, inplace=True)
```

We will drop the pictureURL column as there is not much information to be gained and there is some nulls present.

In [60]:

```
played.drop(columns=['pictureURL'], inplace=True)
```

Analysis and Visualization

In [61]:

```
mean = played['played'].mean()
print("The mean number of times a user plays a song is: " + str(mean))
```

```
The mean number of times a user plays a song is: 745.2439300256372
```

In [62]:

```
median = played['played'].median()
print("The median number of times a user plays a song is: " + str(median))
```

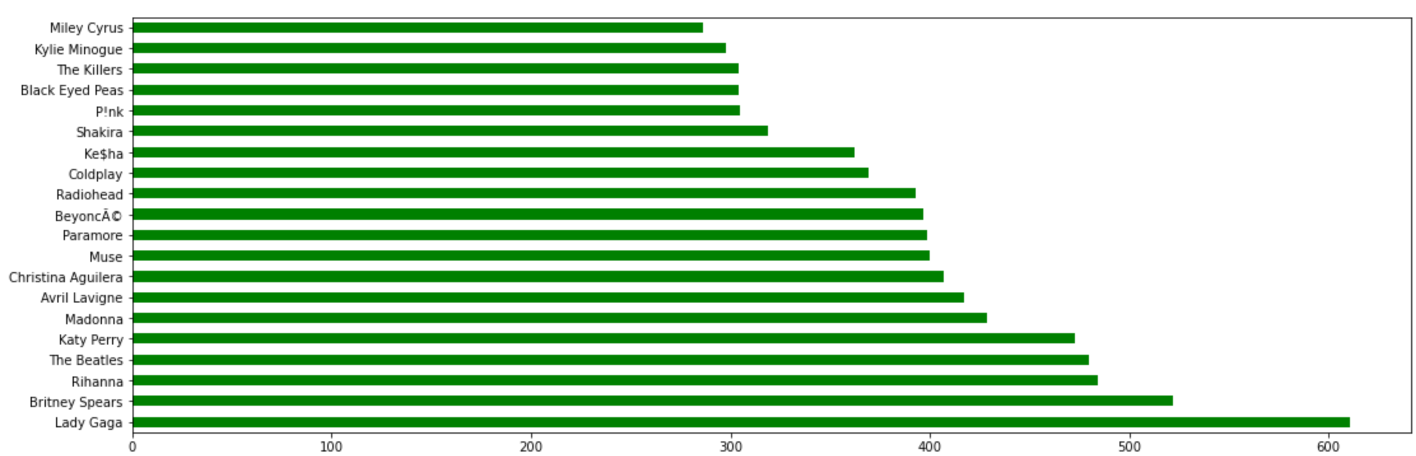
```
The median number of times a user plays a song is: 260.0
```

In [63]:

```
played['name'].value_counts()[:20].plot(kind='barh', color='green', figsize=(18,6))
```

Out[63]:

```
<AxesSubplot:>
```

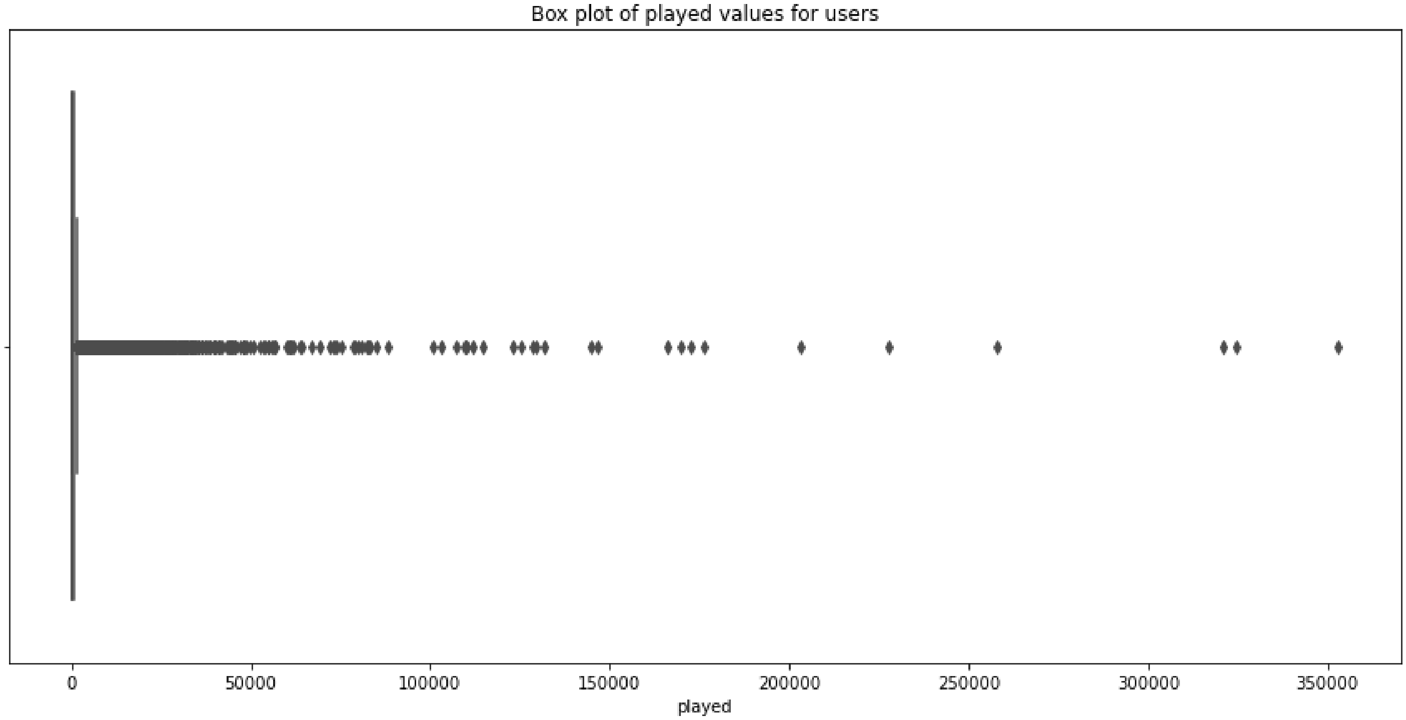


Lady Gaga is by a long distance the most popular artist going by the number of unqiue users listening to her, with approximately 100 more users listening to her in contrast to our second ranked artist.

In [64]:

```
plt.figure(figsize=[15,7])
sns.boxplot(x=played['played'], color="gold").set(title='Box plot of played values for use
```

Out[64]: [Text(0.5, 1.0, 'Box plot of played values for users')]



There appears to be quite a lot of outliers here in the played column. Some users have obviously played their artists songs far more times than the average. We double check our values for mean and median earlier and can confirm there are quite a few outliers here.

In [65]:
```
played.describe()
```

Out[65]:

	artID	userID	artistID	played
count	92834.000000	92834.000000	92834.000000	92834.00000
mean	3235.736724	944.222483	3235.736724	745.24393
std	4197.216910	546.751074	4197.216910	3751.32208
min	0.000000	0.000000	0.000000	1.00000
25%	430.000000	470.000000	430.000000	107.00000
50%	1237.000000	944.000000	1237.000000	260.00000
75%	4266.000000	1416.000000	4266.000000	614.00000
max	17631.000000	1891.000000	17631.000000	352698.00000

Let's now plot some information regarding our artists.

In [66]:
```
grouped_multiple = played.groupby(['artistID', 'name']).agg({'played': ['mean', 'median',
grouped_multiple.columns = ['mean', 'med', 'max', 'sum']
grouped_multiple = grouped_multiple.reset_index()
#grouped_multiple.sort('price_mean', ascending=False)
grouped_multiple = pd.DataFrame(grouped_multiple)
```

In [67]:
```
artdf = grouped_multiple.sort_values(by=['sum'], ascending=False)
```

In [68]:
```
artdf
```

Out[68]:

	artistID	name	mean	med	max	sum
283	283	Britney Spears	4584.559387	1000.5	131733	2393140
66	66	Depeche Mode	4614.567376	567.0	352698	1301308
83	83	Lady Gaga	2113.563011	590.0	114672	1291387
286	286	Christina Aguilera	2600.503686	739.0	176133	1058405
492	492	Paramore	2414.659148	417.0	227829	963449
...	...	...	...	...	...	...
16522	16522	K-Precise	1.000000	1.0	1	1
13713	13713	ZÃœNDER	1.000000	1.0	1	1
13712	13712	Evil Masquerade	1.000000	1.0	1	1
16239	16239	Gosling	1.000000	1.0	1	1
16241	16241	Kalson	1.000000	1.0	1	1

17632 rows × 6 columns

In [69]:

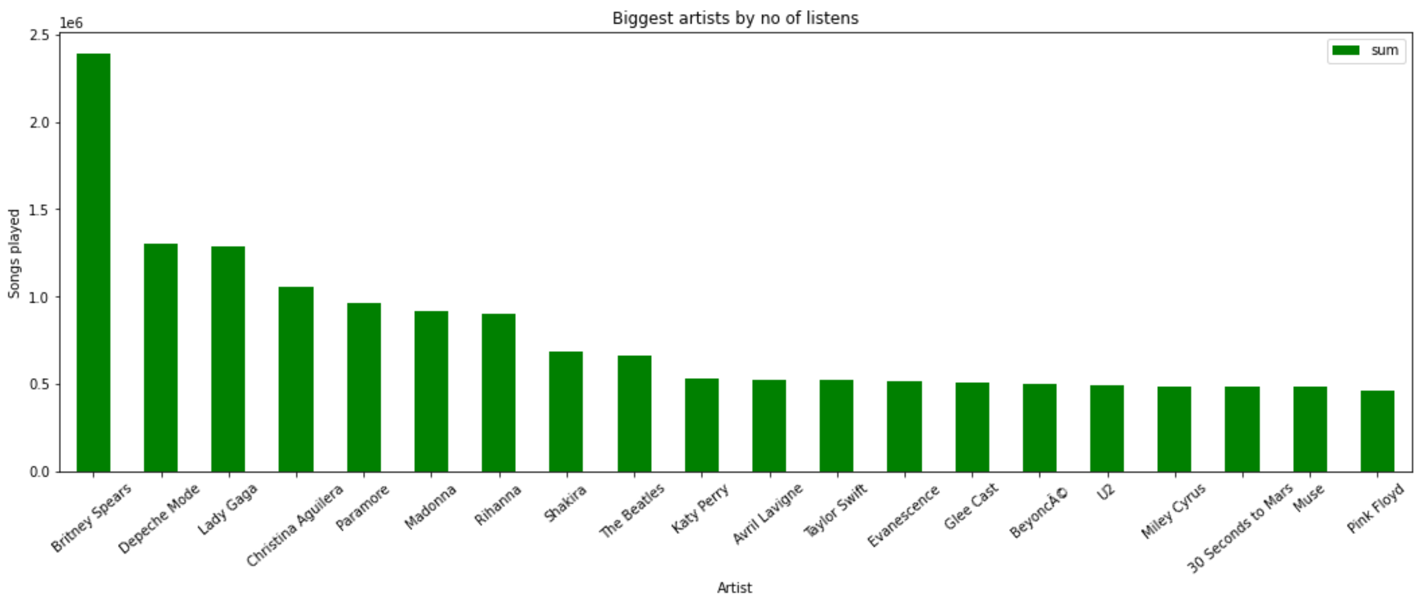
```
pt2 = artdf.head(20)
```

In [70]:

```
pt2.plot.bar(x = 'name', y = 'sum', rot = 40, figsize=(18, 6), color='green', xlabel='Arti
```

Out[70]:

```
<AxesSubplot:title={'center':'Biggest artists by no of listens'}, xlabel='Artist', ylabel
='Songs played'>
```



Despite Lady Gaga having the clear higher number of unique users listening to her she is only third in the most played artist by a distance with Britney Spears having the most amount of times her songs were played. This graph appears to suggest that this dataset is heavily leaned towards the most popular artists. From 'Shakira' on there appears to be a consistent base of artists with 500,000 or more plays. We will look at the same plot for users now before we come back to this.

In [71]:

```
grouped_multiple = played.groupby(['userID']).agg({'played': ['mean', 'median', 'max', 'su
grouped_multiple.columns = ['mean', 'med', 'max', 'sum']
grouped_multiple = grouped_multiple.reset_index()
```

```
#grouped_multiple.sort('price_mean', ascending=False)
grouped_multiple = pd.DataFrame(grouped_multiple)
```

In [72]:

```
userdf = grouped_multiple.sort_values(by=['sum'], ascending=False)
```

In [73]:

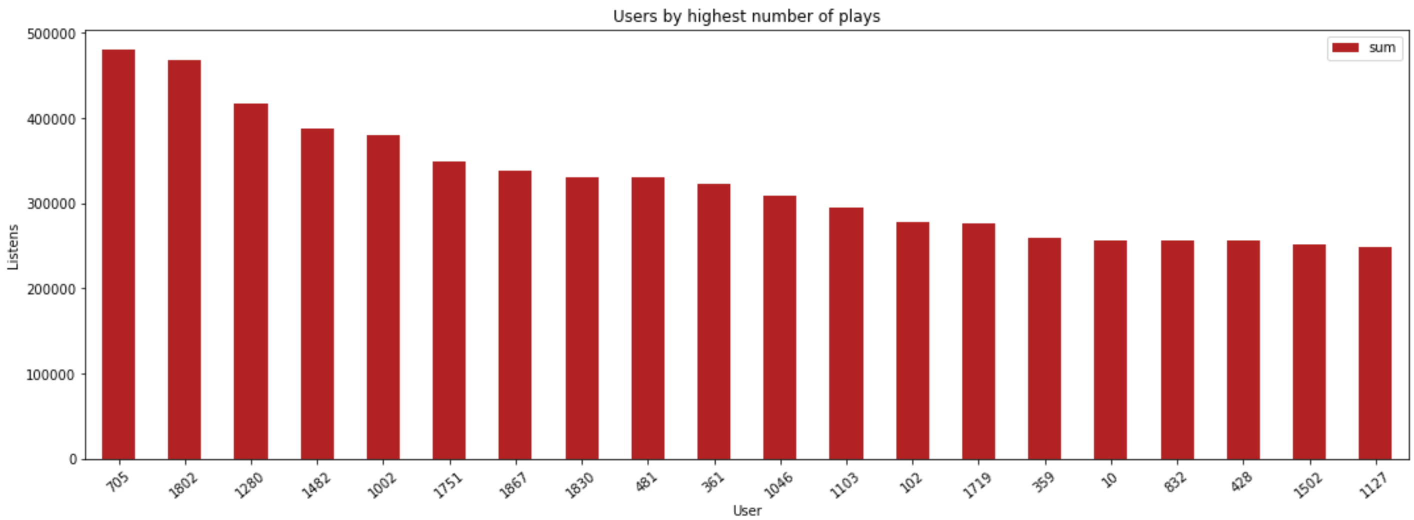
```
pt3 = userdf.head(20)
```

In [74]:

```
pt3.plot.bar(x = 'userID', y = 'sum', rot = 40, figsize=(18, 6), color='firebrick', xlabel
```

Out[74]:

```
<AxesSubplot:title={'center':'Users by highest number of plays'}, xlabel='User', ylabel='L
istens'>
```



Comparing users to artists there doesn't seem to be an as obvious presence of outliers here. The two users with the highest 'played' values are noticeably ahead of rest but not to the extent as with artists. Due to there being a much smaller cohort of users to artists (1892 to 17632 respectively) it is fair to say that users may have a more even distribution with regards to songs played.

In [75]:

```
artdf['mean']
```

Out[75]:

```
283      4584.559387
66       4614.567376
83       2113.563011
286      2600.503686
492      2414.659148
            ...
16522       1.000000
13713       1.000000
13712       1.000000
16239       1.000000
16241       1.000000
Name: mean, Length: 17632, dtype: float64
```

In [76]:

```
played.shape
```

Out[76]:

```
(92834, 6)
```

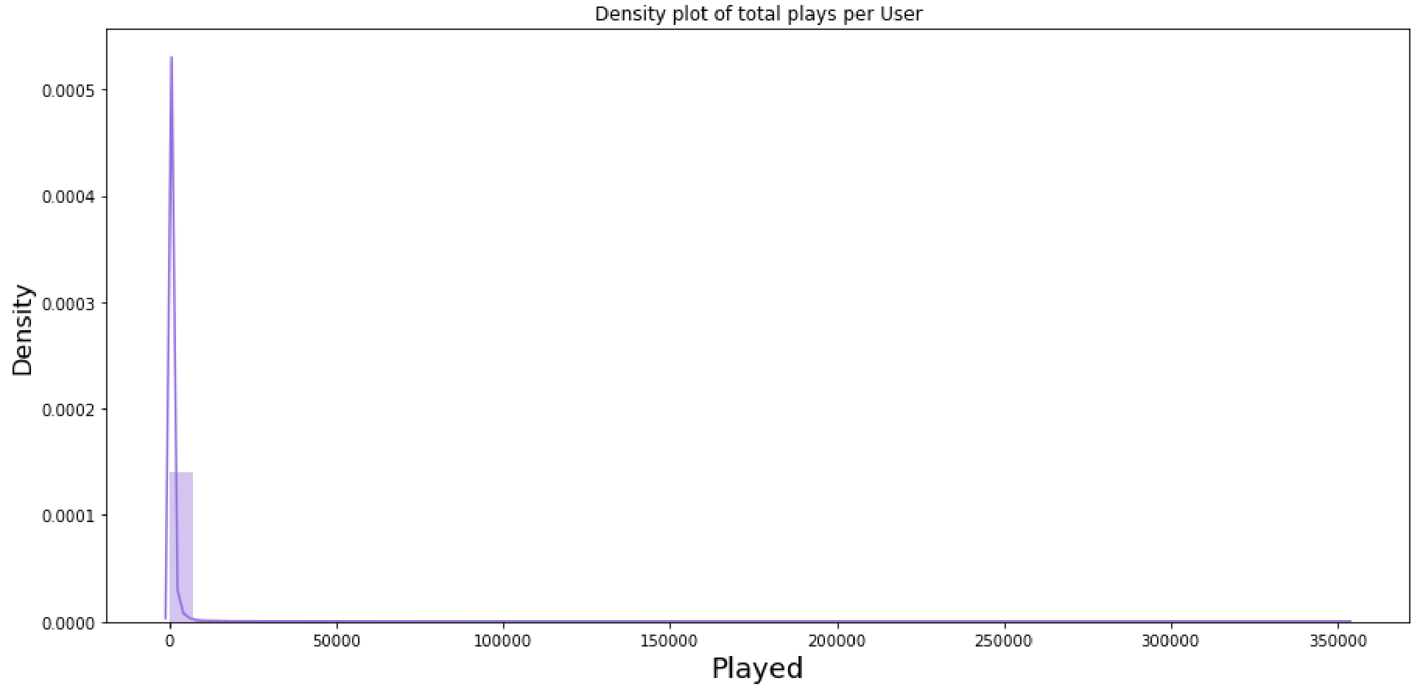
In [77]:

```
plt.figure(figsize=[15,7])
sns.distplot(played['played'], color="mediumpurple").set(title='Density plot of total play
plt.xlabel('Played', fontsize=18)
plt.ylabel('Density', fontsize=16)
```

```
C:\Users\user\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `d
istplot` is a deprecated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar flexibility) or `his
tplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[77]:

```
Text(0, 0.5, 'Density')
```



The majority of values seem around the 1k or less mark. There are a lot of outlier values however going as far as 350,000 for the most extreme values. This confirms our earlier boxplot looking at these values in a clear manner.

In [78]:

```
xyz = pd.DataFrame(played['name'].value_counts())
```

In [79]:

```
xyz = xyz.reset_index()
```

In [80]:

```
xyz.rename(columns={'index': 'name', 'name': 'unique'}, inplace=True)
```

In [81]:

```
xyz
```

Out[81]:

	name	unique
0	Lady Gaga	611
1	Britney Spears	522
2	Rihanna	484
3	The Beatles	480
4	Katy Perry	473
...	...	...
17627	Karmina	1
17628	Alexandre Desplat & Aaron Zigman	1
17629	Burning Brides	1
17630	ozzy	1

	name	unique
17631	Grzegorz Tomczak	1

17632 rows × 2 columns

In [82]:
```
merged_df = artdf.merge(xyz, how = 'inner', on = ['name', 'name'])
```

In [83]:
```
merged_df
```

Out[83]:

	artistID	name	mean	med	max	sum	unique
0	283	Britney Spears	4584.559387	1000.5	131733	2393140	522
1	66	Depeche Mode	4614.567376	567.0	352698	1301308	282
2	83	Lady Gaga	2113.563011	590.0	114672	1291387	611
3	286	Christina Aguilera	2600.503686	739.0	176133	1058405	407
4	492	Paramore	2414.659148	417.0	227829	963449	399
...	...	...	...	...	...	...	...
17627	16522	K-Precise	1.000000	1.0	1	1	1
17628	13713	ZÃœNDER	1.000000	1.0	1	1	1
17629	13712	Evil Masquerade	1.000000	1.0	1	1	1
17630	16239	Gosling	1.000000	1.0	1	1	1
17631	16241	Kalson	1.000000	1.0	1	1	1

17632 rows × 7 columns

In [84]:
```
percent = []
val = merged_df['unique']
total = played['userID'].nunique()
percent = []
for i in range(len(val)):
    y = val[i] / total
    percent.append(y)
    #print(y)
```

In [85]:
```
percent = np.array(percent)
artdf['Percentage'] = percent.tolist()
```

In [86]:
```
artdf
```

Out[86]:

	artistID	name	mean	med	max	sum	Percentage
283	283	Britney Spears	4584.559387	1000.5	131733	2393140	0.275899
66	66	Depeche Mode	4614.567376	567.0	352698	1301308	0.149049
83	83	Lady Gaga	2113.563011	590.0	114672	1291387	0.322939
286	286	Christina Aguilera	2600.503686	739.0	176133	1058405	0.215116

	artistID	name	mean	med	max	sum	Percentage
492	492	Paramore	2414.659148	417.0	227829	963449	0.210888
...	...	...	...	...	...	...	...
16522	16522	K-Precise	1.000000	1.0	1	1	0.000529
13713	13713	ZÃœNDER	1.000000	1.0	1	1	0.000529
13712	13712	Evil Masquerade	1.000000	1.0	1	1	0.000529
16239	16239	Gosling	1.000000	1.0	1	1	0.000529
16241	16241	Kalson	1.000000	1.0	1	1	0.000529

17632 rows × 7 columns

In [87]:

```
artdf['unique'] = merged_df['unique'].values
```

In [88]:

```
artdf
```

Out[88]:

	artistID	name	mean	med	max	sum	Percentage	unique
283	283	Britney Spears	4584.559387	1000.5	131733	2393140	0.275899	522
66	66	Depeche Mode	4614.567376	567.0	352698	1301308	0.149049	282
83	83	Lady Gaga	2113.563011	590.0	114672	1291387	0.322939	611
286	286	Christina Aguilera	2600.503686	739.0	176133	1058405	0.215116	407
492	492	Paramore	2414.659148	417.0	227829	963449	0.210888	399
...	...	...	...	...	...	...	...	...
16522	16522	K-Precise	1.000000	1.0	1	1	0.000529	1
13713	13713	ZÃœNDER	1.000000	1.0	1	1	0.000529	1
13712	13712	Evil Masquerade	1.000000	1.0	1	1	0.000529	1
16239	16239	Gosling	1.000000	1.0	1	1	0.000529	1
16241	16241	Kalson	1.000000	1.0	1	1	0.000529	1

17632 rows × 8 columns

In [89]:

```
artdf['Percentage'] = artdf['Percentage'].multiply(100)
```

In [90]:

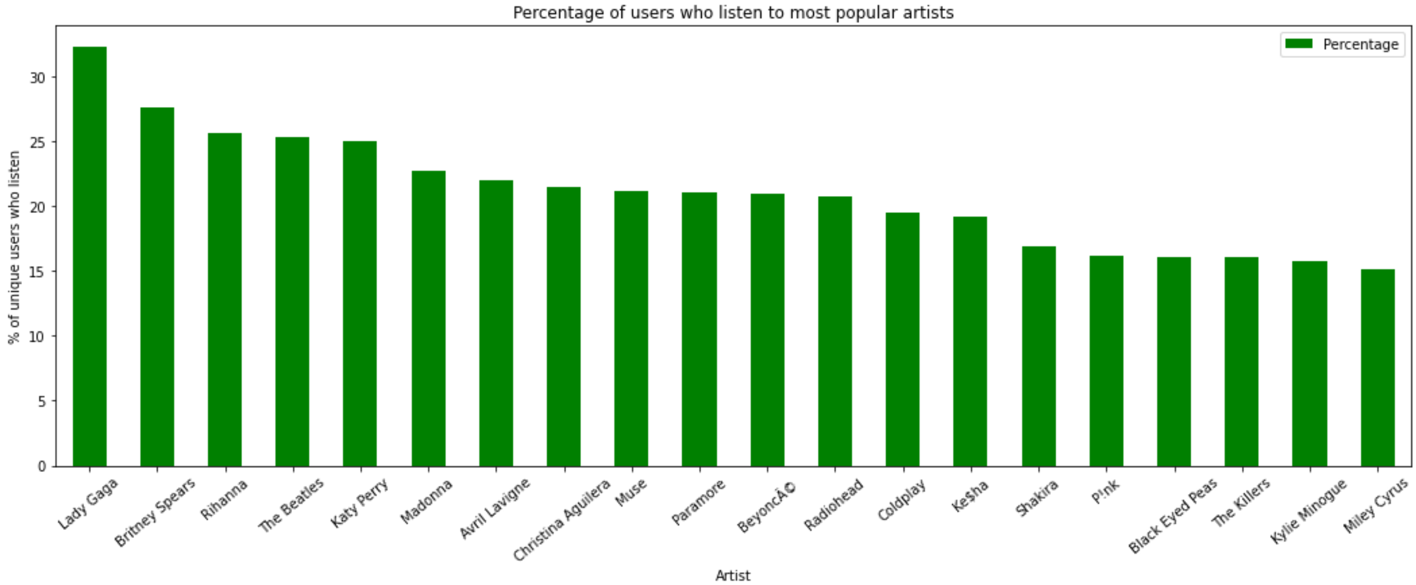
```
artdf = artdf.sort_values(by=['Percentage'], ascending=False)
```

In [91]:

```
pt2 = artdf.head(20)
pt2.plot.bar(x = 'name', y = 'Percentage', rot = 40, figsize=(18, 6), color='green', xlabe
```

Out[91]:

```
<AxesSubplot:title={'center':'Percentage of users who listen to most popular artists'}, xl
abel='Artist', ylabel='% of unique users who listen'>
```



This further seems to confirm our data is more geared towards the top. With such high percentages in relative terms of unique users listening to these artists it may cause issues such as the "cold-start" problem for our recommender. By this I mean with so many popular artists with such a high percent of users (and what appears to be fairly similar artists/genres) the recommender may struggle to recommend new or unknown artists to users. This is certainly the problem we seek to avoid. Let's check this information further below checking how many artists have between 1% and 5% of the total users listening to them.

In [92]:

```
values = [1, 2, 3, 4, 5]
for i in range(len(values)):
    x = len(artdf[artdf['Percentage'] <= values[i]])
    print("The percentage of artists with " + str(values[i]) + "% or less users listening
```

```
The percentage of artists with 1% or less users listening to them is 16794.
The percentage of artists with 2% or less users listening to them is 17200.
The percentage of artists with 3% or less users listening to them is 17350.
The percentage of artists with 4% or less users listening to them is 17430.
The percentage of artists with 5% or less users listening to them is 17497.
```

We can tell on the whole of the 17632 artists that there are actually very few who are listened to by a wide audience. There are less than 1000 artists who have more than 1% of users listening to them. This confirms our data is probably leaned very heavily towards the most popular artists such as Britney Spears or Lady Gaga as per our barchart above. Our below density plot confirms this.

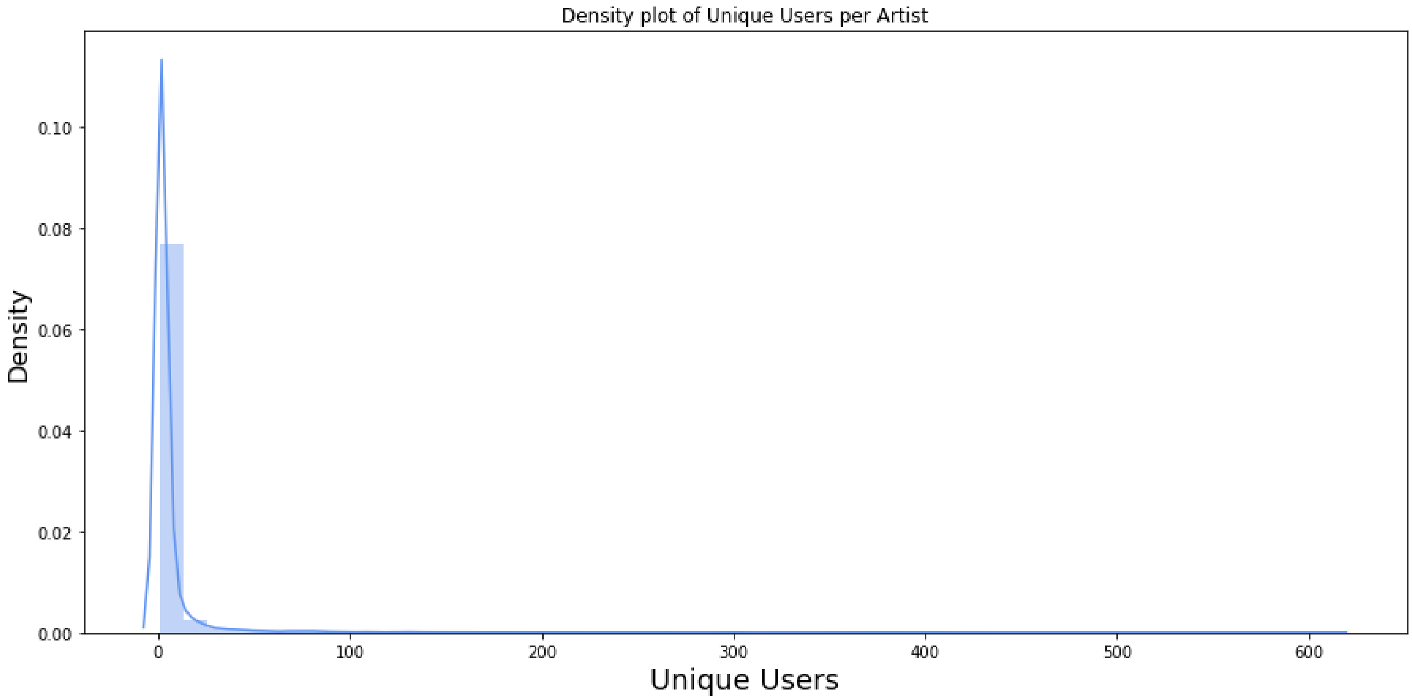
In [93]:

```
plt.figure(figsize=[15,7])
sns.distplot(artdf['unique'], color="cornflowerblue").set(title='Density plot of Unique Us
plt.xlabel('Unique Users', fontsize=18)
plt.ylabel('Density', fontsize=16)
```

```
C:\Users\user\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `d
istplot` is a deprecated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar flexibility) or `his
tplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[93]:

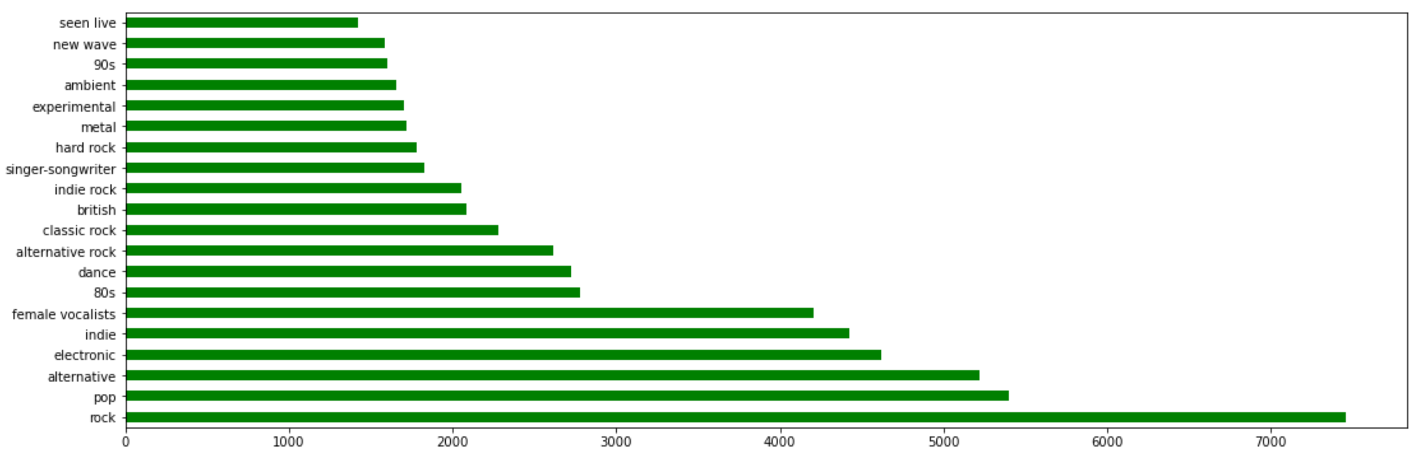
```
Text(0, 0.5, 'Density')
```



In [94]:

```
# Let's check most popular tags
tags['tagValue'].value_counts()[:20].plot(kind='barh', color='green', figsize=(18,6))
```

Out[94]: <AxesSubplot:>



Sparse Representation of Played matrix

In [95]:

```
# Calculate sparsity of matrix
def calculate_sparsity(M):
    matrix_size = float(M.shape[0] * M.shape[1]) # Number of total possible interactions b
    num_plays = len(M.nonzero()[1]) # Number of times any artist has been interacted with
    sparsity = 100 * (1 - float(num_plays / matrix_size))
    return sparsity
```

Normalising our played column

Next, one of the crucial aspects of our recommender system would be dealing with our played column. With such a diverse number of values from the range of 0 to over 350,000 we would have to deal with these appropriately. Our system would not be able to handle values of such a high nature and when I tried to run this I would get very high train errors and "nan" values for test error. I looked at a variety of different ways to normalize this value as a result and I would only incorporate two of these into my dataframe. I looked at capping any values above the 2,000 mark in our played column at 2,000 but errors persisted with this approach. As a result the methods I looked at were:

1) Simple Normalization - normalizing all values based off the highest value in the "played" column.

2) User based Normalization - grouping our played column by users and normalizing each user based off their own max value. I implemented this as a column called "playedUserNorm". This had the best results and was the column I implemented below.

3) Play Count Scaled - here I would take each value in the column and take it away from the minimum value in the column. I would then divide this by the max value of the column minus the minimum value. I implemented this with the column "playCountScaled".

4) Robust Scaling method - here we would scale each feature of the data set by subtracting the median and then dividing by the interquartile range. I tried this method but the results were poor and implementing it took a long time to run.

In [96]:
```
sm = played['played'].groupby(played['userID']).max()
artss = np.array(played['userID'])
playzz = np.array(played['played'])
#artss[-1]
newnorm = []
for i in range(len(playzz)):
    index = artss[i]
    val = playzz[i] / sm[index]
    newnorm.append(val)
```

In [97]:
```
newnorm = np.array(newnorm)

#add newnorm array as new column in DataFrame
played['playedUserNorm'] = newnorm.tolist()
```

In [98]:
```
played['playedUserNorm'].max()
```

Out[98]:
```
1.0
```

In [99]:
```
pc = played.played
play_count_scaled = (pc - pc.min()) / (pc.max() - pc.min())

played = played.assign(playCountScaled=play_count_scaled)
```

In [100…
```
# !!! here is our 1) simple normalisation

# played["playBasicNorm"] = played["played"] / played["played"].max()
```

In [101…
```
# played['playCountScaled'].equals(played['playBasicNorm'])
```

In [102…
```
played.head()
```

Out[102…

	name	url	artID	userID	artistID	played	playedUserNorm	playCountScale
0	MALICE MIZER	http://www.last.fm/music/MALICE+MIZER	0	31	0	212	0.055775	0.0005

	name	url	artID	userID	artistID	played	playedUserNorm	playCountScale
1	MALICE MIZER	http://www.last.fm/music/MALICE+MIZER	0	256	0	483	0.065394	0.0013
2	MALICE MIZER	http://www.last.fm/music/MALICE+MIZER	0	729	0	76	0.025149	0.0002
3	Diary of Dreams	http://www.last.fm/music/Diary+of+Dreams	1	130	1	1021	0.150902	0.0028
4	Diary of Dreams	http://www.last.fm/music/Diary+of+Dreams	1	240	1	152	0.154315	0.0004

In [103…

```
# !!! here is our attempt at robust scaling as per 4)

#newcol = []
#pl = np.array(played['played'])
#for i in range(len(pl)):
#    val = (pl[i] - played['played'].median())  / (played['played'].quantile(0.75) - playe
#    newcol.append(val)
```

In [104…

```
#newcol = np.array(newcol)

#add newnorm array as new column in DataFrame
#played['playedRobust'] = newcol.tolist()
```

We will now begin to build the model. The first step is building a sparse matrix as input for our models. A sparse matrix is a dataset in which most of the entries are zero, one such example would be a large diagonal matrix. In our case this would involve our dataset of userID, artistID and played columns. We will do this by using the SparseTensor function as part of the tensorflow library.

In [105…

```
def build_rating_sparse_tensor(ratings_df):
  # ========================= Complete this section ============================
    indices = ratings_df[['userID', 'artID']].values
    values = ratings_df['playedUserNorm'].values
  # ============================================================================

    return tf.SparseTensor(
      indices=indices,
      values=values,
      dense_shape=[len(played.userID.unique()), len(played.artID.unique())])
```

In [106…

```
len(played.userID.unique())
```

Out[106…

```
1892
```

In [107…

```
def sparse_mean_square_error(sparse_ratings, user_embeddings, artist_embeddings):
    predictions = tf.reduce_sum(
    tf.gather(user_embeddings, sparse_ratings.indices[:, 0]) * tf.gather(artist_embeddings
      axis=1)
    loss = tf.losses.mean_squared_error(sparse_ratings.values, predictions)
    return loss
```

Building the Model

In [108…

```
import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()
class CFModel(object):

  def __init__(self, embedding_vars, loss, metrics=None):

    self._embedding_vars = embedding_vars
    self._loss = loss
    self._metrics = metrics
    self._embeddings = {k: None for k in embedding_vars}
    self._session = None

  @property
  def embeddings(self):
    """The embeddings dictionary."""
    return self._embeddings

  def train(self, num_iterations = 100, learning_rate = 1.0, plot_results=True,
            optimizer=tf.train.GradientDescentOptimizer):

    with self._loss.graph.as_default():
      opt = optimizer(learning_rate)
      train_op = opt.minimize(self._loss)
      local_init_op = tf.group(
          tf.variables_initializer(opt.variables()),
          tf.local_variables_initializer())
      if self._session is None:
        self._session = tf.Session()
        with self._session.as_default():
          self._session.run(tf.global_variables_initializer())
          self._session.run(tf.tables_initializer())
          tf.train.start_queue_runners()

    with self._session.as_default():
      local_init_op.run()
      iterations = []
      metrics = self._metrics or ({},)
      metrics_vals = [collections.defaultdict(list) for _ in self._metrics]

      # Train and append results.
      for i in range(num_iterations + 1):
        _, results = self._session.run((train_op, metrics))
        if (i % 10 == 0) or i == num_iterations:
          print("\r iteration %d: " % i + ", ".join(
                ["%s=%f" % (k, v) for r in results for k, v in r.items()]),
                end='')
          iterations.append(i)
          for metric_val, result in zip(metrics_vals, results):
            for k, v in result.items():
              metric_val[k].append(v)

      for k, v in self._embedding_vars.items():
        self._embeddings[k] = v.eval()

      if plot_results:
        # Plot the metrics.
        num_subplots = len(metrics) + 1
        fig = plt.figure()
        fig.set_size_inches(num_subplots * 10, 8)
        for i, metric_vals in enumerate(metrics_vals):
          ax = fig.add_subplot(1, num_subplots, i + 1)
          for k, v in metric_vals.items():
```

```
            ax.plot(iterations, v, label = k)
          ax.set_xlim([1, num_iterations])
          ax.legend()
      return results
```

Build and Run the Model

In [109…

```
from sklearn.model_selection import train_test_split
def build_model(ratings, embedding_dim=3, init_stddev=1.):

  # Split the ratings DataFrame into train and test.
    #train_ratings, test_ratings = train_test_split(ratings, test_size=0.5)
    train_ratings, test_ratings = split_dataframe(ratings)
  # SparseTensor representation of the train and test datasets.
    A_train = build_rating_sparse_tensor(train_ratings)
    A_test = build_rating_sparse_tensor(test_ratings)
  # Initialize the embeddings using a normal distribution.
    U = tf.Variable(tf.random.normal(
      [A_train.dense_shape[0], embedding_dim], stddev=init_stddev))
    V = tf.Variable(tf.random.normal(
      [A_train.dense_shape[1], embedding_dim], stddev=init_stddev))
    train_loss = sparse_mean_square_error(A_train, U, V)
    test_loss = sparse_mean_square_error(A_test, U, V)
    metrics = {
      'train_error': train_loss,
      'test_error': test_loss
    }
    embeddings = {
      "userID": U,
      "artID": V
    }
    return CFModel(embeddings, train_loss, [metrics])
```

In [110…

```
def split_dataframe(df, holdout_fraction=0.3):

    test = df.sample(frac=holdout_fraction, replace=False)
    train = df[~df.index.isin(test.index)]
    return train, test
```

In [111…

```
# take the relevant columns
xyz = played[['userID', 'artID', 'playedUserNorm']]
```

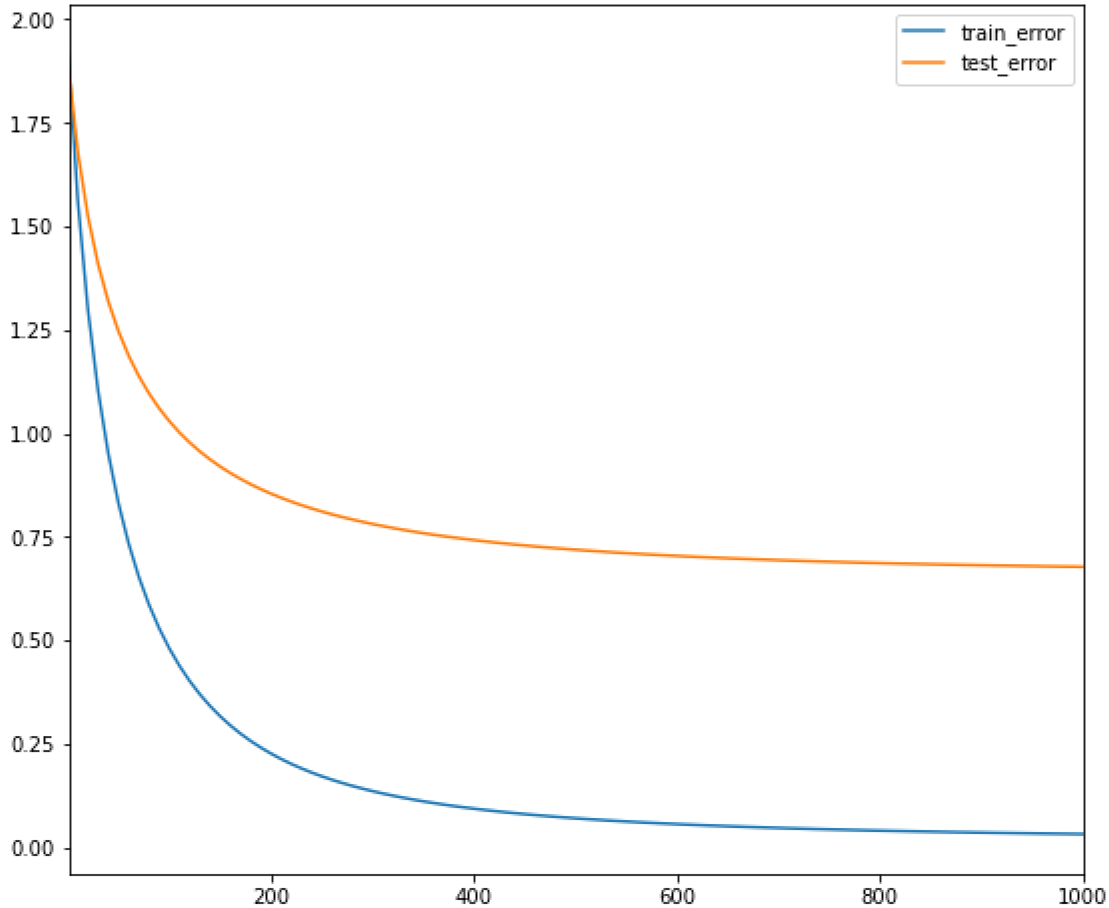
In [112…

```
model = build_model(xyz,  embedding_dim=30, init_stddev=0.5)
model.train(num_iterations=1000, learning_rate=10.)
```

```
 iteration 1000: train_error=0.031453, test_error=0.677229
```

Out[112…

```
[{'train_error': 0.031453103, 'test_error': 0.6772292}]
```



I tried to build my model but the high values for listens was giving me errors like so "InvalidArgumentError: indices[4073] = 2077 is not in [0, 1892)".

This was why I changed the artist and user ID's to 1.) start from zero and 2.) increment by 1 until the length of unique values - 1. I had to normalise my weights then as I kept returning nan values for train and test errors above.

Inspect Embeddings

In [113…

```
DOT = 'dot'
COSINE = 'cosine'
def compute_scores(query_embedding, item_embeddings, measure=DOT):
  u = query_embedding
  V = item_embeddings
  if measure == COSINE:
    V = V / np.linalg.norm(V, axis=1, keepdims=True)
    u = u / np.linalg.norm(u)
  scores = u.dot(V.T)
  return scores
```

In [114…

```
from IPython import display
def artist_neighbors(model, title_substring, measure=DOT, k=6):
  ids =  df[df['name'].str.contains(title_substring)].index.values
  titles = df.iloc[ids]['name'].values
  if len(titles) == 0:
    raise ValueError("Found no artist with title %s" % title_substring)
  print("Nearest neighbors of : %s." % titles[0])
  if len(titles) > 1:
    print("[Found more than one matching artist. Other candidates: {}]".format(
        ", ".join(titles[1:])))
  artistID = ids[0]
```

```
    scores = compute_scores(
        model.embeddings["artID"][artistID], model.embeddings["artID"],
        measure)
    score_key = measure + ' score'
    df7 = pd.DataFrame({
        score_key: list(scores),
        'names': df['name'],
    })
    display.display(df7.sort_values([score_key], ascending=False).head(k))
```

Similarity Scores for our model

Let's test our model on some well known artists and see what recommendations it returns. The two similarity measures will be the dot product and cosine similarity. Higher values of both are better. To start with the cosine similarity can be defined as the cosine of the angle between two n-dimensional vectors in an n-dimensional space. The cosine similarity formula corresponds as:

$$similarity(A, B) = {A \cdot B \over |A| \times |B|}$$

Values range between -1 and 1, where -1 is perfectly dissimilar and 1 is perfectly similar. The dot product can be defined in a couple of different ways. It is seen in the cosine similarity formula. The dot product is defined as is equal to the product of the magnitude of the two vectors and the cosecant of the angle between the two vectors. One way it is notated is as:

$$ A \cdot B = |A| |B| \times \cosθ $$

It can also be denoted in this format:

$$ A \cdot B = \sum_{i=1}^n a_i b_i$$

Where: a = 1st vector, b = 2nd vector, n = dimension of the vector space, a_i = component of vector a, b_i = component of vector b

In [115…

```
artist_grp = ['Lady Gaga', 'The Killers', 'Black Eyed Peas', 'Rihanna', 'Gwen Stefani', 'A
for art in range(len(artist_grp)):
    artist_neighbors(model, artist_grp[art], DOT)
    artist_neighbors(model, artist_grp[art], COSINE)
```

```
Nearest neighbors of : Lady Gaga.
[Found more than one matching artist. Other candidates: Lady Gaga VS Christina Aguilera, B
eyoncÃ© e Lady Gaga, Lady Gaga feat BeyoncÃ©]
```

	dot score	names
16356	0.925098	Shawnna
13511	0.874200	BR5-49
16109	0.864573	Ian Ion
14448	0.848581	John Cale
13800	0.827204	Lyrics Born
9982	0.812858	KÄ±raÃ§

```
Nearest neighbors of : Lady Gaga.
[Found more than one matching artist. Other candidates: Lady Gaga VS Christina Aguilera, B
eyoncÃ© e Lady Gaga, Lady Gaga feat BeyoncÃ©]
```

	cosine score	names
83	1.000000	Lady Gaga
286	0.744032	Christina Aguilera

	cosine score	names
282	0.684765	Rihanna
460	0.663896	Ke$ha
16356	0.651747	Shawnna
61	0.648179	Madonna

```
Nearest neighbors of : The Killers.
[Found more than one matching artist. Other candidates: Arctic Monkeys vs The Killers]
```

	dot score	names
10792	0.669424	Renan Luce
11868	0.667024	Bono, Glen Hansard & Damien Rice
8294	0.640611	Marco Borsato
16342	0.628483	Bruce Dickinson & Montserrat Cabelle
16785	0.624216	TeddyLoid
1181	0.615290	We Are The Ocean

```
Nearest neighbors of : The Killers.
[Found more than one matching artist. Other candidates: Arctic Monkeys vs The Killers]
```

	cosine score	names
223	1.000000	The Killers
8294	0.608293	Marco Borsato
841	0.602849	Haste the Day
9619	0.593279	Republica
9821	0.584922	Dies Irae
294	0.583627	Katy Perry

```
Nearest neighbors of : Black Eyed Peas.
[Found more than one matching artist. Other candidates: The Black Eyed Peas, Juanes feat.B
lack Eyed Peas]
```

	dot score	names
10823	0.345699	The Burglars
16675	0.328751	Sing-Sing
7679	0.326258	Paul Potts
9971	0.322561	è©©æœˆã‚«ã‚ªãƒª
1954	0.320764	Prefuse 73
8310	0.320724	Voces en el Plasma

```
Nearest neighbors of : Black Eyed Peas.
[Found more than one matching artist. Other candidates: The Black Eyed Peas, Juanes feat.B
lack Eyed Peas]
```

	cosine score	names
300	1.000000	Black Eyed Peas
296	0.693031	P!nk
343	0.637236	The Pussycat Dolls

	cosine score	names
282	0.626463	Rihanna
7995	0.619446	Queen Latifah
15626	0.617672	Silver Apples

```
Nearest neighbors of : Rihanna.
[Found more than one matching artist. Other candidates: Rihanna (feat. Drake), Jay-Z, Bon
o, The Edge & Rihanna, RihannaÌ€, Sean Paul ft. Rihanna, Rihanna-remixado REnan, \Eminem f
_ Rihanna]
```

	dot score	names
13925	0.663406	Radionave
17209	0.643368	Dan Griober
4323	0.643271	A Band Featuring Instruments
8310	0.615734	Voces en el Plasma
4399	0.614190	The Bangles
5408	0.606505	Nadine

```
Nearest neighbors of : Rihanna.
[Found more than one matching artist. Other candidates: Rihanna (feat. Drake), Jay-Z, Bon
o, The Edge & Rihanna, RihannaÌ€, Sean Paul ft. Rihanna, Rihanna-remixado REnan, \Eminem f
_ Rihanna]
```

	cosine score	names
282	1.000000	Rihanna
460	0.703720	Ke$ha
83	0.684765	Lady Gaga
283	0.666515	Britney Spears
61	0.660117	Madonna
285	0.635870	Kelly Clarkson

```
Nearest neighbors of : Gwen Stefani.
[Found more than one matching artist. Other candidates: Panic! at the Disco feat. Britney
Spears and Gwen Stefani]
```

	dot score	names
14920	0.509735	Siavash Ghomayshi
10058	0.494921	Johnny Pearson
13030	0.486891	Hollywood Nobody
1085	0.455970	Kent
9893	0.438431	Dino
8371	0.434909	Randy & The Rainbows

```
Nearest neighbors of : Gwen Stefani.
[Found more than one matching artist. Other candidates: Panic! at the Disco feat. Britney
Spears and Gwen Stefani]
```

	cosine score	names
519	1.000000	Gwen Stefani

	cosine score	names
2313	0.615980	HÃ¼meyra
936	0.603509	Journey
10058	0.587979	Johnny Pearson
7263	0.579636	Corrosion of Conformity
14920	0.573819	Siavash Ghomayshi

```
Nearest neighbors of : AC/DC.
```

	dot score	names
11740	1.436519	Lunachicks
10263	1.341249	Knxwledge
12793	1.250240	Sibel Can
2981	1.245365	The Carter Family
7567	1.236822	Semisonic
550	1.193626	The Strollers

```
Nearest neighbors of : AC/DC.
```

	cosine score	names
700	1.000000	AC/DC
1403	0.644673	Led Zeppelin
11740	0.635786	Lunachicks
1906	0.623724	ë□™ë°©ì‹ ê¸°
550	0.621190	The Strollers
6018	0.606945	John Stoneham

While our cosine score results provide very strong recommendations using the dot product model here produces mediocre results at best. This also factors in that the dot product is a very popular method for recommender systems and as a result we will need to incorporate further methods to get better results. We will attempt to use a regularized matrix. The key point of this being that regularization is to enforce conditions, for example sparsity or smoothness, that can produce stable predictive functions and in our case improve our model. Overall, I would have to say this model could definitely be improved upon. Let's try an adaptation of our approach.

Regularized Matrix

We are going to incorporate a regularized matrix into our model. A regularized matrix is utilised to enforce conditions, for example sparsity or smoothness, that can produce stable predictive functions.

In [116…

```
def gravity(U, V):
  return 1. / (U.shape[0].value * V.shape[0].value) * tf.reduce_sum(
      tf.matmul(U, U, transpose_a = True) * tf.matmul(V, V, transpose_a = True))

def build_regularized_model(data, embedding_dim = 3, regularization_coeff = .1, gravity_co
  # Split the ratings DataFrame into train and test.
  train_ratings, test_ratings = split_dataframe(xyz)
  # SparseTensor representation of the train and test datasets.
```

```
    A_train = build_rating_sparse_tensor(train_ratings)
    A_test = build_rating_sparse_tensor(test_ratings)
    U = tf.Variable(tf.random_normal(
        [A_train.dense_shape[0], embedding_dim], stddev = init_stddev))
    V = tf.Variable(tf.random_normal(
        [A_train.dense_shape[1], embedding_dim], stddev = init_stddev))

    error_train = sparse_mean_square_error(A_train, U, V)
    error_test = sparse_mean_square_error(A_test, U, V)
    gravity_loss = gravity_coeff * gravity(U, V)
    regularization_loss = regularization_coeff * (
        tf.reduce_sum(U * U) / U.shape[0].value + tf.reduce_sum(V * V) / V.shape[0].value)
    total_loss = error_train + regularization_loss + gravity_loss
    losses = {
        'train_error_observed': error_train,
        'test_error_observed': error_test,
    }
    loss_components = {
        'observed_loss': error_train,
        'regularization_loss': regularization_loss,
        'gravity_loss': gravity_loss,
    }
    embeddings = {"userID": U, "artID": V}

    return CFModel(embeddings, total_loss, [losses, loss_components]), U, V
```

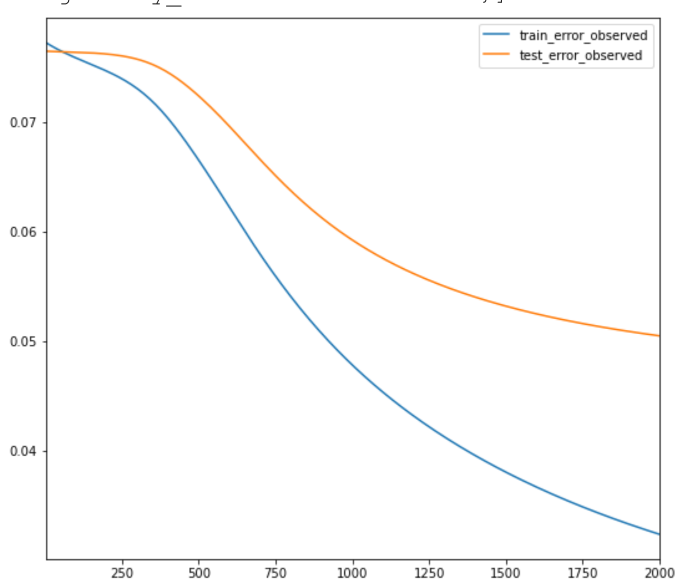
In [117…

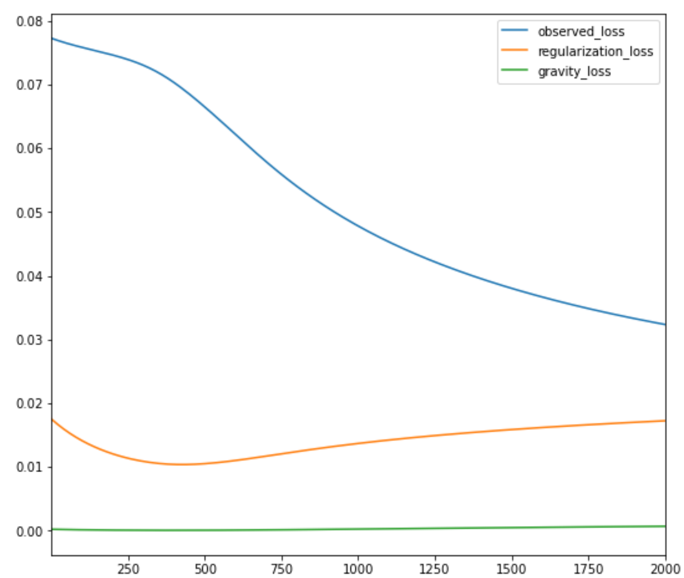
```
reg_model, u, v  = build_regularized_model(xyz, regularization_coeff=0.1, gravity_coeff=1.
reg_model.train(num_iterations=2000, learning_rate=20.)
```

```
 iteration 2000: train_error_observed=0.032361, test_error_observed=0.050478, observed_los
s=0.032361, regularization_loss=0.017247, gravity_loss=0.000685
```

Out[117…

```
[{'train_error_observed': 0.032360815, 'test_error_observed': 0.05047809},
 {'observed_loss': 0.032360815,
  'regularization_loss': 0.01724688,
  'gravity_loss': 0.0006848034}]
```





Let's test our model on the same group of artists from before to get a better understanding of it's recommendations. We will see if these are more valid recommendations than before.

In [118…

```
for art in range(len(artist_grp)):
    artist_neighbors(reg_model, artist_grp[art], DOT)
    artist_neighbors(reg_model, artist_grp[art], COSINE)
```

```
Nearest neighbors of : Lady Gaga.
[Found more than one matching artist. Other candidates: Lady Gaga VS Christina Aguilera, B
```

```
eyoncÃ© e Lady Gaga, Lady Gaga feat BeyoncÃ©]
```

	dot score	names
83	11.956351	Lady Gaga
283	3.328831	Britney Spears
282	3.153648	Rihanna
294	2.786813	Katy Perry
286	2.348049	Christina Aguilera
251	2.305609	Mariah Carey

```
Nearest neighbors of : Lady Gaga.
[Found more than one matching artist. Other candidates: Lady Gaga VS Christina Aguilera, B
eyoncÃ© e Lady Gaga, Lady Gaga feat BeyoncÃ©]
```

	cosine score	names
83	1.000000	Lady Gaga
640	0.672767	RBD
277	0.652832	Ana Carolina
453	0.633385	*NSYNC
3454	0.618443	Agnes
322	0.614605	David Guetta

```
Nearest neighbors of : The Killers.
[Found more than one matching artist. Other candidates: Arctic Monkeys vs The Killers]
```

	dot score	names
223	2.048458	The Killers
201	1.653045	Arctic Monkeys
221	1.651406	The Beatles
184	1.543325	Muse
176	1.438013	Keane
527	1.432857	Oasis

```
Nearest neighbors of : The Killers.
[Found more than one matching artist. Other candidates: Arctic Monkeys vs The Killers]
```

	cosine score	names
223	1.000000	The Killers
2594	0.816148	Razorlight
176	0.807922	Keane
2357	0.800195	Backyard Babies
714	0.796813	Social Distortion
447	0.794060	Silverchair

```
Nearest neighbors of : Black Eyed Peas.
[Found more than one matching artist. Other candidates: The Black Eyed Peas, Juanes feat.B
lack Eyed Peas]
```

	dot score	names

	dot score	names
282	1.478637	Rihanna
283	1.376997	Britney Spears
492	1.176239	Paramore
289	1.093039	BeyoncÃ©
455	0.981739	Miley Cyrus
83	0.976881	Lady Gaga

```
Nearest neighbors of : Black Eyed Peas.
[Found more than one matching artist. Other candidates: The Black Eyed Peas, Juanes feat.B
lack Eyed Peas]
```

	cosine score	names
300	1.000000	Black Eyed Peas
324	0.817529	T.I.
273	0.806191	Brandy
326	0.799197	Kelly Rowland
235	0.776783	Toni Braxton
4472	0.775504	Amerie

```
Nearest neighbors of : Rihanna.
[Found more than one matching artist. Other candidates: Rihanna (feat. Drake), Jay-Z, Bon
o, The Edge & Rihanna, RihannaÌ€, Sean Paul ft. Rihanna, Rihanna-remixado REnan, \Eminem f
_ Rihanna]
```

	dot score	names
282	5.421268	Rihanna
83	3.153648	Lady Gaga
289	2.414663	BeyoncÃ©
283	2.390840	Britney Spears
251	2.156758	Mariah Carey
286	2.048543	Christina Aguilera

```
Nearest neighbors of : Rihanna.
[Found more than one matching artist. Other candidates: Rihanna (feat. Drake), Jay-Z, Bon
o, The Edge & Rihanna, RihannaÌ€, Sean Paul ft. Rihanna, Rihanna-remixado REnan, \Eminem f
_ Rihanna]
```

	cosine score	names
282	1.000000	Rihanna
245	0.718536	Whitney Houston
300	0.702294	Black Eyed Peas
539	0.673360	Flo Rida
4701	0.668658	Cody Simpson
308	0.657774	Ciara

```
Nearest neighbors of : Gwen Stefani.
[Found more than one matching artist. Other candidates: Panic! at the Disco feat. Britney
```

```
Spears and Gwen Stefani]
```

	dot score	names
283	1.048183	Britney Spears
83	0.869819	Lady Gaga
286	0.801397	Christina Aguilera
61	0.795499	Madonna
282	0.791222	Rihanna
673	0.670139	Glee Cast

```
Nearest neighbors of : Gwen Stefani.
[Found more than one matching artist. Other candidates: Panic! at the Disco feat. Britney
Spears and Gwen Stefani]
```

	cosine score	names
519	1.000000	Gwen Stefani
323	0.845820	Justin Timberlake
259	0.821362	CÃ©line Dion
284	0.816289	Jordin Sparks
304	0.795653	Nelly Furtado
296	0.794230	P!nk

```
Nearest neighbors of : AC/DC.
```

	dot score	names
1403	1.574423	Led Zeppelin
700	1.549536	AC/DC
157	1.517109	Pink Floyd
908	1.442897	Iron Maiden
701	1.309008	Metallica
227	1.162440	Nine Inch Nails

```
Nearest neighbors of : AC/DC.
```

	cosine score	names
700	1.000000	AC/DC
2331	0.858586	Aerosmith
2328	0.778910	KISS
726	0.770634	Alice Cooper
1794	0.766881	MÃ¶tley CrÃ¼e
943	0.758303	Skid Row

These are actually very good recommendations produced by our recommender system based off each users unique normalised values based on the highest listened value they obtained. Our regularized model is much superior on initial inspection than our standard model with much better recommendations all around. Our test error has also decreased noticeably here. Let's test this further on one of the artists here: AC/DC, who would be popular but as should earlier not in the top 20. Let's try verify our results with the appropriate tag information.

In [119…

```
played[played['name'] == 'AC/DC'].head(1)
```

Out[119…

	name	url	artID	userID	artistID	played	playedUserNorm	playCountScale
33561	AC/DC	http://www.last.fm/music/AC%252FDC	700	16	700	853	0.390032	0.00241

In [251…

```
# id = 700
ac_dc = tags[tags['artistID'] == 700]
```

Let's just check one of our recommendations for AC/DC as an example. Let's compare the tags left on both these artists by users.

In [253…

```
ac_dc_tags = ac_dc['tagValue'].unique()
```

In [255…

```
recs = ['Led Zeppelin', 'Pink Floyd', 'Iron Maiden', 'Metallica', 'Nine Inch Nails',
        'AeroSmith', 'KISS', 'Alice Cooper', 'MÃ¶tley CrÃ¼e', 'Skid Row']
```

In [285…

```
y = df[df['name'].isin(recs)]
rec_id = y['artID'].unique()
```

In [287…

```
zzzz2 = pd.merge(y, tags, how="inner", left_on=['artID'], right_on=['artistID'])
```

In [288…

```
zzzz2
```

Out[288…

	name	url	pictureURL	artID	tagID	tagValue	userID	artist
0	Pink Floyd	http://www.last.fm/music/Pink+Floyd	http://userserve-ak.last.fm/serve/252/39219129...	157	14	ambient	1655	1
1	Pink Floyd	http://www.last.fm/music/Pink+Floyd	http://userserve-ak.last.fm/serve/252/39219129...	157	18	electronic	1655	1
2	Pink Floyd	http://www.last.fm/music/Pink+Floyd	http://userserve-ak.last.fm/serve/252/39219129...	157	25	80s	296	1
3	Pink Floyd	http://www.last.fm/music/Pink+Floyd	http://userserve-ak.last.fm/serve/252/39219129...	157	25	80s	513	1
4	Pink Floyd	http://www.last.fm/music/Pink+Floyd	http://userserve-ak.last.fm/serve/252/39219129...	157	25	80s	561	1
...	...	...	...	...	...	...	...	
2021	KISS	http://www.last.fm/music/KISS	http://userserve-ak.last.fm/serve/252/45524723...	2328	9973	seen in concert	1431	23
2022	KISS	http://www.last.fm/music/KISS	http://userserve-ak.last.fm/serve/252/45524723...	2328	9997	ae	1438	23
2023	KISS	http://www.last.fm/music/KISS	http://userserve-ak.last.fm/serve/252/45524723...	2328	10231	old time rock n roll	1479	23
2024	KISS	http://www.last.fm/music/KISS	http://userserve-ak.last.fm/serve/252/45524723...	2328	12021	weekly top tracks	1776	23

	name	url	pictureURL	artID	tagID	tagValue	userID	artist
2025	KISS	http://www.last.fm/music/KISS	http://userserve-ak.last.fm/serve/252/45524723...	2328	12056	80s rock	1781	23

2026 rows × 8 columns

In [289…

```
ac_dc = {}
ac_valz = np.array(zzzz2['tagValue'])
ac_vals = np.array(zzzz2['name'])
for i in range(len(ac_valz)):
    if ac_vals[i] not in d:
        ac_dc[ac_vals[i]] = ""
    else:
        continue
print(ac_dc)
```

```
{'Pink Floyd': '', 'Nine Inch Nails': '', 'Metallica': '', 'Alice Cooper': '', 'Iron Maide
n': '', 'Skid Row': '', 'Led Zeppelin': '', 'MÃ¶tley CrÃ¼e': '', 'KISS': ''}
```

In [290…

```
for i in range(len(ac_valz)):
    if ac_vals[i] in ac_dc and ac_valz[i] in ac_dc_tags:
        if ac_valz[i] not in ac_dc[ac_vals[i]]:
            ac_dc[ac_vals[i]] += ac_valz[i] + ","
    else:
        continue
```

In [291…

```
def strip_dict(d):
    return dict((k.strip(), v.strip()) for k, v in d.items())
```

In [292…

```
strip_dict(ac_dc)
```

Out[292…

```
{'Pink Floyd': '80s,hard rock,alternative,classic rock,epic,90s,70s,guitar,rock n roll,hea
vy,colors,',
 'Nine Inch Nails': 'metal,80s,rock,alternative,seen live,epic,sexy,90s,cool,heavy,fave,',
 'Metallica': 'metal,80s,hard rock,alternative,seen live,classic rock,epic,90s,heavy meta
l,cool,arena rock,1008,uhull,famous,',
 'Alice Cooper': 'metal,80s,hard rock,rock and roll,seen live,classic rock,90s,heavy meta
l,70s,rock n roll,watched live,',
 'Iron Maiden': 'metal,80s,hard rock,seen live,classic rock,epic,sexy,90s,heavy metal,coo
l,tags,1008,',
 'Skid Row': 'metal,80s,hard rock,classic rock,90s,heavy metal,rock n roll,anos 80,',
 'Led Zeppelin': 'hard rock,alternative,rock and roll,classic rock,epic,heavy metal,blues
rock,70s,guitar,rock n roll,guitar solo,arena rock,tags,',
 'MÃ¶tley CrÃ¼e': 'metal,80s,hard rock,seen live,classic rock,90s,heavy metal,great,guita
r,rock n roll,cool,tags,watched live,80s rock,',
 'KISS': '80s,hard rock,rock and roll,seen live,classic rock,epic,90s,heavy metal,great,70
s,rock n roll,cool,arena rock,1008,80s rock,'}
```

In [293…

```
def split_dict(d):
    for key, value in d.items():
        d[key] = value.split(",")
```

In [294…

```
split_dict(ac_dc)
```

In [296…

```
def pop_dict(d):
    for k, v in d.items():
```

```
        v.pop()
```

In [297…

```
pop_dict(ac_dc)
```

In [313…

```
def prec_k(d, k):
    l1 = list(d.items())
    #print(l1)
    count = 0
    for i in range(len(l1)):
        if len(l1[i][1]) > 0:
            count += 1
        else:
            continue
    print("Precision at k equal " + str(k) + " for user/artist with tags information is: '
```

In [316…

```
prec_k(ac_dc, 9)
```

```
Precision at k equal 9 for user/artist with tags information is: 1.0
```

Taking AC/DC as an example, the tags appear to be incredibly accurate. I wanted to test this to understand how our recommender works and also because I was not sure on some of the artists. At least one tag matches from each artist, there is some spam tags but most are fairly reasonable. We take one off our precision at k value here as AC/DC was already mentioned. This shows how good our recommendations actually were using this regularized model. It must be said that recommendations such as Metallica make plenty of sense. I did not adjust the tag values to index from 0 to unique values minus one here for tag ID's and this shouldn't affect the tags such as those we see here. The user and artist ID's for all files were reindexed approriately which should align with the tag values at hand. We will now move on and see how another recommender system compares to our models based off the google colab provided.

Alternate method - Recommender based on Neural Network

Here we will try to implement another type of recommender system and see does it produce equally as good of results. Our alternate model is based off a neural network to make predictions for users based off listening numbers. As per this article on Investopedia , a neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. Neural networks can adapt to changing input; so the network generates the best possible result without needing to redesign the output criteria. This will help us uncover any listening patterns found in our data by users.

In [121…

```
sub = played[['userID', 'artID', 'playedUserNorm']]
```

In [122…

```
sub.head()
```

Out[122…

	userID	artID	playedUserNorm
0	31	0	0.055775
1	256	0	0.065394
2	729	0	0.025149

	userID	artID	playedUserNorm
3	130	1	0.150902
4	240	1	0.154315

In [123…

```
train, test = train_test_split(sub, test_size=0.3, train_size=0.7)
```

In [124…

```
n_users = len(sub.userID.unique())
n_users
```

Out[124…

```
1892
```

In [125…

```
n_artist = len(sub.artID.unique())
n_artist
```

Out[125…

```
17632
```

In [126…

```
# creating artist embedding path
artist_input = Input(shape=[1], name="Artist-Input")
artist_embedding = Embedding(n_artist + 1, 5, name="Artist-Embedding")(artist_input)
artist_vec = Flatten(name="Flatten-Artist")(artist_embedding)

# creating user embedding path
user_input = Input(shape=[1], name="User-Input")
user_embedding = Embedding(n_users + 1, 5, name="User-Embedding")(user_input)
user_vec = Flatten(name="Flatten-Users")(user_embedding)

# performing dot product and creating model
prod = Dot(name="Dot-Product", axes=1)([artist_vec, user_vec])
model = Model([user_input, artist_input], prod)
model.compile('adam', 'mean_squared_error')
```

In [127…

```
from keras.models import load_model

if os.path.exists('regression_model.h5'):
    model = load_model('regression_model.h5')
else:
    history = model.fit([train.userID, train.artID], train.playedUserNorm, epochs=5, verbo
    model.save('regression_model.h5')
    plt.plot(history.history['loss'])
    plt.xlabel("Epochs")
    plt.ylabel("Training Error")
```

In [128…

```
model.evaluate([test.userID, test.artID], test.playedUserNorm)
```

Out[128…

```
11.709915019610571
```

In [129…

```
predictions = model.predict([test.userID.head(10), test.artID.head(10)])

[print(predictions[i], test.playedUserNorm.iloc[i]) for i in range(0,10)]
```

```
[0.9539401] 0.1022525192649674
[0.5931071] 0.0883248730964467
[0.7332239] 0.17059708981435023
```

```
[0.05492728] 0.058169375534645
[3.64498] 0.03801526717557252
[3.138496] 0.08087476789766866
[5.732494] 0.022805167413656735
[3.8372645] 0.03981264637002342
[12.145642] 0.09480626545754328
[0.47016686] 0.14745762711864407
```

Out[129…

```
[None, None, None, None, None, None, None, None, None, None]
```

Neural Network

In [130…

```
# creating book embedding path
artist_input = Input(shape=[1], name="Artist-Input")
artist_embedding = Embedding(n_artist + 1, 5, name="Artist-Embedding")(artist_input)
artist_vec = Flatten(name="Flatten-Artists")(artist_embedding)

# creating user embedding path
user_input = Input(shape=[1], name="User-Input")
user_embedding = Embedding(n_users + 1, 5, name="User-Embedding")(user_input)
user_vec = Flatten(name="Flatten-Users")(user_embedding)

# concatenate features
conc = Concatenate()([artist_vec, user_vec])

# add fully-connected-layers
fc1 = Dense(128, activation='relu')(conc)
fc2 = Dense(32, activation='relu')(fc1)
out = Dense(1)(fc2)

# Create model and compile it
model2 = Model([user_input, artist_input], out)
model2.compile('adam', 'mean_squared_error')
```

In [131…

```
from keras.models import load_model

if os.path.exists('regression_model2.h5'):
    model2 = load_model('regression_model2.h5')
else:
    history = model2.fit([train.userID, train.artID], train.playedUserNorm, epochs=5, verb
    model2.save('regression_model2.h5')
    plt.plot(history.history['loss'])
    plt.xlabel("Epochs")
    plt.ylabel("Training Error")
```

In [132…

```
model2.evaluate([test.userID, test.artID], test.playedUserNorm)
```

Out[132…

```
1868465.5019972352
```

In [133…

```
predictions = model2.predict([test.userID.head(10), test.artID.head(10)])

[print(predictions[i], test.playedUserNorm.iloc[i]) for i in range(0,10)]
```

```
[556.89874] 0.1022525192649674
[229.64117] 0.0883248730964467
[1205.8281] 0.17059708981435023
[733.99036] 0.058169375534645
[266.15637] 0.03801526717557252
[308.364] 0.08087476789766866
```

```
[2165.578] 0.022805167413656735
[265.78317] 0.03981264637002342
[270.8289] 0.09480626545754328
[234.89717] 0.14745762711864407
```

Out[133…

```
[None, None, None, None, None, None, None, None, None, None]
```

Visualizing Embeddings

Next, we will visualize our artist embeddings. As per this article here, embeddings can be defined as "vector representations of an entity. Each item in the vector represents a feature or a combination of features for that entity".

In [134…

```
# Extract embeddings
artist_em = model.get_layer("Artist-Embedding")
artist_em_weights = artist_em.get_weights()[0]
```

In [135…

```
artist_em_weights[:5]
```

Out[135…

```
array([[ 0.04103883, -0.2710777 ,  0.28193265,  0.01121594, -0.21962109],
       [ 0.42227656, -0.44878516,  0.46648487, -0.12221594, -0.40105212],
       [-0.18079431, -0.13342255,  0.1553544 , -0.3333101 , -0.00778394],
       [ 0.150518  , -0.19249448,  0.1592992 ,  0.12258738, -0.12723902],
       [ 0.2513393 , -0.21272472,  0.1814355 , -0.22018886, -0.13649407]],
      dtype=float32)
```

PCA

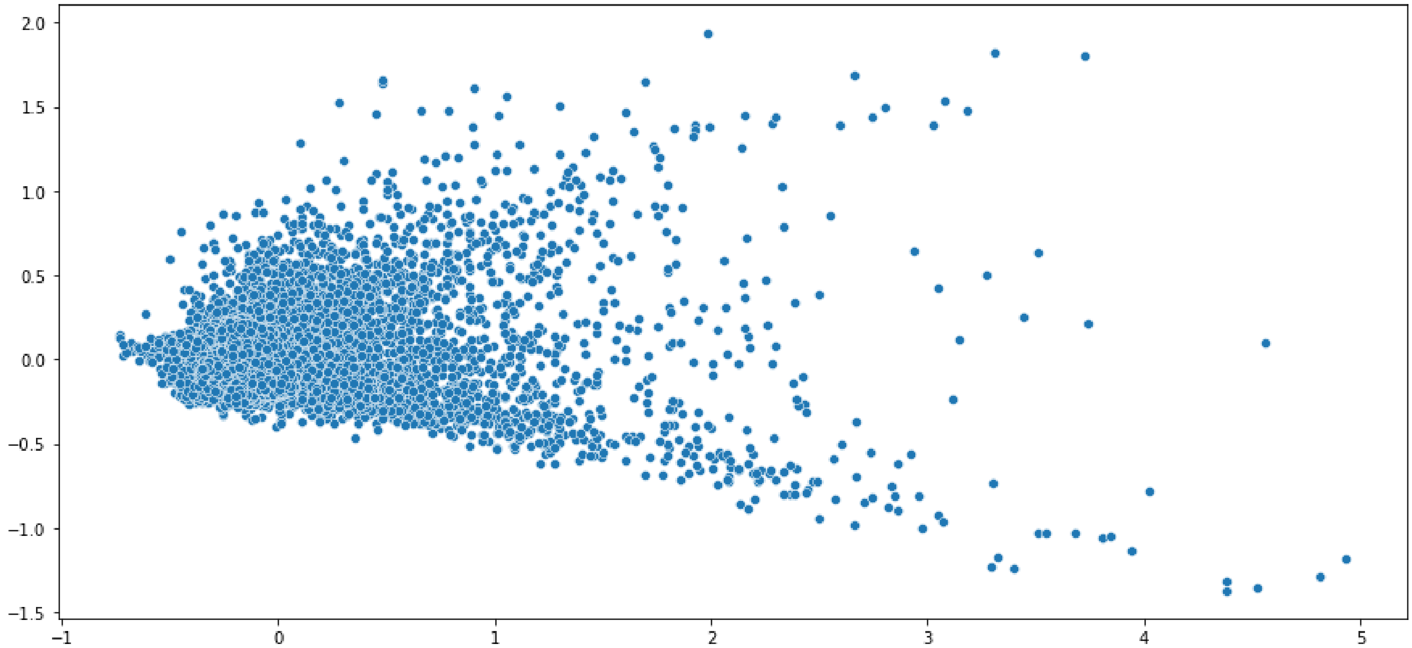
Let's perform principal component analysis (PCA) on our artist embedddings. PCA is defined as the process of computing the principal components and using them to perform a change of basis on the data, sometimes using only the first few principal components and ignoring the rest. It is commonly used in exploratory data analysis.

In [136…

```
from sklearn.decomposition import PCA
import seaborn as sns

pca = PCA(n_components=2)
pca_result = pca.fit_transform(artist_em_weights)
plt.figure(figsize=[15,7])
sns.scatterplot(x=pca_result[:,0], y=pca_result[:,1])
```

Out[136…

```
<AxesSubplot:>
```



In [137…

```
artist_em_weights = artist_em_weights / np.linalg.norm(artist_em_weights, axis = 1).reshap
artist_em_weights[0][:10]
np.sum(np.square(artist_em_weights[0]))
```

Out[137…

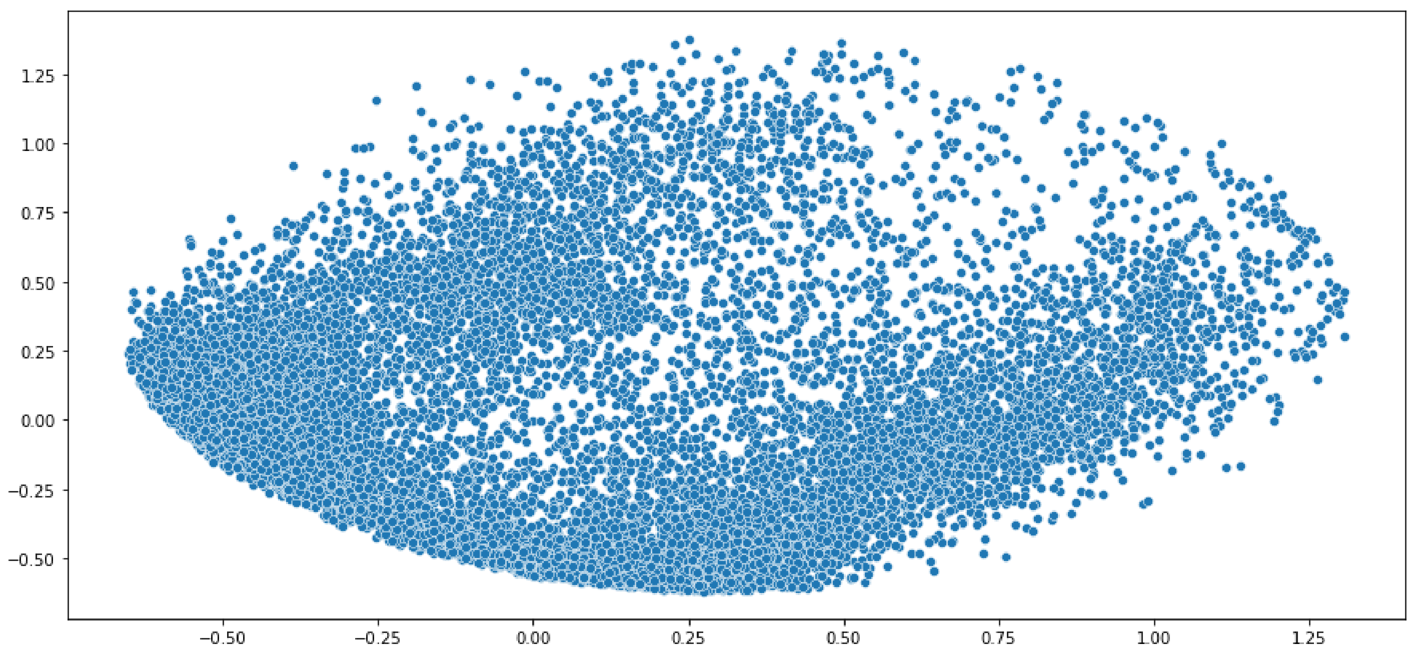
```
1.0
```

In [138…

```
pca = PCA(n_components=2)
pca_result = pca.fit_transform(artist_em_weights)
plt.figure(figsize=[15,7])
sns.scatterplot(x=pca_result[:,0], y=pca_result[:,1])
```

Out[138…

```
<AxesSubplot:>
```



TSNE

Let's now look at the t-Distributed Stochastic Neighbor Embeddings (TSNE) for artists. This allows us to see how the artist embeddings are arranged in a high-dimensional space.

In [139…

```
from sklearn.manifold import TSNE
```

```
tsne = TSNE(n_components=2, verbose=1, perplexity=40, n_iter=300)
tnse_results = tsne.fit_transform(artist_em_weights)
```

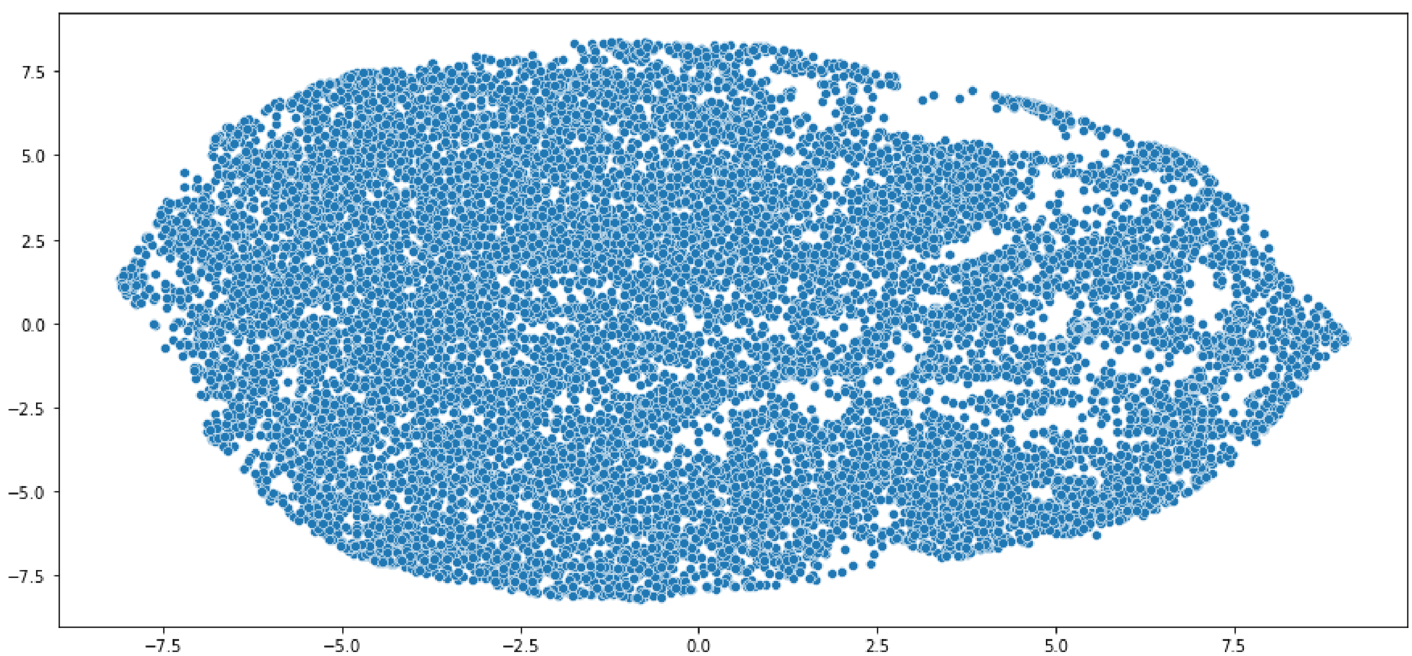
```
[t-SNE] Computing 121 nearest neighbors...
[t-SNE] Indexed 17633 samples in 0.068s...
[t-SNE] Computed neighbors for 17633 samples in 1.557s...
[t-SNE] Computed conditional probabilities for sample 1000 / 17633
[t-SNE] Computed conditional probabilities for sample 2000 / 17633
[t-SNE] Computed conditional probabilities for sample 3000 / 17633
[t-SNE] Computed conditional probabilities for sample 4000 / 17633
[t-SNE] Computed conditional probabilities for sample 5000 / 17633
[t-SNE] Computed conditional probabilities for sample 6000 / 17633
[t-SNE] Computed conditional probabilities for sample 7000 / 17633
[t-SNE] Computed conditional probabilities for sample 8000 / 17633
[t-SNE] Computed conditional probabilities for sample 9000 / 17633
[t-SNE] Computed conditional probabilities for sample 10000 / 17633
[t-SNE] Computed conditional probabilities for sample 11000 / 17633
[t-SNE] Computed conditional probabilities for sample 12000 / 17633
[t-SNE] Computed conditional probabilities for sample 13000 / 17633
[t-SNE] Computed conditional probabilities for sample 14000 / 17633
[t-SNE] Computed conditional probabilities for sample 15000 / 17633
[t-SNE] Computed conditional probabilities for sample 16000 / 17633
[t-SNE] Computed conditional probabilities for sample 17000 / 17633
[t-SNE] Computed conditional probabilities for sample 17633 / 17633
[t-SNE] Mean sigma: 0.059542
[t-SNE] KL divergence after 250 iterations with early exaggeration: 84.982025
[t-SNE] KL divergence after 300 iterations: 3.420733
```

In [140…

```
plt.figure(figsize=[15,7])
sns.scatterplot(x=tnse_results[:,0], y=tnse_results[:,1])
```

Out[140…

```
<AxesSubplot:>
```



There are no clusters here that jump out at me here to delve into further. They are all of a similar distribution and no cluster appears massively obvious.

Making Recommendations

In [176…

```
# Creating dataset for making recommendations for a user
artist_data = np.array(list(set(sub.artID)))
```

```
artist_data
```

Out[176…

```
array([    0,     1,     2, ..., 17629, 17630, 17631])
```

Let's pick a random user to generate recommendations for. We will go with the user of ID equalling 10.

In [177…

```
user = np.array([10 for i in range(len(artist_data))])
user
```

Out[177…

```
array([10, 10, 10, ..., 10, 10, 10])
```

In [178…

```
predictions = model.predict([user, artist_data])

predictions = np.array([a[0] for a in predictions])

recommended_artist_ids = (predictions).argsort()[:10]

recommended_artist_ids
```

Out[178…

```
array([8131, 8135, 8324, 8139, 2754, 8317, 8136, 8151, 8315, 8333],
      dtype=int64)
```

In [179…

```
predictions[recommended_artist_ids]
```

Out[179…

```
array([-0.57746166, -0.57243985, -0.53917485, -0.51835954, -0.5130869 ,
       -0.5057626 , -0.5038766 , -0.49716717, -0.47062764, -0.44993132],
      dtype=float32)
```

In [180…

```
df[df['artID'].isin(recommended_artist_ids)]
```

Out[180…

	name	url	pictureURL	artID
2754	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754
8131	Nahash	http://www.last.fm/music/Nahash	http://userserve-ak.last.fm/serve/252/93322.jpg	8131
8135	Krabaras	http://www.last.fm/music/Krabaras	http://userserve-ak.last.fm/serve/252/44372179...	8135
8136	DiktatÅ«ra	http://www.last.fm/music/Diktat%C5%ABra	http://userserve-ak.last.fm/serve/252/165489.jpg	8136
8139	Luctus	http://www.last.fm/music/Luctus	http://userserve-ak.last.fm/serve/252/8688989.jpg	8139
8151	Anubi	http://www.last.fm/music/Anubi	http://userserve-ak.last.fm/serve/252/27058983...	8151
8315	Gallhammer	http://www.last.fm/music/Gallhammer	http://userserve-ak.last.fm/serve/252/607745.jpg	8315
8317	Ossastorium	http://www.last.fm/music/Ossastorium	http://userserve-ak.last.fm/serve/252/51798.jpg	8317
8324	Dissimulation	http://www.last.fm/music/Dissimulation	http://userserve-ak.last.fm/serve/252/16340589...	8324
8333	Surdr	http://www.last.fm/music/Surdr	http://userserve-ak.last.fm/serve/252/40530837...	8333

Let's check does our recommender produce novel results. In our recommender system as mentioned earlier it can be hard to gauge good recommenders in a formal manner (not a subjective manner such as a user rating the recommendations) as there is no ratings just listening figures. Users would eventually tire of being suggested the same artists so checking our recommender to see if it produces novel results is a good barometer of it's quality to start.

In [182…

```
test = played[played['userID'] == 10]
```

In [183…
```
test[test['artID'].isin(recommended_artist_ids)]
```

Out[183…

name	url	artID	userID	artistID	played	playedUserNorm	playCountScaled

Our recommender has produced completely novel results here for the user. This is potentially a good starting point for our recommender. Let's delve further into it's results looking at the recommendations for this particular user.

In [185…
```
usert = tags[tags['userID'] == 10]
```

In [186…
```
usert
```

Out[186…

	tagID	tagValue	userID	artistID
1	1	metal	10	175
2	1	metal	10	192
3	1	metal	10	494
4	1	metal	10	497
5	1	metal	10	506
...	...	...	...	...
92593	197	gangsta rap	10	13742
92669	198	rapcore	10	483
92670	198	rapcore	10	504
92671	198	rapcore	10	1854
92672	198	rapcore	10	1964

784 rows × 4 columns

In [187…
```
m = usert['tagValue'].unique()
```

In [188…
```
tagtest =  pd.merge(usert, test, how="inner", left_on=['userID', 'artistID'], right_on=['u
```

In [190…
```
zzzz = df[df['artID'].isin(recommended_artist_ids)]
```

In [191…
```
zzzz1 = pd.merge(zzzz, tags, how="inner", left_on=['artID'], right_on=['artistID'])
```

In [203…
```
zzzz1
```

Out[203…

	name	url	pictureURL	artID	tagID	tagValue	userI
0	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754	1	metal	4(
1	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754	4	black metal	2`

	name	url	pictureURL	artID	tagID	tagValue	userI
2	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754	4	black metal	40
3	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754	4	black metal	65
4	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754	4	black metal	94
5	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754	2091	true black metal	40
6	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754	3343	melodic black metal	40
7	Dark Funeral	http://www.last.fm/music/Dark+Funeral	http://userserve-ak.last.fm/serve/252/13074411...	2754	3509	extreme metal	40
8	Nahash	http://www.last.fm/music/Nahash	http://userserve-ak.last.fm/serve/252/93322.jpg	8131	4	black metal	54
9	Krabaras	http://www.last.fm/music/Krabaras	http://userserve-ak.last.fm/serve/252/44372179...	8135	4366	flar flar flar	54
10	DiktatÅ«ra	http://www.last.fm/music/Diktat%C5%ABra	http://userserve-ak.last.fm/serve/252/165489.jpg	8136	4358	lithuanian metal	54
11	DiktatÅ«ra	http://www.last.fm/music/Diktat%C5%ABra	http://userserve-ak.last.fm/serve/252/165489.jpg	8136	4359	patriotic metal	54
12	DiktatÅ«ra	http://www.last.fm/music/Diktat%C5%ABra	http://userserve-ak.last.fm/serve/252/165489.jpg	8136	4360	patriotic metal	54
13	Gallhammer	http://www.last.fm/music/Gallhammer	http://userserve-ak.last.fm/serve/252/607745.jpg	8315	4	black metal	63
14	Gallhammer	http://www.last.fm/music/Gallhammer	http://userserve-ak.last.fm/serve/252/607745.jpg	8315	10847	pot goes to 11	158

Let's Evaluate our alternate system's recommendations

Let's try calculate precision here for values. We will look to see what tags have been assigned by user 10 that has been assigned to the recommended artists our new system has left them. If at least one tag is found in both the user and the recommended artists tags we assign a score of 1 (relevant) to our user. I will use a method of "precision at K". As per Wikipedia#Precision_at_k), it is defined as "Precision at k documents (P@k) is still a useful metric (e.g., P@10 or "Precision at 10" corresponds to the number of relevant results among the top 10 retrieved documents), but fails to take into account the positions of the relevant documents among the top k". It is commonly used for evaluating music recommender systems. Out of the first K artists recommended we see how many of these are deemed relevant. As mentioned earlier our relevance can be deemed as an artist who has been given a tag by other users that is also a tag given by the user in question, user 10. I feel this is the most practical method of evaluating this system. Anyone with experience of using Spotify or SoundCloud would see that for recommendations you would only look at the first few maybe and lose interest after that. It is also hoped the first few recommendations are of a higher quality and more likely to attract a user's attention.

In [304…

```
d = {}
valz = np.array(zzzz1['tagValue'])
vals = np.array(zzzz1['name'])
for i in range(len(valz)):
    if vals[i] not in d:
```

```
        d[vals[i]] = ""
    else:
        continue
print(d)
```

```
{'Dark Funeral': '', 'Nahash': '', 'Krabaras': '', 'DiktatÅ«ra': '', 'Gallhammer': ''}
```

In [305…

```
# only these artists from recommended had tags left on them
valz = np.array(zzzz1['tagValue'])
vals = np.array(zzzz1['name'])
for i in range(len(valz)):
    if vals[i] in d and valz[i] in m:
        if valz[i] not in d[vals[i]]:
            d[vals[i]] += valz[i] + ","
    else:
        continue
```

In [306…

```
strip_dict(d)
```

Out[306…

```
{'Dark Funeral': 'metal,',
 'Nahash': '',
 'Krabaras': '',
 'DiktatÅ«ra': '',
 'Gallhammer': ''}
```

In [307…

```
split_dict(d)
```

In [308…

```
pop_dict(d)
```

In [309…

```
d
```

Out[309…

```
{'Dark Funeral': ['metal'],
 'Nahash': [],
 'Krabaras': [],
 'DiktatÅ«ra': [],
 'Gallhammer': []}
```

In [315…

```
prec_k(d, 10)
```

```
Precision at k equal 10 for user/artist with tags information is: 0.1
```

Looking at the results at face value the recommendations actually seem quite good for this user. A lot of these recommended artists have metal related types of tags, something that definitely seemed to resonate with this user. The only real reason are precision at k value is not higher here is because of values such as "industrial mental" and "doom mental", while some of he tags related to the recommendations are the likes of "black metal" and "extreme metal", much more personalized tags instead of a mainstream tag such as "mental". One thing I found was that the removal of users with ID's not part of the wider dataset that some of these tags appeared relevant to mental and some of these recommendations. This definitely is why not all 10 recommended artists appeared here and why the precision at k was slightly lower. However, this probably does highlight the limitations of such an approach as strings need to perfectly align but I felt it was the most appropriate approach for testing user based recommendations and not artist based recommendations like before.

Spotify Recommender system with regularized

model

Here I will attempt to test my recommender system on my own personal spotify account to see what recommendations it provides. While it must be noted my music taste is not exactly mainstream for the most part, this should be a good test of the sturdiness of the recommender system. We will be using our first recommender system based on user and artist ID and each users uniquely normalised listening column. We will do this using the Tekore python library. This is the most popular spotify api library alongside "spotipy" but I felt tekore was more appropriate for the work at hand here.

In [163…

```
import tekore as tk
```

In [207…

```
# covering these details
client_id = '#'
client_secret = '#'
```

In [208…

```
# always use this link
redirect_url = 'https://example.com/callback'
```

In [209…

```
conf = (client_id, client_secret, redirect_url)
token = tk.prompt_for_user_token(*conf, scope = tk.scope.every)

spotify = tk.Spotify(token)

# paste in link from new webpage opened up by this spotify call above into cell below
```

```
Opening browser for Spotify login...
Please paste redirect URL: https://example.com/callback?code=AQAsHCBINxWnnPm38B_u8r4qOMf4V
TCl7CzMTIlw9HIRaWam5E9rESKEx9jnGe0nICHdmdiMgFxsYdW8s1vH3Zw-NMb4w9gNm5L6QtuTaveZYfdkA1ZuDfh
dQUsUHP2feIWOq4VyJwSfMqe_oqkmT2mYeQ1S0f51LrS8JUUQprF-l_PeptEOBXpRZTm5O4HRZDTyhxpnHBNViMCaz
PVjaYxiN6aY99f2hqBT2CLPsKmTkgw9bjGkHLfkqWImhDltJpfpYNgDbd8Zmyg8oi2sBwBaqV3SZR6kTFJtbz9jOjx
PDba3qSZaYj_1RSC3Ntb3I_gGVIBwGLeCwTSVLItiUjAMcLgApS16zYmqFTnhQrKKtsFaAM4COR7JbKHMaeQ7Oby3n
1PprhTRCkhigvACujhCD0LaUMbqPBfri54Y1LMLnOx00HEOjcQzG4MDM3RVN7kh14VmRTnaJ3tFuE1MB5GK486-AA3
CBJ6AIEdYErupIIBST-y_AgZx1zx_3S6bNtn54aMuwrte_fxqxEX-jfNuqGGhVafG7kWwNZr-pg1qr-l2gfB8_c3ot
rxNJHzWIxeqGyj6KpkO2VnQElnfhJVShRi5gyEgWBf0WP9jwcqogvmRG3oW4hwqSTmUx-v_ZtX9LjfxXZ4bBJXL_Bh
QK1-U-fQSfU7pcJAyE4byCBNmJCg&state=AR_0J-L7FvkMek7U9N5iKI2BSpq1KtYw3x7fb6Wj344
```

In [210…

```
artists = spotify.current_user_top_artists(limit = 10)
spotify_artists = artists.items
```

In [211…

```
t = np.array(df['name'])
for i in range(len(spotify_artists)):
    if spotify_artists[i].name in t:
        artist_neighbors(reg_model, spotify_artists[i].name, DOT)
        artist_neighbors(reg_model, spotify_artists[i].name, COSINE)
    else:
        print(str(spotify_artists[i].name) + " is not in the LastFM data.")
```

```
Nearest neighbors of : Calvin Harris.
```

	dot score	names
148	0.757569	Radiohead
673	0.645099	Glee Cast
167	0.643843	Placebo

	dot score	names
283	0.581608	Britney Spears
1089	0.579911	BjÃ¶rk
184	0.563266	Muse

```
Nearest neighbors of : Calvin Harris.
```

	cosine score	names
1400	1.000000	Calvin Harris
1081	0.827695	Franz Ferdinand
748	0.823963	Crystal Castles
5424	0.809302	Passion Pit
161	0.799802	Scissor Sisters
1088	0.798873	Patrick Wolf

```
Mark Blair is not in the LastFM data.
Tobu is not in the LastFM data.
Bissett is not in the LastFM data.
Uniting Nations is not in the LastFM data.
Nearest neighbors of : David Guetta.
[Found more than one matching artist. Other candidates: Chris Willis; David Guetta; Fergi
e; LMFAO]
```

	dot score	names
83	1.401576	Lady Gaga
283	1.329221	Britney Spears
61	0.809036	Madonna
282	0.781358	Rihanna
492	0.779988	Paramore
286	0.767425	Christina Aguilera

```
Nearest neighbors of : David Guetta.
[Found more than one matching artist. Other candidates: Chris Willis; David Guetta; Fergi
e; LMFAO]
```

	cosine score	names
322	1.000000	David Guetta
458	0.871919	3OH!3
517	0.862911	Lindsay Lohan
155	0.803901	Enrique Iglesias
1023	0.802028	Jessie J
317	0.800165	The Saturdays

```
Low Steppa is not in the LastFM data.
Sonny Fodera is not in the LastFM data.
Ewan McVicar is not in the LastFM data.
Pete Heller's Big Love is not in the LastFM data.
```

Personal Opinions on these recommendations

As referenced earlier some of these artists aren't exactly mainstream, massively popular artists to a wider audience, hence the limited number of found artists. Calvin Harris and David Guetta are popular artists and the recommendations made by our recommender are actually good between dot score and cosine scores. On the whole I definitely find these recommendations quite good. These artists recommended are definitely not in my more popular artists and it is a good sign of the recommender system it is showing new artists. The recommendations for David Guetta and Calvin Harris are in my opinion very logical. There are artists that have collaborated with the pair in both sets of recommendations and other artists of a similar ilk who are not in my top artists. It must also be noted this dataset is from 2011 so the recommendations are based off a slightly more limited market of artists too which is why some of these artists could not be found and why some recommendations may be slightly more predictable.

Evaluation

We will now try to evaluate our results and methods attempted so far. I will look at using methods such as Recall, Precision, Coverage and F1 to validate our methods. I feel methods such as mean absolute error (MAE) and root mean square error (RMSE) are not suitable to our data provided. These look at the difference between the actual and predicted values, which are not really applicable to the data here. The predicted artist could be number 1 and the actual artist could be 2 and this would appear as a very good result using this method. However, the difference in genres and similarity of artist could be completely different and hence the result is misleading. We will look to implement evaluation using the "LightFM" python library.

In [212…

```
import implicit
from tqdm import tqdm_notebook as tqdm
import matplotlib.ticker as ticker
from matplotlib import rc
from pandas.api.types import CategoricalDtype
import string
import re
import random
import math
from math import sqrt
from math import log
from collections import Counter, defaultdict
from operator import itemgetter
from pylab import rcParams
from pylab import savefig
```

In [217…

```
# Create sparse matrix from dataframe object
def create_sparse_matrix(data):
  #get unique user ids and unique artist ids
  users = list(np.sort(data.userID.unique()))
  artists = list(data.artistID.unique())
# change data.col below to whatever column's precision etc is to be evaluated
  plays = list(data.playedUserNorm)

  cat_type = CategoricalDtype(categories=users, ordered=True)
  rows = data.userID.astype(cat_type).cat.codes

  cat_type = CategoricalDtype(categories=artists, ordered=True)
  cols = data.artistID.astype(cat_type).cat.codes
  # we get the rows (user ids) and columns (artist ids) and populate them using plays
  plays_sparse = scipy.sparse.csr_matrix((plays, (rows, cols)), shape=(len(users),len(arti
  return plays_sparse
```

In [214…

```
# Calculate sparsity of matrix
```

```
def calculate_sparsity(M):
  matrix_size = float(M.shape[0] * M.shape[1]) # Number of total possible interactions bet
  num_plays = len(M.nonzero()[0]) # Number of times any artist has been interacted with
  sparsity = 100 * (1 - float(num_plays / matrix_size))
  return sparsity
```

In [215…

```
def evaluate_lightfm(model, original, train, test, user_features=None, item_features=None,
    print("Evaluating LightFM...")
    print("Calculating Coverage...")
    catalog = []
    for user in tqdm(range(0, original.shape[0])):
      #get scores for this particular user for all artists
      rec_scores = model.predict(user,np.arange(original.shape[1]),user_features=user_feat
      #get top k items to recommend
      rec_items = (-rec_scores).argsort()[:20]
      #calculate coverage
      #coverage calculation
      for recs in rec_items:
        if recs not in catalog:
          catalog.append(recs)

    coverage = len(catalog)/float(original.shape[1])
    print("Calculating Recall at k...")
    recall = recall_at_k(model, test, user_features = user_features, item_features = item_
    print("Calculating Precision at k...")
    precision = precision_at_k(model, test, user_features = user_features, item_features =
    f1 = (2 * precision * recall) / (precision + recall)
    return coverage, precision, recall, f1
```

In [218…

```
playedx = played[['userID','artistID', 'playedUserNorm']]
playedx.columns = ['userID','artistID', 'playedUserNorm']

#create sparse matrix like earlier
plays_sparse_light = create_sparse_matrix(playedx).astype('float')
print('Matrix Sparsity:', calculate_sparsity(plays_sparse_light))

train_ratings, test_ratings = split_dataframe(xyz)
# SparseTensor representation of the train and test datasets.
A_train = build_rating_sparse_tensor(train_ratings)
A_test = build_rating_sparse_tensor(test_ratings)

train_light, test_light = lightfm.cross_validation.random_train_test_split(plays_sparse_li
model_fm_vanilla = LightFM(learning_rate=0.05, loss='bpr')

#train model
print("Fitting model...")
model_fm_vanilla.fit(train_light, epochs=10)

#evaluate model
coverage, precision, recall, f1 = evaluate_lightfm(model_fm_vanilla, plays_sparse_light, t
print("Precision:", precision * 100, '%')
print("Recall:", recall * 100, '%')
print("Coverage:", coverage * 100, '%')
print("F1:", f1 * 100, '%')
```

```
Matrix Sparsity: 99.72171848800758
Fitting model...
Evaluating LightFM...
Calculating Coverage...

C:\Users\user\AppData\Local\Temp/ipykernel_28620/314659252.py:5: TqdmDeprecationWarning: T
his function will be removed in tqdm==5.0.0
```

```
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for user in tqdm(range(0, original.shape[0])):

Calculating Recall at k...
Calculating Precision at k...
Precision: 12.798941135406494 %
Recall: 7.443328632047587 %
Coverage: 0.8847549909255897 %
F1: 9.41265244535319 %
```

In [216…

```
playedx = played[['userID','artistID', 'playCountScaled']]
playedx.columns = ['userID','artistID', 'playCountScaled']

#create sparse matrix like earlier just compatible with lightFM
plays_sparse_light = create_sparse_matrix(playedx).astype('float')
print('Matrix Sparsity:', calculate_sparsity(plays_sparse_light))

# split up data like we did earlier with our split_dataframe function
train_light, test_light = lightfm.cross_validation.random_train_test_split(plays_sparse_li
model_fm_vanilla = LightFM(learning_rate=0.05, loss='bpr')

#train model
print("Fitting model...")
model_fm_vanilla.fit(train_light, epochs=10)

#evaluate model
coverage, precision, recall, f1 = evaluate_lightfm(model_fm_vanilla, plays_sparse_light, t
print("Precision:", precision * 100, '%')
print("Recall:", recall * 100, '%')
print("Coverage:", coverage * 100, '%')
print("F1:", f1 * 100, '%')
```

```
Matrix Sparsity: 99.72362497745786
Fitting model...
Evaluating LightFM...
Calculating Coverage...
C:\Users\user\AppData\Local\Temp/ipykernel_28620/314659252.py:5: TqdmDeprecationWarning: T
his function will be removed in tqdm==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for user in tqdm(range(0, original.shape[0])):

Calculating Recall at k...
Calculating Precision at k...
Precision: 13.239957392215729 %
Recall: 7.707198593051993 %
Coverage: 0.7599818511796733 %
F1: 9.742895986177876 %
```

Our chosen accuracy when normalising with each user's max score is actually worse than our play count scaled metric. However, when I ran this with playCountScaled used for our recommender the recommendations were dreadful with very low dot and cosine scores. Of the sample of artists and my spotify recommendations the recommendations using the playedUserNorm column seemed far more accurate. This is probably because the scores are better scaled between 0 and 1, identifying popular artists more easily with values closer to 1 and also less known artists would have a better chance of being noticed if a handful of users listened to them a lot. However, it could also be said that it may produce more novel recommendations like our alternate approach. By this I mean that while on initial inspection the results seemed poor the recommender actually makes relevant recommendations to the user that they have not seen before.

Clustering Attempt

Here, I am going to attempt to cluster on the most popular tags. I will take the top 100 tags and cluster accordingly off one of their mean, median, sum of plays or other to see what trends seem to appear in the data. We will be implementing our k-means algorithm used in assignment 1.

In [219…
```
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn import preprocessing
```

In [220…
```
m = tags['tagValue'].value_counts()[:100]
```

In [221…
```
df23 = pd.DataFrame(m)
```

In [222…
```
df23 = df23.reset_index()
```

In [223…
```
df23.rename(columns={'index': 'tagValue', 'tagValue': 'count'}, inplace=True)
```

In [224…
```
df23.drop(columns=['count'], inplace=True)
```

In [225…
```
a = np.array(df23['tagValue'])
df24 = tags[tags['tagValue'].isin(a)]
```

In [226…
```
df24.shape
```

Out[226…
```
(112379, 4)
```

In [227…
```
df2.head()
```

Out[227…

	userID	artistID	weight
0	0	45	13883
1	0	46	11690
2	0	47	11351
3	0	48	10300
4	0	49	8983

In [228…
```
df25 = pd.merge(df24, df2, how="inner", left_on=["artistID", "userID"], right_on=["artistI
```

In [229…
```
df25['tagValue'].nunique()
```

Out[229…
```
100
```

In [230…
```
df25.head()
```

Out[230…

	tagID	tagValue	userID	artistID	weight
0	1	metal	10	494	2471
1	176	emo	10	494	2471
2	1	metal	10	497	1714
3	5	death metal	10	497	1714
4	1	metal	10	506	1260

In [231…

```
grouped_multiple11 = df25.groupby(['tagValue']).agg({'weight': ['mean', 'median', 'max', '
```

In [232…

```
grouped_multiple11.head()
```

Out[232…

	weight			
	mean	**median**	**max**	**sum**
tagValue				
00s	3197.503311	626.0	172496	965646
60s	1513.513089	460.0	23792	289081
70s	1090.209559	370.5	22851	296537
80s	1817.259705	430.0	107031	1357493
90s	2682.854651	612.5	172496	1384353

In [233…

```
grouped_multiple11 = grouped_multiple11.reset_index()
```

In [234…

```
grouped_multiple11.columns = ['tagValue', 'mean', 'med', 'max', 'sum']
```

In [235…

```
grouped_multiple11.head()
```

Out[235…

	tagValue	mean	med	max	sum
0	00s	3197.503311	626.0	172496	965646
1	60s	1513.513089	460.0	23792	289081
2	70s	1090.209559	370.5	22851	296537
3	80s	1817.259705	430.0	107031	1357493
4	90s	2682.854651	612.5	172496	1384353

In [236…

```
tag_nos = []
for i in range(0, 100):
    tag_nos.append(i)
```

In [237…

```
tag_nos[-1]
```

Out[237…

```
99
```

In [238…

```
grouped_multiple11['tagNo'] = tag_nos
```

In [239…

```
grouped_multiple11.head()
```

Out[239…

	tagValue	mean	med	max	sum	tagNo
0	00s	3197.503311	626.0	172496	965646	0
1	60s	1513.513089	460.0	23792	289081	1
2	70s	1090.209559	370.5	22851	296537	2
3	80s	1817.259705	430.0	107031	1357493	3
4	90s	2682.854651	612.5	172496	1384353	4

In [240…

```
b = np.array(grouped_multiple11['tagValue'])
test7 = np.array(df23['tagValue'][:20])
ind = []
for i in range(len(b)):
    if b[i] in test7:
        ind.append(i)
    else:
        continue
```

In [241…

```
ind
```

Out[241…

```
[3, 4, 7, 8, 10, 17, 22, 27, 33, 36, 40, 47, 54, 56, 66, 68, 71, 85, 88, 90]
```

In [242…

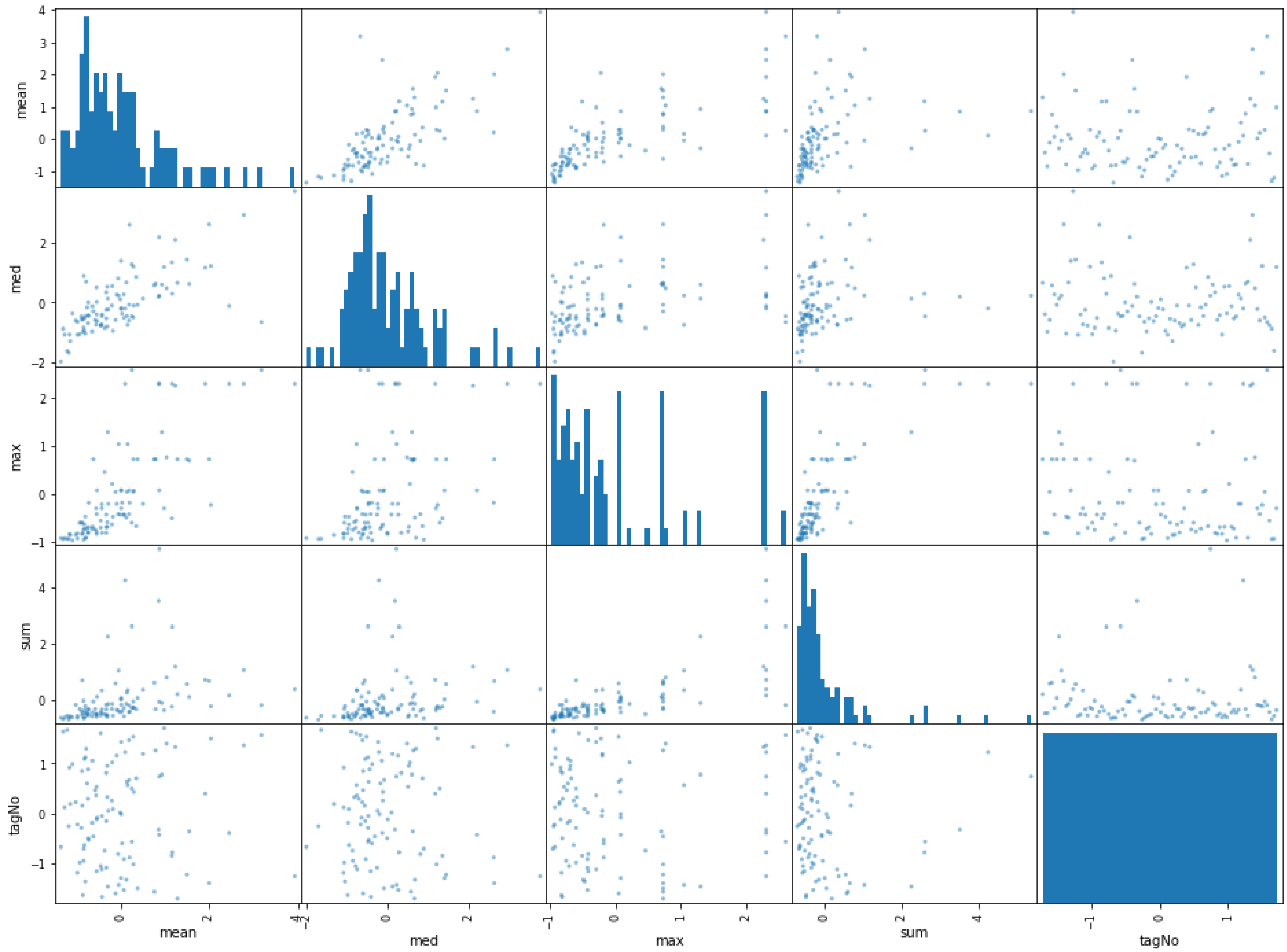
```
grouped_multiple11.drop(columns=['tagValue'], inplace=True)
scaler = preprocessing.StandardScaler().fit(grouped_multiple11)
X_scaled = scaler.transform(grouped_multiple11)
X_scaled.std(axis=0)

standard_all = pd.DataFrame(X_scaled)
```

In [243…

```
standard_all = standard_all.rename(columns={0:'mean', 1: 'med', 2: 'max', 3: 'sum',
                                            4: 'tagNo'})
```

In [244…

```
pd.plotting.scatter_matrix(standard_all, figsize=(16,12), hist_kwds=dict(bins=50), cmap="S
plt.show()
```



In [245…

```
for n in range(2, 11):
    km = KMeans(n_clusters=n)
# Fit the KMeans model
    km.fit_predict(standard_all)
# Calculate Silhoutte Score
    score = silhouette_score(standard_all, km.labels_, metric='euclidean')
# Print the score
    print('K = ' + str(n) + ' Silhouette Score: %.3f' % score)
```

```
K = 2 Silhouette Score: 0.426
K = 3 Silhouette Score: 0.427
K = 4 Silhouette Score: 0.269
K = 5 Silhouette Score: 0.284
K = 6 Silhouette Score: 0.270
K = 7 Silhouette Score: 0.269
K = 8 Silhouette Score: 0.268
K = 9 Silhouette Score: 0.255
K = 10 Silhouette Score: 0.234
```

K = 3 is the optimal value it appears for our value of K.

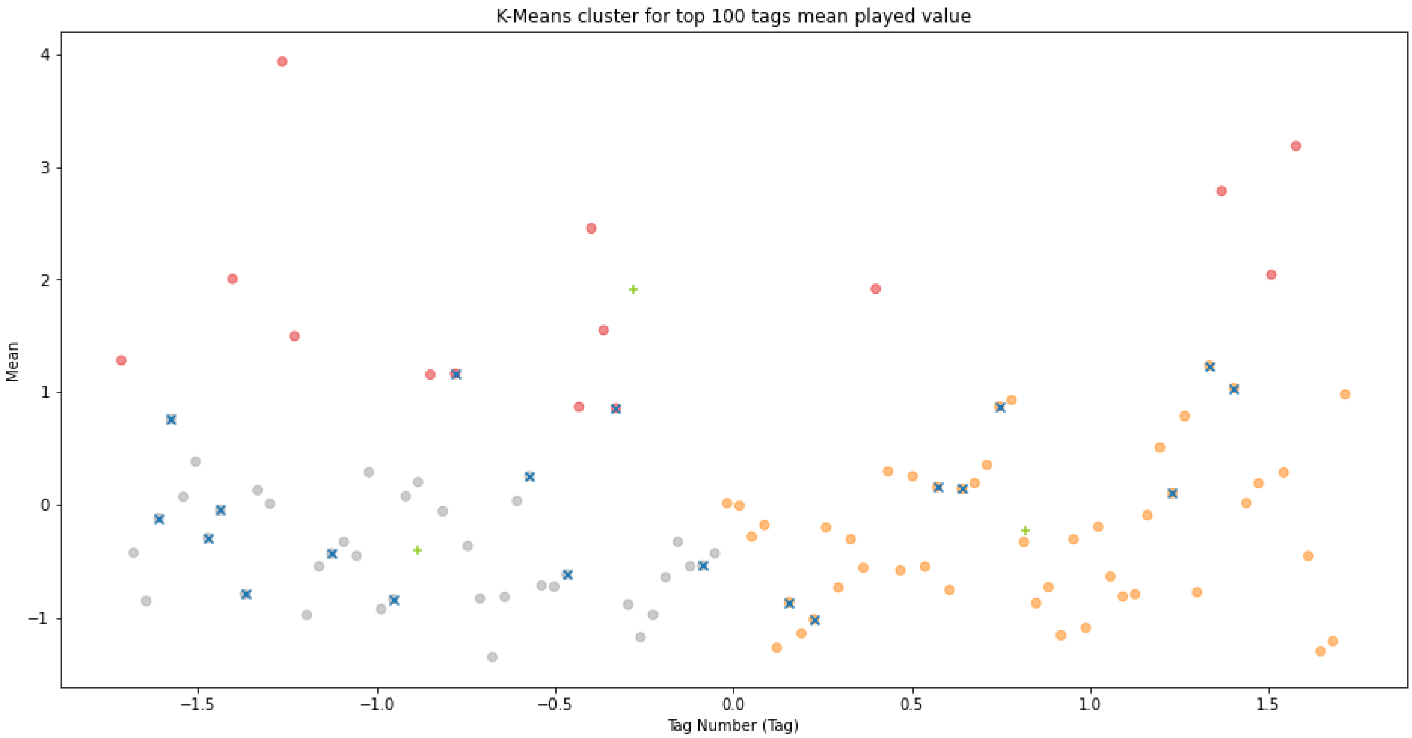
In [246…

```
kmeans_margin_standard = KMeans(n_clusters=3).fit(standard_all[["tagNo", "mean"]])
centroids_betas_standard = kmeans_margin_standard.cluster_centers_
```

In [247…

```
# df44 is top 20 most popular tags, designated by x's on points
df44 = standard_all[standard_all.index.isin(ind)]
plt.figure(figsize=(16,8))
plt.scatter(standard_all['tagNo'], standard_all['mean'], c= kmeans_margin_standard.labels_
plt.scatter(centroids_betas_standard[:, 0], centroids_betas_standard[:, 1], c='yellowgreer
```

```
plt.scatter(df44['tagNo'], df44['mean'], marker='x')
plt.title('K-Means cluster for top 100 tags mean played value')
plt.xlabel('Tag Number (Tag)')
plt.ylabel('Mean')
plt.show()
```



When we cluster on tag numbers (tag values essentially) against the mean played value for the tag, it is interesting to note that the top 20 most popular tags have roughly only an average mean value, which is the clusters denoted by grey and orange here. This was despite tags such as "rock" which had by a distance the most value counts of either tag being seemingly more popular than the less popular of our 100 collected tags. Comparing the three clusters we have here the cluster with the highest values of the mean contains only two tags from our top 20 tags. This is certainly interesting to note that the most popular tags don't appear to have the necessarily the highest mean values. The slightly less mainstream tags may attract a smaller audience but our cluster suggests that these users are huge fans of these types of music genres and hence have a higher mean. It also suggests that there could be more spam tags with much smaller "played" values attached to them bringing these tags respective mean values down. Some users might try listen to some of these artists aligned with popular tags and not be huge fans, hence a lower played value and a lower mean average for this tag value.