song-recommendation-ml-project

December 29, 2022

1 Song-Recommendation-ML

~~~Image has been taken from Google Image.

Recommendation of a song for the listener nased on gender, age, region, artist they like and many more.

Let's connect our jupyter notebook to jovian.

2 Problem Statement

I selected the 15th data set from the resources tab in Jovian. Link from where I downloaded the dataset: https://www.kaggle.com/c/MusicHackathon/data

This data has ratings given by the listeners, qualitative feedback, answers to the question on music and listeners demographics. We will use this dataset to get the rating of the test dataset.

It is a Regression type problem.

Installing the required libraries for making the model

[1]:
```
!pip install plotly==5.11.0
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting plotly==5.11.0
  Downloading plotly-5.11.0-py2.py3-none-any.whl (15.3 MB)
     |                  | 15.3 MB 4.8 MB/s
Requirement already satisfied: tenacity>=6.2.0 in
/usr/local/lib/python3.8/dist-packages (from plotly==5.11.0) (8.1.0)
Installing collected packages: plotly
  Attempting uninstall: plotly
    Found existing installation: plotly 5.5.0
    Uninstalling plotly-5.5.0:
      Successfully uninstalled plotly-5.5.0
Successfully installed plotly-5.11.0
```
~~~

[2]:
```
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
%matplotlib inline

sns.set_style('darkgrid')
matplotlib.rcParams['font.size'] = 16
matplotlib.rcParams['figure.figsize'] = (14, 10)
matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

[3]:
```
!pip install opendatasets
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting opendatasets
  Downloading opendatasets-0.1.22-py3-none-any.whl (15 kB)
Requirement already satisfied: tqdm in /usr/local/lib/python3.8/dist-packages
(from opendatasets) (4.64.1)
Requirement already satisfied: kaggle in /usr/local/lib/python3.8/dist-packages
(from opendatasets) (1.5.12)
Requirement already satisfied: click in /usr/local/lib/python3.8/dist-packages
(from opendatasets) (7.1.2)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.8/dist-
packages (from kaggle->opendatasets) (7.0.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.8/dist-packages
(from kaggle->opendatasets) (2022.12.7)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.8/dist-
packages (from kaggle->opendatasets) (1.15.0)
Requirement already satisfied: requests in /usr/local/lib/python3.8/dist-
packages (from kaggle->opendatasets) (2.23.0)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.8/dist-packages
(from kaggle->opendatasets) (1.24.3)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.8/dist-
packages (from kaggle->opendatasets) (2.8.2)
Requirement already satisfied: text-unidecode>=1.3 in
/usr/local/lib/python3.8/dist-packages (from python-
slugify->kaggle->opendatasets) (1.3)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.8/dist-packages (from requests->kaggle->opendatasets)
(3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.8/dist-
packages (from requests->kaggle->opendatasets) (2.10)
Installing collected packages: opendatasets
Successfully installed opendatasets-0.1.22
```

[4]:
```
import os
import opendatasets as od
import pandas as pd
import numpy as np
pd.set_option("display.max_columns", 120)
pd.set_option("display.max_rows", 120)
```

Downloading data set from Kaggle in the notebook

[5]:
```
od.download('https://www.kaggle.com/c/MusicHackathon/data')
```

```
Downloading MusicHackathon.zip to ./MusicHackathon
100%|      | 6.62M/6.62M [00:00<00:00, 47.9MB/s]

Extracting archive ./MusicHackathon/MusicHackathon.zip to ./MusicHackathon
```

[6]:
```
os.listdir('MusicHackathon')
```

[6]:
```
['UserKey.csv',
 'global_mean_benchmark.csv',
 'words.csv',
 'tracks_mean_benchmark.csv',
 'sample.r',
 'artists_mean_benchmark.csv',
 'users_mean_benchmark.csv',
 'test.csv',
 'logo_greenplum_main.png',
 'users.csv',
 'train.csv']
```

Converting the dataset to dataframe

[7]:
```
train_df = pd.read_csv('./MusicHackathon/train.csv')
test_df = pd.read_csv('./MusicHackathon/test.csv')
words_df = pd.read_csv('./MusicHackathon/words.csv', encoding = "ISO-8859-1")
users_df = pd.read_csv('./MusicHackathon/users.csv')
```

[8]:
```
train_df
```

[8]:

	Artist	Track	User	Rating	Time
0	40	179	47994	9	17
1	9	23	8575	58	7
2	46	168	45475	13	16
3	11	153	39508	42	15
4	14	32	11565	54	19

```
…         …     …     …      …    …
188685      0     3   1278     29    6
188686      1     6   2839     30   18
188687     10   142  35756     61   12
188688     22    54  20163     46   21
188689     47   171  45580     12    4

[188690 rows x 5 columns]
```

[9]:
```
test_df
```

[9]:
```
        Artist  Track   User  Time
0            1      6   3475    18
1            6    149  39210    15
2           40    177  47861    17
3           31     79  27413    11
4           26     66  23232    22
…         …     …     …    …
125789      14     95  30004    23
125790      10     25   8186     7
125791      40    146  38180    13
125792      22    113  32918     0
125793       2     70  24231    22

[125794 rows x 4 columns]
```

[10]:
```
words_df
```

[10]:
```
        Artist   User                                HEARD_OF  \
0           47  45969                                Heard of
1           35  29118                           Never heard of
2           14  31544                                Heard of
3           23  18085                           Never heard of
4           23  18084                           Never heard of
…         …     …                                        …
118296       4   3932      Heard of and listened to music EVER
118297       4   3935      Heard of and listened to music EVER
118298      12  11216  Heard of and listened to music RECENTLY
118299      33  35142      Heard of and listened to music EVER
118300       4   3915      Heard of and listened to music EVER

                  OWN_ARTIST_MUSIC  LIKE_ARTIST  Uninspired  Sophisticated  \
0                              NaN          NaN         NaN            0.0
1                              NaN          NaN         0.0            NaN
2                              NaN          NaN         0.0            NaN
3                              NaN          NaN         NaN            NaN
4                              NaN          NaN         NaN            NaN
```

```
…                              …          …         …             …
118296  Own a little of their music         26.0        NaN           NaN
118297  Own a little of their music         30.0        NaN           NaN
118298      Own none of their music         71.0        NaN           NaN
118299      Own none of their music         31.0        NaN           NaN
118300  Own a little of their music         46.0        NaN           NaN

        Aggressive  Edgy  Sociable  Laid back  Wholesome  Uplifting  \
0              NaN     0       0.0        0.0        NaN        0.0
1              0.0     0       NaN        NaN        NaN        NaN
2              0.0     0       NaN        NaN        NaN        NaN
3              0.0     0       NaN        NaN        NaN        NaN
4              0.0     0       NaN        NaN        NaN        NaN
…              …   …       …          …          …          …
118296         0.0     0       NaN        NaN        NaN        NaN
118297         0.0     0       NaN        NaN        NaN        NaN
118298         0.0     0       NaN        NaN        NaN        NaN
118299         0.0     0       NaN        NaN        NaN        NaN
118300         0.0     0       NaN        NaN        NaN        NaN

        Intriguing  Legendary  Free  Thoughtful  Outspoken  Serious  \
0              0.0        NaN   0.0           0        0.0      NaN
1              NaN        NaN   NaN           0        NaN      0.0
2              NaN        NaN   NaN           1        NaN      0.0
3              NaN        NaN   NaN           0        NaN      0.0
4              NaN        NaN   NaN           0        NaN      0.0
…              …          …     …             …        …        …
118296         NaN        NaN   NaN           0        NaN      0.0
118297         NaN        NaN   NaN           0        NaN      0.0
118298         NaN        NaN   NaN           0        NaN      0.0
118299         NaN        NaN   NaN           0        NaN      0.0
118300         NaN        NaN   NaN           0        NaN      0.0

        Good lyrics  Unattractive  Confident  Old  Youthful  Boring  Current  \
0               NaN           NaN        NaN  NaN       0.0     1.0        0
1               0.0           0.0        0.0  NaN       0.0     0.0        0
2               0.0           0.0        0.0  NaN       0.0     0.0        0
3               0.0           0.0        0.0  NaN       0.0     1.0        0
4               0.0           0.0        0.0  NaN       0.0     0.0        0
…               …             …          …    …         …       …          …
118296          0.0           0.0        0.0  NaN       0.0     NaN        0
118297          0.0           0.0        0.0  NaN       0.0     NaN        0
118298          0.0           0.0        0.0  NaN       0.0     0.0        1
118299          0.0           0.0        0.0  NaN       0.0     0.0        1
118300          0.0           0.0        0.0  NaN       0.0     NaN        0

        Colourful  Stylish  Cheap  Irrelevant  Heartfelt  Calm  Pioneer  \
```

```
0             0.0        0    NaN         NaN        0.0   NaN      NaN
1             NaN        0    0.0         0.0        NaN   0.0      NaN
2             NaN        0    0.0         0.0        NaN   1.0      NaN
3             NaN        0    0.0         NaN        NaN   0.0      NaN
4             NaN        0    0.0         NaN        NaN   0.0      NaN
…             …      …    …         …       …   …      …
118296        NaN        0    0.0         NaN        NaN   0.0      NaN
118297        NaN        0    1.0         NaN        NaN   0.0      NaN
118298        NaN        0    0.0         NaN        NaN   0.0      NaN
118299        NaN        0    0.0         NaN        NaN   0.0      NaN
118300        NaN        0    0.0         NaN        NaN   0.0      NaN

        Outgoing  Inspiring  Beautiful  Fun  Authentic  Credible  Way out  \
0            NaN        NaN          0    0          0         0      0.0
1            0.0        0.0          0    1          0         0      NaN
2            0.0        0.0          1    0          0         0      NaN
3            0.0        0.0          0    0          0         0      NaN
4            0.0        0.0          0    0          0         0      NaN
…          …        …      …  …       …      …      …
118296       0.0        0.0          0    0          0         0      NaN
118297       0.0        0.0          0    0          0         0      NaN
118298       0.0        0.0          1    1          0         0      NaN
118299       0.0        0.0          0    0          0         0      NaN
118300       0.0        0.0          0    0          0         0      NaN

        Cool  Catchy  Sensitive  Mainstream  Superficial  Annoying  Dark  \
0          0     0.0        NaN         NaN          NaN       NaN   NaN
1          0     1.0        0.0         0.0          0.0       0.0   NaN
2          0     0.0        0.0         0.0          0.0       0.0   NaN
3          0     0.0        0.0         0.0          0.0       NaN   NaN
4          0     0.0        0.0         0.0          0.0       NaN   NaN
…      …      …      …         …      …           …       …   …
118296     0     0.0        0.0         NaN          0.0       NaN   NaN
118297     0     0.0        0.0         NaN          0.0       NaN   NaN
118298     0     1.0        0.0         0.0          0.0       NaN   NaN
118299     1     0.0        0.0         NaN          0.0       NaN   NaN
118300     0     0.0        0.0         NaN          0.0       NaN   NaN

        Passionate  Not authentic  Good Lyrics  Background  Timeless  \
0                0            NaN          0.0         0.0         0
1                0            0.0          NaN         NaN         0
2                0            0.0          NaN         NaN         0
3                0            NaN          NaN         NaN         0
4                0            NaN          NaN         NaN         0
…            …            …          …       …
118296           0            NaN          NaN         NaN         0
118297           0            NaN          NaN         NaN         0
```

```
118298           0            NaN          NaN         NaN         0
118299           0            NaN          NaN         NaN         0
118300           0            NaN          NaN         NaN         0

        Depressing  Original  Talented  Worldly  Distinctive  Approachable  \
0              NaN         0         0      NaN            0             0
1              0.0         0         0      NaN            1             0
2              0.0         0         1      NaN            0             0
3              0.0         0         0      NaN            0             0
4              0.0         0         0      NaN            0             0
…              …           …         …      …              …             …
118296         0.0         0         0      NaN            0             0
118297         0.0         1         0      NaN            0             0
118298         0.0         0         0      NaN            0             1
118299         0.0         0         0      NaN            0             0
118300         0.0         1         0      NaN            1             0

        Genius  Trendsetter  Noisy  Upbeat  Relatable  Energetic  Exciting  \
0          0.0            0    NaN     0.0        NaN          0       0.0
1          NaN            0    0.0     0.0        0.0          0       NaN
2          NaN            0    0.0     0.0        0.0          0       NaN
3          NaN            0    0.0     0.0        0.0          0       NaN
4          NaN            0    0.0     0.0        0.0          0       NaN
…          …              …    …       …          …            …       …
118296     NaN            0    0.0     0.0        NaN          0       NaN
118297     NaN            0    0.0     1.0        NaN          0       NaN
118298     NaN            0    0.0     0.0        0.0          0       NaN
118299     NaN            0    0.0     0.0        NaN          1       NaN
118300     NaN            0    0.0     0.0        NaN          1       NaN

        Emotional  Nostalgic  None of these  Progressive  Sexy  Over  \
0             0.0        NaN              0          NaN     0   NaN
1             NaN        NaN              0          NaN     0   0.0
2             NaN        NaN              0          NaN     0   0.0
3             NaN        NaN              0          NaN     0   0.0
4             NaN        NaN              1          NaN     0   0.0
…             …          …                …          …   …   …
118296        NaN        NaN              0          NaN     0   0.0
118297        NaN        NaN              0          NaN     0   0.0
118298        NaN        NaN              0          NaN     0   0.0
118299        NaN        NaN              0          NaN     0   0.0
118300        NaN        NaN              0          NaN     0   0.0

        Rebellious  Fake  Cheesy  Popular  Superstar  Relaxed  Intrusive  \
0              0.0   NaN     NaN      0.0        NaN      0.0        NaN
1              NaN   0.0     0.0      NaN        0.0      NaN        0.0
2              NaN   0.0     0.0      NaN        0.0      NaN        0.0
```

```
3              NaN   0.0     0.0      NaN        0.0      NaN        NaN
4              NaN   0.0     0.0      NaN        0.0      NaN        NaN
…              …     …       …        …          …        …
118296         NaN   0.0     0.0      NaN        NaN      NaN        NaN
118297         NaN   0.0     0.0      NaN        NaN      NaN        NaN
118298         NaN   0.0     0.0      NaN        0.0      NaN        NaN
118299         NaN   0.0     0.0      NaN        NaN      NaN        NaN
118300         NaN   0.0     0.0      NaN        NaN      NaN        NaN

        Unoriginal  Dated  Iconic  Unapproachable  Classic  Playful  Arrogant  \
0              NaN    0.0     NaN             NaN      0.0      NaN       NaN
1              0.0    0.0     NaN             0.0      0.0      0.0       0.0
2              0.0    0.0     NaN             0.0      0.0      0.0       0.0
3              0.0    0.0     NaN             0.0      0.0      0.0       0.0
4              0.0    0.0     NaN             0.0      0.0      0.0       0.0
…              …      …       …               …        …        …         …
118296         0.0    1.0     NaN             0.0      0.0      0.0       0.0
118297         0.0    0.0     NaN             0.0      0.0      0.0       0.0
118298         0.0    0.0     NaN             0.0      0.0      1.0       0.0
118299         0.0    0.0     NaN             0.0      NaN      0.0       1.0
118300         0.0    0.0     NaN             0.0      0.0      1.0       0.0

        Warm  Soulful  Unnamed: 87
0          0      0.0          NaN
1          0      NaN          NaN
2          0      NaN          NaN
3          0      NaN          NaN
4          0      NaN          NaN
…      …       …            …
118296     0      NaN          NaN
118297     0      NaN          NaN
118298     0      NaN          NaN
118299     0      NaN          NaN
118300     0      NaN          NaN

[118301 rows x 88 columns]
```

[11]:
```
users_df
```

[11]:
```
       RESPID  GENDER   AGE                              WORKING    REGION  \
0       36927  Female  60.0                                Other     South
1        3566  Female  36.0  Full-time housewife / househusband     South
2       20054  Female  52.0           Employed 30+ hours a week  Midlands
3       41749  Female  40.0         Employed 8-29 hours per week     South
4       23108  Female  16.0                    Full-time student     North
…       …      …       …                                  …         …
48640   19361    Male  48.0                        Self-employed  Midlands
```

```
48641   17639  Female  60.0  Full-time housewife / househusband  Midlands
48642   28753  Female  25.0           Employed 30+ hours a week  Midlands
48643   26197    Male  44.0           Employed 30+ hours a week  Midlands
48644   16225  Female  43.0                                 NaN     North

                                                    MUSIC           LIST_OWN  \
0      Music is important to me but not necessarily m…              1 hour
1      Music is important to me but not necessarily m…              1 hour
2      I like music but it does not feature heavily i…              1 hour
3       Music means a lot to me and is a passion of mine             2 hours
4       Music means a lot to me and is a passion of mine             3 hours
…                                                    …               …
48640  I like music but it does not feature heavily i…  Less than an hour
48641   Music means a lot to me and is a passion of mine             2 hours
48642   Music means a lot to me and is a passion of mine             2 hours
48643   Music means a lot to me and is a passion of mine             2 hours
48644  I like music but it does not feature heavily i…                NaN

               LIST_BACK    Q1    Q2    Q3    Q4    Q5    Q6     Q7    Q8  \
0                    NaN  49.0  50.0  49.0  50.0  32.0  33.0   32.0   0.0
1                 1 hour  55.0  55.0  62.0   9.0   9.0   9.0   10.0  11.0
2      Less than an hour  11.0  50.0   9.0   8.0  45.0  10.0   30.0  29.0
3               3 hours  81.0  80.0  88.0  88.0  31.0  31.0   51.0  30.0
4               6 hours  76.0  79.0  78.0  73.0  71.0  68.0   73.0  67.0
…                   …    …     …     …     …     …     …      …
48640           2 hours   9.0  73.0  33.0   6.0  10.0  68.0   51.0  52.0
48641            1 hour  26.0  50.0  49.0  58.0  59.0  48.0    6.0   5.0
48642           6 hours  89.0  89.0  89.0   6.0   6.0  51.0   26.0   5.0
48643           4 hours  95.0  97.0  97.0  98.0  97.0  99.0  100.0  99.0
48644                 2  49.0  48.0  50.0  51.0  49.0  25.0   45.0  51.0

          Q9   Q10   Q11   Q12   Q13   Q14   Q15   Q16    Q17   Q18   Q19
0       74.0  50.0  50.0  71.0  52.0  71.0   9.0   7.0   72.0  49.0  26.0
1       55.0  12.0  65.0  65.0  80.0  79.0  51.0  31.0   68.0  54.0  33.0
2        8.0  50.0  94.0  51.0  74.0  66.0  27.0  46.0   73.0   8.0  31.0
3        8.0  76.0  74.0  64.0  73.0  85.0  61.0  77.0   76.0  78.0  88.0
4       31.0  56.0  13.0  82.0  79.0  68.0  71.0   NaN   86.0  80.0  32.0
…       …     …     …     …     …     …     …     …      …     …     …
48640   93.0  53.0  74.0  36.0  13.0  38.0  12.0  10.0   50.0  10.0  28.0
48641   88.0  58.0  62.0  79.0  17.0  24.0  30.0   6.0   73.0  20.0  21.0
48642    0.0  70.0  70.0  70.0  51.0  70.0  70.0   NaN  100.0  70.0  69.0
48643  100.0  97.0  98.0  99.0  97.0  99.0  99.0  99.0  100.0  91.0  96.0
48644   40.0  10.0  69.0  70.0  53.0  54.0  10.0   4.0    7.0   NaN   NaN

[48645 rows x 27 columns]
```

[12]:
```
words_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 118301 entries, 0 to 118300
Data columns (total 88 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Artist            118301 non-null  int64
 1   User              118301 non-null  int64
 2   HEARD_OF          118277 non-null  object
 3   OWN_ARTIST_MUSIC  33507 non-null   object
 4   LIKE_ARTIST       33308 non-null   float64
 5   Uninspired        26154 non-null   float64
 6   Sophisticated     20724 non-null   float64
 7   Aggressive        97577 non-null   float64
 8   Edgy              118301 non-null  int64
 9   Sociable          20724 non-null   float64
 10  Laid back         20724 non-null   float64
 11  Wholesome         1040 non-null    float64
 12  Uplifting         20724 non-null   float64
 13  Intriguing        20724 non-null   float64
 14  Legendary         1040 non-null    float64
 15  Free              20724 non-null   float64
 16  Thoughtful        118301 non-null  int64
 17  Outspoken         20724 non-null   float64
 18  Serious           97577 non-null   float64
 19  Good lyrics       97577 non-null   float64
 20  Unattractive      97577 non-null   float64
 21  Confident         97577 non-null   float64
 22  Old               1040 non-null    float64
 23  Youthful          117261 non-null  float64
 24  Boring            87080 non-null   float64
 25  Current           118301 non-null  int64
 26  Colourful         20724 non-null   float64
 27  Stylish           118301 non-null  int64
 28  Cheap             97577 non-null   float64
 29  Irrelevant        26154 non-null   float64
 30  Heartfelt         20724 non-null   float64
 31  Calm              97577 non-null   float64
 32  Pioneer           1040 non-null    float64
 33  Outgoing          97577 non-null   float64
 34  Inspiring         97577 non-null   float64
 35  Beautiful         118301 non-null  int64
 36  Fun               118301 non-null  int64
 37  Authentic         118301 non-null  int64
 38  Credible          118301 non-null  int64
 39  Way out           20724 non-null   float64
 40  Cool              118301 non-null  int64
 41  Catchy            117261 non-null  float64
 42  Sensitive         97577 non-null   float64
```

```
 43  Mainstream        46254 non-null   float64
 44  Superficial       97577 non-null   float64
 45  Annoying          26154 non-null   float64
 46  Dark              1040 non-null    float64
 47  Passionate        118301 non-null  int64
 48  Not authentic     26154 non-null   float64
 49  Good Lyrics       20724 non-null   float64
 50  Background        20724 non-null   float64
 51  Timeless          118301 non-null  int64
 52  Depressing        97577 non-null   float64
 53  Original          118301 non-null  int64
 54  Talented          118301 non-null  int64
 55  Worldly           1040 non-null    float64
 56  Distinctive       118301 non-null  int64
 57  Approachable      118301 non-null  int64
 58  Genius            20724 non-null   float64
 59  Trendsetter       118301 non-null  int64
 60  Noisy             97577 non-null   float64
 61  Upbeat            117261 non-null  float64
 62  Relatable         46254 non-null   float64
 63  Energetic         118301 non-null  int64
 64  Exciting          20724 non-null   float64
 65  Emotional         20724 non-null   float64
 66  Nostalgic         1040 non-null    float64
 67  None of these     118301 non-null  int64
 68  Progressive       1040 non-null    float64
 69  Sexy              118301 non-null  int64
 70  Over              90157 non-null   float64
 71  Rebellious        20724 non-null   float64
 72  Fake              97577 non-null   float64
 73  Cheesy            97577 non-null   float64
 74  Popular           19684 non-null   float64
 75  Superstar         46254 non-null   float64
 76  Relaxed           20724 non-null   float64
 77  Intrusive         26154 non-null   float64
 78  Unoriginal        97577 non-null   float64
 79  Dated             117261 non-null  float64
 80  Iconic            1040 non-null    float64
 81  Unapproachable    97577 non-null   float64
 82  Classic           105235 non-null  float64
 83  Playful           97577 non-null   float64
 84  Arrogant          97577 non-null   float64
 85  Warm              118301 non-null  int64
 86  Soulful           19684 non-null   float64
 87  Unnamed: 87       0 non-null       float64
dtypes: float64(64), int64(22), object(2)
memory usage: 79.4+ MB
```

3 Score to words DF

Now i will be giving score to 'words_df' by preprocessing the df.

The score system works like this:

- For each value 1 in the positive columns, we **add 1 point to the total score**
- For each value 1 in the negative columns, we **subtract 1 point to the total score**
- Any 0 and NaN value we **ignore as they are neutral**

[13]:
```
positive_score = ['Sophisticated', 'Sociable', 'Laid back', 'Wholesome',␣
↪'Uplifting', 'Intriguing', 'Legendary', 'Free', 'Outspoken', 'Good lyrics',␣
↪'Confident', 'Youthful', 'Current', 'Colourful', 'Stylish', 'Heartfelt',␣
↪'Pioneer', 'Outgoing', 'Inspiring', 'Beautiful', 'Fun', 'Authentic',␣
↪'Credible', 'Way out', 'Cool', 'Catchy', 'Sensitive', 'Passionate', 'Good␣
↪Lyrics', 'Timeless', 'Original', 'Talented', 'Distinctive', 'Approachable',␣
↪'Genius', 'Trendsetter', 'Upbeat', 'Relatable', 'Energetic', 'Exciting',␣
↪'Emotional', 'Nostalgic', 'Progressive', 'Sexy', 'Over', 'Popular',␣
↪'Superstar', 'Relaxed', 'Iconic', 'Classic', 'Playful', 'Warm', 'Soulful']
```

[14]:
```
negative_score = ['Uninspired', 'Unattractive', 'Boring', 'Cheap',␣
↪'Irrelevant', 'Superficial', 'Annoying', 'Not authentic', 'Depressing',␣
↪'Noisy', 'Fake', 'Cheesy', 'Intrusive', 'Unoriginal', 'Dated',␣
↪'Unapproachable']
```

[15]:
```
words_df['plus_score'] = words_df[positive_score].sum(axis=1)
words_df['minus_score'] = words_df[negative_score].sum(axis=1)
words_df['words_score'] = words_df['plus_score'] - words_df['minus_score']
```

[16]:
```
words_df[words_df.LIKE_ARTIST > 90].sample(15)
```

[16]:

	Artist	User	HEARD_OF	\
109843	4	38089	Heard of and listened to music RECENTLY	
28247	41	42540	Heard of and listened to music RECENTLY	
104792	4	36390	Heard of and listened to music RECENTLY	
57761	17	14331	Heard of and listened to music RECENTLY	
20595	32	25628	Heard of and listened to music RECENTLY	
62408	40	36255	Heard of and listened to music RECENTLY	
6553	43	42931	Heard of and listened to music RECENTLY	
105115	4	36778	Heard of and listened to music RECENTLY	
107250	22	32235	Listened to recently	
31728	10	10421	Heard of and listened to music RECENTLY	
72534	34	28566	Heard of and listened to music EVER	
30895	12	14055	Heard of and listened to music RECENTLY	
75007	36	30841	Heard of and listened to music EVER	
61166	24	21099	Heard of and listened to music RECENTLY	
24462	4	2198	Heard of and listened to music RECENTLY	

	OWN_ARTIST_MUSIC	LIKE_ARTIST	Uninspired	\

```
109843  Own all or most of their music        100.0         NaN
28247   Own all or most of their music         95.0         NaN
104792  Own all or most of their music         91.0         NaN
57761         Own a lot of their music         91.0         NaN
20595         Own a lot of their music        100.0         NaN
62408   Own all or most of their music         93.0         NaN
6553    Own all or most of their music         94.0         NaN
105115  Own all or most of their music         93.0         NaN
107250  Own all or most of their music         91.0         NaN
31728         Own a lot of their music         93.0         NaN
72534          Own none of their music        100.0         0.0
30895     Own a little of their music        100.0         NaN
75007         Own a lot of their music         91.0         0.0
61166   Own all or most of their music        100.0         NaN
24462   Own all or most of their music         91.0         NaN

        Sophisticated  Aggressive  Edgy  Sociable  Laid back  Wholesome  \
109843            NaN         0.0     1       NaN        NaN        NaN
28247             NaN         0.0     0       NaN        NaN        NaN
104792            NaN         0.0     0       NaN        NaN        NaN
57761             0.0         NaN     0       0.0        0.0        NaN
20595             NaN         0.0     1       NaN        NaN        NaN
62408             NaN         0.0     0       NaN        NaN        NaN
6553              NaN         0.0     1       NaN        NaN        NaN
105115            NaN         0.0     0       NaN        NaN        NaN
107250            0.0         NaN     0       0.0        0.0        0.0
31728             0.0         NaN     0       0.0        0.0        NaN
72534             NaN         0.0     0       NaN        NaN        NaN
30895             1.0         NaN     0       0.0        0.0        NaN
75007             NaN         0.0     0       NaN        NaN        NaN
61166             NaN         1.0     0       NaN        NaN        NaN
24462             NaN         0.0     0       NaN        NaN        NaN

        Uplifting  Intriguing  Legendary  Free  Thoughtful  Outspoken  \
109843        NaN         NaN        NaN   NaN           1        NaN
28247         NaN         NaN        NaN   NaN           0        NaN
104792        NaN         NaN        NaN   NaN           0        NaN
57761         1.0         0.0        NaN   1.0           0        0.0
20595         NaN         NaN        NaN   NaN           0        NaN
62408         NaN         NaN        NaN   NaN           0        NaN
6553          NaN         NaN        NaN   NaN           1        NaN
105115        NaN         NaN        NaN   NaN           1        NaN
107250        0.0         0.0        0.0   0.0           1        1.0
31728         0.0         0.0        NaN   0.0           0        0.0
72534         NaN         NaN        NaN   NaN           1        NaN
30895         0.0         0.0        NaN   1.0           1        0.0
75007         NaN         NaN        NaN   NaN           0        NaN
```

```
61166         NaN          NaN         NaN   NaN           0         NaN
24462         NaN          NaN         NaN   NaN           0         NaN

        Serious  Good lyrics  Unattractive  Confident  Old  Youthful  Boring  \
109843      0.0          1.0           0.0        0.0  NaN       0.0     0.0
28247       0.0          1.0           0.0        0.0  NaN       0.0     NaN
104792      0.0          0.0           0.0        0.0  NaN       0.0     0.0
57761       NaN          NaN           NaN        NaN  NaN       1.0     0.0
20595       0.0          1.0           0.0        1.0  NaN       0.0     0.0
62408       0.0          0.0           0.0        0.0  NaN       0.0     0.0
6553        1.0          1.0           0.0        1.0  NaN       0.0     NaN
105115      0.0          1.0           0.0        1.0  NaN       0.0     0.0
107250      NaN          NaN           NaN        NaN  0.0       NaN     NaN
31728       NaN          NaN           NaN        NaN  NaN       0.0     0.0
72534       0.0          0.0           0.0        0.0  NaN       0.0     0.0
30895       NaN          NaN           NaN        NaN  NaN       1.0     0.0
75007       0.0          0.0           0.0        0.0  NaN       0.0     0.0
61166       0.0          0.0           0.0        0.0  NaN       0.0     0.0
24462       0.0          1.0           0.0        1.0  NaN       0.0     NaN

        Current  Colourful  Stylish  Cheap  Irrelevant  Heartfelt  Calm  \
109843        0        NaN        0    0.0         NaN        NaN   0.0
28247         0        NaN        0    0.0         NaN        NaN   0.0
104792        0        NaN        0    0.0         NaN        NaN   0.0
57761         1        1.0        0    NaN         NaN        0.0   NaN
20595         1        NaN        1    0.0         NaN        NaN   0.0
62408         1        NaN        0    0.0         NaN        NaN   0.0
6553          1        NaN        0    0.0         NaN        NaN   1.0
105115        0        NaN        0    0.0         NaN        NaN   0.0
107250        0        0.0        1    NaN         NaN        0.0   NaN
31728         0        0.0        0    NaN         NaN        0.0   NaN
72534         0        NaN        0    0.0         0.0        NaN   0.0
30895         1        1.0        1    NaN         NaN        1.0   NaN
75007         0        NaN        0    0.0         0.0        NaN   0.0
61166         1        NaN        0    0.0         NaN        NaN   0.0
24462         0        NaN        0    0.0         NaN        NaN   1.0

        Pioneer  Outgoing  Inspiring  Beautiful  Fun  Authentic  Credible  \
109843      NaN       0.0        1.0          1    0          1         1
28247       NaN       0.0        0.0          1    0          0         0
104792      NaN       0.0        1.0          0    0          0         0
57761       NaN       NaN        NaN          1    1          0         0
20595       NaN       1.0        1.0          0    1          0         1
62408       NaN       0.0        0.0          0    0          0         0
6553        NaN       0.0        1.0          1    0          1         0
105115      NaN       0.0        1.0          0    0          0         1
107250      0.0       NaN        NaN          0    1          0         0
```

```
31728       NaN       NaN        NaN          0    1          0         0
72534       NaN       0.0        0.0          0    1          0         0
30895       NaN       NaN        NaN          1    1          1         1
75007       NaN       0.0        0.0          0    0          0         0
61166       NaN       0.0        0.0          1    1          0         0
24462       NaN       0.0        0.0          1    1          0         0

        Way out  Cool  Catchy  Sensitive  Mainstream  Superficial  Annoying  \
109843      NaN     1     1.0        0.0         NaN          0.0       NaN
28247       NaN     0     1.0        0.0         NaN          0.0       NaN
104792      NaN     0     0.0        0.0         NaN          0.0       NaN
57761       0.0     0     0.0        NaN         NaN          NaN       NaN
20595       NaN     1     1.0        0.0         NaN          0.0       NaN
62408       NaN     1     1.0        0.0         NaN          0.0       NaN
6553        NaN     1     1.0        1.0         NaN          0.0       NaN
105115      NaN     0     1.0        0.0         NaN          0.0       NaN
107250      0.0     0     NaN        NaN         NaN          NaN       NaN
31728       0.0     0     1.0        NaN         NaN          NaN       NaN
72534       NaN     0     0.0        0.0         0.0          0.0       0.0
30895       0.0     1     1.0        NaN         NaN          NaN       NaN
75007       NaN     0     1.0        0.0         0.0          0.0       0.0
61166       NaN     1     0.0        0.0         1.0          0.0       NaN
24462       NaN     0     1.0        0.0         NaN          0.0       NaN

        Dark  Passionate  Not authentic  Good Lyrics  Background  Timeless  \
109843   NaN           1            NaN          NaN         NaN         1
28247    NaN           1            NaN          NaN         NaN         0
104792   NaN           0            NaN          NaN         NaN         1
57761    NaN           0            NaN          0.0         0.0         0
20595    NaN           1            NaN          NaN         NaN         0
62408    NaN           1            NaN          NaN         NaN         0
6553     NaN           1            NaN          NaN         NaN         1
105115   NaN           0            NaN          NaN         NaN         1
107250   0.0           1            NaN          0.0         0.0         0
31728    NaN           1            NaN          1.0         0.0         0
72534    NaN           0            0.0          NaN         NaN         0
30895    NaN           0            NaN          1.0         0.0         0
75007    NaN           0            0.0          NaN         NaN         0
61166    NaN           0            NaN          NaN         NaN         0
24462    NaN           0            NaN          NaN         NaN         0

        Depressing  Original  Talented  Worldly  Distinctive  Approachable  \
109843         0.0         1         0      NaN            0             0
28247          0.0         1         0      NaN            0             0
104792         0.0         0         1      NaN            0             0
57761          NaN         0         0      NaN            1             0
20595          0.0         0         1      NaN            0             0
```

```
62408          0.0         0         0      NaN            0             0
6553           1.0         1         1      NaN            1             1
105115         0.0         1         1      NaN            1             1
107250         NaN         1         1      0.0            0             0
31728          NaN         0         1      NaN            0             0
72534          0.0         0         0      NaN            0             0
30895          NaN         1         1      NaN            1             0
75007          0.0         0         0      NaN            0             0
61166          0.0         0         0      NaN            0             0
24462          0.0         1         0      NaN            0             0

        Genius  Trendsetter  Noisy  Upbeat  Relatable  Energetic  Exciting  \
109843     NaN            0    0.0     0.0        NaN          0       NaN
28247      NaN            0    0.0     0.0        NaN          0       NaN
104792     NaN            0    0.0     0.0        NaN          0       NaN
57761      0.0            0    NaN     1.0        NaN          1       1.0
20595      NaN            0    0.0     0.0        NaN          1       NaN
62408      NaN            0    0.0     0.0        NaN          1       NaN
6553       NaN            0    0.0     0.0        NaN          1       NaN
105115     NaN            0    0.0     0.0        NaN          1       NaN
107250     0.0            0    NaN     NaN        NaN          0       1.0
31728      0.0            0    NaN     0.0        NaN          0       0.0
72534      NaN            0    0.0     0.0        0.0          0       NaN
30895      0.0            0    NaN     0.0        NaN          1       1.0
75007      NaN            0    0.0     0.0        0.0          0       NaN
61166      NaN            0    1.0     0.0        0.0          1       NaN
24462      NaN            0    0.0     0.0        NaN          0       NaN

        Emotional  Nostalgic  None of these  Progressive  Sexy  Over  \
109843        NaN        NaN              0          NaN     0   0.0
28247         NaN        NaN              0          NaN     0   0.0
104792        NaN        NaN              0          NaN     0   0.0
57761         0.0        NaN              0          NaN     0   NaN
20595         NaN        NaN              0          NaN     1   NaN
62408         NaN        NaN              0          NaN     0   0.0
6553          NaN        NaN              0          NaN     0   0.0
105115        NaN        NaN              0          NaN     0   0.0
107250        0.0        0.0              0          0.0     1   NaN
31728         0.0        NaN              0          NaN     0   NaN
72534         NaN        NaN              0          NaN     0   0.0
30895         1.0        NaN              0          NaN     0   NaN
75007         NaN        NaN              0          NaN     0   0.0
61166         NaN        NaN              0          NaN     0   0.0
24462         NaN        NaN              0          NaN     0   0.0

        Rebellious  Fake  Cheesy  Popular  Superstar  Relaxed  Intrusive  \
109843         NaN   0.0     0.0      NaN        NaN      NaN        NaN
```

28247	NaN	0.0	0.0	NaN	NaN	NaN	NaN
104792	NaN	0.0	0.0	NaN	NaN	NaN	NaN
57761	0.0	NaN	NaN	0.0	NaN	0.0	NaN
20595	NaN	0.0	0.0	NaN	NaN	NaN	NaN
62408	NaN	0.0	0.0	NaN	NaN	NaN	NaN
6553	NaN	0.0	0.0	NaN	NaN	NaN	NaN
105115	NaN	0.0	0.0	NaN	NaN	NaN	NaN
107250	0.0	NaN	NaN	NaN	NaN	1.0	NaN
31728	0.0	NaN	NaN	1.0	NaN	0.0	NaN
72534	NaN	0.0	1.0	NaN	0.0	NaN	0.0
30895	0.0	NaN	NaN	1.0	NaN	0.0	NaN
75007	NaN	0.0	0.0	NaN	0.0	NaN	0.0
61166	NaN	0.0	0.0	NaN	0.0	NaN	NaN
24462	NaN	0.0	0.0	NaN	NaN	NaN	NaN

	Unoriginal	Dated	Iconic	Unapproachable	Classic	Playful	Arrogant	\
109843	0.0	0.0	NaN	0.0	1.0	1.0	0.0	
28247	0.0	0.0	NaN	0.0	1.0	0.0	0.0	
104792	0.0	0.0	NaN	0.0	1.0	0.0	0.0	
57761	NaN	0.0	NaN	NaN	0.0	NaN	NaN	
20595	0.0	0.0	NaN	0.0	NaN	0.0	0.0	
62408	0.0	0.0	NaN	0.0	0.0	1.0	0.0	
6553	0.0	0.0	NaN	0.0	1.0	0.0	0.0	
105115	0.0	0.0	NaN	0.0	1.0	0.0	0.0	
107250	NaN	NaN	0.0	NaN	0.0	NaN	NaN	
31728	NaN	0.0	NaN	NaN	0.0	NaN	NaN	
72534	0.0	0.0	NaN	1.0	0.0	0.0	0.0	
30895	NaN	0.0	NaN	NaN	0.0	NaN	NaN	
75007	0.0	0.0	NaN	0.0	0.0	0.0	0.0	
61166	0.0	0.0	NaN	0.0	1.0	0.0	0.0	
24462	0.0	0.0	NaN	0.0	1.0	0.0	0.0	

	Warm	Soulful	Unnamed: 87	plus_score	minus_score	words_score
109843	0	NaN	NaN	12.0	0.0	12.0
28247	0	NaN	NaN	6.0	0.0	6.0
104792	0	NaN	NaN	4.0	0.0	4.0
57761	0	0.0	NaN	11.0	0.0	11.0
20595	0	NaN	NaN	14.0	0.0	14.0
62408	0	NaN	NaN	6.0	0.0	6.0
6553	0	NaN	NaN	17.0	1.0	16.0
105115	0	NaN	NaN	12.0	0.0	12.0
107250	1	NaN	NaN	10.0	0.0	10.0
31728	0	0.0	NaN	6.0	0.0	6.0
72534	0	NaN	NaN	1.0	2.0	-1.0
30895	1	1.0	NaN	23.0	0.0	23.0
75007	0	NaN	NaN	1.0	0.0	1.0
61166	0	NaN	NaN	6.0	1.0	5.0

```
24462      1      NaN          NaN         8.0          0.0          8.0
```

As now we gave the word score we don't need the words columns in the words_df dataframe. Now we will create a dateframe where the columns will be the **word score of above 90**

[17]:
```
words_red_df = words_df[['Artist', 'User', 'HEARD_OF', 'OWN_ARTIST_MUSIC',␣
↪'LIKE_ARTIST', 'words_score']]
```

[18]:
```
words_red_df
```

[18]:
```
        Artist   User                                HEARD_OF  \
0           47  45969                                Heard of
1           35  29118                           Never heard of
2           14  31544                                Heard of
3           23  18085                           Never heard of
4           23  18084                           Never heard of
…          …    …                                        …
118296       4   3932      Heard of and listened to music EVER
118297       4   3935      Heard of and listened to music EVER
118298      12  11216  Heard of and listened to music RECENTLY
118299      33  35142      Heard of and listened to music EVER
118300       4   3915      Heard of and listened to music EVER

                   OWN_ARTIST_MUSIC  LIKE_ARTIST  words_score
0                               NaN          NaN         -1.0
1                               NaN          NaN          3.0
2                               NaN          NaN          2.0
3                               NaN          NaN         -1.0
4                               NaN          NaN          0.0
…                               …            …           …
118296  Own a little of their music         26.0         -1.0
118297  Own a little of their music         30.0          1.0
118298      Own none of their music         71.0          6.0
118299      Own none of their music         31.0          3.0
118300  Own a little of their music         46.0          4.0

[118301 rows x 6 columns]
```

[19]:
```
words_red_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 118301 entries, 0 to 118300
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Artist            118301 non-null  int64
 1   User              118301 non-null  int64
 2   HEARD_OF          118277 non-null  object
```

```
 3   OWN_ARTIST_MUSIC  33507 non-null   object
 4   LIKE_ARTIST       33308 non-null   float64
 5   words_score       118301 non-null  float64
dtypes: float64(2), int64(2), object(2)
memory usage: 5.4+ MB
```

4 Merging

Now we will merge words_red_df & users_df into training_merge_df dataframe

[20]:
```
users_df.rename(columns={'RESPID': 'User'}, inplace=True)
```

[21]:
```
training_merge_df = train_df.merge(words_red_df, how='left', on=['Artist',␣
↪'User'])
```

[22]:
```
users_df
```

[22]:

	User	GENDER	AGE	WORKING	REGION	\
0	36927	Female	60.0	Other	South	
1	3566	Female	36.0	Full-time housewife / househusband	South	
2	20054	Female	52.0	Employed 30+ hours a week	Midlands	
3	41749	Female	40.0	Employed 8-29 hours per week	South	
4	23108	Female	16.0	Full-time student	North	
…	…	…	…	…	…	
48640	19361	Male	48.0	Self-employed	Midlands	
48641	17639	Female	60.0	Full-time housewife / househusband	Midlands	
48642	28753	Female	25.0	Employed 30+ hours a week	Midlands	
48643	26197	Male	44.0	Employed 30+ hours a week	Midlands	
48644	16225	Female	43.0	NaN	North	

	MUSIC	LIST_OWN	\
0	Music is important to me but not necessarily m…	1 hour	
1	Music is important to me but not necessarily m…	1 hour	
2	I like music but it does not feature heavily i…	1 hour	
3	Music means a lot to me and is a passion of mine	2 hours	
4	Music means a lot to me and is a passion of mine	3 hours	
…	…	…	
48640	I like music but it does not feature heavily i…	Less than an hour	
48641	Music means a lot to me and is a passion of mine	2 hours	
48642	Music means a lot to me and is a passion of mine	2 hours	
48643	Music means a lot to me and is a passion of mine	2 hours	
48644	I like music but it does not feature heavily i…	NaN	

	LIST_BACK	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	\
0	NaN	49.0	50.0	49.0	50.0	32.0	33.0	32.0	0.0	
1	1 hour	55.0	55.0	62.0	9.0	9.0	9.0	10.0	11.0	
2	Less than an hour	11.0	50.0	9.0	8.0	45.0	10.0	30.0	29.0	

```
3                3 hours  81.0  80.0  88.0  88.0  31.0  31.0   51.0  30.0
4                6 hours  76.0  79.0  78.0  73.0  71.0  68.0   73.0  67.0
…                  …   …   …   …   …   …   …    …   …
48640            2 hours   9.0  73.0  33.0   6.0  10.0  68.0   51.0  52.0
48641             1 hour  26.0  50.0  49.0  58.0  59.0  48.0    6.0   5.0
48642            6 hours  89.0  89.0  89.0   6.0   6.0  51.0   26.0   5.0
48643            4 hours  95.0  97.0  97.0  98.0  97.0  99.0  100.0  99.0
48644                  2  49.0  48.0  50.0  51.0  49.0  25.0   45.0  51.0

          Q9   Q10   Q11   Q12   Q13   Q14   Q15   Q16    Q17   Q18   Q19
0       74.0  50.0  50.0  71.0  52.0  71.0   9.0   7.0   72.0  49.0  26.0
1       55.0  12.0  65.0  65.0  80.0  79.0  51.0  31.0   68.0  54.0  33.0
2        8.0  50.0  94.0  51.0  74.0  66.0  27.0  46.0   73.0   8.0  31.0
3        8.0  76.0  74.0  64.0  73.0  85.0  61.0  77.0   76.0  78.0  88.0
4       31.0  56.0  13.0  82.0  79.0  68.0  71.0   NaN   86.0  80.0  32.0
…      …   …   …   …   …   …   …   …    …   …   …
48640   93.0  53.0  74.0  36.0  13.0  38.0  12.0  10.0   50.0  10.0  28.0
48641   88.0  58.0  62.0  79.0  17.0  24.0  30.0   6.0   73.0  20.0  21.0
48642    0.0  70.0  70.0  70.0  51.0  70.0  70.0   NaN  100.0  70.0  69.0
48643  100.0  97.0  98.0  99.0  97.0  99.0  99.0  99.0  100.0  91.0  96.0
48644   40.0  10.0  69.0  70.0  53.0  54.0  10.0   4.0    7.0   NaN   NaN

[48645 rows x 27 columns]
```

[23]:
```
training_merge_df
```

[23]:
```
        Artist  Track   User  Rating  Time  \
0           40    179  47994       9    17
1            9     23   8575      58     7
2           46    168  45475      13    16
3           11    153  39508      42    15
4           14     32  11565      54    19
…         …    …    …     …   …
188685       0      3   1278      29     6
188686       1      6   2839      30    18
188687      10    142  35756      61    12
188688      22     54  20163      46    21
188689      47    171  45580      12     4

                                      HEARD_OF          OWN_ARTIST_MUSIC  \
0                              Never heard of                       NaN
1                              Never heard of                       NaN
2                              Never heard of                       NaN
3           Heard of and listened to music EVER  Own none of their music
4           Heard of and listened to music EVER  Own none of their music
…                                         …                       …
188685                         Never heard of                       NaN
```

```
188686                                Heard of                        NaN
188687                                Heard of                        NaN
188688  Heard of and listened to music RECENTLY  Own a lot of their music
188689  Heard of and listened to music RECENTLY   Own none of their music

        LIKE_ARTIST  words_score
0               NaN         -2.0
1               NaN          5.0
2               NaN          1.0
3              28.0          4.0
4              18.0          2.0
…               …           …
188685          NaN          3.0
188686          NaN         -1.0
188687          NaN          3.0
188688         74.0         10.0
188689          7.0          1.0

[188690 rows x 9 columns]
```

[24]:
```
training_merge_df = training_merge_df.merge(users_df, how='left', on=['User'])
```

[25]:
```
training_merge_df
```

[25]:
```
        Artist  Track   User  Rating  Time  \
0           40    179  47994       9    17
1            9     23   8575      58     7
2           46    168  45475      13    16
3           11    153  39508      42    15
4           14     32  11565      54    19
…         …     …     …      …     …
188685       0      3   1278      29     6
188686       1      6   2839      30    18
188687      10    142  35756      61    12
188688      22     54  20163      46    21
188689      47    171  45580      12     4

                                      HEARD_OF          OWN_ARTIST_MUSIC  \
0                               Never heard of                       NaN
1                               Never heard of                       NaN
2                               Never heard of                       NaN
3           Heard of and listened to music EVER  Own none of their music
4           Heard of and listened to music EVER  Own none of their music
…                                          …                         …
188685                          Never heard of                       NaN
188686                                Heard of                       NaN
188687                                Heard of                       NaN
```

```
188688  Heard of and listened to music RECENTLY  Own a lot of their music
188689  Heard of and listened to music RECENTLY   Own none of their music

        LIKE_ARTIST  words_score  GENDER   AGE  \
0               NaN         -2.0  Female  41.0
1               NaN          5.0  Female  45.0
2               NaN          1.0    Male  23.0
3              28.0          4.0  Female  61.0
4              18.0          2.0  Female  20.0
…               …           …      …   …
188685          NaN          3.0  Female  53.0
188686          NaN         -1.0    Male  52.0
188687          NaN          3.0  Female  28.0
188688         74.0         10.0  Female  35.0
188689          7.0          1.0  Female  82.0

                                  WORKING    REGION  \
0                   Temporarily unemployed     North
1                                      NaN    Centre
2              Employed 8-29 hours per week  Midlands
3              Retired from self-employment  Midlands
4                   Temporarily unemployed     South
…                                       …       …
188685                                 NaN     North
188686            Employed 30+ hours a week  Midlands
188687  Full-time housewife / househusband     North
188688            Employed 30+ hours a week     North
188689                                 NaN    Centre

                                                    MUSIC           LIST_OWN  \
0        Music means a lot to me and is a passion of mine            3 hours
1       Music is important to me but not necessarily m…                 1
2        Music means a lot to me and is a passion of mine            5 hours
3       Music is important to me but not necessarily m…             1 hour
4       Music is important to me but not necessarily m…  Less than an hour
…                                                       …               …
188685  Music is important to me but not necessarily m…                 1
188686  I like music but it does not feature heavily i…             1 hour
188687  Music is important to me but not necessarily m…                NaN
188688  Music is important to me but not necessarily m…             1 hour
188689  Music is important to me but not necessarily m…                 0

       LIST_BACK     Q1    Q2    Q3    Q4    Q5    Q6    Q7    Q8    Q9   Q10  \
0        0 Hours   62.0  22.0  62.0  48.0  35.0  30.0  48.0  28.0  88.0  70.0
1              2   32.0  57.0  52.0  10.0  10.0  29.0  73.0  51.0  12.0  50.0
2            NaN  100.0  75.0  90.0  48.0  25.0  34.0  46.0  29.0  29.0  71.0
3            NaN   62.0  57.0  55.0  44.0  53.0  66.0  33.0  27.0  41.0  52.0
```

```
4        3 hours   22.0  69.0  28.0  52.0  32.0  22.0   9.0  10.0  11.0  55.0
…          …    …   …   …   …   …   …   …   …   …   …
188685      NaN   68.0  52.0  66.0  49.0  49.0  31.0  30.0   8.0  29.0  49.0
188686    1 hour  75.0  50.0  32.0   7.0  48.0  50.0  66.0  30.0  48.0  48.0
188687      NaN   52.0  67.0  51.0  52.0  53.0  35.0  15.0  14.0  53.0  51.0
188688    1 hour   9.0  27.0  13.0  13.0   6.0  58.0  45.0  30.0  61.0  13.0
188689         0   73.0  92.0  93.0   7.0  11.0   9.0  11.0   9.0  34.0  73.0

         Q11   Q12    Q13    Q14   Q15   Q16   Q17   Q18   Q19
0       49.0  49.0   32.0   32.0  50.0  31.0  31.0  10.0   9.0
1       91.0  72.0   32.0   55.0  53.0  54.0  75.0   NaN   NaN
2       72.0  48.0  100.0  100.0  28.0  65.0  72.0  73.0  83.0
3       71.0  73.0   53.0   61.0  49.0  52.0  63.0  50.0  45.0
4       84.0  70.0   20.0   19.0  11.0  47.0  71.0  37.0  26.0
…      …   …    …    …   …   …   …   …   …
188685  74.0  69.0   50.0   30.0  11.0  51.0  51.0   NaN   NaN
188686  48.0  30.0   30.0   49.0  32.0  32.0  47.0  31.0   8.0
188687  50.0  51.0   57.0   51.0  52.0  52.0  52.0  54.0  47.0
188688  54.0  49.0   65.0   50.0   4.0  46.0  77.0  47.0  39.0
188689  73.0  73.0   54.0   69.0   8.0  10.0  70.0   NaN   NaN

[188690 rows x 35 columns]
```

[26]:
```
training_merge_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 188690 entries, 0 to 188689
Data columns (total 35 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Artist            188690 non-null  int64
 1   Track             188690 non-null  int64
 2   User              188690 non-null  int64
 3   Rating            188690 non-null  int64
 4   Time              188690 non-null  int64
 5   HEARD_OF          186418 non-null  object
 6   OWN_ARTIST_MUSIC  56835 non-null   object
 7   LIKE_ARTIST       55028 non-null   float64
 8   words_score       186636 non-null  float64
 9   GENDER            176833 non-null  object
 10  AGE               174982 non-null  float64
 11  WORKING           140545 non-null  object
 12  REGION            167481 non-null  object
 13  MUSIC             176833 non-null  object
 14  LIST_OWN          158651 non-null  object
 15  LIST_BACK         158790 non-null  object
 16  Q1                176833 non-null  float64
```

```
 17  Q2                176833 non-null  float64
 18  Q3                176833 non-null  float64
 19  Q4                176833 non-null  float64
 20  Q5                176833 non-null  float64
 21  Q6                176833 non-null  float64
 22  Q7                176833 non-null  float64
 23  Q8                176833 non-null  float64
 24  Q9                176833 non-null  float64
 25  Q10               176833 non-null  float64
 26  Q11               176833 non-null  float64
 27  Q12               176833 non-null  float64
 28  Q13               176833 non-null  float64
 29  Q14               176833 non-null  float64
 30  Q15               176833 non-null  float64
 31  Q16               142754 non-null  float64
 32  Q17               176833 non-null  float64
 33  Q18               140545 non-null  float64
 34  Q19               140545 non-null  float64
dtypes: float64(22), int64(5), object(8)
memory usage: 51.8+ MB
```

[27]:
```
training_merge_df.sample(15)
```

[27]:

	Artist	Track	User	Rating	Time	\
52030	35	91	30678	58	23	
175760	4	12	5536	89	18	
164836	11	29	9928	12	7	
101302	34	87	28862	41	23	
151739	40	176	50514	3	17	
96733	30	77	22275	10	22	
87059	46	169	45280	10	16	
100404	22	128	32931	10	0	
59518	40	176	50861	64	17	
65877	22	114	32187	32	0	
142221	22	122	33185	24	0	
31295	6	14	5817	50	7	
164837	15	33	13203	5	19	
40160	2	69	21549	66	22	
20632	48	172	47979	56	17	

	HEARD_OF	OWN_ARTIST_MUSIC	\
52030	Never heard of	NaN	
175760	Heard of and listened to music EVER	Own a lot of their music	
164836	Never heard of	NaN	
101302	Never heard of	NaN	
151739	Never heard of	NaN	
96733	Never heard of	NaN	

```
87059                                 Heard of                            NaN
100404                      Ever heard music by      Own none of their music
59518   Heard of and listened to music RECENTLY     Own a lot of their music
65877                       Ever heard music by  Own a little of their music
142221                      Ever heard music by      Own none of their music
31295       Heard of and listened to music EVER  Own a little of their music
164837                             Never heard of                            NaN
40160                              Never heard of                            NaN
20632                              Never heard of                            NaN

        LIKE_ARTIST  words_score  GENDER   AGE  \
52030           NaN          6.0  Female  29.0
175760         72.0          6.0  Female  60.0
164836          NaN          0.0    Male  53.0
101302          NaN          2.0  Female  18.0
151739          NaN         -1.0    Male  40.0
96733           NaN         -2.0     NaN   NaN
87059           NaN         -1.0    Male  64.0
100404          8.0          0.0  Female  34.0
59518          87.0          3.0  Female  29.0
65877          30.0          8.0    Male  30.0
142221         27.0          4.0  Female  24.0
31295          50.0         12.0    Male  18.0
164837          NaN         -3.0    Male  40.0
40160           NaN          4.0     NaN   NaN
20632           NaN          2.0  Female  43.0

                                                 WORKING            REGION  \
52030                          Employed 30+ hours a week          Midlands
175760  Retired from full-time employment (30+ hours p…             South
164836                                              NaN              South
101302     Employed part-time less than 8 hours per week              South
151739                                     Self-employed  Northern Ireland
96733                                               NaN               NaN
87059                                             Other              North
100404                                              NaN               NaN
59518                          Employed 30+ hours a week          Midlands
65877                                               NaN               NaN
142221                                              NaN               NaN
31295                                               NaN              North
164837                                     Self-employed              South
40160                                               NaN               NaN
20632                          Employed 30+ hours a week          Midlands

                                                  MUSIC   LIST_OWN  \
52030   Music is important to me but not necessarily m…    2 hours
175760  Music is no longer as important as it used to …    0 Hours
```

```
164836  I like music but it does not feature heavily i…        NaN
101302  Music is important to me but not necessarily m…    8 hours
151739   Music means a lot to me and is a passion of mine  16+ hours
96733                                                 NaN        NaN
87059    Music means a lot to me and is a passion of mine    2 hours
100404   Music means a lot to me and is a passion of mine          2
59518   Music is important to me but not necessarily m…     1 hour
65877   Music is important to me but not necessarily m…          5
142221  Music is important to me but not necessarily m…        NaN
31295   Music is important to me but not necessarily m…          3
164837  Music is no longer as important as it used to …    0 Hours
40160                                                 NaN        NaN
20632   Music is important to me but not necessarily m…     1 hour

       LIST_BACK     Q1     Q2     Q3    Q4    Q5     Q6     Q7     Q8     Q9  \
52030    5 hours   62.0   68.0   83.0  67.0  56.0    1.0    1.0    1.0   54.0
175760   2 hours   51.0   52.0   51.0  52.0  70.0   52.0   53.0   54.0   74.0
164836       NaN    2.0  100.0    2.0   2.0   2.0   99.0    2.0    2.0  100.0
101302    1 hour   73.0   78.0   88.0  95.0  99.0   74.0   93.0   82.0   15.0
151739   0 Hours  100.0  100.0  100.0   3.0  50.0  100.0   20.0   27.0   39.0
96733        NaN    NaN    NaN    NaN   NaN   NaN    NaN    NaN    NaN    NaN
87059    4 hours   72.0   72.0   72.0  31.0  29.0   66.0   20.0   20.0   19.0
100404         4   41.0   79.0   85.0  30.0  35.0    9.0   12.0   15.0   13.0
59518    3 hours    8.0   71.0   49.0  13.0  30.0   14.0   69.0   64.0   28.0
65877          7   67.0   96.0   82.0  14.0  14.0   13.0    4.0    5.0   28.0
142221         9   67.0   64.0   66.0  43.0  60.0   27.0   67.0   77.0   18.0
31295        NaN  100.0  100.0   65.0  75.0  72.0    9.0  100.0  100.0   12.0
164837  10 hours   16.0   48.0    9.0  19.0  50.0   51.0   37.0   31.0   58.0
40160        NaN    NaN    NaN    NaN   NaN   NaN    NaN    NaN    NaN    NaN
20632     1 hour   34.0   65.0   46.0  18.0  40.0    9.0   10.0   12.0   32.0

          Q10    Q11    Q12    Q13   Q14   Q15   Q16    Q17   Q18   Q19
52030    85.0   66.0   49.0   91.0  74.0  55.0   NaN   73.0  73.0  70.0
175760   38.0   75.0   47.0   48.0  49.0  39.0  53.0   55.0  53.0  53.0
164836    2.0    2.0    2.0    2.0   2.0   2.0   2.0    2.0   NaN   NaN
101302   94.0   90.0   90.0   74.0  81.0  72.0   NaN   86.0  81.0  96.0
151739   49.0   33.0   40.0   36.0  78.0  50.0   3.0    3.0  50.0  25.0
96733     NaN    NaN    NaN    NaN   NaN   NaN   NaN    NaN   NaN   NaN
87059    54.0   17.0   18.0   23.0  69.0  69.0   8.0   10.0  11.0  11.0
100404   84.0   15.0   37.0   88.0  83.0  89.0  76.0   43.0   NaN   NaN
59518    46.0   66.0   46.0   31.0  43.0  29.0  29.0   47.0  48.0  47.0
65877    78.0   99.0   81.0    7.0  28.0  76.0  38.0   94.0   NaN   NaN
142221   61.0   81.0   71.0   50.0  61.0  60.0  56.0   61.0   NaN   NaN
31295   100.0  100.0  100.0  100.0  68.0  48.0   0.0  100.0   NaN   NaN
164837   38.0   47.0   47.0   33.0  30.0  11.0  12.0   15.0  16.0   8.0
40160     NaN    NaN    NaN    NaN   NaN   NaN   NaN    NaN   NaN   NaN
20632    59.0   66.0   66.0   94.0  62.0  31.0  29.0   64.0  40.0  30.0
```

Merging the test dataset

[28]:
```
test_merge_df = test_df.merge(words_red_df, how='left', on=['Artist', 'User'])
test_merge_df = test_merge_df.merge(users_df, how='left', on=['User'])
```

[29]:
```
test_merge_df
```

[29]:
```
        Artist  Track   User  Time                                HEARD_OF  \
0            1      6   3475    18  Heard of and listened to music EVER
1            6    149  39210    15                                  NaN
2           40    177  47861    17                     Never heard of
3           31     79  27413    11                     Never heard of
4           26     66  23232    22                     Never heard of
…          …    …    …   …                                   …
125789      14     95  30004    23                          Heard of
125790      10     25   8186     7                     Never heard of
125791      40    146  38180    13                          Heard of
125792      22    113  32918     0               Ever heard music by
125793       2     70  24231    22                     Never heard of

                OWN_ARTIST_MUSIC  LIKE_ARTIST  words_score  GENDER   AGE  \
0       Own none of their music          3.0          2.0  Female  48.0
1                           NaN          NaN          NaN    Male  28.0
2                           NaN          NaN         -2.0  Female  59.0
3                           NaN          NaN          0.0  Female  25.0
4                           NaN          NaN          0.0     NaN   NaN
…                          …           …          …      …   …
125789                      NaN          NaN         12.0    Male  36.0
125790                      NaN          NaN          6.0    Male  49.0
125791                      NaN          NaN          3.0  Female  40.0
125792  Own none of their music         48.0          2.0  Female  48.0
125793                      NaN          NaN          4.0    Male  43.0

                                            WORKING    REGION  \
0                          Employed 30+ hours a week     South
1                          Employed 30+ hours a week  Midlands
2                                              Other  Midlands
3       Employed part-time less than 8 hours per week  Midlands
4                                                NaN       NaN
…                                                …       …
125789                     Employed 30+ hours a week  Midlands
125790                                           NaN     North
125791           Full-time housewife / househusband  Midlands
125792                                           NaN       NaN
125793                     Employed 30+ hours a week     North

                                                MUSIC           LIST_OWN  \
```

```
0        Music means a lot to me and is a passion of mine             1 hour
1       Music is important to me but not necessarily m…             1 hour
2       Music is no longer as important as it used to …  Less than an hour
3       I like music but it does not feature heavily i…             1 hour
4                                                   NaN                NaN
…                                                   …                  …
125789   Music means a lot to me and is a passion of mine           10 hours
125790  I like music but it does not feature heavily i…                NaN
125791   Music means a lot to me and is a passion of mine           15 hours
125792   Music means a lot to me and is a passion of mine                  0
125793  Music is important to me but not necessarily m…             1 hour

                LIST_BACK    Q1    Q2     Q3    Q4    Q5    Q6    Q7    Q8  \
0                3 hours   8.0  69.0   27.0  27.0  50.0  27.0  26.0   8.0
1                 1 hour  81.0  67.0   94.0  61.0  53.0  32.0  41.0  42.0
2       Less than an hour   9.0  94.0   49.0  48.0  49.0   8.0  13.0  56.0
3                 1 hour  53.0  38.0   51.0  53.0  53.0  53.0  33.0  51.0
4                    NaN   NaN   NaN    NaN   NaN   NaN   NaN   NaN   NaN
…                    …     …     …      …     …     …     …     …
125789           4 hours  84.0  69.0  100.0  32.0   9.0  28.0   9.0  12.0
125790                 3  29.0  70.0   30.0  30.0  69.0  14.0  12.0  12.0
125791           9 hours  59.0  51.0   51.0  83.0  32.0  43.0  14.0  41.0
125792                 1  69.0  30.0   76.0  74.0  73.0  11.0  11.0  11.0
125793           3 hours  15.0  68.0   51.0  51.0  51.0  71.0   2.0   2.0

          Q9   Q10   Q11   Q12   Q13   Q14   Q15   Q16   Q17   Q18   Q19
0       51.0  50.0  66.0  49.0  20.0   7.0   8.0   9.0   7.0   4.0   8.0
1       36.0  76.0  70.0  76.0  58.0  61.0  66.0  51.0  75.0  70.0  72.0
2       92.0  92.0  55.0  57.0  11.0  57.0  10.0  11.0  91.0   7.0   9.0
3       47.0  33.0  41.0  45.0  49.0  49.0  49.0  49.0  35.0  52.0  52.0
4        NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
…       …     …     …     …     …     …     …     …     …     …     …
125789  50.0  75.0  68.0  72.0  64.0  70.0  75.0   NaN  72.0  56.0  54.0
125790  70.0  29.0  50.0  48.0  54.0  66.0  10.0  34.0  70.0   NaN   NaN
125791  71.0  58.0  36.0  43.0  81.0  63.0  45.0  65.0  30.0  46.0  21.0
125792  92.0  34.0  74.0  72.0  36.0  37.0   9.0   9.0  64.0   NaN   NaN
125793  94.0  65.0   2.0   3.0   3.0   3.0   3.0   NaN  30.0   5.0   5.0

[125794 rows x 34 columns]
```

5 Data Analysis

Now we will try to get the insights from the dataset and see if there is any relationship between the columns. We must also check if any of the columns are interdependent. We ask Question and then we visualize the dataset to get the Answer.

We can do this by plotting the graphs for various columns and observing the relation between the

two or more columns depending on the plot we choose.

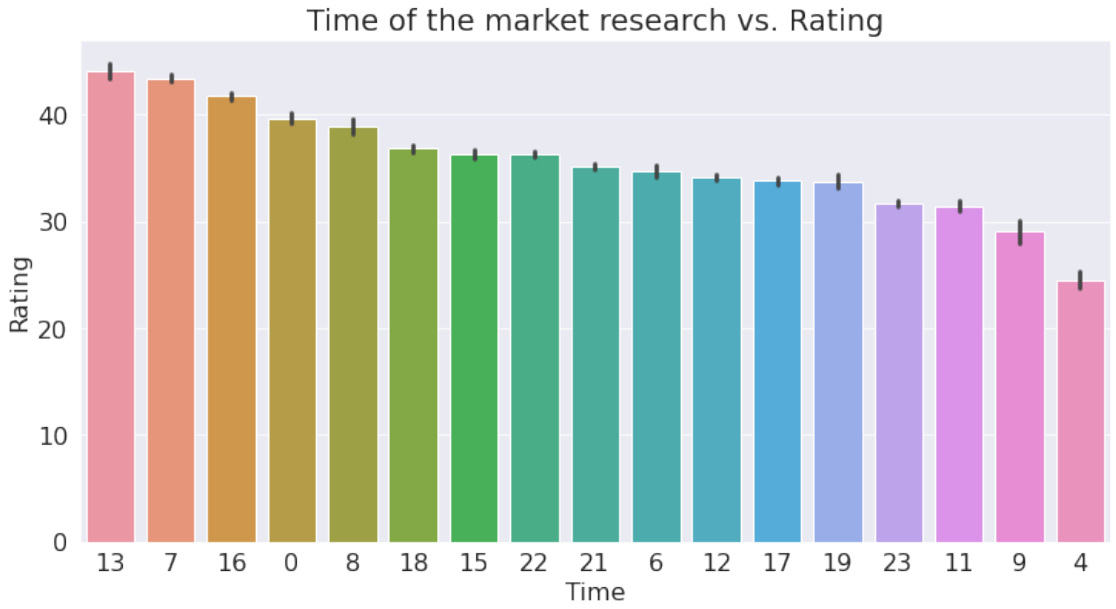
[30]:
```
# Do you love or hate the the song?
px.histogram(training_merge_df, x='Rating', nbins=101, marginal='box',␣
 ↪title='Rating(Love/Hate) Distribution')
```

[31]:
```
training_merge_df.columns
```

[31]:
```
Index(['Artist', 'Track', 'User', 'Rating', 'Time', 'HEARD_OF',
       'OWN_ARTIST_MUSIC', 'LIKE_ARTIST', 'words_score', 'GENDER', 'AGE',
       'WORKING', 'REGION', 'MUSIC', 'LIST_OWN', 'LIST_BACK', 'Q1', 'Q2', 'Q3',
       'Q4', 'Q5', 'Q6', 'Q7', 'Q8', 'Q9', 'Q10', 'Q11', 'Q12', 'Q13', 'Q14',
       'Q15', 'Q16', 'Q17', 'Q18', 'Q19'],
      dtype='object')
```

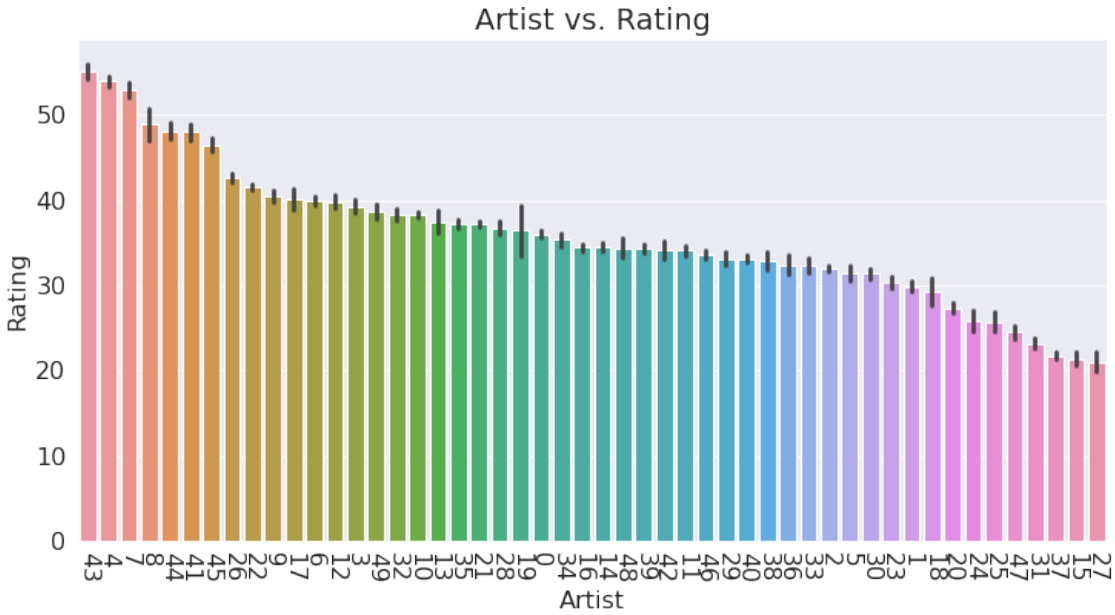
[32]:
```
plot_order= training_merge_df.groupby('Time')['Rating'].mean().
 ↪sort_values(ascending=False).index.values
```

[33]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Time of the market research vs. Rating')
sns.barplot(x='Time', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=0, ha='center')
plt.show();
```

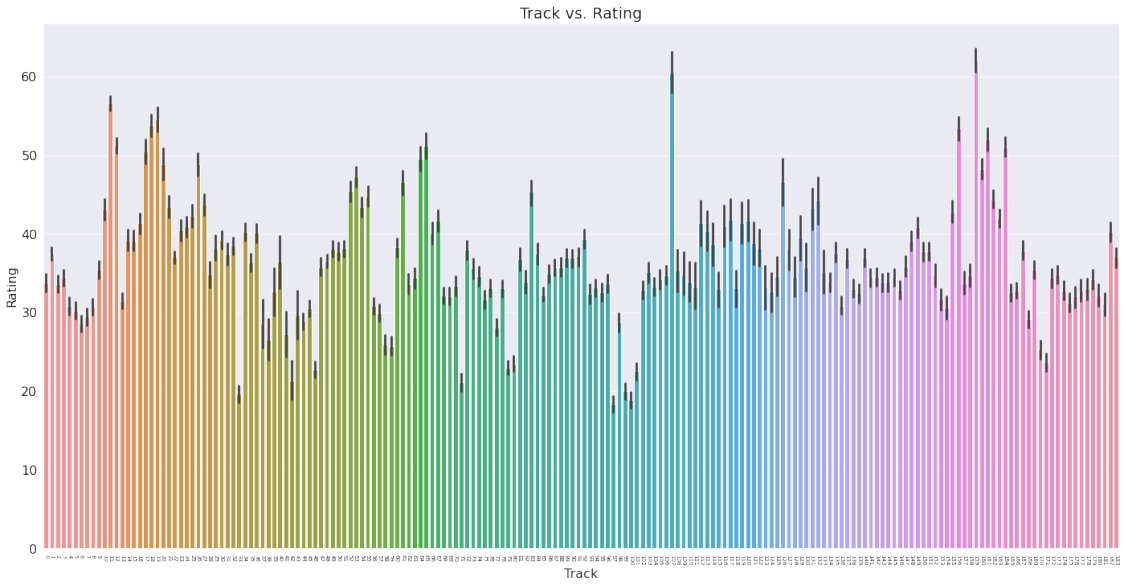


[34]:
```
plot_order= training_merge_df.groupby('Artist')['Rating'].mean().
 ↪sort_values(ascending=False).index.values
```

[35]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Artist vs. Rating')
sns.barplot(x='Artist', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=270, ha='center')
plt.show();
```



[36]:
```
fig, ax = plt.subplots(figsize=(24,12))

plt.title('Track vs. Rating')
sns.barplot(x='Track', y='Rating', data=training_merge_df)
plt.xticks(rotation=-90, fontsize=7, ha='center')
plt.show();
```



6 Change of columns

[37]:
```
training_merge_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 188690 entries, 0 to 188689
Data columns (total 35 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Artist            188690 non-null  int64
 1   Track             188690 non-null  int64
 2   User              188690 non-null  int64
 3   Rating            188690 non-null  int64
 4   Time              188690 non-null  int64
 5   HEARD_OF          186418 non-null  object
 6   OWN_ARTIST_MUSIC  56835 non-null   object
 7   LIKE_ARTIST       55028 non-null   float64
 8   words_score       186636 non-null  float64
 9   GENDER            176833 non-null  object
 10  AGE               174982 non-null  float64
 11  WORKING           140545 non-null  object
 12  REGION            167481 non-null  object
 13  MUSIC             176833 non-null  object
 14  LIST_OWN          158651 non-null  object
 15  LIST_BACK         158790 non-null  object
 16  Q1                176833 non-null  float64
 17  Q2                176833 non-null  float64
```

```
 18  Q3                176833 non-null  float64
 19  Q4                176833 non-null  float64
 20  Q5                176833 non-null  float64
 21  Q6                176833 non-null  float64
 22  Q7                176833 non-null  float64
 23  Q8                176833 non-null  float64
 24  Q9                176833 non-null  float64
 25  Q10               176833 non-null  float64
 26  Q11               176833 non-null  float64
 27  Q12               176833 non-null  float64
 28  Q13               176833 non-null  float64
 29  Q14               176833 non-null  float64
 30  Q15               176833 non-null  float64
 31  Q16               142754 non-null  float64
 32  Q17               176833 non-null  float64
 33  Q18               140545 non-null  float64
 34  Q19               140545 non-null  float64
dtypes: float64(22), int64(5), object(8)
memory usage: 55.9+ MB
```

[38]:
```
training_merge_df['HEARD_OF'].value_counts()
```

[38]:
```
Never heard of                              94090
Heard of                                    35493
Heard of and listened to music EVER         29854
Heard of and listened to music RECENTLY     17847
Ever heard music by                          5136
Listened to recently                         2191
Ever heard of                                1807
Name: HEARD_OF, dtype: int64
```

[39]:
```
print('Missing values in HEARD_OF column {}'.
 ↪format(training_merge_df['HEARD_OF'].isna().sum()))
```

```
Missing values in HEARD_OF column 2272
```

[40]:
```
training_merge_df['HEARD_OF'].replace(['Ever heard of'], 'Never heard of',␣
 ↪inplace=True)
training_merge_df['HEARD_OF'].replace(['Ever heard music by'], 'Heard of and␣
 ↪listened to music EVER', inplace=True)
training_merge_df['HEARD_OF'].replace(['Listened to recently'], 'Heard of and␣
 ↪listened to music RECENTLY', inplace=True)
training_merge_df['HEARD_OF'].fillna('Never heard of', inplace=True)
```

[41]:
```
training_merge_df['HEARD_OF'].unique()
```

[41]:
```
array(['Never heard of', 'Heard of and listened to music EVER',
       'Heard of', 'Heard of and listened to music RECENTLY'],
      dtype=object)
```

[42]:
```
test_merge_df['HEARD_OF'].replace(['Ever heard of'], 'Never heard of',␣
↪inplace=True)
test_merge_df['HEARD_OF'].replace(['Ever heard music by'], 'Heard of and␣
↪listened to music EVER', inplace=True)
test_merge_df['HEARD_OF'].replace(['Listened to recently'], 'Heard of and␣
↪listened to music RECENTLY', inplace=True)
test_merge_df['HEARD_OF'].fillna('Never heard of', inplace=True)
```

[43]:
```
test_merge_df['HEARD_OF'].unique()
```

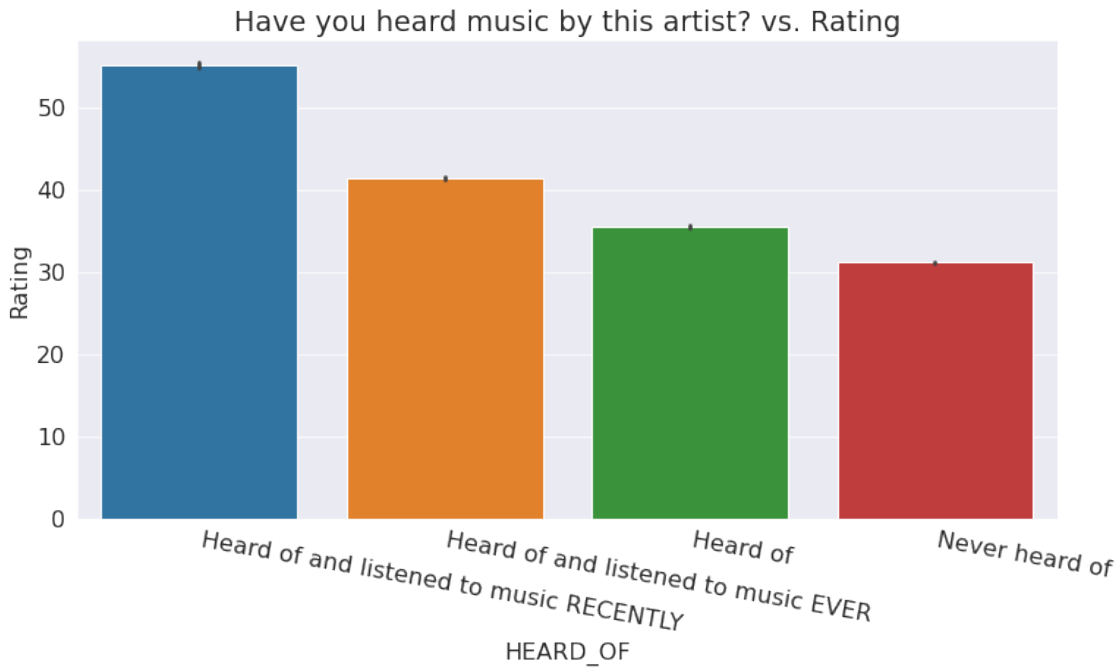
[43]:
```
array(['Heard of and listened to music EVER', 'Never heard of',
       'Heard of', 'Heard of and listened to music RECENTLY'],
      dtype=object)
```

[44]:
```
training_merge_df['HEARD_OF'].value_counts()
```

[44]:
```
Never heard of                          98169
Heard of                                35493
Heard of and listened to music EVER     34990
Heard of and listened to music RECENTLY    20038
Name: HEARD_OF, dtype: int64
```

[45]:
```
plot_order= training_merge_df.groupby('HEARD_OF')['Rating'].mean().
↪sort_values(ascending=False).index.values
```

[46]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Have you heard music by this artist? vs. Rating')
sns.barplot(x='HEARD_OF', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=350, ha='left')
plt.show();
```



7 Own_Artist_Music

[47]:
```
training_merge_df['OWN_ARTIST_MUSIC'].unique()
```

[47]:
```
array([nan, 'Own none of their music', 'Own a little of their music',
       'Own all or most of their music', 'DonÕt know',
       'Own a lot of their music', 'DonÍt know', 'don`t know'],
      dtype=object)
```

[48]:
```
training_merge_df['OWN_ARTIST_MUSIC'].value_counts()
```

[48]:
```
Own none of their music          26810
Own a little of their music      18721
Own a lot of their music          7263
Own all or most of their music    2593
DonÕt know                        1265
DonÍt know                         147
don`t know                          36
Name: OWN_ARTIST_MUSIC, dtype: int64
```

[49]:
```
training_merge_df['OWN_ARTIST_MUSIC'].replace(['DonÕt know'], 'Own none of␣
 ↪their music', inplace=True)
training_merge_df['OWN_ARTIST_MUSIC'].replace(['DonÍt know'], 'Own none of␣
 ↪their music', inplace=True)
```

```
training_merge_df['OWN_ARTIST_MUSIC'].replace(['don`t know'], 'Own none of␣
↪their music', inplace=True)
training_merge_df['OWN_ARTIST_MUSIC'].fillna('Own none of their music',␣
↪inplace=True)
```

[50]:
```
test_merge_df['OWN_ARTIST_MUSIC'].replace(['DonÕt know'], 'Own none of their␣
↪music', inplace=True)
test_merge_df['OWN_ARTIST_MUSIC'].replace(['DonÍt know'], 'Own none of their␣
↪music', inplace=True)
test_merge_df['OWN_ARTIST_MUSIC'].replace(['don`t know'], 'Own none of their␣
↪music', inplace=True)
test_merge_df['OWN_ARTIST_MUSIC'].fillna('Own none of their music',␣
↪inplace=True)
```

[51]:
```
training_merge_df['OWN_ARTIST_MUSIC'].unique()
```

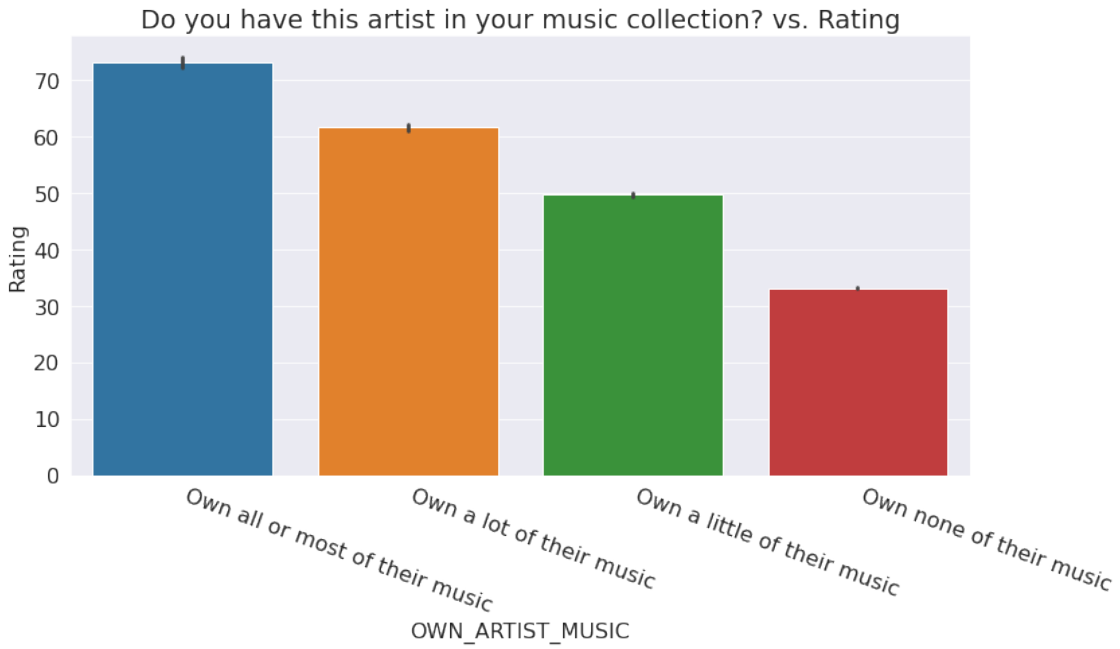
[51]:
```
array(['Own none of their music', 'Own a little of their music',
       'Own all or most of their music', 'Own a lot of their music'],
      dtype=object)
```

[52]:
```
training_merge_df['OWN_ARTIST_MUSIC'].value_counts()
```

[52]:
```
Own none of their music           160113
Own a little of their music        18721
Own a lot of their music            7263
Own all or most of their music      2593
Name: OWN_ARTIST_MUSIC, dtype: int64
```

[53]:
```
plot_order= training_merge_df.groupby('OWN_ARTIST_MUSIC')['Rating'].mean().
↪sort_values(ascending=False).index.values
```

[54]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Do you have this artist in your music collection? vs. Rating')
sns.barplot(x='OWN_ARTIST_MUSIC', y='Rating', data=training_merge_df,␣
↪order=plot_order)
plt.xticks(rotation=340, ha='left')
plt.show();
```



8 LIKE_ARTIST

[55]:
```
training_merge_df['LIKE_ARTIST'].unique()
```

[55]:
```
array([   nan,  28.  ,  18.  ,  33.  ,  36.  ,  53.  ,  50.  ,  63.  ,
        68.  ,  56.  ,  74.  ,  51.  ,  38.  ,  29.  ,  71.  ,  90.  ,
        70.  ,  30.  ,  52.  ,  84.  ,  59.  ,  66.  ,  42.  ,  48.  ,
        32.  ,  49.  ,  81.  , 100.  ,  45.  ,  87.  ,  57.  ,  83.  ,
        92.  ,  75.  ,  47.  ,  13.  ,  41.  ,  17.  ,  12.  ,   1.  ,
         4.  ,  55.  ,  65.  ,  16.  ,  58.  ,  99.  ,  69.  ,  15.  ,
        27.  ,  46.  ,  10.  ,  44.  ,  35.  ,   6.  ,  31.  ,  73.  ,
        26.  ,   2.  ,  43.  ,  54.  ,  61.  ,   9.  ,  14.  ,  62.  ,
        67.  ,  89.  ,  72.  ,  39.  ,   7.  ,   5.  ,  31.34,  20.  ,
        88.  ,  25.  ,  94.  ,  77.  ,  82.  ,  64.  ,  80.  ,  22.  ,
        23.  ,  86.  ,  40.  ,  37.  ,  34.  ,  21.  ,  93.  ,  11.  ,
        91.  ,  30.92,  98.  ,  79.  ,   8.  ,  33.05,   3.  ,  76.  ,
        85.  ,  78.  ,  60.  ,  24.  ,  97.  ,  19.  ,  95.  ,  29.21,
        28.14,  96.  ,  62.47,  48.83,  54.58,  23.24,  39.45,   0.  ,
        23.88,  32.84,  82.73,  78.25,  55.01,  78.68,  39.02,  65.88,
        13.01,   8.53,  38.59,  49.04,  22.6 ,  70.15,  18.34,  45.84,
        21.32,  55.44,  28.57,  37.74,  75.48,  38.17,  60.34,  32.41,
        27.51,  56.72,  80.81,  26.23,  51.81,  44.99,  57.57,  60.55,
        98.08,  16.63,  66.74,  20.9 ,  27.72,  46.91,  86.78,  62.69,
        72.92,  61.19,  29.85,  47.76,  69.72,  71.64,  84.01,  75.91,
        52.24,  29.64,  51.06,  43.28,  47.55,  25.37,   2.99,  50.32,
```

```
          80.38])
```

[56]:
```
training_merge_df['LIKE_ARTIST'].value_counts()
```

[56]:
```
49.00    2707
51.00    2463
30.00    2425
50.00    2218
29.00    2114
         …
44.99       1
57.57       1
60.55       1
98.08       1
80.38       1
Name: LIKE_ARTIST, Length: 168, dtype: int64
```

[57]:
```
training_merge_df
```

[57]:

	Artist	Track	User	Rating	Time	\
0	40	179	47994	9	17	
1	9	23	8575	58	7	
2	46	168	45475	13	16	
3	11	153	39508	42	15	
4	14	32	11565	54	19	
…	…	…	…	…	…	
188685	0	3	1278	29	6	
188686	1	6	2839	30	18	
188687	10	142	35756	61	12	
188688	22	54	20163	46	21	
188689	47	171	45580	12	4	

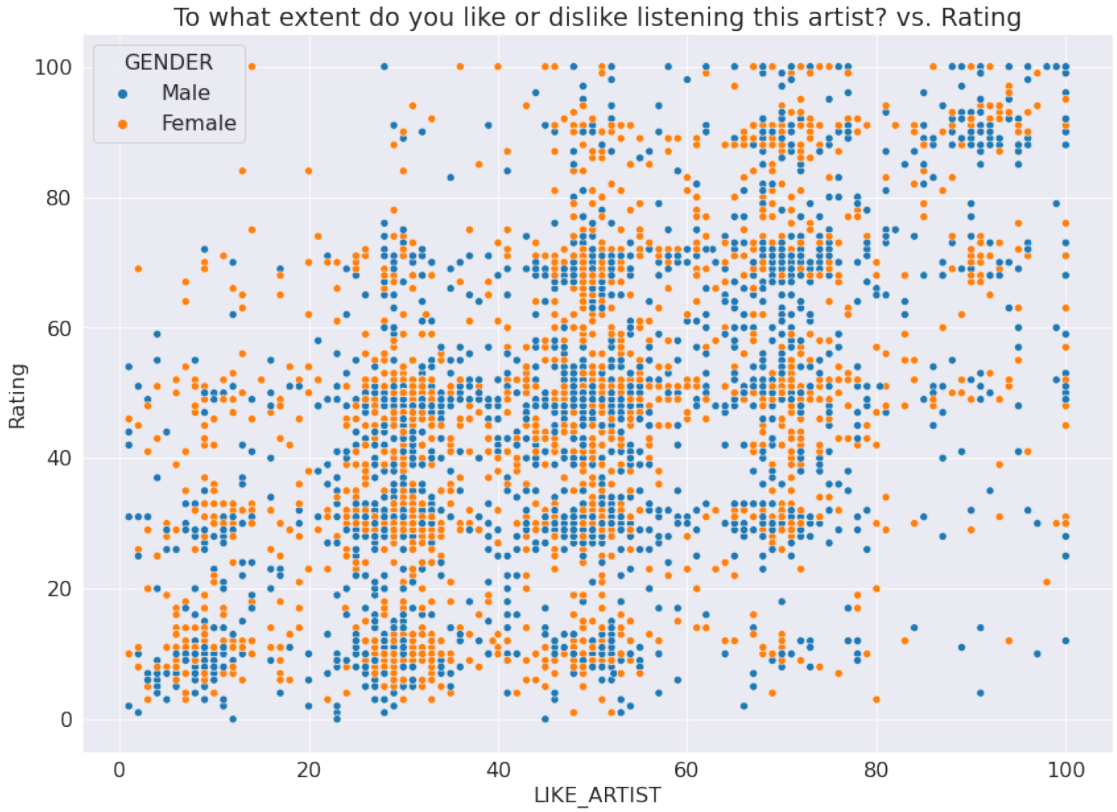
	HEARD_OF	OWN_ARTIST_MUSIC	\
0	Never heard of	Own none of their music	
1	Never heard of	Own none of their music	
2	Never heard of	Own none of their music	
3	Heard of and listened to music EVER	Own none of their music	
4	Heard of and listened to music EVER	Own none of their music	
…	…	…	
188685	Never heard of	Own none of their music	
188686	Heard of	Own none of their music	
188687	Heard of	Own none of their music	
188688	Heard of and listened to music RECENTLY	Own a lot of their music	
188689	Heard of and listened to music RECENTLY	Own none of their music	

	LIKE_ARTIST	words_score	GENDER	AGE	\
0	NaN	-2.0	Female	41.0	

```
1               NaN          5.0  Female  45.0
2               NaN          1.0    Male  23.0
3              28.0          4.0  Female  61.0
4              18.0          2.0  Female  20.0
…               …            …     …   …
188685          NaN          3.0  Female  53.0
188686          NaN         -1.0    Male  52.0
188687          NaN          3.0  Female  28.0
188688         74.0         10.0  Female  35.0
188689          7.0          1.0  Female  82.0

                                    WORKING    REGION  \
0                   Temporarily unemployed     North
1                                      NaN    Centre
2              Employed 8-29 hours per week  Midlands
3              Retired from self-employment  Midlands
4                   Temporarily unemployed     South
…                                        …       …
188685                                 NaN     North
188686            Employed 30+ hours a week  Midlands
188687  Full-time housewife / househusband     North
188688            Employed 30+ hours a week     North
188689                                 NaN    Centre

                                                    MUSIC           LIST_OWN  \
0        Music means a lot to me and is a passion of mine            3 hours
1       Music is important to me but not necessarily m…                 1
2        Music means a lot to me and is a passion of mine            5 hours
3       Music is important to me but not necessarily m…             1 hour
4       Music is important to me but not necessarily m…  Less than an hour
…                                                       …               …
188685  Music is important to me but not necessarily m…                 1
188686  I like music but it does not feature heavily i…             1 hour
188687  Music is important to me but not necessarily m…                NaN
188688  Music is important to me but not necessarily m…             1 hour
188689  Music is important to me but not necessarily m…                 0

       LIST_BACK     Q1    Q2    Q3    Q4    Q5    Q6    Q7    Q8    Q9   Q10  \
0        0 Hours   62.0  22.0  62.0  48.0  35.0  30.0  48.0  28.0  88.0  70.0
1              2   32.0  57.0  52.0  10.0  10.0  29.0  73.0  51.0  12.0  50.0
2            NaN  100.0  75.0  90.0  48.0  25.0  34.0  46.0  29.0  29.0  71.0
3            NaN   62.0  57.0  55.0  44.0  53.0  66.0  33.0  27.0  41.0  52.0
4        3 hours   22.0  69.0  28.0  52.0  32.0  22.0   9.0  10.0  11.0  55.0
…          …     …   …   …   …   …   …   …   …   …   …
188685       NaN   68.0  52.0  66.0  49.0  49.0  31.0  30.0   8.0  29.0  49.0
188686    1 hour   75.0  50.0  32.0   7.0  48.0  50.0  66.0  30.0  48.0  48.0
188687       NaN   52.0  67.0  51.0  52.0  53.0  35.0  15.0  14.0  53.0  51.0
```

```
188688    1 hour    9.0  27.0  13.0  13.0   6.0  58.0  45.0  30.0  61.0  13.0
188689         0   73.0  92.0  93.0   7.0  11.0   9.0  11.0   9.0  34.0  73.0

          Q11   Q12    Q13    Q14   Q15   Q16   Q17   Q18   Q19
0        49.0  49.0   32.0   32.0  50.0  31.0  31.0  10.0   9.0
1        91.0  72.0   32.0   55.0  53.0  54.0  75.0   NaN   NaN
2        72.0  48.0  100.0  100.0  28.0  65.0  72.0  73.0  83.0
3        71.0  73.0   53.0   61.0  49.0  52.0  63.0  50.0  45.0
4        84.0  70.0   20.0   19.0  11.0  47.0  71.0  37.0  26.0
…         …     …      …      …     …     …     …     …
188685   74.0  69.0   50.0   30.0  11.0  51.0  51.0   NaN   NaN
188686   48.0  30.0   30.0   49.0  32.0  32.0  47.0  31.0   8.0
188687   50.0  51.0   57.0   51.0  52.0  52.0  52.0  54.0  47.0
188688   54.0  49.0   65.0   50.0   4.0  46.0  77.0  47.0  39.0
188689   73.0  73.0   54.0   69.0   8.0  10.0  70.0   NaN   NaN

[188690 rows x 35 columns]
```

[58]:
```
plt.title('To what extent do you like or dislike listening this artist? vs.␣
 ↪Rating')
sns.scatterplot(x='LIKE_ARTIST', y='Rating', hue='GENDER',␣
 ↪data=training_merge_df.sample(15000));
```



[59]:
```
training_merge_df[training_merge_df['LIKE_ARTIST'].isna()].Rating.describe()
```

[59]:
```
count    133662.000000
mean         32.326353
std          20.782582
min           0.000000
25%          12.000000
50%          30.000000
75%          48.000000
max         100.000000
Name: Rating, dtype: float64
```

[60]:
```
training_merge_df.Rating.describe()
```

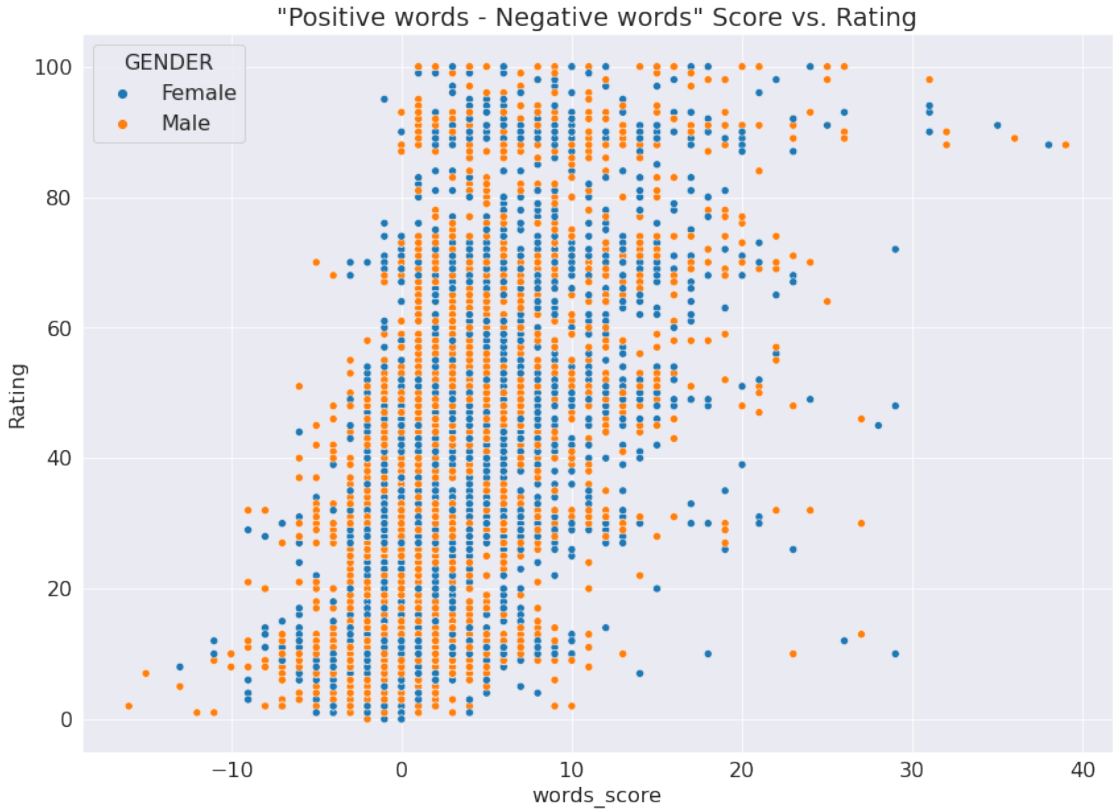
[60]:
```
count    188690.000000
mean         36.435391
std          22.586036
min           0.000000
25%          15.000000
50%          32.000000
75%          50.000000
max         100.000000
Name: Rating, dtype: float64
```

[61]:
```
training_merge_df[~training_merge_df['LIKE_ARTIST'].isna()].Rating.describe()
```

[61]:
```
count    55028.000000
mean        46.416170
std         23.653523
min          0.000000
25%         30.000000
50%         48.000000
75%         64.250000
max        100.000000
Name: Rating, dtype: float64
```

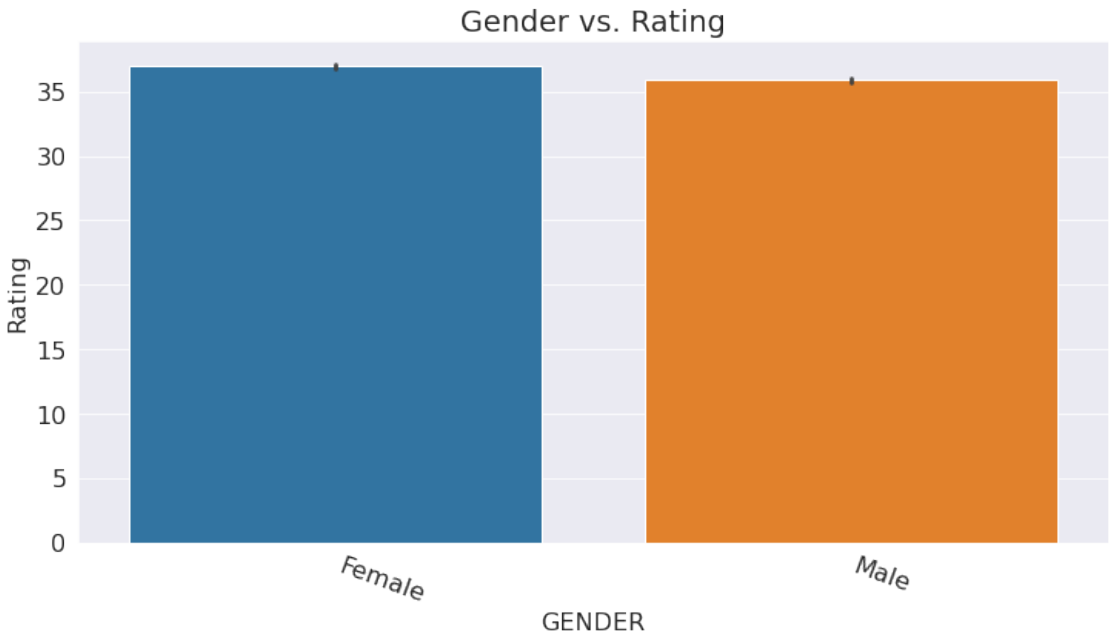
9 Words_Score

[62]:
```
plt.title('"Positive words - Negative words" Score vs. Rating')
sns.scatterplot(x='words_score', y='Rating', hue='GENDER',␣
↪data=training_merge_df.sample(10000));
```



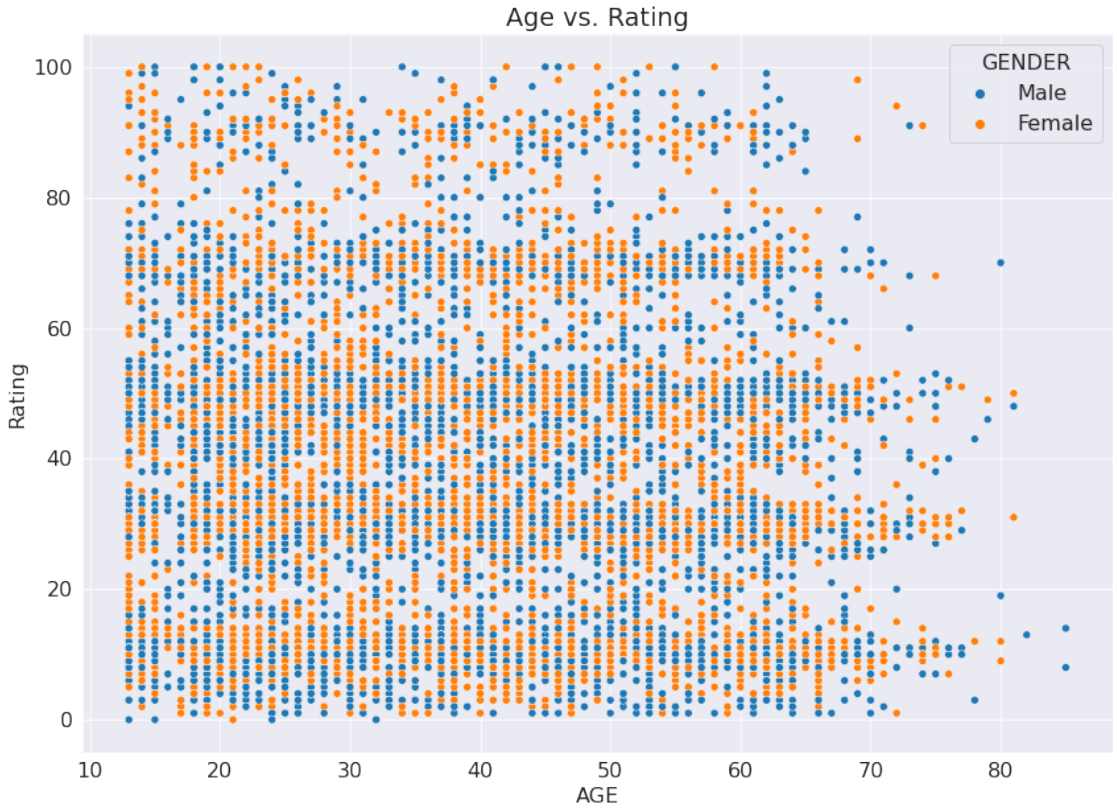
10 GENDER

[63]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Gender vs. Rating')
sns.barplot(x='GENDER', y='Rating', data=training_merge_df)
plt.xticks(rotation=340, ha='left')
plt.show();
```



11 AGE

[64]:
```
plt.title('Age vs. Rating')
sns.scatterplot(x='AGE', y='Rating', hue='GENDER', data=training_merge_df.
 ↪sample(10000));
```



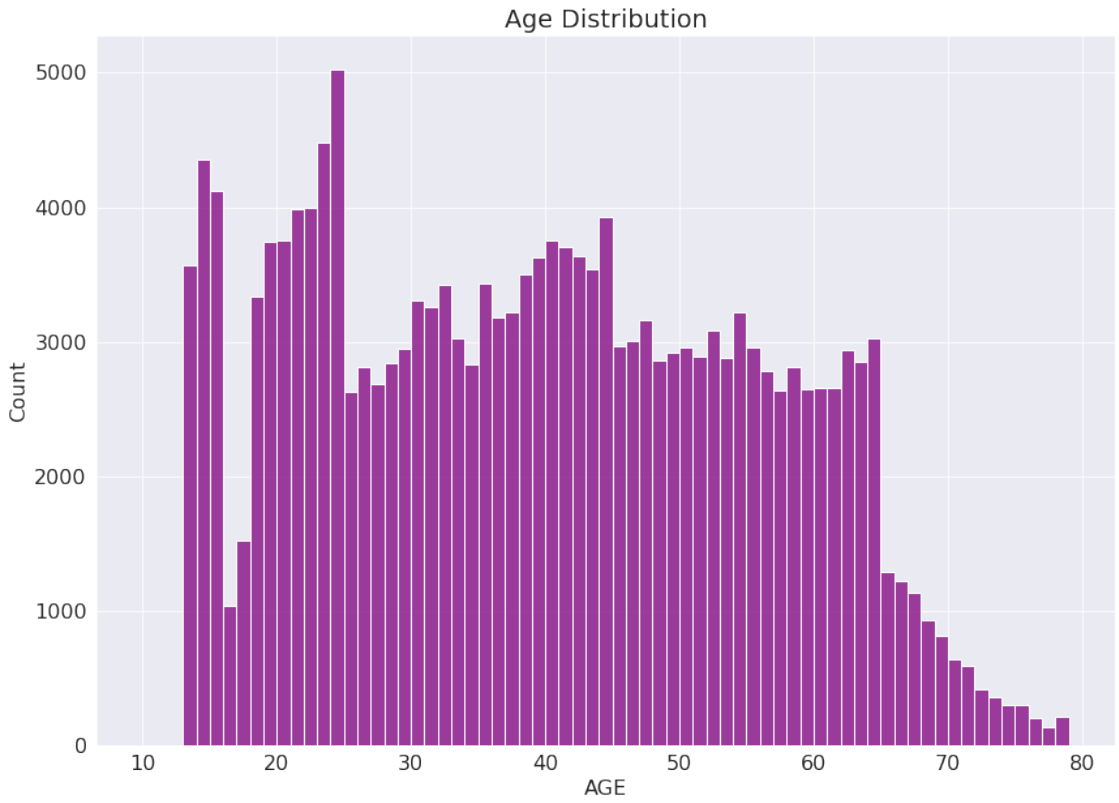
[65]:
```
training_merge_df['AGE'].describe()
```

[65]:
```
count    174982.000000
mean         39.246923
std          16.035515
min          13.000000
25%          25.000000
50%          39.000000
75%          52.000000
max          94.000000
Name: AGE, dtype: float64
```

[66]:
```
print('Nan cells in the training_merge_df table {}'.
 ↪format(training_merge_df['AGE'].isna().sum()))
```

```
Nan cells in the training_merge_df table 13708
```

[67]:
```
plt.title('Age Distribution')
sns.histplot(training_merge_df.AGE, bins=np.arange(10,80,1), color='purple');
```



[68]:
```
training_merge_df[training_merge_df['AGE'] > 50].AGE.count()
```

[68]: 48897

[69]:
```
def age_to_categorical(x):
  try:
    if int(x) <= 17:
      return '13-17'
    elif 17< int(x) <= 25:
      return '18-25'
    elif 25< int(x) <= 35:
      return '26-35'
    elif 35< int(x) <= 50:
      return '36-50'
    elif 50< int(x) <= 65:
      return '51-65'
    else:
      return 'older than 65'
  except:
    return np.nan
```

[70]:
```
training_merge_df['AGE_GROUP'] = training_merge_df['AGE'].apply(lambda x:␣
↪age_to_categorical(x))
```

[71]:
```
training_merge_df['AGE_GROUP'].value_counts()
```

[71]:
```
36-50            49963
51-65            41315
18-25            30944
26-35            30573
13-17            14605
older than 65     7582
Name: AGE_GROUP, dtype: int64
```

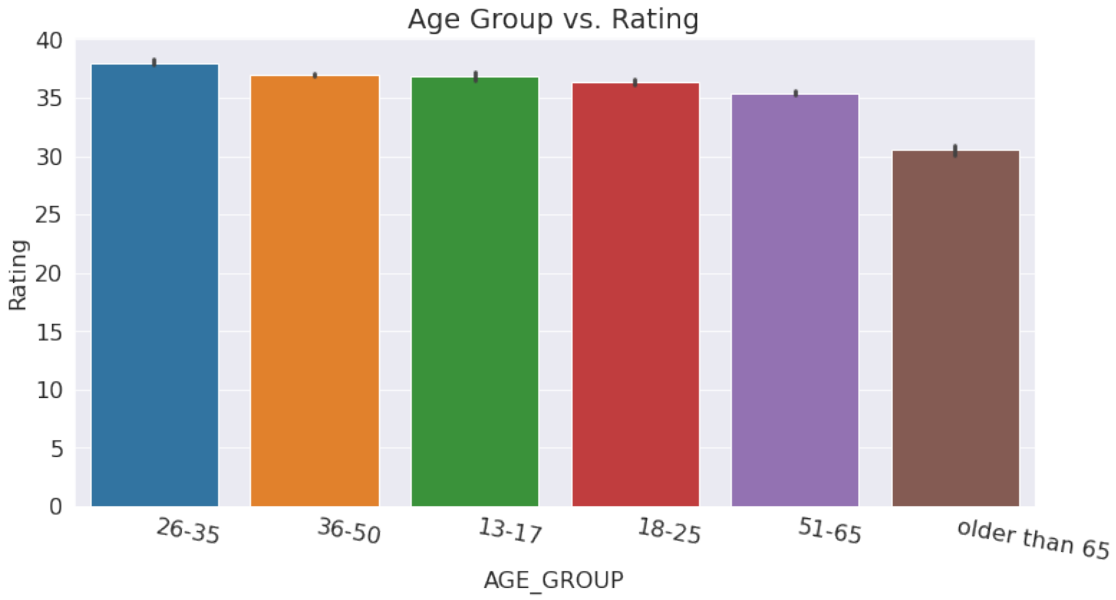
[72]:
```
training_merge_df['AGE_GROUP'].fillna('36-50', inplace=True)
training_merge_df['AGE'].fillna(39, inplace=True)
```

Test DataFrame

[73]:
```
test_merge_df['AGE_GROUP'] = test_merge_df['AGE'].apply(lambda x:␣
↪age_to_categorical(x))
test_merge_df['AGE_GROUP'].fillna('36-50', inplace=True)
test_merge_df['AGE'].fillna(39, inplace=True)
```

[74]:
```
plot_order= training_merge_df.groupby('AGE_GROUP')['Rating'].mean().
↪sort_values(ascending=False).index.values
```

[75]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Age Group vs. Rating')
sns.barplot(x='AGE_GROUP', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=350, ha='left')
plt.show();
```



12 Working

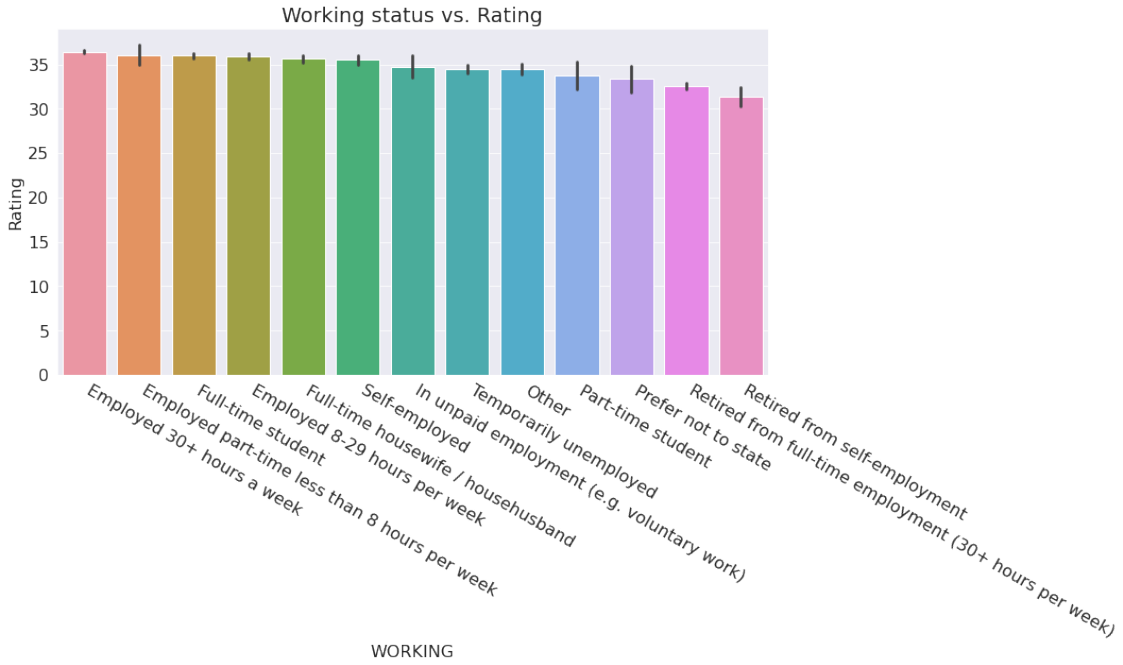
[76]:
```
training_merge_df['WORKING'].value_counts()
```

[76]:
```
Employed 30+ hours a week                                53347
Full-time student                                        20244
Employed 8-29 hours per week                             16284
Retired from full-time employment (30+ hours per week)   13234
Full-time housewife / househusband                       10367
Self-employed                                             7629
Temporarily unemployed                                    7528
Other                                                     5725
Retired from self-employment                              1480
Employed part-time less than 8 hours per week             1480
In unpaid employment (e.g. voluntary work)                1407
Prefer not to state                                        947
Part-time student                                          873
Name: WORKING, dtype: int64
```

[77]:
```
plot_order= training_merge_df.groupby('WORKING')['Rating'].mean().
 ↪sort_values(ascending=False).index.values
```

[78]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Working status vs. Rating')
sns.barplot(x='WORKING', y='Rating', data=training_merge_df, order=plot_order)
```

```
plt.xticks(rotation=330, ha='left')
plt.show();
```



13 Region

[79]:
```
training_merge_df['REGION'].unique()
```

[79]:
```
array(['North', 'Centre', 'Midlands', 'South', nan, 'Northern Ireland',
       'North Ireland'], dtype=object)
```

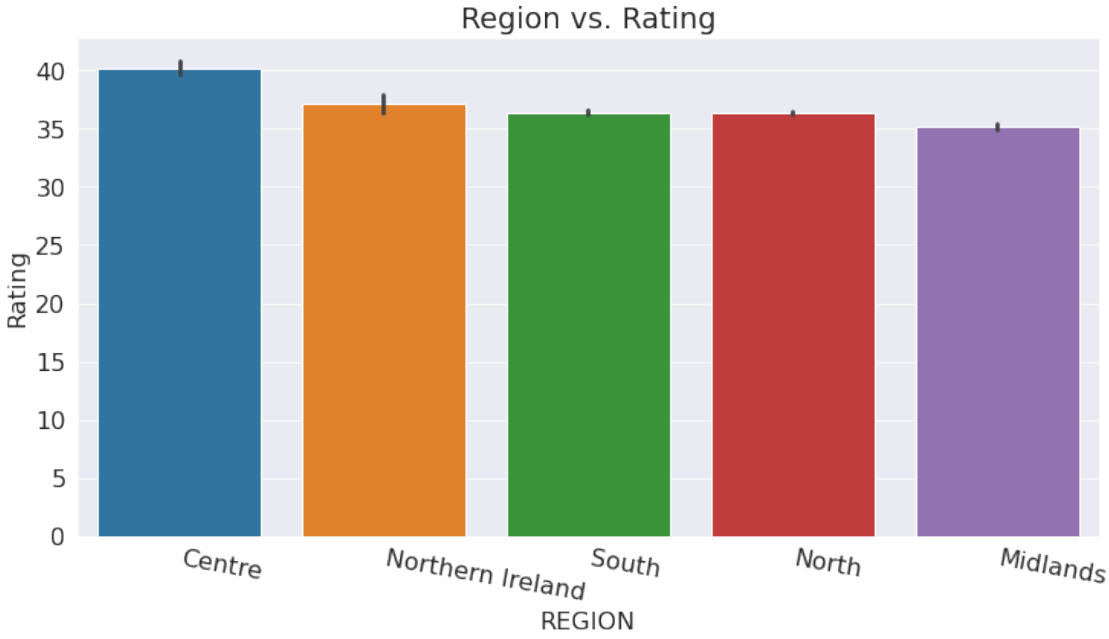
[80]:
```
training_merge_df['REGION'].value_counts()
```

[80]:
```
North              58707
South              54005
Midlands           44220
Centre              7284
Northern Ireland    2890
North Ireland        375
Name: REGION, dtype: int64
```

[81]:
```
training_merge_df['REGION'].replace(['North Ireland'], 'Northern Ireland',␣
↪inplace=True)
test_merge_df['REGION'].replace(['North Ireland'], 'Northern Ireland',␣
↪inplace=True)
```

[82]:
```
plot_order= training_merge_df.groupby('REGION')['Rating'].mean().
 ↪sort_values(ascending=False).index.values
```

[83]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Region vs. Rating')
sns.barplot(x='REGION', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=350, ha='left')
plt.show();
```



14 Music

[84]:
```
training_merge_df['MUSIC'].unique()
```

[84]:
```
array(['Music means a lot to me and is a passion of mine',
       'Music is important to me but not necessarily more important',
       'I like music but it does not feature heavily in my life',
       'Music is important to me but not necessarily more important than other
hobbies or interests',
       nan, 'Music has no particular interest for me',
       'Music is no longer as important as it used to be to me'],
      dtype=object)
```

[85]:
```
training_merge_df['MUSIC'].value_counts()
```

[85]:
```
Music is important to me but not necessarily more important
56695
Music means a lot to me and is a passion of mine
54793
I like music but it does not feature heavily in my life
43023
Music is important to me but not necessarily more important than other hobbies
or interests    12977
Music is no longer as important as it used to be to me
5702
Music has no particular interest for me
3643
Name: MUSIC, dtype: int64
```

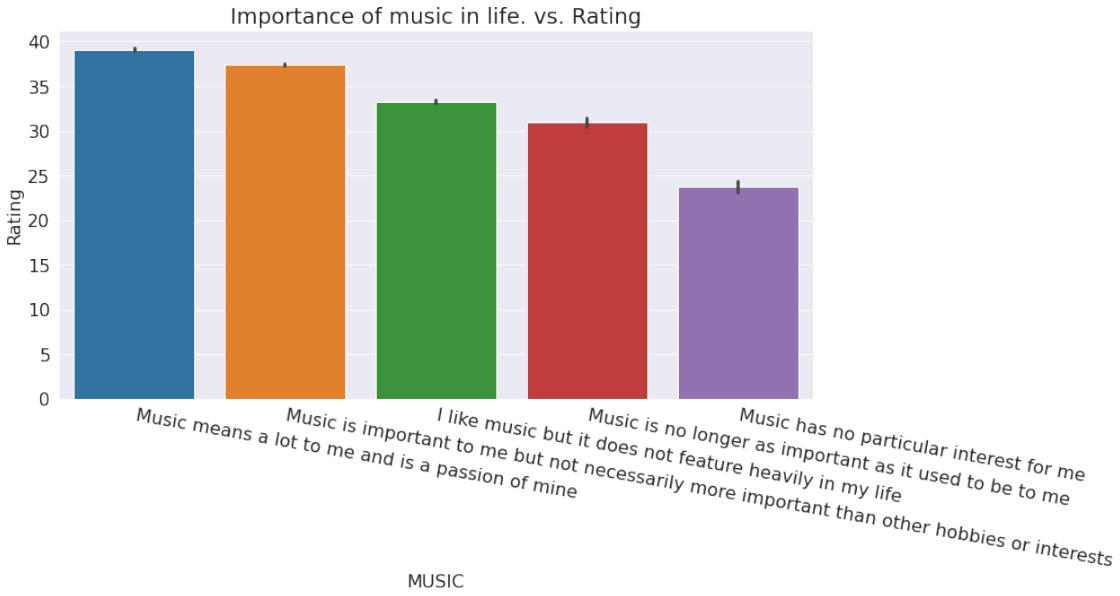
[86]:
```
training_merge_df['MUSIC'].replace(['Music is important to me but not␣
 ↪necessarily more important'], 'Music is important to me but not necessarily␣
 ↪more important than other hobbies or interests', inplace=True)
test_merge_df['MUSIC'].replace(['Music is important to me but not necessarily␣
 ↪more important'], 'Music is important to me but not necessarily more␣
 ↪important than other hobbies or interests', inplace=True)
```

[87]:
```
training_merge_df['MUSIC'].value_counts()
```

[87]:
```
Music is important to me but not necessarily more important than other hobbies
or interests    69672
Music means a lot to me and is a passion of mine
54793
I like music but it does not feature heavily in my life
43023
Music is no longer as important as it used to be to me
5702
Music has no particular interest for me
3643
Name: MUSIC, dtype: int64
```

[88]:
```
plot_order= training_merge_df.groupby('MUSIC')['Rating'].mean().
 ↪sort_values(ascending=False).index.values
```

[89]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('Importance of music in life. vs. Rating')
sns.barplot(x='MUSIC', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=350, ha='left')
plt.show();
```



15 List own

[90]:
```
training_merge_df['LIST_OWN'].unique()
```

[90]:
```
array(['3 hours', '1', '5 hours', '1 hour', 'Less than an hour',
       '0 Hours', nan, '2', '2 hours', '4 hours', '10 hours', '16+ hours',
       '0', '6 hours', '8 hours', '4', '3', '14 hours', '15 hours',
       '7 hours', '13 hours', '12 hours', '5', '6', '8', '10', '12',
       '9 hours', '7', '11 hours', '16 hours', '15', 'More than 16 hours',
       '20', '16', '9', '17', '14', '11', '18', '22', '24', '13'],
      dtype=object)
```

[91]:
```
training_merge_df['LIST_OWN'].value_counts()
```

[91]:
```
1 hour                29683
2 hours               27505
Less than an hour     26697
3 hours               13078
0 Hours               12367
1                      8801
4 hours                8116
2                      6937
5 hours                4430
3                      2959
0                      2792
6 hours                2744
16+ hours              1978
```

```
8 hours                1874
10 hours               1807
4                      1465
7 hours                1164
5                       940
12 hours                774
9 hours                 471
6                       361
11 hours                235
8                       234
15 hours                231
10                      217
14 hours                193
16 hours                130
7                       121
13 hours                106
12                       94
9                        40
15                       22
14                       20
16                       17
20                       13
More than 16 hours       13
17                        7
11                        6
22                        3
13                        3
24                        2
18                        1
Name: LIST_OWN, dtype: int64
```

[92]:
```
training_merge_df['LIST_OWN'].isna().sum()
```

[92]:
```
30039
```

[93]:
```
training_merge_df['LIST_OWN'].replace(['0 Hours'], '0', inplace=True)
training_merge_df['LIST_OWN'].replace(['Less than an hour'], '0.5',␣
 ↪inplace=True)
training_merge_df['LIST_OWN'].replace(['1 hour'], '1', inplace=True)
training_merge_df['LIST_OWN'].replace(['2 hours'], '2', inplace=True)
training_merge_df['LIST_OWN'].replace(['3 hours'], '3', inplace=True)
training_merge_df['LIST_OWN'].replace(['4 hours'], '4', inplace=True)
training_merge_df['LIST_OWN'].replace(['5 hours'], '5', inplace=True)
training_merge_df['LIST_OWN'].replace(['6 hours'], '6', inplace=True)
training_merge_df['LIST_OWN'].replace(['7 hours'], '7', inplace=True)
training_merge_df['LIST_OWN'].replace(['8 hours'], '8', inplace=True)
training_merge_df['LIST_OWN'].replace(['9 hours'], '9', inplace=True)
```

```
training_merge_df['LIST_OWN'].replace(['10 hours'], '10', inplace=True)
training_merge_df['LIST_OWN'].replace(['11 hours'], '11', inplace=True)
training_merge_df['LIST_OWN'].replace(['12 hours'], '12', inplace=True)
training_merge_df['LIST_OWN'].replace(['13 hours'], '13', inplace=True)
training_merge_df['LIST_OWN'].replace(['14 hours'], '14', inplace=True)
training_merge_df['LIST_OWN'].replace(['15 hours'], '15', inplace=True)
training_merge_df['LIST_OWN'].replace(['16 hours'], '16', inplace=True)
training_merge_df['LIST_OWN'].replace(['16+ hours'], '16', inplace=True)
training_merge_df['LIST_OWN'].replace(['More than 16 hours'], '16',␣
↪inplace=True)
```

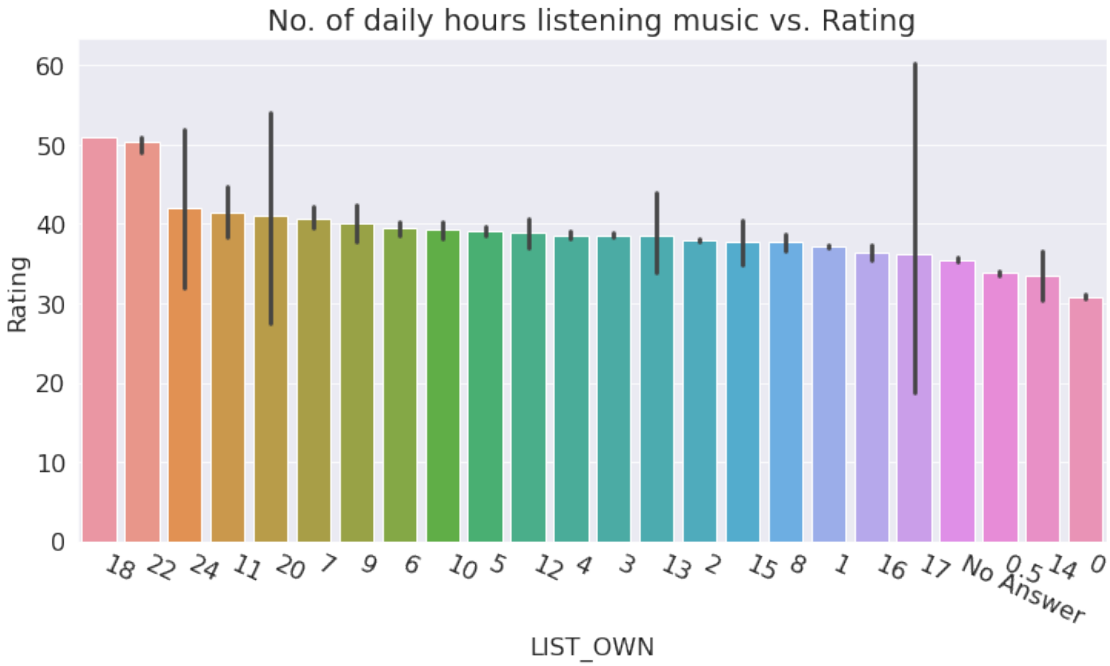
[94]:
```
training_merge_df['LIST_OWN'].fillna('No Answer', inplace=True)
```

Test DataFrame

[95]:
```
test_merge_df['LIST_OWN'].replace(['0 Hours'], '0', inplace=True)
test_merge_df['LIST_OWN'].replace(['Less than an hour'], '0.5', inplace=True)
test_merge_df['LIST_OWN'].replace(['1 hour'], '1', inplace=True)
test_merge_df['LIST_OWN'].replace(['2 hours'], '2', inplace=True)
test_merge_df['LIST_OWN'].replace(['3 hours'], '3', inplace=True)
test_merge_df['LIST_OWN'].replace(['4 hours'], '4', inplace=True)
test_merge_df['LIST_OWN'].replace(['5 hours'], '5', inplace=True)
test_merge_df['LIST_OWN'].replace(['6 hours'], '6', inplace=True)
test_merge_df['LIST_OWN'].replace(['7 hours'], '7', inplace=True)
test_merge_df['LIST_OWN'].replace(['8 hours'], '8', inplace=True)
test_merge_df['LIST_OWN'].replace(['9 hours'], '9', inplace=True)
test_merge_df['LIST_OWN'].replace(['10 hours'], '10', inplace=True)
test_merge_df['LIST_OWN'].replace(['11 hours'], '11', inplace=True)
test_merge_df['LIST_OWN'].replace(['12 hours'], '12', inplace=True)
test_merge_df['LIST_OWN'].replace(['13 hours'], '13', inplace=True)
test_merge_df['LIST_OWN'].replace(['14 hours'], '14', inplace=True)
test_merge_df['LIST_OWN'].replace(['15 hours'], '15', inplace=True)
test_merge_df['LIST_OWN'].replace(['16 hours'], '16', inplace=True)
test_merge_df['LIST_OWN'].replace(['16+ hours'], '16', inplace=True)
test_merge_df['LIST_OWN'].replace(['More than 16 hours'], '16', inplace=True)
test_merge_df['LIST_OWN'].fillna('No Answer', inplace=True)
```

[96]:
```
plot_order= training_merge_df.groupby('LIST_OWN')['Rating'].mean().
↪sort_values(ascending=False).index.values
```

[97]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('No. of daily hours listening music vs. Rating')
sns.barplot(x='LIST_OWN', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=335, ha='left')
plt.show();
```



[98]:
```
lo_mapper = {'No Answer': 'No Answer',
             '0': '0',
             '0.5': '0.5',
             '1': '1',
             '2': '2',
             '3': '3-6',
             '4': '3-6',
             '5': '3-6',
             '6': '3-6',
             '7': '7-10',
             '8': '7-10',
             '9': '7-10',
             '10': '7-10',
             '11': '11-14',
             '12':  '11-14',
             '13': '11-14',
             '14': '11-14',
             '15': '15-19',
             '16': '15-19',
             '17': '15-19',
             '18': '15-19',
             '19': '15-19',
             '20': '20 and plus',
             '21': '20 and plus',
             '22': '20 and plus',
```

```
          '23': '20 and plus',
          '24': '20 and plus'
          }
```

[99]:
```
training_merge_df['LIST_OWN'] = training_merge_df['LIST_OWN'].map(lo_mapper)
```

[100]:
```
training_merge_df['LIST_OWN'].unique()
```

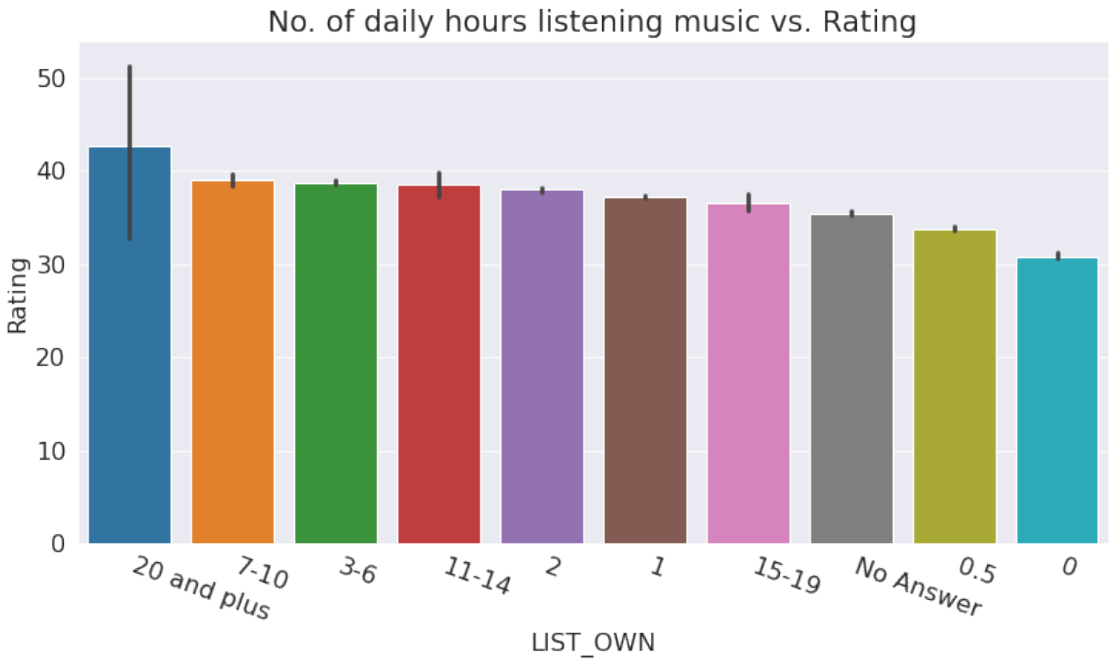
[100]:
```
array(['3-6', '1', '0.5', '0', 'No Answer', '2', '7-10', '15-19', '11-14',
       '20 and plus'], dtype=object)
```

[101]:
```
training_merge_df['LIST_OWN'].value_counts()
```

[101]:
```
1              38484
2              34442
3-6            34093
No Answer      30039
0.5            26697
0              15159
7-10            5928
15-19           2399
11-14           1431
20 and plus       18
Name: LIST_OWN, dtype: int64
```

[102]:
```
plot_order= training_merge_df.groupby('LIST_OWN')['Rating'].mean().
 ↪sort_values(ascending=False).index.values
```

[103]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('No. of daily hours listening music vs. Rating')
sns.barplot(x='LIST_OWN', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=340, ha='left')
plt.show();
```



[104]:
```
test_merge_df['LIST_OWN'] = test_merge_df['LIST_OWN'].map(lo_mapper)
```

16 List Back

[105]:
```
training_merge_df['LIST_BACK'].unique()
```

[105]:
```
array(['0 Hours', '2', nan, '3 hours', 'Less than an hour', '4 hours',
       '8 hours', '5 hours', '4', '3', '1 hour', '2 hours', '5', '1',
       '6 hours', '7 hours', 'More than 16 hours', '0', '9 hours', '6',
       '14 hours', '16+ hours', '8', '10 hours', '9', '16 hours',
       '15 hours', '12', '12 hours', '10', '20', '18', '11 hours',
       '13 hours', '7', '14', '15', '19', '24', '16', '11', '21'],
      dtype=object)
```

[106]:
```
training_merge_df['LIST_BACK'].value_counts()
```

[106]:
```
2 hours               24663
1 hour                23409
Less than an hour     22232
3 hours               13679
0 Hours               10565
4 hours               10492
1                      6856
5 hours                6170
2                      6027
```

```
6 hours                5099
8 hours                4473
3                      3097
16+ hours              2890
0                      2768
7 hours                2572
10 hours               2544
4                      2284
5                      1587
9 hours                1200
12 hours               1171
6                      1119
8                      1013
7                       498
14 hours                369
11 hours                334
15 hours                325
10                      319
16 hours                278
12                      213
13 hours                213
9                       189
20                       36
More than 16 hours       23
15                       17
14                       14
19                       11
24                       11
16                       11
11                       10
18                        8
21                        1
Name: LIST_BACK, dtype: int64
```

[107]:
```
training_merge_df['LIST_BACK'].replace(['0 Hours'], '0', inplace=True)
training_merge_df['LIST_BACK'].replace(['Less than an hour'], '0.5',␣
 ↪inplace=True)
training_merge_df['LIST_BACK'].replace(['1 hour'], '1', inplace=True)
training_merge_df['LIST_BACK'].replace(['2 hours'], '2', inplace=True)
training_merge_df['LIST_BACK'].replace(['3 hours'], '3', inplace=True)
training_merge_df['LIST_BACK'].replace(['4 hours'], '4', inplace=True)
training_merge_df['LIST_BACK'].replace(['5 hours'], '5', inplace=True)
training_merge_df['LIST_BACK'].replace(['6 hours'], '6', inplace=True)
training_merge_df['LIST_BACK'].replace(['7 hours'], '7', inplace=True)
training_merge_df['LIST_BACK'].replace(['8 hours'], '8', inplace=True)
training_merge_df['LIST_BACK'].replace(['9 hours'], '9', inplace=True)
training_merge_df['LIST_BACK'].replace(['10 hours'], '10', inplace=True)
```

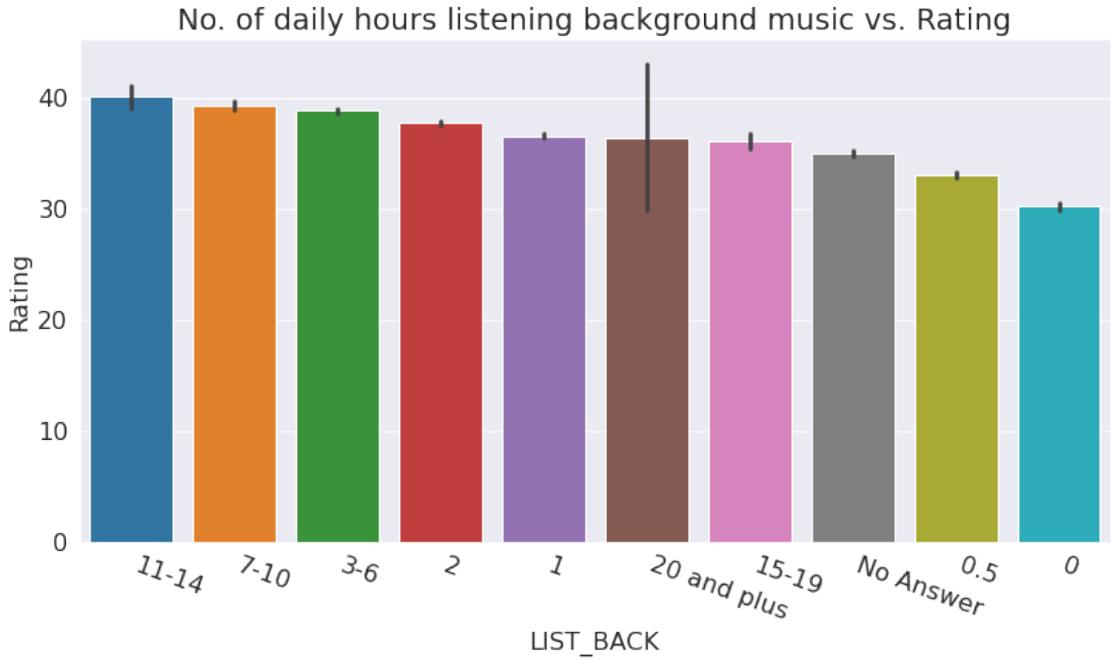
```
training_merge_df['LIST_BACK'].replace(['11 hours'], '11', inplace=True)
training_merge_df['LIST_BACK'].replace(['12 hours'], '12', inplace=True)
training_merge_df['LIST_BACK'].replace(['13 hours'], '13', inplace=True)
training_merge_df['LIST_BACK'].replace(['14 hours'], '14', inplace=True)
training_merge_df['LIST_BACK'].replace(['15 hours'], '15', inplace=True)
training_merge_df['LIST_BACK'].replace(['16 hours'], '16', inplace=True)
training_merge_df['LIST_BACK'].replace(['16+ hours'], '16', inplace=True)
training_merge_df['LIST_BACK'].replace(['More than 16 hours'], '16',␣
↪inplace=True)
```

[108]:
```
training_merge_df['LIST_BACK'].fillna('No Answer', inplace=True)
```

[109]:
```
training_merge_df['LIST_BACK'] = training_merge_df['LIST_BACK'].map(lo_mapper)
```

[110]:
```
plot_order= training_merge_df.groupby('LIST_BACK')['Rating'].mean().
↪sort_values(ascending=False).index.values
```

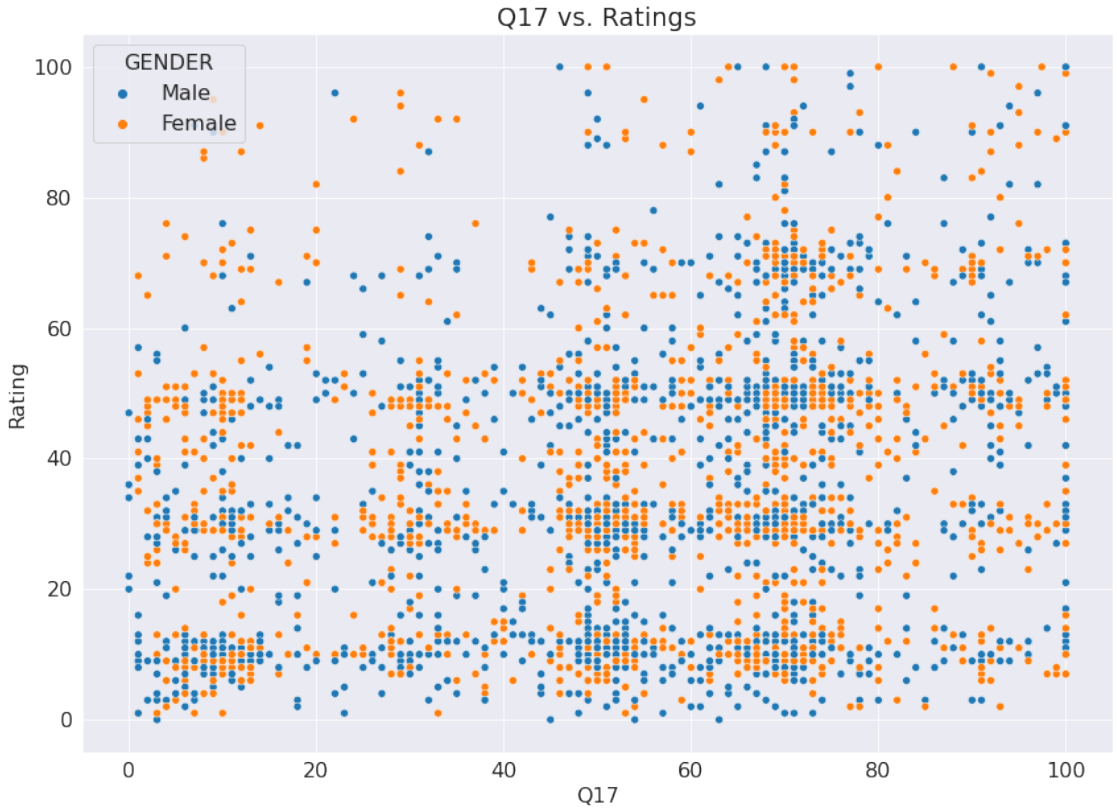
[111]:
```
fig, ax = plt.subplots(figsize=(12,6))

plt.title('No. of daily hours listening background music vs. Rating')
sns.barplot(x='LIST_BACK', y='Rating', data=training_merge_df, order=plot_order)
plt.xticks(rotation=340, ha='left')
plt.show();
```



17 Test DataFrame

[112]:
```
test_merge_df['LIST_BACK'].replace(['0 Hours'], '0', inplace=True)
test_merge_df['LIST_BACK'].replace(['Less than an hour'], '0.5', inplace=True)
test_merge_df['LIST_BACK'].replace(['1 hour'], '1', inplace=True)
test_merge_df['LIST_BACK'].replace(['2 hours'], '2', inplace=True)
test_merge_df['LIST_BACK'].replace(['3 hours'], '3', inplace=True)
test_merge_df['LIST_BACK'].replace(['4 hours'], '4', inplace=True)
test_merge_df['LIST_BACK'].replace(['5 hours'], '5', inplace=True)
test_merge_df['LIST_BACK'].replace(['6 hours'], '6', inplace=True)
test_merge_df['LIST_BACK'].replace(['7 hours'], '7', inplace=True)
test_merge_df['LIST_BACK'].replace(['8 hours'], '8', inplace=True)
test_merge_df['LIST_BACK'].replace(['9 hours'], '9', inplace=True)
test_merge_df['LIST_BACK'].replace(['10 hours'], '10', inplace=True)
test_merge_df['LIST_BACK'].replace(['11 hours'], '11', inplace=True)
test_merge_df['LIST_BACK'].replace(['12 hours'], '12', inplace=True)
test_merge_df['LIST_BACK'].replace(['13 hours'], '13', inplace=True)
test_merge_df['LIST_BACK'].replace(['14 hours'], '14', inplace=True)
test_merge_df['LIST_BACK'].replace(['15 hours'], '15', inplace=True)
test_merge_df['LIST_BACK'].replace(['16 hours'], '16', inplace=True)
test_merge_df['LIST_BACK'].replace(['16+ hours'], '16', inplace=True)
test_merge_df['LIST_BACK'].replace(['More than 16 hours'], '16', inplace=True)
test_merge_df['LIST_BACK'].fillna('No Answer', inplace=True)

test_merge_df['LIST_BACK'] = test_merge_df['LIST_BACK'].map(lo_mapper)
```

[113]:
```
plt.title('Q17 vs. Ratings')
sns.scatterplot(x='Q17', y='Rating', hue='GENDER', data=training_merge_df.
 ↪sample(3000));
```



[114]:
```
training_merge_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 188690 entries, 0 to 188689
Data columns (total 36 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Artist            188690 non-null  int64
 1   Track             188690 non-null  int64
 2   User              188690 non-null  int64
 3   Rating            188690 non-null  int64
 4   Time              188690 non-null  int64
 5   HEARD_OF          188690 non-null  object
 6   OWN_ARTIST_MUSIC  188690 non-null  object
 7   LIKE_ARTIST       55028 non-null   float64
 8   words_score       186636 non-null  float64
 9   GENDER            176833 non-null  object
 10  AGE               188690 non-null  float64
 11  WORKING           140545 non-null  object
 12  REGION            167481 non-null  object
 13  MUSIC             176833 non-null  object
 14  LIST_OWN          188690 non-null  object
```

```
 15  LIST_BACK         188690 non-null  object
 16  Q1                176833 non-null  float64
 17  Q2                176833 non-null  float64
 18  Q3                176833 non-null  float64
 19  Q4                176833 non-null  float64
 20  Q5                176833 non-null  float64
 21  Q6                176833 non-null  float64
 22  Q7                176833 non-null  float64
 23  Q8                176833 non-null  float64
 24  Q9                176833 non-null  float64
 25  Q10               176833 non-null  float64
 26  Q11               176833 non-null  float64
 27  Q12               176833 non-null  float64
 28  Q13               176833 non-null  float64
 29  Q14               176833 non-null  float64
 30  Q15               176833 non-null  float64
 31  Q16               142754 non-null  float64
 32  Q17               176833 non-null  float64
 33  Q18               140545 non-null  float64
 34  Q19               140545 non-null  float64
 35  AGE_GROUP         188690 non-null  object
dtypes: float64(22), int64(5), object(9)
memory usage: 57.3+ MB
```

18 HEARD_OF

[115]:
```
mapper = {'Heard of and listened to music RECENTLY': 4,
          'Heard of and listened to music EVER': 3,
          'Heard of': 2,
          'Never heard of': 1}
```

[116]:
```
training_merge_df['HEARD_OF'] = training_merge_df['HEARD_OF'].map(mapper)
```

Test DataFrame

[117]:
```
test_merge_df['HEARD_OF'] = test_merge_df['HEARD_OF'].map(mapper)
```

[118]:
```
training_merge_df['HEARD_OF'].unique()
```

[118]:
```
array([1, 3, 2, 4])
```

[119]:
```
training_merge_df['HEARD_OF'].value_counts()
```

[119]:
```
1    98169
2    35493
3    34990
4    20038
```

```
Name: HEARD_OF, dtype: int64
```

19 Own Art Music

[120]:
```
oam_mapper = {'Own all or most of their music': 4,
              'Own a lot of their music': 3,
              'Own a little of their music': 2,
              'Own none of their music': 1}
```

[121]:
```
training_merge_df['OWN_ARTIST_MUSIC'] = training_merge_df['OWN_ARTIST_MUSIC'].
↪map(oam_mapper)
```

Test DataFrame

[122]:
```
test_merge_df['OWN_ARTIST_MUSIC'] = test_merge_df['OWN_ARTIST_MUSIC'].
↪map(oam_mapper)
```

[123]:
```
training_merge_df['OWN_ARTIST_MUSIC'].unique()
```

[123]:
```
array([1, 2, 4, 3])
```

[124]:
```
training_merge_df['OWN_ARTIST_MUSIC'].value_counts()
```

[124]:
```
1    160113
2     18721
3      7263
4      2593
Name: OWN_ARTIST_MUSIC, dtype: int64
```

20 Like Artist

[125]:
```
training_merge_df['LIKE_ARTIST'].isna().sum()
```

[125]:
```
133662
```

[126]:
```
def to_categorical(x):
  try:
    if 1<= int(x) <= 10:
      return '1-10'
    elif 11<= int(x) <= 20:
      return '11-20'
    elif 21<= int(x) <= 30:
      return '21-30'
    elif 31<= int(x) <= 40:
      return '31-40'
    elif 41<= int(x) <= 50:
```

```
      return '41-50'
    elif 51<= int(x) <= 60:
      return '51-60'
    elif 61<= int(x) <= 70:
      return '61-70'
    elif 71<= int(x) <= 80:
      return '71-80'
    elif 81<= int(x) <= 90:
      return '81-90'
    else:
      return '91-100'
  except:
    return np.nan
```

[127]:
```
training_merge_df['LIKE_ARTIST'] = training_merge_df['LIKE_ARTIST'].
↪apply(lambda x: to_categorical(x))

test_merge_df['LIKE_ARTIST'] = test_merge_df['LIKE_ARTIST'].apply(lambda x:␣
↪to_categorical(x))
```

[128]:
```
training_merge_df['LIKE_ARTIST'].fillna('No Answer', inplace=True)

test_merge_df['LIKE_ARTIST'].fillna('No Answer', inplace=True)
```

[129]:
```
training_merge_df['LIKE_ARTIST'].value_counts()
```

[129]:
```
No Answer    133662
41-50         11114
21-30          8804
51-60          8244
31-40          6574
61-70          6415
71-80          4976
1-10           2825
91-100         2269
11-20          2126
81-90          1681
Name: LIKE_ARTIST, dtype: int64
```

21 Music

[130]:
```
training_merge_df['MUSIC'].unique()
```

[130]:
```
array(['Music means a lot to me and is a passion of mine',
       'Music is important to me but not necessarily more important than other
hobbies or interests',
```

```
       'I like music but it does not feature heavily in my life', nan,
       'Music has no particular interest for me',
       'Music is no longer as important as it used to be to me'],
      dtype=object)
```

[131]:
```
training_merge_df['MUSIC'].value_counts()
```

[131]:
```
Music is important to me but not necessarily more important than other hobbies
or interests    69672
Music means a lot to me and is a passion of mine
54793
I like music but it does not feature heavily in my life
43023
Music is no longer as important as it used to be to me
5702
Music has no particular interest for me
3643
Name: MUSIC, dtype: int64
```

[132]:
```
m_mapper = {'Music means a lot to me and is a passion of mine': 6,
          'Music is important to me but not necessarily more important than␣
 ↪other hobbies or interests': 5,
          'No Answer': 4,
          'I like music but it does not feature heavily in my life': 3,
          'Music is no longer as important as it used to be to me': 2,
          'Music has no particular interest for me': 1,
          }
```

[133]:
```
training_merge_df['MUSIC'] = training_merge_df['MUSIC'].map(m_mapper)
```

Test DataFrame

[134]:
```
test_merge_df['MUSIC'] = test_merge_df['MUSIC'].map(m_mapper)
```

#Missing Values in DF

[135]:
```
training_merge_df['GENDER'].fillna('No Answer', inplace=True)
training_merge_df['WORKING'].fillna('No Answer', inplace=True)
training_merge_df['REGION'].fillna('No Answer', inplace=True)

test_merge_df['GENDER'].fillna('No Answer', inplace=True)
test_merge_df['WORKING'].fillna('No Answer', inplace=True)
test_merge_df['REGION'].fillna('No Answer', inplace=True)
```

#Training & Validation Sets

21.0.1 As test set is already given.

We put 20% of Training test into calidation set.

[136]:
```
from sklearn.model_selection import train_test_split
```

[137]:
```
training_df, validation_df = train_test_split(training_merge_df, test_size=0.2)
```

[138]:
```
print('training_df.shape :', training_df.shape)
print('validation_df.shape :', validation_df.shape)
```

```
training_df.shape : (150952, 36)
validation_df.shape : (37738, 36)
```

[139]:
```
training_df
```

[139]:

	Artist	Track	User	Rating	Time	HEARD_OF	OWN_ARTIST_MUSIC	\
168265	35	88	30594	69	23	1	1	
186415	15	41	16939	30	9	2	1	
186064	48	172	47900	28	17	1	1	
38552	26	63	23658	79	22	1	1	
149111	23	57	21142	28	21	1	1	
…	…	…	…	…	…	…	…	
31991	45	163	45329	31	16	3	1	
25672	16	134	34029	13	12	1	1	
81988	6	14	5979	68	7	1	1	
97594	15	33	13060	14	19	1	1	
53332	28	72	23225	31	22	1	1	

	LIKE_ARTIST	words_score	GENDER	AGE	\
168265	No Answer	-1.0	Female	37.0	
186415	No Answer	2.0	Male	21.0	
186064	No Answer	3.0	Male	34.0	
38552	No Answer	11.0	No Answer	39.0	
149111	No Answer	-3.0	Female	47.0	
…	…	…	…	…	
31991	21-30	0.0	Male	63.0	
25672	No Answer	0.0	Female	63.0	
81988	No Answer	3.0	Male	34.0	
97594	No Answer	-2.0	Male	53.0	
53332	No Answer	-2.0	No Answer	39.0	

	WORKING	REGION	MUSIC	\
168265	Full-time housewife / househusband	Midlands	3.0	
186415	Full-time student	South	6.0	
186064	Employed 30+ hours a week	South	5.0	
38552	No Answer	No Answer	NaN	
149111	Employed 8-29 hours per week	Midlands	6.0	

```
…                                                    …        …    …
31991                                      Self-employed      North    5.0
25672   Retired from full-time employment (30+ hours p…      North    3.0
81988                                          No Answer      North    6.0
97594                          Employed 30+ hours a week      North    3.0
53332                                          No Answer  No Answer    NaN

         LIST_OWN  LIST_BACK    Q1     Q2    Q3    Q4    Q5    Q6    Q7    Q8  \
168265          1          1  53.0  100.0  35.0  12.0  12.0  36.0  14.0  14.0
186415          2        3-6  79.0   73.0  84.0  57.0  35.0  16.0  28.0  21.0
186064        0.5          0  35.0   47.0  35.0  48.0  33.0   3.0  35.0  29.0
38552   No Answer  No Answer   NaN    NaN   NaN   NaN   NaN   NaN   NaN   NaN
149111          2        3-6  58.0   62.0  55.0  30.0  29.0  51.0  25.0  20.0
…             …        …    …     …    …   …   …   …   …   …
31991           0          0  50.0   50.0  11.0  11.0  51.0  94.0   9.0   9.0
25672         0.5       7-10  10.0   49.0  48.0  48.0  48.0  46.0  71.0  72.0
81988         3-6        3-6  47.0   46.0  48.0  47.0  48.0  48.0  48.0  49.0
97594           1        0.5  14.0   47.0  12.0  34.0  69.0   8.0   6.0   5.0
53332   No Answer  No Answer   NaN    NaN   NaN   NaN   NaN   NaN   NaN   NaN

          Q9   Q10   Q11   Q12    Q13   Q14   Q15   Q16    Q17   Q18   Q19  \
168265  50.0  68.0  65.0  51.0  100.0  86.0   4.0   NaN  100.0   4.0  52.0
186415  44.0  67.0  73.0  62.0   88.0  67.0  48.0  70.0   69.0  60.0  30.0
186064  72.0  60.0  51.0  53.0   41.0  45.0   6.0   3.0   48.0  34.0  33.0
38552    NaN   NaN   NaN   NaN    NaN   NaN   NaN   NaN    NaN   NaN   NaN
149111  51.0  99.0  67.0  69.0   46.0  46.0  43.0  20.0   86.0  22.0  34.0
…       …   …   …   …    …   …   …   …    …   …   …
31991   70.0  10.0  34.0  10.0   10.0  11.0  11.0  13.0   55.0  10.0  11.0
25672   71.0  46.0  48.0  51.0   51.0  31.0  96.0   7.0   51.0   8.0   9.0
81988   55.0  54.0  55.0  54.0   53.0  54.0  53.0  55.0   55.0   NaN   NaN
97594   75.0  52.0  57.0  21.0   15.0  27.0  11.0  14.0   75.0  18.0  13.0
53332    NaN   NaN   NaN   NaN    NaN   NaN   NaN   NaN    NaN   NaN   NaN

       AGE_GROUP
168265     36-50
186415     18-25
186064     26-35
38552      36-50
149111     36-50
…          …
31991      51-65
25672      51-65
81988      26-35
97594      51-65
53332      36-50

[150952 rows x 36 columns]
```

[140]:
```
validation_df
```

[140]:

	Artist	Track	User	Rating	Time	HEARD_OF	OWN_ARTIST_MUSIC	\
109566	4	11	5357	74	18	2	1	
49742	20	44	17177	53	21	1	1	
92733	28	73	23226	49	22	3	2	
38465	22	122	32594	54	0	4	2	
20298	31	79	26606	12	11	1	1	
…	…	…	…	…	…	…	…	
84579	26	64	22187	31	22	1	1	
47851	10	145	35978	9	12	3	1	
165143	37	97	30961	46	23	4	2	
51210	46	168	44138	11	16	3	1	
116670	46	165	44448	30	16	1	1	

	LIKE_ARTIST	words_score	GENDER	AGE	\
109566	No Answer	7.0	Male	55.0	
49742	No Answer	7.0	Male	15.0	
92733	41-50	2.0	No Answer	39.0	
38465	91-100	21.0	Male	54.0	
20298	No Answer	-3.0	Male	56.0	
…	…	…	…	…	
84579	No Answer	5.0	Female	39.0	
47851	11-20	-1.0	Male	22.0	
165143	71-80	5.0	Female	14.0	
51210	21-30	0.0	Male	41.0	
116670	No Answer	3.0	Female	42.0	

	WORKING	REGION	MUSIC	LIST_OWN	LIST_BACK	\
109566	Employed 30+ hours a week	Midlands	5.0	1	3-6	
49742	Full-time student	South	5.0	1	2	
92733	No Answer	No Answer	NaN	No Answer	No Answer	
38465	No Answer	No Answer	5.0	1	7-10	
20298	Employed 30+ hours a week	South	5.0	1	3-6	
…	…	…	…	…	…	
84579	Employed 30+ hours a week	South	6.0	3-6	7-10	
47851	Full-time student	North	5.0	1	0.5	
165143	Self-employed	South	6.0	3-6	3-6	
51210	Employed 30+ hours a week	Midlands	6.0	3-6	7-10	
116670	Employed 8-29 hours per week	South	3.0	0.5	3-6	

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	\
109566	31.0	86.0	54.0	26.0	4.0	5.0	4.0	3.0	55.0	88.0	89.0	
49742	29.0	28.0	17.0	44.0	45.0	65.0	43.0	31.0	31.0	32.0	64.0	
92733	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
38465	53.0	54.0	55.0	55.0	69.0	37.0	67.0	65.0	56.0	32.0	57.0	
20298	15.0	14.0	14.0	11.0	13.0	13.0	14.0	12.0	51.0	51.0	92.0	

```
…       …    …    …    …    …    …    …    …    …    …    …
84579    79.0  83.0  79.0  35.0   6.0   3.0   5.0  55.0   6.0  100.0   57.0
47851   100.0  49.0  49.0  26.0  11.0  25.0  11.0  11.0  29.0   47.0  100.0
165143   85.0  76.0  74.0  87.0  66.0  48.0  57.0  44.0  22.0   66.0   72.0
51210    52.0  64.0  46.0  69.0  40.0  95.0  19.0  21.0  20.0   67.0   49.0
116670   30.0  52.0  30.0  30.0  29.0  31.0  53.0  28.0  29.0   30.0   70.0

          Q12    Q13    Q14   Q15    Q16   Q17   Q18   Q19 AGE_GROUP
109566   63.0    4.0   51.0  51.0  100.0  55.0  72.0   7.0     51-65
49742    61.0   44.0   61.0  22.0   29.0  49.0  50.0  27.0     13-17
92733     NaN    NaN    NaN   NaN    NaN   NaN   NaN   NaN     36-50
38465    56.0   55.0   54.0  69.0   32.0  54.0   NaN   NaN     51-65
20298    92.0   53.0   53.0  10.0   12.0  14.0  12.0  12.0     51-65
…       …    …    …    …    …    …    …    …       …
84579    54.0   62.0   59.0  56.0    NaN  72.0  65.0  56.0     36-50
47851   100.0  100.0  100.0   9.0   30.0  52.0  29.0  29.0     18-25
165143   64.0   52.0   88.0  85.0    NaN  79.0  77.0  76.0     13-17
51210    66.0   72.0   71.0  73.0    4.0  78.0  53.0  52.0     36-50
116670   69.0   31.0   51.0  30.0   30.0  70.0  30.0  30.0     36-50

[37738 rows x 36 columns]
```

22 Input and Target Col's

[141]:
```
input_cols = list(training_df.columns)
input_cols.remove('Rating')
input_cols.remove('AGE')

target_col = 'Rating'
```

[142]:
```
training_inputs = training_df[input_cols].copy()
training_targets = training_df[target_col].copy()
```

[143]:
```
validation_inputs = validation_df[input_cols].copy()
validation_targets = validation_df[target_col].copy()
```

[144]:
```
test_inputs = test_merge_df[input_cols].copy()
```

[145]:
```
training_inputs
```

[145]:
```
        Artist  Track   User  Time  HEARD_OF  OWN_ARTIST_MUSIC LIKE_ARTIST  \
168265      35     88  30594    23         1                 1   No Answer
186415      15     41  16939     9         2                 1   No Answer
186064      48    172  47900    17         1                 1   No Answer
38552       26     63  23658    22         1                 1   No Answer
149111      23     57  21142    21         1                 1   No Answer
```

```
…        …    …    …   …       …                 …          …
31991       45    163  45329    16         3                 1       21-30
25672       16    134  34029    12         1                 1   No Answer
81988        6     14   5979     7         1                 1   No Answer
97594       15     33  13060    19         1                 1   No Answer
53332       28     72  23225    22         1                 1   No Answer

        words_score     GENDER  \
168265         -1.0     Female
186415          2.0       Male
186064          3.0       Male
38552          11.0  No Answer
149111         -3.0     Female
…                 …        …
31991           0.0       Male
25672           0.0     Female
81988           3.0       Male
97594          -2.0       Male
53332          -2.0  No Answer

                                                  WORKING     REGION  MUSIC  \
168265                 Full-time housewife / househusband   Midlands    3.0
186415                                   Full-time student      South    6.0
186064                           Employed 30+ hours a week      South    5.0
38552                                          No Answer  No Answer    NaN
149111                       Employed 8-29 hours per week   Midlands    6.0
…                                                     …        …    …
31991                                      Self-employed      North    5.0
25672   Retired from full-time employment (30+ hours p…      North    3.0
81988                                          No Answer      North    6.0
97594                            Employed 30+ hours a week      North    3.0
53332                                          No Answer  No Answer    NaN

         LIST_OWN  LIST_BACK    Q1     Q2    Q3    Q4    Q5    Q6    Q7    Q8  \
168265          1          1  53.0  100.0  35.0  12.0  12.0  36.0  14.0  14.0
186415          2        3-6  79.0   73.0  84.0  57.0  35.0  16.0  28.0  21.0
186064        0.5          0  35.0   47.0  35.0  48.0  33.0   3.0  35.0  29.0
38552   No Answer  No Answer   NaN    NaN   NaN   NaN   NaN   NaN   NaN   NaN
149111          2        3-6  58.0   62.0  55.0  30.0  29.0  51.0  25.0  20.0
…             …          …    …      …     …     …     …     …     …     …
31991           0          0  50.0   50.0  11.0  11.0  51.0  94.0   9.0   9.0
25672         0.5       7-10  10.0   49.0  48.0  48.0  48.0  46.0  71.0  72.0
81988         3-6        3-6  47.0   46.0  48.0  47.0  48.0  48.0  48.0  49.0
97594           1        0.5  14.0   47.0  12.0  34.0  69.0   8.0   6.0   5.0
53332   No Answer  No Answer   NaN    NaN   NaN   NaN   NaN   NaN   NaN   NaN

          Q9   Q10   Q11   Q12    Q13   Q14   Q15   Q16    Q17   Q18   Q19  \
```

```
168265  50.0  68.0  65.0  51.0  100.0  86.0   4.0   NaN  100.0   4.0  52.0
186415  44.0  67.0  73.0  62.0   88.0  67.0  48.0  70.0   69.0  60.0  30.0
186064  72.0  60.0  51.0  53.0   41.0  45.0   6.0   3.0   48.0  34.0  33.0
38552    NaN   NaN   NaN   NaN    NaN   NaN   NaN   NaN    NaN   NaN   NaN
149111  51.0  99.0  67.0  69.0   46.0  46.0  43.0  20.0   86.0  22.0  34.0
…       …     …     …     …      …     …     …     …      …     …     …
31991   70.0  10.0  34.0  10.0   10.0  11.0  11.0  13.0   55.0  10.0  11.0
25672   71.0  46.0  48.0  51.0   51.0  31.0  96.0   7.0   51.0   8.0   9.0
81988   55.0  54.0  55.0  54.0   53.0  54.0  53.0  55.0   55.0   NaN   NaN
97594   75.0  52.0  57.0  21.0   15.0  27.0  11.0  14.0   75.0  18.0  13.0
53332    NaN   NaN   NaN   NaN    NaN   NaN   NaN   NaN    NaN   NaN   NaN

       AGE_GROUP
168265     36-50
186415     18-25
186064     26-35
38552      36-50
149111     36-50
…          …
31991      51-65
25672      51-65
81988      26-35
97594      51-65
53332      36-50

[150952 rows x 34 columns]
```

[146]:
```
validation_inputs
```

[146]:
```
        Artist  Track   User  Time  HEARD_OF  OWN_ARTIST_MUSIC LIKE_ARTIST  \
109566       4     11   5357    18         2                 1   No Answer
49742       20     44  17177    21         1                 1   No Answer
92733       28     73  23226    22         3                 2       41-50
38465       22    122  32594     0         4                 2      91-100
20298       31     79  26606    11         1                 1   No Answer
…          …     …     …     …        …                 …          …
84579       26     64  22187    22         1                 1   No Answer
47851       10    145  35978    12         3                 1       11-20
165143      37     97  30961    23         4                 2       71-80
51210       46    168  44138    16         3                 1       21-30
116670      46    165  44448    16         1                 1   No Answer

        words_score     GENDER                      WORKING     REGION  \
109566          7.0       Male  Employed 30+ hours a week   Midlands
49742           7.0       Male            Full-time student      South
92733           2.0  No Answer                    No Answer  No Answer
38465          21.0       Male                    No Answer  No Answer
```

```
20298          -3.0       Male     Employed 30+ hours a week      South
…               …          …                              …        …
84579           5.0     Female     Employed 30+ hours a week      South
47851          -1.0       Male               Full-time student      North
165143          5.0     Female                   Self-employed      South
51210           0.0       Male     Employed 30+ hours a week   Midlands
116670          3.0     Female  Employed 8-29 hours per week      South

        MUSIC   LIST_OWN  LIST_BACK     Q1    Q2    Q3    Q4    Q5    Q6  \
109566    5.0          1        3-6   31.0  86.0  54.0  26.0   4.0   5.0
49742     5.0          1          2   29.0  28.0  17.0  44.0  45.0  65.0
92733     NaN  No Answer  No Answer    NaN   NaN   NaN   NaN   NaN   NaN
38465     5.0          1       7-10   53.0  54.0  55.0  55.0  69.0  37.0
20298     5.0          1        3-6   15.0  14.0  14.0  11.0  13.0  13.0
…       …         …         …    …   …   …   …   …   …
84579     6.0        3-6       7-10   79.0  83.0  79.0  35.0   6.0   3.0
47851     5.0          1        0.5  100.0  49.0  49.0  26.0  11.0  25.0
165143    6.0        3-6        3-6   85.0  76.0  74.0  87.0  66.0  48.0
51210     6.0        3-6       7-10   52.0  64.0  46.0  69.0  40.0  95.0
116670    3.0        0.5        3-6   30.0  52.0  30.0  30.0  29.0  31.0

          Q7    Q8    Q9    Q10    Q11    Q12    Q13    Q14   Q15    Q16  \
109566   4.0   3.0  55.0   88.0   89.0   63.0    4.0   51.0  51.0  100.0
49742   43.0  31.0  31.0   32.0   64.0   61.0   44.0   61.0  22.0   29.0
92733    NaN   NaN   NaN    NaN    NaN    NaN    NaN    NaN   NaN    NaN
38465   67.0  65.0  56.0   32.0   57.0   56.0   55.0   54.0  69.0   32.0
20298   14.0  12.0  51.0   51.0   92.0   92.0   53.0   53.0  10.0   12.0
…       …   …   …    …    …    …    …    …   …    …
84579    5.0  55.0   6.0  100.0   57.0   54.0   62.0   59.0  56.0    NaN
47851   11.0  11.0  29.0   47.0  100.0  100.0  100.0  100.0   9.0   30.0
165143  57.0  44.0  22.0   66.0   72.0   64.0   52.0   88.0  85.0    NaN
51210   19.0  21.0  20.0   67.0   49.0   66.0   72.0   71.0  73.0    4.0
116670  53.0  28.0  29.0   30.0   70.0   69.0   31.0   51.0  30.0   30.0

          Q17   Q18   Q19 AGE_GROUP
109566   55.0  72.0   7.0     51-65
49742    49.0  50.0  27.0     13-17
92733     NaN   NaN   NaN     36-50
38465    54.0   NaN   NaN     51-65
20298    14.0  12.0  12.0     51-65
…       …   …   …       …
84579    72.0  65.0  56.0     36-50
47851    52.0  29.0  29.0     18-25
165143   79.0  77.0  76.0     13-17
51210    78.0  53.0  52.0     36-50
116670   70.0  30.0  30.0     36-50
```

[37738 rows x 34 columns]

[147]:
```
test_inputs
```

[147]:

	Artist	Track	User	Time	HEARD_OF	OWN_ARTIST_MUSIC	LIKE_ARTIST
0	1	6	3475	18	3	1	1-10
1	6	149	39210	15	1	1	No Answer
2	40	177	47861	17	1	1	No Answer
3	31	79	27413	11	1	1	No Answer
4	26	66	23232	22	1	1	No Answer
…	…	…	…	…	…	…	…
125789	14	95	30004	23	2	1	No Answer
125790	10	25	8186	7	1	1	No Answer
125791	40	146	38180	13	2	1	No Answer
125792	22	113	32918	0	3	1	41-50
125793	2	70	24231	22	1	1	No Answer

	words_score	GENDER	WORKING
0	2.0	Female	Employed 30+ hours a week
1	NaN	Male	Employed 30+ hours a week
2	-2.0	Female	Other
3	0.0	Female	Employed part-time less than 8 hours per week
4	0.0	No Answer	No Answer
…	…	…	…
125789	12.0	Male	Employed 30+ hours a week
125790	6.0	Male	No Answer
125791	3.0	Female	Full-time housewife / househusband
125792	2.0	Female	No Answer
125793	4.0	Male	Employed 30+ hours a week

	REGION	MUSIC	LIST_OWN	LIST_BACK	Q1	Q2	Q3	Q4	Q5
0	South	6.0	1	3-6	8.0	69.0	27.0	27.0	50.0
1	Midlands	5.0	1	1	81.0	67.0	94.0	61.0	53.0
2	Midlands	2.0	0.5	0.5	9.0	94.0	49.0	48.0	49.0
3	Midlands	3.0	1	1	53.0	38.0	51.0	53.0	53.0
4	No Answer	NaN	No Answer	No Answer	NaN	NaN	NaN	NaN	NaN
…	…	…	…	…	…	…	…	…	…
125789	Midlands	6.0	7-10	3-6	84.0	69.0	100.0	32.0	9.0
125790	North	3.0	No Answer	3-6	29.0	70.0	30.0	30.0	69.0
125791	Midlands	6.0	15-19	7-10	59.0	51.0	51.0	83.0	32.0
125792	No Answer	6.0	0	1	69.0	30.0	76.0	74.0	73.0
125793	North	5.0	1	3-6	15.0	68.0	51.0	51.0	51.0

	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16
0	27.0	26.0	8.0	51.0	50.0	66.0	49.0	20.0	7.0	8.0	9.0
1	32.0	41.0	42.0	36.0	76.0	70.0	76.0	58.0	61.0	66.0	51.0
2	8.0	13.0	56.0	92.0	92.0	55.0	57.0	11.0	57.0	10.0	11.0

```
3        53.0  33.0  51.0  47.0  33.0  41.0  45.0  49.0  49.0  49.0  49.0
4         NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
…         …     …     …     …     …     …     …     …     …     …     …
125789   28.0   9.0  12.0  50.0  75.0  68.0  72.0  64.0  70.0  75.0   NaN
125790   14.0  12.0  12.0  70.0  29.0  50.0  48.0  54.0  66.0  10.0  34.0
125791   43.0  14.0  41.0  71.0  58.0  36.0  43.0  81.0  63.0  45.0  65.0
125792   11.0  11.0  11.0  92.0  34.0  74.0  72.0  36.0  37.0   9.0   9.0
125793   71.0   2.0   2.0  94.0  65.0   2.0   3.0   3.0   3.0   3.0   NaN

          Q17   Q18   Q19 AGE_GROUP
0         7.0   4.0   8.0     36-50
1        75.0  70.0  72.0     26-35
2        91.0   7.0   9.0     51-65
3        35.0  52.0  52.0     18-25
4         NaN   NaN   NaN     36-50
…         …     …     …         …
125789   72.0  56.0  54.0     36-50
125790   70.0   NaN   NaN     36-50
125791   30.0  46.0  21.0     36-50
125792   64.0   NaN   NaN     36-50
125793   30.0   5.0   5.0     36-50

[125794 rows x 34 columns]
```

23 Segregation of Numeric and Catego... Cols

[148]:
```
numeric_cols = ['Artist', 'Track', 'User', 'Time', 'HEARD_OF',␣
↪'OWN_ARTIST_MUSIC', 'words_score', 'MUSIC', 'Q1',␣
↪'Q2','Q3','Q4','Q5','Q6','Q7','Q8','Q9','Q10','Q11','Q12','Q13','Q14','Q15','Q16','Q17','Q1

categorical_cols = ['LIKE_ARTIST', 'GENDER', 'WORKING', 'REGION', 'LIST_OWN',␣
↪'LIST_BACK', 'AGE_GROUP' ]
```

[149]:
```
training_inputs[numeric_cols].describe()
```

[149]:
```
              Artist          Track           User           Time  \
count  150952.000000  150952.000000  150952.000000  150952.000000
mean       22.206688      86.473912   26463.279082      15.656050
std        14.478913      55.988137   13628.240967       6.443697
min         0.000000       0.000000       0.000000       0.000000
25%        10.000000      36.000000   17700.000000      12.000000
50%        22.000000      80.000000   27805.000000      17.000000
75%        35.000000     142.000000   35924.000000      21.000000
max        49.000000     183.000000   50927.000000      23.000000

            HEARD_OF  OWN_ARTIST_MUSIC    words_score          MUSIC  \
```

count	150952.000000	150952.000000	149299.000000	141389.000000
mean	1.877252	1.217314	2.684285	4.643445
std	1.057053	0.573414	4.841826	1.333523
min	1.000000	1.000000	-16.000000	1.000000
25%	1.000000	1.000000	0.000000	3.000000
50%	1.000000	1.000000	2.000000	5.000000
75%	3.000000	1.000000	5.000000	6.000000
max	4.000000	4.000000	39.000000	6.000000

	Q1	Q2	Q3	Q4	\
count	141389.000000	141389.000000	141389.000000	141389.000000	
mean	49.046179	54.551589	51.256483	37.331147	
std	27.626250	23.826195	26.497574	23.634200	
min	0.000000	0.000000	0.000000	0.000000	
25%	28.000000	43.000000	31.000000	14.000000	
50%	51.000000	53.000000	52.000000	34.000000	
75%	70.000000	71.000000	71.000000	52.000000	
max	100.000000	100.000000	100.000000	100.000000	

	Q5	Q6	Q7	Q8	\
count	141389.000000	141389.000000	141389.000000	141389.000000	
mean	34.558534	39.268697	33.975129	29.185177	
std	23.263877	25.748706	25.777516	24.241491	
min	0.000000	0.000000	0.000000	0.000000	
25%	12.000000	14.000000	10.000000	9.000000	
50%	32.000000	35.000000	30.000000	23.000000	
75%	51.000000	53.000000	52.000000	49.000000	
max	100.000000	100.000000	100.000000	100.000000	

	Q9	Q10	Q11	Q12	\
count	141389.000000	141389.000000	141389.000000	141389.000000	
mean	47.797154	54.877063	58.602724	53.569845	
std	27.354361	25.452177	23.878980	25.393843	
min	0.000000	0.000000	0.000000	0.000000	
25%	28.000000	40.000000	48.000000	35.000000	
50%	50.000000	53.000000	64.000000	53.000000	
75%	70.000000	72.000000	73.000000	71.000000	
max	100.000000	100.000000	100.000000	100.000000	

	Q13	Q14	Q15	Q16	\
count	141389.000000	141389.000000	141389.000000	114178.000000	
mean	47.040583	53.379278	39.532544	35.832825	
std	26.763479	25.876483	26.019576	25.427310	
min	0.000000	0.000000	0.000000	0.000000	
25%	28.000000	33.000000	13.000000	11.000000	
50%	50.000000	53.000000	36.000000	32.000000	
75%	68.000000	71.000000	55.000000	52.000000	

```
max       100.000000     100.000000     100.000000     100.000000

                Q17            Q18            Q19
count  141389.000000  112310.000000  112310.000000
mean       53.798933      42.284300      41.325660
std        25.913654      25.698482      26.473832
min         0.000000       0.000000       0.000000
25%        35.000000      17.000000      14.000000
50%        56.000000      47.000000      45.000000
75%        71.000000      58.000000      57.000000
max       100.000000     100.000000     100.000000
```

[150]:
```
training_inputs[numeric_cols].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 150952 entries, 168265 to 53332
Data columns (total 27 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Artist            150952 non-null  int64
 1   Track             150952 non-null  int64
 2   User              150952 non-null  int64
 3   Time              150952 non-null  int64
 4   HEARD_OF          150952 non-null  int64
 5   OWN_ARTIST_MUSIC  150952 non-null  int64
 6   words_score       149299 non-null  float64
 7   MUSIC             141389 non-null  float64
 8   Q1                141389 non-null  float64
 9   Q2                141389 non-null  float64
 10  Q3                141389 non-null  float64
 11  Q4                141389 non-null  float64
 12  Q5                141389 non-null  float64
 13  Q6                141389 non-null  float64
 14  Q7                141389 non-null  float64
 15  Q8                141389 non-null  float64
 16  Q9                141389 non-null  float64
 17  Q10               141389 non-null  float64
 18  Q11               141389 non-null  float64
 19  Q12               141389 non-null  float64
 20  Q13               141389 non-null  float64
 21  Q14               141389 non-null  float64
 22  Q15               141389 non-null  float64
 23  Q16               114178 non-null  float64
 24  Q17               141389 non-null  float64
 25  Q18               112310 non-null  float64
 26  Q19               112310 non-null  float64
dtypes: float64(21), int64(6)
```

```
memory usage: 32.2 MB
```

[151]:
```
training_inputs[categorical_cols].nunique()
```

[151]:
```
LIKE_ARTIST    11
GENDER          3
WORKING        14
REGION          6
LIST_OWN       10
LIST_BACK      10
AGE_GROUP       6
dtype: int64
```

24 Replacing Missing Data

[152]:
```
training_merge_df[numeric_cols].isna().sum()
```

[152]:
```
Artist                0
Track                 0
User                  0
Time                  0
HEARD_OF              0
OWN_ARTIST_MUSIC      0
words_score        2054
MUSIC             11857
Q1                11857
Q2                11857
Q3                11857
Q4                11857
Q5                11857
Q6                11857
Q7                11857
Q8                11857
Q9                11857
Q10               11857
Q11               11857
Q12               11857
Q13               11857
Q14               11857
Q15               11857
Q16               45936
Q17               11857
Q18               48145
Q19               48145
dtype: int64
```

[153]:
```
from sklearn.impute import SimpleImputer
```

[154]:
```
imputer = SimpleImputer(strategy='mean')
```

[155]:
```
imputer.fit(training_merge_df[numeric_cols])
```

[155]:
```
SimpleImputer()
```

[156]:
```
training_inputs[numeric_cols] = imputer.transform(training_inputs[numeric_cols])
validation_inputs[numeric_cols] = imputer.
 ↪transform(validation_inputs[numeric_cols])
test_inputs[numeric_cols] = imputer.transform(test_inputs[numeric_cols])
```

[157]:
```
training_inputs[numeric_cols].isna().sum()
```

[157]:
```
Artist              0
Track               0
User                0
Time                0
HEARD_OF            0
OWN_ARTIST_MUSIC    0
words_score         0
MUSIC               0
Q1                  0
Q2                  0
Q3                  0
Q4                  0
Q5                  0
Q6                  0
Q7                  0
Q8                  0
Q9                  0
Q10                 0
Q11                 0
Q12                 0
Q13                 0
Q14                 0
Q15                 0
Q16                 0
Q17                 0
Q18                 0
Q19                 0
dtype: int64
```

25 Scaling of Numeric Col's

[158]:
```
from sklearn.preprocessing import MinMaxScaler
```

[159]:
```
scaler = MinMaxScaler()
```

[160]:
```
scaler.fit(training_merge_df[numeric_cols])
```

[160]:
```
MinMaxScaler()
```

[161]:
```
training_inputs[numeric_cols] = scaler.transform(training_inputs[numeric_cols])
validation_inputs[numeric_cols] = scaler.
 ↪transform(validation_inputs[numeric_cols])
test_inputs[numeric_cols] = scaler.transform(test_inputs[numeric_cols])
```

[162]:
```
training_inputs[numeric_cols].describe()
```

[162]:

	Artist	Track	User	Time	\
count	150952.000000	150952.000000	150952.000000	150952.000000	
mean	0.453198	0.472535	0.519632	0.680698	
std	0.295488	0.305946	0.267603	0.280161	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.204082	0.196721	0.347556	0.521739	
50%	0.448980	0.437158	0.545978	0.739130	
75%	0.714286	0.775956	0.705402	0.913043	
max	1.000000	1.000000	1.000000	1.000000	

	HEARD_OF	OWN_ARTIST_MUSIC	words_score	MUSIC	\
count	150952.000000	150952.000000	150952.000000	150952.000000	
mean	0.292417	0.072438	0.339714	0.728698	
std	0.352351	0.191138	0.087550	0.258118	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.290909	0.400000	
50%	0.000000	0.000000	0.327273	0.800000	
75%	0.666667	0.000000	0.381818	1.000000	
max	1.000000	1.000000	1.000000	1.000000	

	Q1	Q2	Q3	Q4	\
count	150952.000000	150952.000000	150952.000000	150952.000000	
mean	0.490447	0.545506	0.512547	0.373323	
std	0.267368	0.230591	0.256445	0.228733	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.290000	0.460000	0.320000	0.150000	
50%	0.500000	0.545362	0.512284	0.360000	
75%	0.700000	0.710000	0.700000	0.520000	
max	1.000000	1.000000	1.000000	1.000000	

```
                Q5             Q6             Q7             Q8  \
count  150952.000000  150952.000000  150952.000000  150952.000000
mean        0.345585       0.392703       0.339740       0.291840
std         0.225149       0.249198       0.249476       0.234611
min         0.000000       0.000000       0.000000       0.000000
25%         0.120000       0.160000       0.100000       0.100000
50%         0.330000       0.390000       0.320000       0.280000
75%         0.510000       0.520000       0.510000       0.480000
max         1.000000       1.000000       1.000000       1.000000

                Q9            Q10            Q11            Q12  \
count  150952.000000  150952.000000  150952.000000  150952.000000
mean        0.477973       0.548777       0.586040       0.535700
std         0.264737       0.246328       0.231102       0.245763
min         0.000000       0.000000       0.000000       0.000000
25%         0.290000       0.450000       0.490000       0.400000
50%         0.490000       0.540000       0.600000       0.535720
75%         0.690000       0.710000       0.720000       0.710000
max         1.000000       1.000000       1.000000       1.000000

                Q13            Q14            Q15            Q16  \
count  150952.000000  150952.000000  150952.000000  150952.000000
mean        0.470381       0.533772       0.395320       0.358427
std         0.259019       0.250434       0.251819       0.221142
min         0.000000       0.000000       0.000000       0.000000
25%         0.290000       0.350000       0.140000       0.150000
50%         0.490000       0.533462       0.395239       0.358732
75%         0.670000       0.710000       0.540000       0.500000
max         1.000000       1.000000       1.000000       1.000000

                Q17            Q18            Q19
count  150952.000000  150952.000000  150952.000000
mean        0.537964       0.422666       0.413127
std         0.250794       0.221665       0.228353
min         0.000000       0.000000       0.000000
25%         0.390000       0.300000       0.280000
50%         0.537583       0.422153       0.412752
75%         0.710000       0.520000       0.520000
max         1.000000       1.000000       1.000000
```

[163]:
```
training_inputs[numeric_cols].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 150952 entries, 168265 to 53332
Data columns (total 27 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
```

```
 0   Artist            150952 non-null  float64
 1   Track             150952 non-null  float64
 2   User              150952 non-null  float64
 3   Time              150952 non-null  float64
 4   HEARD_OF          150952 non-null  float64
 5   OWN_ARTIST_MUSIC  150952 non-null  float64
 6   words_score       150952 non-null  float64
 7   MUSIC             150952 non-null  float64
 8   Q1                150952 non-null  float64
 9   Q2                150952 non-null  float64
 10  Q3                150952 non-null  float64
 11  Q4                150952 non-null  float64
 12  Q5                150952 non-null  float64
 13  Q6                150952 non-null  float64
 14  Q7                150952 non-null  float64
 15  Q8                150952 non-null  float64
 16  Q9                150952 non-null  float64
 17  Q10               150952 non-null  float64
 18  Q11               150952 non-null  float64
 19  Q12               150952 non-null  float64
 20  Q13               150952 non-null  float64
 21  Q14               150952 non-null  float64
 22  Q15               150952 non-null  float64
 23  Q16               150952 non-null  float64
 24  Q17               150952 non-null  float64
 25  Q18               150952 non-null  float64
 26  Q19               150952 non-null  float64
dtypes: float64(27)
memory usage: 32.2 MB
```

[164]:
```
# Encoding Categorical data
```

[165]:
```
training_merge_df[categorical_cols].isna().sum()
```

[165]:
```
LIKE_ARTIST    0
GENDER         0
WORKING        0
REGION         0
LIST_OWN       0
LIST_BACK      0
AGE_GROUP      0
dtype: int64
```

[166]:
```
training_merge_df[categorical_cols].nunique()
```

[166]:
```
LIKE_ARTIST    11
GENDER          3
```

```
WORKING        14
REGION          6
LIST_OWN       10
LIST_BACK      10
AGE_GROUP       6
dtype: int64
```

[167]:
```
from sklearn.preprocessing import OneHotEncoder
```

[168]:
```
encoder = OneHotEncoder(sparse=False, handle_unknown='ignore')
```

[169]:
```
encoder.fit(training_merge_df[categorical_cols])
```

[169]:
```
OneHotEncoder(handle_unknown='ignore', sparse=False)
```

[170]:
```
encoded_cols = list(encoder.get_feature_names(categorical_cols));
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning:

Function get_feature_names is deprecated; get_feature_names is deprecated in 1.0
and will be removed in 1.2. Please use get_feature_names_out instead.
```

[171]:
```
training_inputs[encoded_cols] = encoder.
 ↪transform(training_inputs[categorical_cols])
validation_inputs[encoded_cols] = encoder.
 ↪transform(validation_inputs[categorical_cols])
test_inputs[encoded_cols] = encoder.transform(test_inputs[categorical_cols])
```

[172]:
```
training_inputs
```

[172]:

	Artist	Track	User	Time	HEARD_OF	OWN_ARTIST_MUSIC	\
168265	0.714286	0.480874	0.600742	1.000000	0.000000	0.0	
186415	0.306122	0.224044	0.332613	0.391304	0.333333	0.0	
186064	0.979592	0.939891	0.940562	0.739130	0.000000	0.0	
38552	0.530612	0.344262	0.464547	0.956522	0.000000	0.0	
149111	0.469388	0.311475	0.415143	0.913043	0.000000	0.0	
…	…	…	…	…	…	…	
31991	0.918367	0.890710	0.890078	0.695652	0.666667	0.0	
25672	0.326531	0.732240	0.668192	0.521739	0.000000	0.0	
81988	0.122449	0.076503	0.117403	0.304348	0.000000	0.0	
97594	0.306122	0.180328	0.256446	0.826087	0.000000	0.0	
53332	0.571429	0.393443	0.456045	0.956522	0.000000	0.0	

	LIKE_ARTIST	words_score	GENDER	\
168265	No Answer	0.272727	Female	

```
186415   No Answer     0.327273       Male
186064   No Answer     0.345455       Male
38552    No Answer     0.490909  No Answer
149111   No Answer     0.236364     Female
…            …          …        …
31991        21-30     0.290909       Male
25672    No Answer     0.290909     Female
81988    No Answer     0.345455       Male
97594    No Answer     0.254545       Male
53332    No Answer     0.254545  No Answer

                                                 WORKING     REGION  \
168265                Full-time housewife / househusband   Midlands
186415                                  Full-time student      South
186064                           Employed 30+ hours a week      South
38552                                         No Answer  No Answer
149111                      Employed 8-29 hours per week   Midlands
…                                                    …        …
31991                                     Self-employed      North
25672   Retired from full-time employment (30+ hours p…      North
81988                                         No Answer      North
97594                            Employed 30+ hours a week      North
53332                                         No Answer  No Answer

           MUSIC   LIST_OWN  LIST_BACK        Q1        Q2        Q3  \
168265  0.400000          1          1  0.530000  1.000000  0.350000
186415  1.000000          2        3-6  0.790000  0.730000  0.840000
186064  0.800000        0.5          0  0.350000  0.470000  0.350000
38552   0.728824  No Answer  No Answer  0.490234  0.545362  0.512284
149111  1.000000          2        3-6  0.580000  0.620000  0.550000
…          …        …        …       …       …       …
31991   0.800000          0          0  0.500000  0.500000  0.110000
25672   0.400000        0.5       7-10  0.100000  0.490000  0.480000
81988   1.000000        3-6        3-6  0.470000  0.460000  0.480000
97594   0.400000          1        0.5  0.140000  0.470000  0.120000
53332   0.728824  No Answer  No Answer  0.490234  0.545362  0.512284

             Q4        Q5        Q6        Q7        Q8        Q9       Q10  \
168265  0.120000  0.120000  0.360000  0.140000  0.140000  0.500000  0.680000
186415  0.570000  0.350000  0.160000  0.280000  0.210000  0.440000  0.670000
186064  0.480000  0.330000  0.030000  0.350000  0.290000  0.720000  0.600000
38552   0.373498  0.345578  0.392939  0.339569  0.291659  0.477997  0.548875
149111  0.300000  0.290000  0.510000  0.250000  0.200000  0.510000  0.990000
…          …         …         …         …         …         …
31991   0.110000  0.510000  0.940000  0.090000  0.090000  0.700000  0.100000
25672   0.480000  0.480000  0.460000  0.710000  0.720000  0.710000  0.460000
81988   0.470000  0.480000  0.480000  0.480000  0.490000  0.550000  0.540000
```

```
97594   0.340000  0.690000  0.080000  0.060000  0.050000  0.750000  0.520000
53332   0.373498  0.345578  0.392939  0.339569  0.291659  0.477997  0.548875

            Q11      Q12      Q13       Q14       Q15       Q16       Q17  \
168265  0.650000  0.51000  1.00000  0.860000  0.040000  0.358732  1.000000
186415  0.730000  0.62000  0.88000  0.670000  0.480000  0.700000  0.690000
186064  0.510000  0.53000  0.41000  0.450000  0.060000  0.030000  0.480000
38552   0.586235  0.53572  0.47002  0.533462  0.395239  0.358732  0.537583
149111  0.670000  0.69000  0.46000  0.460000  0.430000  0.200000  0.860000
…          …       …        …         …         …         …
31991   0.340000  0.10000  0.10000  0.110000  0.110000  0.130000  0.550000
25672   0.480000  0.51000  0.51000  0.310000  0.960000  0.070000  0.510000
81988   0.550000  0.54000  0.53000  0.540000  0.530000  0.550000  0.550000
97594   0.570000  0.21000  0.15000  0.270000  0.110000  0.140000  0.750000
53332   0.586235  0.53572  0.47002  0.533462  0.395239  0.358732  0.537583

            Q18       Q19 AGE_GROUP  LIKE_ARTIST_1-10  LIKE_ARTIST_11-20  \
168265  0.040000  0.520000     36-50               0.0                0.0
186415  0.600000  0.300000     18-25               0.0                0.0
186064  0.340000  0.330000     26-35               0.0                0.0
38552   0.422153  0.412752     36-50               0.0                0.0
149111  0.220000  0.340000     36-50               0.0                0.0
…          …        …        …                 …                  …
31991   0.100000  0.110000     51-65               0.0                0.0
25672   0.080000  0.090000     51-65               0.0                0.0
81988   0.422153  0.412752     26-35               0.0                0.0
97594   0.180000  0.130000     51-65               0.0                0.0
53332   0.422153  0.412752     36-50               0.0                0.0

        LIKE_ARTIST_21-30  LIKE_ARTIST_31-40  LIKE_ARTIST_41-50  \
168265                0.0                0.0                0.0
186415                0.0                0.0                0.0
186064                0.0                0.0                0.0
38552                 0.0                0.0                0.0
149111                0.0                0.0                0.0
…                     …                  …                  …
31991                 1.0                0.0                0.0
25672                 0.0                0.0                0.0
81988                 0.0                0.0                0.0
97594                 0.0                0.0                0.0
53332                 0.0                0.0                0.0

        LIKE_ARTIST_51-60  LIKE_ARTIST_61-70  LIKE_ARTIST_71-80  \
168265                0.0                0.0                0.0
186415                0.0                0.0                0.0
186064                0.0                0.0                0.0
38552                 0.0                0.0                0.0
```

```
149111                0.0                0.0                0.0
…                   …                  …                  …
31991                 0.0                0.0                0.0
25672                 0.0                0.0                0.0
81988                 0.0                0.0                0.0
97594                 0.0                0.0                0.0
53332                 0.0                0.0                0.0

        LIKE_ARTIST_81-90  LIKE_ARTIST_91-100  LIKE_ARTIST_No Answer  \
168265                0.0                 0.0                    1.0
186415                0.0                 0.0                    1.0
186064                0.0                 0.0                    1.0
38552                 0.0                 0.0                    1.0
149111                0.0                 0.0                    1.0
…                   …                   …                    …
31991                 0.0                 0.0                    0.0
25672                 0.0                 0.0                    1.0
81988                 0.0                 0.0                    1.0
97594                 0.0                 0.0                    1.0
53332                 0.0                 0.0                    1.0

        GENDER_Female  GENDER_Male  GENDER_No Answer  \
168265            1.0          0.0               0.0
186415            0.0          1.0               0.0
186064            0.0          1.0               0.0
38552             0.0          0.0               1.0
149111            1.0          0.0               0.0
…               …            …                 …
31991             0.0          1.0               0.0
25672             1.0          0.0               0.0
81988             0.0          1.0               0.0
97594             0.0          1.0               0.0
53332             0.0          0.0               1.0

        WORKING_Employed 30+ hours a week  \
168265                                0.0
186415                                0.0
186064                                1.0
38552                                 0.0
149111                                0.0
…                                   …
31991                                 0.0
25672                                 0.0
81988                                 0.0
97594                                 1.0
53332                                 0.0
```

```
        WORKING_Employed 8-29 hours per week  \
168265                                   0.0
186415                                   0.0
186064                                   0.0
38552                                    0.0
149111                                   1.0
…                                        …
31991                                    0.0
25672                                    0.0
81988                                    0.0
97594                                    0.0
53332                                    0.0

        WORKING_Employed part-time less than 8 hours per week  \
168265                                                   0.0
186415                                                   0.0
186064                                                   0.0
38552                                                    0.0
149111                                                   0.0
…                                                        …
31991                                                    0.0
25672                                                    0.0
81988                                                    0.0
97594                                                    0.0
53332                                                    0.0

        WORKING_Full-time housewife / househusband  WORKING_Full-time student  \
168265                                         1.0                        0.0
186415                                         0.0                        1.0
186064                                         0.0                        0.0
38552                                          0.0                        0.0
149111                                         0.0                        0.0
…                                              …                          …
31991                                          0.0                        0.0
25672                                          0.0                        0.0
81988                                          0.0                        0.0
97594                                          0.0                        0.0
53332                                          0.0                        0.0

        WORKING_In unpaid employment (e.g. voluntary work)  WORKING_No Answer  \
168265                                                 0.0                 0.0
186415                                                 0.0                 0.0
186064                                                 0.0                 0.0
38552                                                  0.0                 1.0
149111                                                 0.0                 0.0
…                                                      …                   …
31991                                                  0.0                 0.0
```

```
25672                                                 0.0                 0.0
81988                                                 0.0                 1.0
97594                                                 0.0                 0.0
53332                                                 0.0                 1.0

        WORKING_Other  WORKING_Part-time student  WORKING_Prefer not to state  \
168265            0.0                        0.0                          0.0
186415            0.0                        0.0                          0.0
186064            0.0                        0.0                          0.0
38552             0.0                        0.0                          0.0
149111            0.0                        0.0                          0.0
…                 …                          …                            …
31991             0.0                        0.0                          0.0
25672             0.0                        0.0                          0.0
81988             0.0                        0.0                          0.0
97594             0.0                        0.0                          0.0
53332             0.0                        0.0                          0.0

        WORKING_Retired from full-time employment (30+ hours per week)  \
168265                                                 0.0
186415                                                 0.0
186064                                                 0.0
38552                                                  0.0
149111                                                 0.0
…                                                      …
31991                                                  0.0
25672                                                  1.0
81988                                                  0.0
97594                                                  0.0
53332                                                  0.0

        WORKING_Retired from self-employment  WORKING_Self-employed  \
168265                                   0.0                    0.0
186415                                   0.0                    0.0
186064                                   0.0                    0.0
38552                                    0.0                    0.0
149111                                   0.0                    0.0
…                                        …                      …
31991                                    0.0                    1.0
25672                                    0.0                    0.0
81988                                    0.0                    0.0
97594                                    0.0                    0.0
53332                                    0.0                    0.0

        WORKING_Temporarily unemployed  REGION_Centre  REGION_Midlands  \
168265                             0.0            0.0              1.0
186415                             0.0            0.0              0.0
```

```
186064                          0.0            0.0             0.0
38552                           0.0            0.0             0.0
149111                          0.0            0.0             1.0
…                               …              …               …
31991                           0.0            0.0             0.0
25672                           0.0            0.0             0.0
81988                           0.0            0.0             0.0
97594                           0.0            0.0             0.0
53332                           0.0            0.0             0.0

        REGION_No Answer  REGION_North  REGION_Northern Ireland  REGION_South  \
168265               0.0           0.0                      0.0           0.0
186415               0.0           0.0                      0.0           1.0
186064               0.0           0.0                      0.0           1.0
38552                1.0           0.0                      0.0           0.0
149111               0.0           0.0                      0.0           0.0
…                    …             …                        …             …
31991                0.0           1.0                      0.0           0.0
25672                0.0           1.0                      0.0           0.0
81988                0.0           1.0                      0.0           0.0
97594                0.0           1.0                      0.0           0.0
53332                1.0           0.0                      0.0           0.0

        LIST_OWN_0  LIST_OWN_0.5  LIST_OWN_1  LIST_OWN_11-14  LIST_OWN_15-19  \
168265         0.0           0.0         1.0             0.0             0.0
186415         0.0           0.0         0.0             0.0             0.0
186064         0.0           1.0         0.0             0.0             0.0
38552          0.0           0.0         0.0             0.0             0.0
149111         0.0           0.0         0.0             0.0             0.0
…              …             …           …               …               …
31991          1.0           0.0         0.0             0.0             0.0
25672          0.0           1.0         0.0             0.0             0.0
81988          0.0           0.0         0.0             0.0             0.0
97594          0.0           0.0         1.0             0.0             0.0
53332          0.0           0.0         0.0             0.0             0.0

        LIST_OWN_2  LIST_OWN_20 and plus  LIST_OWN_3-6  LIST_OWN_7-10  \
168265         0.0                   0.0           0.0            0.0
186415         1.0                   0.0           0.0            0.0
186064         0.0                   0.0           0.0            0.0
38552          0.0                   0.0           0.0            0.0
149111         1.0                   0.0           0.0            0.0
…              …                     …             …              …
31991          0.0                   0.0           0.0            0.0
25672          0.0                   0.0           0.0            0.0
81988          0.0                   0.0           1.0            0.0
97594          0.0                   0.0           0.0            0.0
```

```
53332          0.0                    0.0           0.0            0.0

        LIST_OWN_No Answer  LIST_BACK_0  LIST_BACK_0.5  LIST_BACK_1  \
168265                 0.0          0.0            0.0          1.0
186415                 0.0          0.0            0.0          0.0
186064                 0.0          1.0            0.0          0.0
38552                  1.0          0.0            0.0          0.0
149111                 0.0          0.0            0.0          0.0
…                      …            …              …            …
31991                  0.0          1.0            0.0          0.0
25672                  0.0          0.0            0.0          0.0
81988                  0.0          0.0            0.0          0.0
97594                  0.0          0.0            1.0          0.0
53332                  1.0          0.0            0.0          0.0

        LIST_BACK_11-14  LIST_BACK_15-19  LIST_BACK_2  LIST_BACK_20 and plus  \
168265              0.0              0.0          0.0                    0.0
186415              0.0              0.0          0.0                    0.0
186064              0.0              0.0          0.0                    0.0
38552               0.0              0.0          0.0                    0.0
149111              0.0              0.0          0.0                    0.0
…                   …                …            …                      …
31991               0.0              0.0          0.0                    0.0
25672               0.0              0.0          0.0                    0.0
81988               0.0              0.0          0.0                    0.0
97594               0.0              0.0          0.0                    0.0
53332               0.0              0.0          0.0                    0.0

        LIST_BACK_3-6  LIST_BACK_7-10  LIST_BACK_No Answer  AGE_GROUP_13-17  \
168265            0.0             0.0                  0.0              0.0
186415            1.0             0.0                  0.0              0.0
186064            0.0             0.0                  0.0              0.0
38552             0.0             0.0                  1.0              0.0
149111            1.0             0.0                  0.0              0.0
…                 …               …                    …                …
31991             0.0             0.0                  0.0              0.0
25672             0.0             1.0                  0.0              0.0
81988             1.0             0.0                  0.0              0.0
97594             0.0             0.0                  0.0              0.0
53332             0.0             0.0                  1.0              0.0

        AGE_GROUP_18-25  AGE_GROUP_26-35  AGE_GROUP_36-50  AGE_GROUP_51-65  \
168265              0.0              0.0              1.0              0.0
186415              1.0              0.0              0.0              0.0
186064              0.0              1.0              0.0              0.0
38552               0.0              0.0              1.0              0.0
149111              0.0              0.0              1.0              0.0
```

```
…                 …               …               …               …
31991             0.0             0.0             0.0             1.0
25672             0.0             0.0             0.0             1.0
81988             0.0             1.0             0.0             0.0
97594             0.0             0.0             0.0             1.0
53332             0.0             0.0             1.0             0.0

        AGE_GROUP_older than 65
168265                      0.0
186415                      0.0
186064                      0.0
38552                       0.0
149111                      0.0
…                           …
31991                       0.0
25672                       0.0
81988                       0.0
97594                       0.0
53332                       0.0

[150952 rows x 94 columns]
```

[173]:
```
# Saving to Disk
```

[174]:
```
print('training_inputs:', training_inputs.shape)
print('training_targets:', training_targets.shape)
print('validation_inputs:', validation_inputs.shape)
print('validation_targets:', validation_targets.shape)
print('test_inputs:', test_inputs.shape)
```

```
training_inputs: (150952, 94)
training_targets: (150952,)
validation_inputs: (37738, 94)
validation_targets: (37738,)
test_inputs: (125794, 94)
```

[175]:
```
!pip install pyarrow --quiet
```

[176]:
```
training_inputs.to_parquet('training_inputs.parquet')
validation_inputs.to_parquet('validation_inputs.parquet')
test_inputs.to_parquet('test_inputs.parquet')
```

[177]:
```
pd.DataFrame(training_targets).to_parquet('training_targets.parquet')
pd.DataFrame(validation_targets).to_parquet('validation_targets.parquet')
```

Getting Data Back

[178]:
```
training_inputs = pd.read_parquet('training_inputs.parquet')
validation_inputs = pd.read_parquet('validation_inputs.parquet')
test_inputs = pd.read_parquet('test_inputs.parquet')

training_targets = pd.read_parquet('training_targets.parquet')[target_col]
validation_targets = pd.read_parquet('validation_targets.parquet')[target_col]
```

[179]:
```
print('training_inputs:', training_inputs.shape)
print('training_targets:', training_targets.shape)
print('validation_inputs:', validation_inputs.shape)
print('validation_targets:', validation_targets.shape)
print('test_inputs:', test_inputs.shape)
```

```
training_inputs: (150952, 94)
training_targets: (150952,)
validation_inputs: (37738, 94)
validation_targets: (37738,)
test_inputs: (125794, 94)
```

26 Starting Modeling

[180]:
```
X_training = training_inputs[numeric_cols + encoded_cols]

X_validation = validation_inputs[numeric_cols + encoded_cols]

X_test = test_inputs[numeric_cols + encoded_cols]
```

26.1 Training

[181]:
```
from xgboost import XGBRegressor
```

[182]:
```
model = XGBRegressor(n_jobs=0)
```

[183]:
```
model.fit(X_training, training_targets)
```

```
[11:34:29] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
```

[183]:
```
XGBRegressor(n_jobs=0)
```

[184]:
```
prediction = model.predict(X_training)
```

[185]:
```
from sklearn.metrics import mean_squared_error

def rmse(a, b):
  return mean_squared_error(a, b, squared=False)
```

[186]:
```
rmse(prediction, training_targets)
```

[186]:
```
15.97886769351449
```

[187]:
```
impt_df = pd.DataFrame({'feature': X_training.columns,
'importance': model.feature_importances_}).sort_values('importance',␣
↪ascending=False)
```

[188]:
```
impt_df.head(10)
```

[188]:

	feature	importance
6	words_score	0.467572
5	OWN_ARTIST_MUSIC	0.083540
4	HEARD_OF	0.042305
3	Time	0.029398
18	Q11	0.026738
14	Q7	0.025278
36	LIKE_ARTIST_91-100	0.022223
19	Q12	0.020269
23	Q16	0.018554
15	Q8	0.016989

27 Hyperparametre Tuning

[190]:
```
def test_params(**params):
  model = XGBRegressor(n_jobs=-1, **params)
  model.fit(X_training, training_targets)
  training_rmse = rmse(model.predict(X_training), training_targets)
  validation_rmse = rmse(model.predict(X_validation), validation_targets)
  print('Training RMSE: {}, Validation RMSE: {}'.format(training_rmse,␣
↪validation_rmse))
```

[191]:
```
test_params(n_estimators=100)
```

```
[11:35:23] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 15.97886769351449, Validation RMSE: 15.909823636844786
```

[192]:
```
test_params(n_estimators=200)
```

```
[11:35:52] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 15.77299591949312, Validation RMSE: 15.741147592019022
```

[193]:
```
test_params(n_estimators=400)
```

```
[11:36:48] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 15.526375941069244, Validation RMSE: 15.569182444072737
```

[194]:
```
test_params(n_estimators=800)
```

```
[11:38:41] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 15.193733025548545, Validation RMSE: 15.370873997573677
```

28 Tree depth & Learning rate

[195]:
```
test_params(n_estimators=175, max_depth=8, learning_rate=0.3)
```

```
[11:42:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 10.777195811333101, Validation RMSE: 14.35447977385776
```

[196]:
```
test_params(n_estimators=175, max_depth=8, learning_rate=0.2)
```

```
[11:44:56] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 11.705383800905652, Validation RMSE: 14.38046099437259
```

[197]:
```
test_params(booster='gblinear', n_estimators=400)
```

```
[11:47:14] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 21.690106222953066, Validation RMSE: 21.679318734157885
```

[198]:
```
test_params(n_estimators=500, max_depth=9, learning_rate=0.15)
```

```
[11:48:11] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 8.170350841099964, Validation RMSE: 14.031425644970993
```

[199]:
```
test_params(n_estimators=1000, max_depth=10, learning_rate=0.10, subsample=0.9,␣
↪colsample_bytree=0.7)
```

```
[11:56:22] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Training RMSE: 5.912378909481084, Validation RMSE: 14.06289233604193
```

[200]:
```
from sklearn.model_selection import KFold
```

[201]:
```
def train_and_evaluate(X_train_k, Y_train_k, X_val_k, Y_val_k, **params):
  model = XGBRegressor(n_jobs=-1, **params)
  model.fit(X_train_k, Y_train_k)
```

```
  train_rmse = rmse(model.predict(X_train_k), Y_train_k)
  val_rmse = rmse(model.predict(X_val_k), Y_val_k)
  return model, train_rmse, val_rmse
```

[202]:
```
kfold = KFold(n_splits=5)
```

[203]:
```
models = []

for train_idxs, val_idxs in kfold.split(X_training):
  X_train_k, Y_train_k = X_training.iloc[train_idxs], training_targets.
 ↪iloc[train_idxs]
  X_val_k, Y_val_k = X_training.iloc[val_idxs], training_targets.iloc[val_idxs]
  model, train_rmse, val_rmse = train_and_evaluate(X_train_k, Y_train_k,␣
 ↪X_val_k, Y_val_k, n_estimators=500, max_depth=9, learning_rate=0.10,␣
 ↪subsample=0.9, colsample_bytree=0.7)
  models.append(model)
  print('Train RMSE: {}, Validation RMSE: {}'.format(train_rmse, val_rmse))
```

```
[12:11:43] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Train RMSE: 8.87027198507148, Validation RMSE: 14.309372055537372
[12:17:14] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Train RMSE: 8.930045003488926, Validation RMSE: 14.326546756947248
[12:22:31] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Train RMSE: 8.883624648870502, Validation RMSE: 14.325172790349075
[12:27:49] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Train RMSE: 8.964643709238226, Validation RMSE: 14.379924947602829
[12:33:01] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear
is now deprecated in favor of reg:squarederror.
Train RMSE: 8.926999279240505, Validation RMSE: 14.242177838373042
```

[204]:
```
def predict_avg(models, inputs):
    return np.mean([model.predict(inputs) for model in models], axis=0)
```

[205]:
```
preds_kfold = predict_avg(models, X_validation)
rmse(preds_kfold, validation_targets)
```

[205]:
```
13.852739686869784
```

[206]:
```
test_preds = predict_avg(models, X_test)
```

29 Final Answer

[207]:
```
test_preds.shape
```

[207]:
```
(125794,)
```

30 Model 2

30.1 RandomForestRegressor

[208]:
```
from sklearn.ensemble import RandomForestRegressor
```

[209]:
```
model_randomForestRegressor = RandomForestRegressor()
```

[210]:
```
model_randomForestRegressor.fit(X_training, training_targets)
```

[210]:
```
RandomForestRegressor()
```

[211]:
```
def test_params(**params):
    model = RandomForestRegressor(random_state=42, n_jobs=-1, **params).
↪fit(X_training, training_targets)
    return model.score(X_training, training_targets), model.score(X_validation,␣
↪validation_targets)
```

30.2 Hyperparameter Tuning

[212]:
```
test_params(max_depth=100, max_leaf_nodes=2**4)
```

[212]:
```
(0.44986499029102844, 0.4560022614096648)
```

[213]:
```
test_params(max_depth=400, max_leaf_nodes=2**10)
```

[213]:
```
(0.5880712862974407, 0.5376298342989975)
```

[214]:
```
test_params(max_depth=600, max_leaf_nodes=2**15)
```

[214]:
```
(0.9241145573397733, 0.5908789148855196)
```

[215]:
```
test_params(max_depth=1000, max_leaf_nodes=2**25)
```

[215]:
```
(0.9419978303117578, 0.5872249941906067)
```

30.2.1 Now we can see that the optimum value occurs at `max_depth=600` & `max_leaf_nodes=2**15`

Now we will use these values to predict the performance of RFR.

31 Performance of RFR

[216]:
```
preds_randomForestRegressor = model_randomForestRegressor.predict(X_validation)
rmse(preds_randomForestRegressor, validation_targets)
```

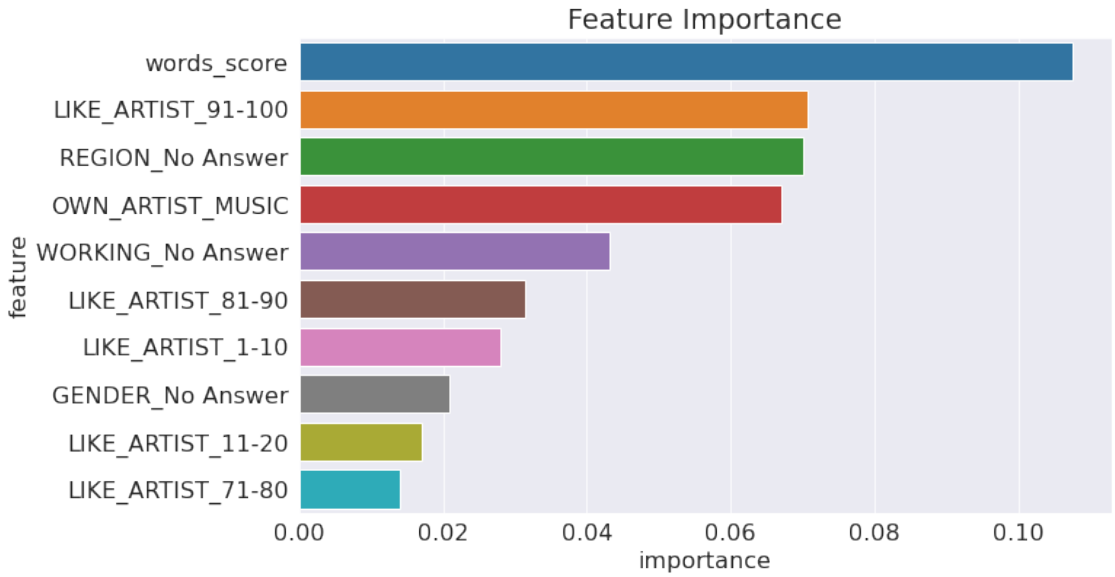
[216]:
```
14.504533421368059
```

Performance of RFR is less than XGBR
So, we will continue with XGBR Model

32 Importance of columns

[217]:
```
importance_df = pd.DataFrame({'feature': X_training.columns,
'importance': model.feature_importances_}).sort_values('importance',␣
↪ascending=False)
```

[218]:
```
plt.figure(figsize=(10,6))
plt.title('Feature Importance')
sns.barplot(data=importance_df.head(10), x='importance', y='feature');
```



Saving the model

[219]:
```
import joblib
```

[220]:
```
song_recommendation_ml = {
    'model': models,
    'imputer': imputer,
    'scaler': scaler,
```

```
    'encoder': encoder,
    'input_cols': input_cols,
    'target_cols': target_col,
    'numeric_cols': numeric_cols,
    'categorical_cols': categorical_cols,
    'encoded_cols': encoded_cols
}
```

[221]:
```
joblib.dump(song_recommendation_ml, 'song_recommendation_ml')
```

[221]:
```
['song_recommendation_ml']
```

[222]:
```
['song_recommendation_ml']
```

[222]:
```
['song_recommendation_ml']
```

33 Conclusion

I downloded this dataset from kaggle. Then after I imported the requried python libraries. Now, I started cleaning the dataset like deleting the rows in which data is missing or substituting the average value of the column in the missing data. Then to get the insights from the columns of the dataset, I started to make the visualizations of the dataset. After I got th einsights from the dataset and the relationship betweeen the columns of the dataset I started to make the model. I used XGBoosta and RFR models. After checking the performances of both the models, I had come to a conclusion that XGBoost model had high performance than RFR. So, at last I used the XGBoost model to predict the values of dataset.

34 References and Future Work

References: The websites that I found useful during this project work are Scikit-learn, Stackoverflow, W3schools, GFG, and many more.

- GFG
- scikit-learn
- GFG
- Stack overflow
- Medium

34.1 Future work

Now, I will continue on this project, by adding the songs data and selecting the recommended song for the listner from the dataset. In the dataset of the song we have to differentiate the songs by the lyrics in the song, by the lyrics of the song we can is it a sad, happy or romatic song. By the words in the lyrics of the song we can recommed the type of song that the listerner wants.