EDA_-_Spotify_Top_200_Charts_2020-2021

May 1, 2022

1 Exploratory Data Analysis - Spotify Top 200 Charts (2020-2021)

The dataset I have used for EDA contains the **Top 200 Weekly (Global) charts of Spotify in 2020 & 2021**. The chart is made by Spotify and is updated regularly, so our dataset doesn't include just 200 songs but 1556 songs that made it to Top 200 charts during 2020-21 even if it was just for a single day.

The dataset include the following features:

Highest Charting Position: The highest position that the song has been on in the Spotify Top 200 Weekly Global Charts in 2020 & 2021.

Number of Times Charted: The number of times that the song has been on in the Spotify Top 200 Weekly Global Charts in 2020 & 2021.

Week of Highest Charting: The week when the song had the Highest Position in the Spotify Top 200 Weekly Global Charts in 2020 & 2021.

Song Name: Name of the song that has been on in the Spotify Top 200 Weekly Global Charts in 2020 & 2021.

Song iD: The song ID provided by Spotify (unique to each song).

Streams: Approximate number of streams the song has.

Artist: The main artist/ artists involved in making the song.

Artist Followers: The number of followers the main artist has on Spotify.

Genre: The genres the song belongs to.

Release Date: The initial date that the song was released.

Weeks Charted: The weeks that the song has been on in the Spotify Top 200 Weekly Global Charts in 2020 & 2021.

Popularity: The popularity of the track. The value will be between 0 and 100, with 100 being the most popular.

Danceability: Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.

Acousticness: A measure from 0.0 to 1.0 of whether the track is acoustic.

Energy: Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy.

Instrumentalness: Predicts whether a track contains no vocals. The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content.

Liveness: Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live.

Loudness: The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track. Values typical range between -60 and 0 db.

Speechiness: Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value.

Tempo: The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.

Valence: A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

Chord: The main chord of the song instrumental.

1.1 Downloading the Dataset

We will be downloading the data set using **opendatasets**. It is a Python library for downloading datasets from Kaggle, Google Drive, and other online sources. The dataset we are using has CSV format.

[5]:

```
!pip install jovian opendatasets --upgrade --quiet
```

Let's begin by downloading the data, and listing the files within the dataset.

[6]:

```
# URL where the data set is present
dataset_url = 'https://www.kaggle.com/datasets/sashankpillai/
 ↪spotify-top-200-charts-20202021'
```

[7]:

```
# downloading dataset using opendatasets
import opendatasets as od
od.download(dataset_url)
```

```
Please provide your Kaggle credentials to download this dataset. Learn more:
http://bit.ly/kaggle-creds
Your Kaggle username: ayushkr07
Your Kaggle Key: ········
Downloading spotify-top-200-charts-20202021.zip to ./spotify-
top-200-charts-20202021

100%|     | 165k/165k [00:00<00:00, 63.4MB/s]
```

The dataset has been downloaded and extracted.

[8]:
```
# storing location of dataset to point it for our analysis
data_dir = './spotify-top-200-charts-20202021'
```

[9]:
```
import os
os.listdir(data_dir)
```

[9]:
```
['spotify_dataset.csv']
```

[10]:
```
project_name = "spotify-top-200-chart-eda"
```

1.2 Data Preparation and Cleaning

In this process we will clean the dataset that we have and make it usable for us, it's crucial for removing faulty data and filling in gaps. Important tasks here include:

- Removing extraneous data and outliers.
- Filling in missing values.
- Conforming data to a standardized pattern.
- Masking private or sensitive data entries.

[11]:
```
import pandas as pd
import numpy as np
```

[12]:
```
# saving data in our dataset as pandas dataframe
spotify_raw_df = pd.read_csv(data_dir + '/spotify_dataset.csv')
```

[13]:
```
spotify_raw_df
```

[13]:
```
      Index  Highest Charting Position  Number of Times Charted  \
0         1                          1                        8
1         2                          2                        3
2         3                          1                       11
3         4                          3                        5
4         5                          5                        1
…     …                        …                      …
1551   1552                        195                        1
1552   1553                        196                        1
1553   1554                        197                        1
1554   1555                        198                        1
1555   1556                        199                        1

     Week of Highest Charting                           Song Name     Streams  \
0      2021-07-23--2021-07-30                             Beggin'  48,633,449
1      2021-07-23--2021-07-30           STAY (with Justin Bieber)  47,248,719
2      2021-06-25--2021-07-02                            good 4 u  40,162,559
3      2021-07-02--2021-07-09                          Bad Habits  37,799,456
```

```
4      2021-07-23--2021-07-30   INDUSTRY BABY (feat. Jack Harlow)  33,948,454
…                       …                                  …          …
1551   2019-12-27--2020-01-03                           New Rules   4,630,675
1552   2019-12-27--2020-01-03                  Cheirosa - Ao Vivo   4,623,030
1553   2019-12-27--2020-01-03           Havana (feat. Young Thug)   4,620,876
1554   2019-12-27--2020-01-03          Surtada - Remix Brega Funk   4,607,385
1555   2019-12-27--2020-01-03  Lover (Remix) [feat. Shawn Mendes]   4,595,450

                             Artist Artist Followers                 Song ID  \
0                          Måneskin          3377762  3Wrjm47oTz2sjIgck11l5e
1                     The Kid LAROI          2230022  5HCyWlXZPP0y6Gqq8TgA20
2                    Olivia Rodrigo          6266514  4ZtFanR9U6ndgddUvNcjcG
3                        Ed Sheeran         83293380  6PQ88X9TkUIAUIZJHW2upE
4                         Lil Nas X          5473565  27NovPIUIRrOZoCHxABJwK
…                             …              …                      …
1551                       Dua Lipa         27167675  2ekn2ttSfGqwhhate0LSR0
1552                 Jorge & Mateus         15019109  2PWjKmjyTZeDpm0Ua3a5da
1553                 Camila Cabello         22698747  1rfofaqEpACxVEHIZBJe6W
1554  Dadá Boladão, Tati Zaqui, OIK           208630  5F8ffc8KWKNawllr5WsW0r
1555                   Taylor Swift         42227614  3i9UVldZOE0aD0JnyfAZZ0

                                                  Genre  … Danceability  \
0                ['indie rock italiano', 'italian pop']  …        0.714
1                                ['australian hip hop']  …        0.591
2                                               ['pop']  …        0.563
3                                     ['pop', 'uk pop']  …        0.808
4                         ['lgbtq+ hip hop', 'pop rap']  …        0.736
…                                                 …  …          …
1551                     ['dance pop', 'pop', 'uk pop']  …        0.762
1552           ['sertanejo', 'sertanejo universitario']  …        0.528
1553  ['dance pop', 'electropop', 'pop', 'post-teen …  …        0.765
1554                     ['brega funk', 'funk carioca']  …        0.832
1555                           ['pop', 'post-teen pop']  …        0.448

     Energy Loudness Speechiness Acousticness Liveness    Tempo Duration (ms)  \
0       0.8   -4.808      0.0504        0.127    0.359  134.002        211560
1     0.764   -5.484      0.0483       0.0383    0.103  169.928        141806
2     0.664   -5.044       0.154        0.335   0.0849  166.928        178147
3     0.897   -3.712      0.0348       0.0469    0.364  126.026        231041
4     0.704   -7.409      0.0615       0.0203   0.0501  149.995        212000
…     …      …         …          …      …      …           …
1551    0.7   -6.021      0.0694      0.00261    0.153  116.073        209320
1552   0.87   -3.123      0.0851         0.24    0.333   152.37        181930
1553  0.523   -4.333        0.03        0.184    0.132  104.988        217307
1554   0.55   -7.026      0.0587        0.249    0.182  154.064        152784
1555  0.603   -7.176       0.064        0.433   0.0862  205.272        221307
```

```
     Valence  Chord
0      0.589      B
1      0.478  C#/Db
2      0.688      A
3      0.591      B
4      0.894  D#/Eb
…        …    …
1551   0.608      A
1552   0.714      B
1553   0.394      D
1554   0.881      F
1555   0.422      G

[1556 rows x 23 columns]
```

[14]:

```
spotify_raw_df.describe()
```

[14]:

```
             Index  Highest Charting Position  Number of Times Charted
count  1556.000000                1556.000000              1556.000000
mean    778.500000                  87.744216                10.668380
std     449.322824                  58.147225                16.360546
min       1.000000                   1.000000                 1.000000
25%     389.750000                  37.000000                 1.000000
50%     778.500000                  80.000000                 4.000000
75%    1167.250000                 137.000000                12.000000
max    1556.000000                 200.000000               142.000000
```

[15]:

```
pd.isnull(spotify_raw_df).sum()
```

[15]:

```
Index                        0
Highest Charting Position    0
Number of Times Charted      0
Week of Highest Charting     0
Song Name                    0
Streams                      0
Artist                       0
Artist Followers             0
Song ID                      0
Genre                        0
Release Date                 0
Weeks Charted                0
Popularity                   0
Danceability                 0
Energy                       0
Loudness                     0
Speechiness                  0
Acousticness                 0
```

```
Liveness                      0
Tempo                         0
Duration (ms)                 0
Valence                       0
Chord                         0
dtype: int64
```

Here we have just checked the count of null value in each column of our dataset, and from the output we can see there isn't any null value.

[16]:

```
spotify_raw_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1556 entries, 0 to 1555
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Index                      1556 non-null   int64
 1   Highest Charting Position  1556 non-null   int64
 2   Number of Times Charted    1556 non-null   int64
 3   Week of Highest Charting   1556 non-null   object
 4   Song Name                  1556 non-null   object
 5   Streams                    1556 non-null   object
 6   Artist                     1556 non-null   object
 7   Artist Followers           1556 non-null   object
 8   Song ID                    1556 non-null   object
 9   Genre                      1556 non-null   object
 10  Release Date               1556 non-null   object
 11  Weeks Charted              1556 non-null   object
 12  Popularity                 1556 non-null   object
 13  Danceability               1556 non-null   object
 14  Energy                     1556 non-null   object
 15  Loudness                   1556 non-null   object
 16  Speechiness                1556 non-null   object
 17  Acousticness               1556 non-null   object
 18  Liveness                   1556 non-null   object
 19  Tempo                      1556 non-null   object
 20  Duration (ms)              1556 non-null   object
 21  Valence                    1556 non-null   object
 22  Chord                      1556 non-null   object
dtypes: int64(3), object(20)
memory usage: 279.7+ KB
```

From the output here we can see that we have 1556 non-null value in each of our columns in the dataset, but the **Dtype** i.e data-type of some of the fields like Popularity, Energy, Loudnesss, Tempo e.t.c is **object** rather than float or int that we can see in the data itself.

From this we percive there's something wrong with our data.

[17]:

```
for col in spotify_raw_df.columns:
    # check if the columns contains string data
    if pd.api.types.is_string_dtype(spotify_raw_df[col]):
        spotify_raw_df[col] = spotify_raw_df[col].str.strip()
spotify_raw_df = spotify_raw_df.replace({"":np.nan})
```

After checking the data again more thoroughly I found that in some of the rows instead of the Null value for data not available, we had an string with just a space. The string with just space value isn't considered as NULL value, that's why all our column showed to have no null value.

The above cell finds the strings with only space value in the dataframe and replaces it with NULL value.

[18]:

```
spotify_raw_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1556 entries, 0 to 1555
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Index                      1556 non-null   int64
 1   Highest Charting Position  1556 non-null   int64
 2   Number of Times Charted    1556 non-null   int64
 3   Week of Highest Charting   1556 non-null   object
 4   Song Name                  1556 non-null   object
 5   Streams                    1556 non-null   object
 6   Artist                     1556 non-null   object
 7   Artist Followers           1545 non-null   object
 8   Song ID                    1545 non-null   object
 9   Genre                      1545 non-null   object
 10  Release Date               1545 non-null   object
 11  Weeks Charted              1556 non-null   object
 12  Popularity                 1545 non-null   object
 13  Danceability               1545 non-null   object
 14  Energy                     1545 non-null   object
 15  Loudness                   1545 non-null   object
 16  Speechiness                1545 non-null   object
 17  Acousticness               1545 non-null   object
 18  Liveness                   1545 non-null   object
 19  Tempo                      1545 non-null   object
 20  Duration (ms)              1545 non-null   object
 21  Valence                    1545 non-null   object
 22  Chord                      1545 non-null   object
dtypes: int64(3), object(20)
memory usage: 279.7+ KB
```

Now we can see that we have 11 rows that has null value in it. We now need to get rid of this problem in the data. So, I tried searching the data that isn't available in the dataset but was unable to find it and we can't other techniques to remove NULL values as all songs will have very differnt values for different categories.

That's why we will be dropping the rows with null values.

[19]:

```
spotify_raw_df = spotify_raw_df.dropna()
```

[20]:

```
spotify_raw_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1545 entries, 0 to 1555
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Index                      1545 non-null   int64
 1   Highest Charting Position  1545 non-null   int64
 2   Number of Times Charted    1545 non-null   int64
 3   Week of Highest Charting   1545 non-null   object
 4   Song Name                  1545 non-null   object
 5   Streams                    1545 non-null   object
 6   Artist                     1545 non-null   object
 7   Artist Followers           1545 non-null   object
 8   Song ID                    1545 non-null   object
 9   Genre                      1545 non-null   object
 10  Release Date               1545 non-null   object
 11  Weeks Charted              1545 non-null   object
 12  Popularity                 1545 non-null   object
 13  Danceability               1545 non-null   object
 14  Energy                     1545 non-null   object
 15  Loudness                   1545 non-null   object
 16  Speechiness                1545 non-null   object
 17  Acousticness               1545 non-null   object
 18  Liveness                   1545 non-null   object
 19  Tempo                      1545 non-null   object
 20  Duration (ms)              1545 non-null   object
 21  Valence                    1545 non-null   object
 22  Chord                      1545 non-null   object
dtypes: int64(3), object(20)
memory usage: 289.7+ KB
```

We have now got rid of the NULL values but the dtype still shows to be object so I am explicitly changing the values to what I see fit.

[21]:

```
spotify_raw_df[['Danceability', 'Energy', 'Loudness', 'Speechiness',␣
 ↪'Acousticness', 'Liveness', 'Tempo', 'Valence']] =␣
 ↪spotify_raw_df[['Danceability', 'Energy', 'Loudness', 'Speechiness',␣
 ↪'Acousticness', 'Liveness', 'Tempo', 'Valence']].astype(float)
```

[22]:

```
spotify_raw_df[['Artist Followers', 'Popularity', 'Duration (ms)']] =␣
↪spotify_raw_df[['Artist Followers', 'Popularity', 'Duration (ms)']].apply(pd.
↪to_numeric)
```

[23]:

```
spotify_raw_df['Streams'] = spotify_raw_df['Streams'].str.replace(',', '').
↪apply(pd.to_numeric)
```

For streams I got an issue in the dataframe that the numbers were represented with commas in it i.e '7,234,437' format and I can't use it for any numberic operation or plotting. So, the commas were removed and then it's data type was changed.

[24]:

```
spotify_raw_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1545 entries, 0 to 1555
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Index                      1545 non-null   int64
 1   Highest Charting Position  1545 non-null   int64
 2   Number of Times Charted    1545 non-null   int64
 3   Week of Highest Charting   1545 non-null   object
 4   Song Name                  1545 non-null   object
 5   Streams                    1545 non-null   int64
 6   Artist                     1545 non-null   object
 7   Artist Followers           1545 non-null   int64
 8   Song ID                    1545 non-null   object
 9   Genre                      1545 non-null   object
 10  Release Date               1545 non-null   object
 11  Weeks Charted              1545 non-null   object
 12  Popularity                 1545 non-null   int64
 13  Danceability               1545 non-null   float64
 14  Energy                     1545 non-null   float64
 15  Loudness                   1545 non-null   float64
 16  Speechiness                1545 non-null   float64
 17  Acousticness               1545 non-null   float64
 18  Liveness                   1545 non-null   float64
 19  Tempo                      1545 non-null   float64
 20  Duration (ms)              1545 non-null   int64
 21  Valence                    1545 non-null   float64
 22  Chord                      1545 non-null   object
dtypes: float64(8), int64(7), object(8)
memory usage: 289.7+ KB
```

Now all the data is clean and we are ready to do our analysis

1.3 Exploratory Analysis and Visualization

We will now do some Data Visualiztion and try to get some insight through it.

Let's begin by importingmatplotlib.pyplot and seaborn.

[25]:

```
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline

sns.set_style('darkgrid')
matplotlib.rcParams['font.size'] = 14
matplotlib.rcParams['figure.figsize'] = (17, 9)
matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

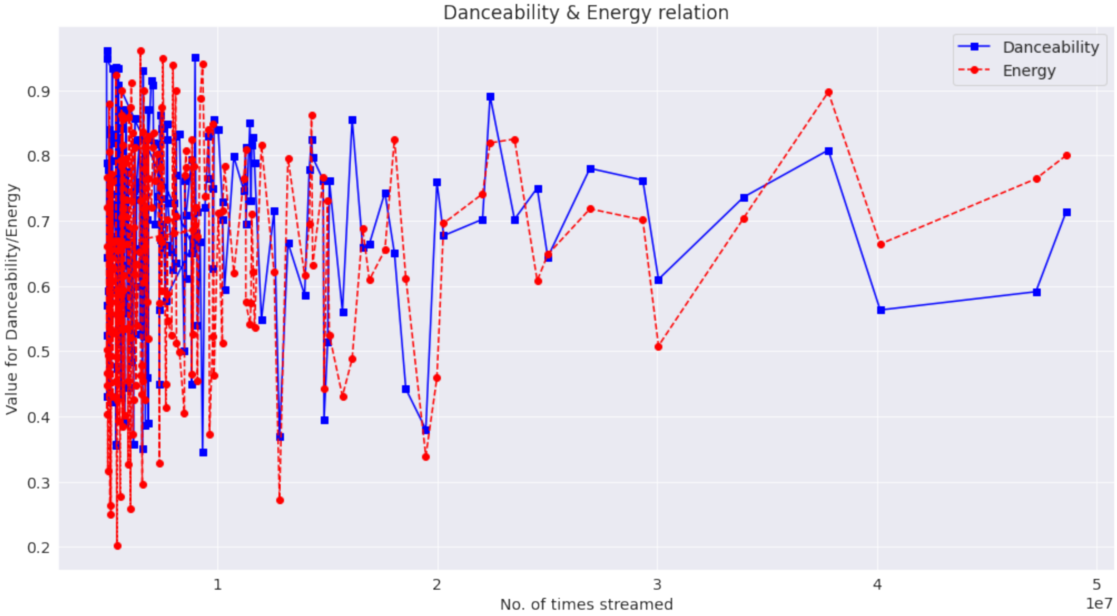
Here we are considering only the top 200 most popular song in our dataset because plotting all 1545 songs will not give us clear insight as detail on them might vary but top 200 songs can show us better pattern in what makes a song go top of the charts.

[26]:

```
spotify_top_200 = spotify_raw_df.head(200)
```

[27]:

```
plt.plot(spotify_top_200.Streams, spotify_top_200.Danceability, 's-b')
plt.plot(spotify_top_200.Streams, spotify_top_200.Energy, 'o--r')

plt.xlabel('No. of times streamed')
plt.ylabel('Value for Danceability/Energy');

plt.title("Danceability & Energy relation")
plt.legend(['Danceability', 'Energy']);
```

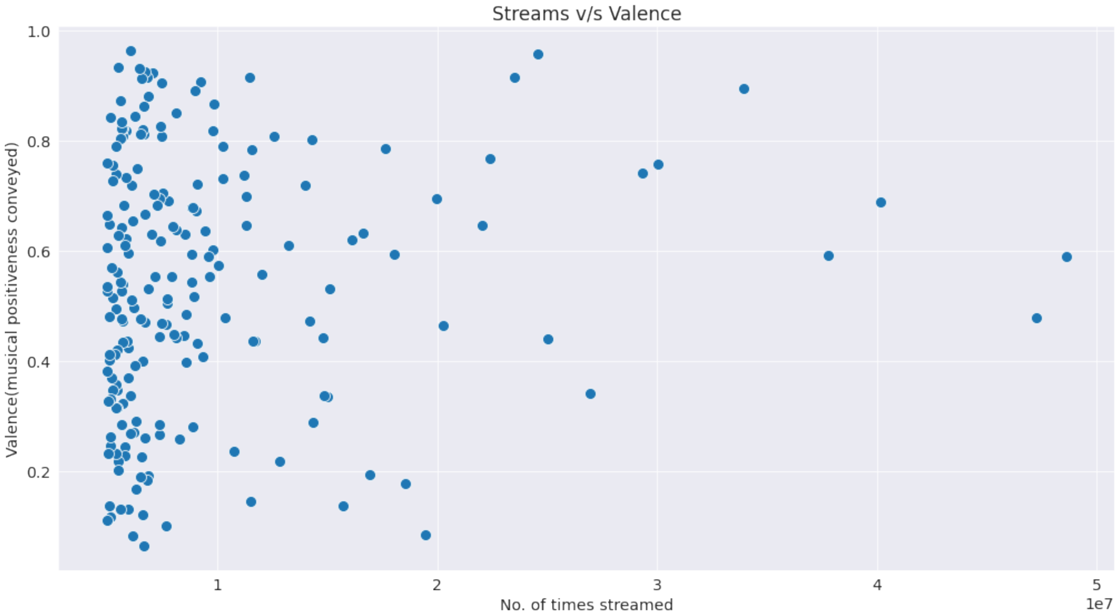


Here I have tried to see a relation between Danceability and Energy of a song and how much it gets streamed.

From the graph we can see that the **Danceability and Energy of the most stream songs is above 0.5** and this goes for the top 13 most streamed song and only when we come the 14th song that we see a low Danceability and Energy.

So, the more Danceable and Energy invoking the song is, higher are the chances of it getting stramed a lot.

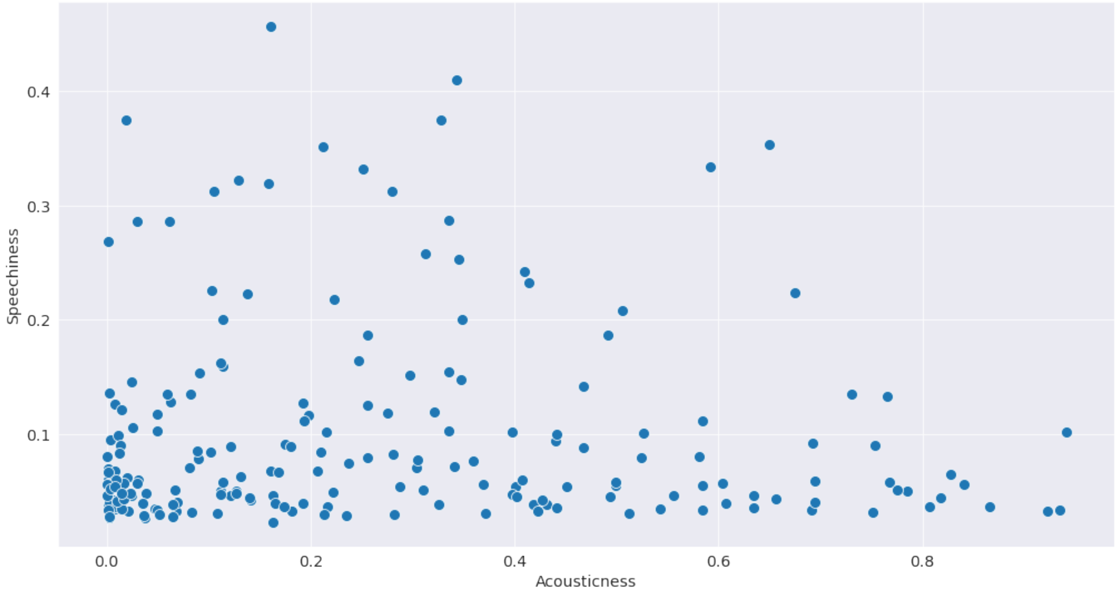
[28]:
```
sns.scatterplot(x=spotify_top_200.Streams,
                y=spotify_top_200.Valence,
                s=100);

plt.xlabel('No. of times streamed')
plt.ylabel('Valence(musical positiveness conveyed)');
plt.title("Streams v/s Valence");
```



Again here we can see that in the songs that got streamed the most does have higher valance, especially for songs that have been streamed more than 20M times. While for songs streamed less than 10M times the value for valance is evenly distributed.

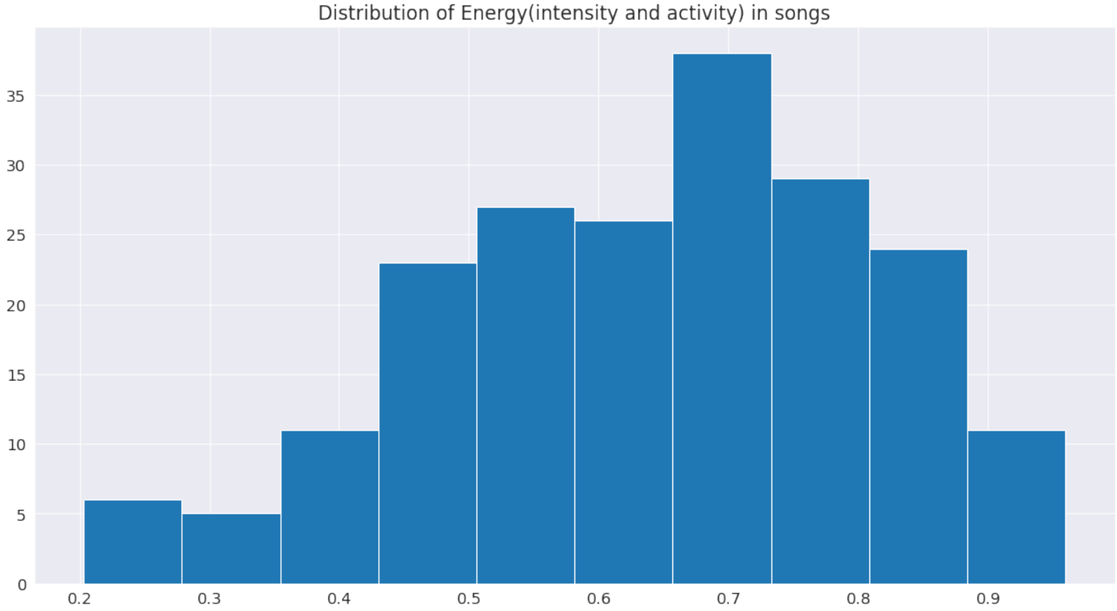
[29]:
```
sns.scatterplot(x=spotify_top_200.Acousticness,
                y=spotify_top_200.Speechiness,
                s=100);

plt.xlabel('Acousticness')
plt.ylabel('Speechiness')
```

[29]:
```
Text(0, 0.5, 'Speechiness')
```



In this graph we can see that almost all the song has less score on speechiness and the acousticness is evenly distributed apart for the cluster of songs that we see at left bottom of the graph. We can understand from this grpah that songs generally has more acousticness in it than speechiness.

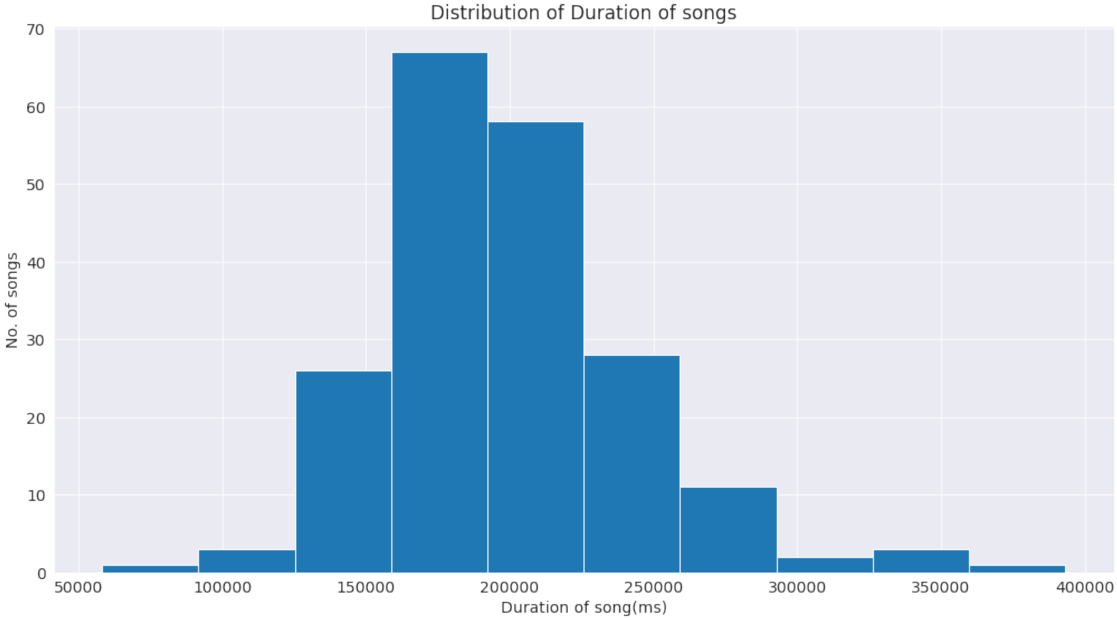
```
[30]: plt.title("Distribution of Energy(intensity and activity) in songs")
      plt.hist(spotify_top_200.Energy);
```



Here from this grpah we can take note that 152 of the top 200 songs scores 0.5 or higher score at

Energy.

[31]:
```
plt.hist(spotify_top_200["Duration (ms)"]);

plt.xlabel("Duration of song(ms)")
plt.ylabel("No. of songs")
plt.title("Distribution of Duration of songs");
```



Here I have tried to check what is durtion of most of the songs in top 200 of our dataset, we can see that most songs are between 160 secs to 225 secs long.

1.4 Asking and Answering Questions

Let's see more of statistical inference that we can make from the data and this time I am switching between the top 200 popular songs and whole dataset to get better result.

Q1: Which artis had most song feature in the top 200 chart throught the duration of our data?

[34]:
```
artists_top200_count = spotify_raw_df['Artist'].value_counts()
```

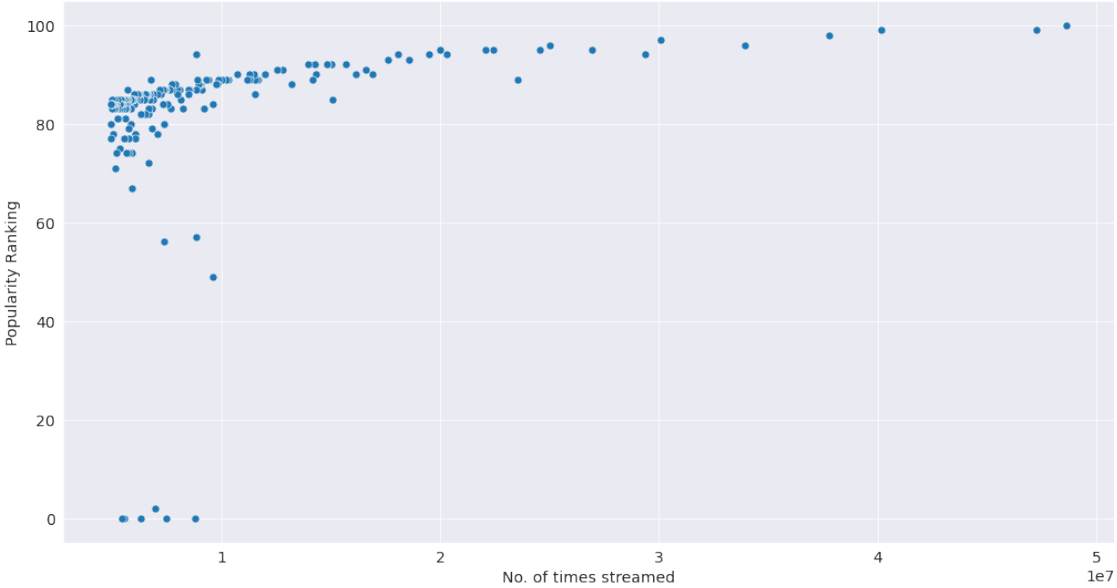
[35]:
```
artists_top200_count
```

[35]:
```
Taylor Swift                     52
Justin Bieber                    32
Lil Uzi Vert                     32
Juice WRLD                       30
Pop Smoke                        29
```

```
                                  ..
NF, Hopsin                         1
Madame                             1
Francesca Michielin, Fedez         1
Booba, JSX                         1
Dadá Boladão, Tati Zaqui, OIK      1
Name: Artist, Length: 712, dtype: int64
```

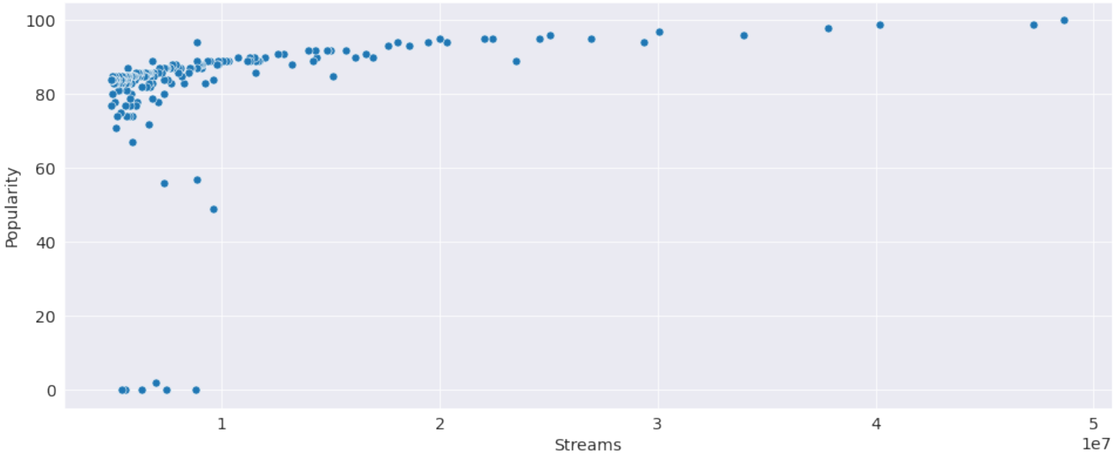
Q2: How no. of times streamed and popularity of a song varies in ou dataset?

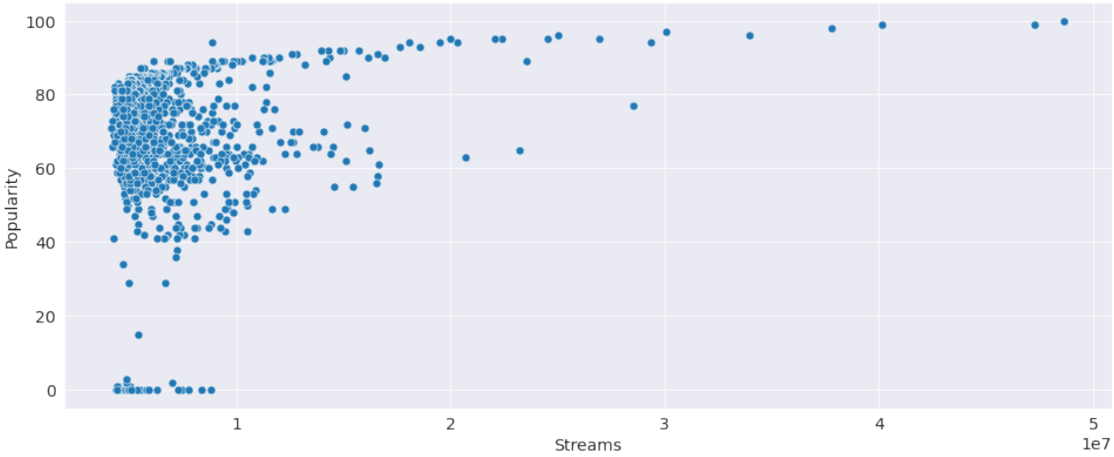
```
[36]: sns.scatterplot(x=spotify_top_200.Streams, y=spotify_top_200.Popularity, s=50)

      plt.xlabel('No. of times streamed')
      plt.ylabel('Popularity Ranking');
```



The above graph shows us the popularity v/s stream graph. We can a cluster of songs that has below 10M stream and above rank above 60 in the popularity, while we also have few songs that score low on both popularity and ranking.

```
[52]: fig, axes = plt.subplots(2, 1, figsize=(16, 14))

      # popularity v/s streams of top 200 popular songs
      sns.scatterplot(x=spotify_top_200.Streams, y=spotify_top_200.Popularity, s=50,␣
       ↪ax=axes[0]);

      # popularity v/s streams of all songs in the dataset
      sns.scatterplot(x=spotify_raw_df.Streams, y=spotify_raw_df.Popularity, s=50,␣
       ↪ax=axes[1]);
```





Here I have tried to see if the patten is different in the entire dataset, the conclusion being there is not much difference the popularity v/s stream grpah is almost same for both the top 200 songs and the entire dataset apart from the clusters becoming bigger.

Q3: Which song is the least streamed in out dataset?

```
[38]: least_streamed = spotify_raw_df[spotify_raw_df.Streams == spotify_raw_df.
       ↪Streams.min()]
```

```
[39]: least_streamed[["Song Name", "Artist", "Streams"]]
```

```
[39]:                                    Song Name Artist   Streams
      1250   Good as Hell (feat. Ariana Grande)  Lizzo   4176083
```

Q4: How many songs in our dataset have less popularity? I have taken 50 as the threshold because in our previous graph we can see that the cluster in the top left starts somewhere around 50.

[72]:

```
popularity_mean = spotify_raw_df.Popularity.mean()
```

[73]:

```
least_popular = spotify_raw_df[spotify_raw_df.Popularity < popularity_mean]
```

[74]:

```
least_popular
```

[74]:

```
      Index  Highest Charting Position  Number of Times Charted  \
53       54                         40                       14
65       66                          2                       83
83       84                         76                        3
95       96                         96                        4
118     119                          5                       21
…       …                          …                       …
1547   1548                        156                        1
1550   1551                        190                        1
1552   1553                        196                        1
1554   1555                        198                        1
1555   1556                        199                        1

     Week of Highest Charting                            Song Name  Streams  \
53     2021-06-18--2021-06-25                             Rasputin  9600707
65     2020-03-27--2020-04-03                       Don't Start Now  8821971
83     2020-03-27--2020-04-03                            Love Again  7465445
95     2021-07-23--2021-07-30                           In Da Getto  6984262
118    2021-03-19--2021-03-26                               Hold On  6300416
…                         …                                    …        …
1547   2019-12-27--2020-01-03         Combatchy (feat. MC Rebecca)  5149797
1550   2019-12-27--2020-01-03                      Ne reviens pas  4676857
1552   2019-12-27--2020-01-03                   Cheirosa - Ao Vivo  4623030
1554   2019-12-27--2020-01-03            Surtada - Remix Brega Funk  4607385
1555   2019-12-27--2020-01-03  Lover (Remix) [feat. Shawn Mendes]  4595450

                            Artist  Artist Followers                 Song ID  \
53               Majestic, Boney M.             32178  6FO4K7MrMoYkc5BlpX5LNV
65                         Dua Lipa           1250353  7njGslFmqBm0SS0pTyZCs9
83                         Dua Lipa           1250353  2sN1pMv6d2t5GlvN6IBMlK
95              J Balvin, Skrillex           1250353  5lGtPshEJlsJgmqKLi41LY
118                   Justin Bieber           1250353  49xx65gvlD7xXjDTavFqaJ
…                                …                 …                      …
1547        Anitta, Lexa, Luísa Sonza          10741972  2bPtwnrpFNEe8N7Q85kLHw
1550          Gradur, Heuss L'enfoiré           1390813  4TnFANpjVwVKWzkxNzIyFH
1552                  Jorge & Mateus          15019109  2PWjKmjyTZeDpm0Ua3a5da
1554   Dadá Boladão, Tati Zaqui, OIK            208630  5F8ffc8KWKNawllr5WsW0r
1555                    Taylor Swift          42227614  3i9UVldZOE0aD0JnyfAZZ0

                                       Genre  … Danceability  \
53               ['house', 'pop dance', 'uk dance']  …        0.830
```

```
65                                                    []  …        0.793
83                                                    []  …        0.659
95                                                    []  …        0.915
118                                                   []  …        0.658
…                                                 …  …          …
1547  ['funk carioca', 'funk pop', 'pagode baiano', …  …        0.826
1550  ['francoton', 'french hip hop', 'pop urbaine',…  …        0.932
1552           ['sertanejo', 'sertanejo universitario']  …        0.528
1554                     ['brega funk', 'funk carioca']  …        0.832
1555                           ['pop', 'post-teen pop']  …        0.448

     Energy  Loudness  Speechiness  Acousticness  Liveness    Tempo  \
53    0.839    -6.985       0.0699       0.00201    0.0353  128.012
65    0.793    -4.521       0.0830       0.01230    0.0951  123.950
83    0.667    -4.668       0.0339       0.00173    0.1000  115.982
95    0.720    -3.126       0.0459       0.02500    0.0942  126.986
118   0.634    -5.797       0.0413       0.01060    0.1320  139.980
…     …        …          …           …       …      …
1547  0.730    -3.032       0.0809       0.38300    0.0197  150.134
1550  0.778    -3.384       0.0638       0.21200    0.1680  124.996
1552  0.870    -3.123       0.0851       0.24000    0.3330  152.370
1554  0.550    -7.026       0.0587       0.24900    0.1820  154.064
1555  0.603    -7.176       0.0640       0.43300    0.0862  205.272

      Duration (ms)  Valence  Chord
53           345543    0.590  F#/Gb
65           183290    0.679      B
83           258004    0.468      B
95           131067    0.631  G#/Ab
118          170813    0.290  C#/Db
…              …      …    …
1547         157600    0.605  C#/Db
1550         188613    0.933  A#/Bb
1552         181930    0.714      B
1554         152784    0.881      F
1555         221307    0.422      G

[645 rows x 23 columns]
```

[75]:
```
len(least_popular)
```

[75]:
```
645
```

Q5: How many songs were streamed more than avarage?

[66]:
```
mean_streams = spotify_raw_df.Streams.mean()
```

[67]:

```
more_streamed = spotify_raw_df[spotify_raw_df.Streams > mean_streams]
```

[68]:

```
more_streamed
```

[68]:

```
      Index  Highest Charting Position  Number of Times Charted  \
0         1                          1                        8
1         2                          2                        3
2         3                          1                       11
3         4                          3                        5
4         5                          5                        1
…     …                        …                      …
1511   1512                         90                        1
1512   1513                        107                        1
1513   1514                        111                        1
1543   1544                         59                        1
1544   1545                         72                        1

     Week of Highest Charting                          Song Name   Streams  \
0      2021-07-23--2021-07-30                            Beggin'  48633449
1      2021-07-23--2021-07-30          STAY (with Justin Bieber)  47248719
2      2021-06-25--2021-07-02                           good 4 u  40162559
3      2021-07-02--2021-07-09                         Bad Habits  37799456
4      2021-07-23--2021-07-30  INDUSTRY BABY (feat. Jack Harlow)  33948454
…                       …                                …       …
1511   2020-01-10--2020-01-17                        Dance Again   7394604
1512   2020-01-10--2020-01-17                               Ring   6693229
1513   2020-01-10--2020-01-17         Crowded Room (feat. 6LACK)   6483001
1543   2019-12-27--2020-01-03                         Trampoline   8896030
1544   2019-12-27--2020-01-03                              GATTI   7685470

                                 Artist  Artist Followers  \
0                              Måneskin           3377762
1                         The Kid LAROI           2230022
2                        Olivia Rodrigo           6266514
3                            Ed Sheeran          83293380
4                             Lil Nas X           5473565
…                                 …               …
1511                       Selena Gomez          28931149
1512                       Selena Gomez          28931149
1513                       Selena Gomez          28931149
1543                        SHAED, ZAYN            139434
1544  JACKBOYS, Pop Smoke, Travis Scott            437907

                     Song ID                                   Genre  …  \
0     3Wrjm47oTz2sjIgck11l5e  ['indie rock italiano', 'italian pop']  …
1     5HCyWlXZPP0y6Gqq8TgA20                  ['australian hip hop']  …
2     4ZtFanR9U6ndgddUvNcjcG                                 ['pop']  …
```

```
3     6PQ88X9TkUIAUIZJHW2upE                       ['pop', 'uk pop']  …
4     27NovPIUIRrOZoCHxABJwK           ['lgbtq+ hip hop', 'pop rap']  …
…                       …                                      …  …
1511  5sK3o66yupTNIK6gWgzGjf   ['dance pop', 'pop', 'post-teen pop']  …
1512  11Ey4yJVeWEsA73KjACkVY   ['dance pop', 'pop', 'post-teen pop']  …
1513  2C0hTkdEoikhKzDCJl32QZ   ['dance pop', 'pop', 'post-teen pop']  …
1543  1iQDltZqI7BXnHrFy4Qo1k                   ['electropop', 'pop']  …
1544  40mjsnRjCpycdUw3xhS20g                         ['rap', 'trap']  …

     Danceability Energy  Loudness  Speechiness  Acousticness  Liveness  \
0           0.714  0.800    -4.808       0.0504        0.1270    0.3590
1           0.591  0.764    -5.484       0.0483        0.0383    0.1030
2           0.563  0.664    -5.044       0.1540        0.3350    0.0849
3           0.808  0.897    -3.712       0.0348        0.0469    0.3640
4           0.736  0.704    -7.409       0.0615        0.0203    0.0501
…            …    …       …          …           …       …
1511        0.784  0.552    -7.261       0.0871        0.0447    0.1920
1512        0.873  0.510    -5.350       0.0661        0.5650    0.0738
1513        0.724  0.415    -8.408       0.0518        0.7640    0.1030
1543        0.619  0.459    -5.782       0.0334        0.5600    0.1370
1544        0.594  0.676    -5.808       0.3440        0.1350    0.1630

        Tempo  Duration (ms)  Valence  Chord
0     134.002         211560    0.589      B
1     169.928         141806    0.478  C#/Db
2     166.928         178147    0.688      A
3     126.026         231041    0.591      B
4     149.995         212000    0.894  D#/Eb
…       …            …      …    …
1511  111.984         170498    0.465  C#/Db
1512  110.953         148776    0.871  D#/Eb
1513   89.999         186459    0.328      G
1543  126.803         184280    0.498      G
1544  143.477         181145    0.472      D

[401 rows x 23 columns]
```

[69]:

```
len(more_streamed)
```

[69]:

```
401
```

1.5 Inferences and Conclusion

- Most popular songs tends to have higher danceability and Energy. Such songs fits good to lighten up our mood or to be played at parties.
- Almost 75% of the songs that makes it to Top 200 charts throught the year is streamed less than the avaerage. The reason could be

- 645 of the 1545 songs that made it to the Top 200 chart ranks below average in Popularity among all the songs that make it there
- Taylor Swift had 52 songs featuring in the Top 200 chart, second in the list was Justin Bieber with 32 songs. A difference of 20 songs.
- The song with least number of stream that made it to the char was “Good as Hell (feat. Ariana Grande)” by Lizzo which got 4176083 streams.
- Songs generally score low on Speachiness and evenly on Acousticness which means lesser the lyrics/vocal/speech part of the song makes up to a lower percentage of everything involved in the song and the Acoustic plays important role in the song as we have the music and beats throughout the duration of song.

1.6 References and Future Work

- The weeks can be broken up into day, month, year and more insights can be found through it.
- More analysis can be done on the basis of **Genre** and **Chord** of song.
- A better knowlwdge on all the types of data provided about the music can help making more inferences.