PROJECT REPORT

1. **Introduction: -**

The onset of the pandemic had forced everyone to stay at home for a significant period of time. Staying home we needed some form recreation, Therefore, during this period human recreation went digital resulting in a sudden spike in media streaming (Video on Demand, Music etc.). The music streaming traffic globally increased by 20% during the pandemic resulting in an accelerated increase in media consumption. The main aim of our project is to analyze and visualize the regional usage of one such music streaming application – Spotify. Our main focus is to analyze "Spotify Regional Charts" of 3 particular countries – USA, India and England for the year 2020 grouping the year into quarters to better understand the impact of the pandemic on music streaming in these countries. Using the music streaming trends in the countries we will understand the mood of the streamers in these regions. Analyzing the data will help us understand the transitional effect of the pandemic and its impact on what people listened to during that period. Analyzing the "Spotify Regional Charts", will also help us understand the day-to-day music streaming in these countries and in turn visualize the mood of streamers in these regions based on the genre of music during the aforementioned pandemic. For example, if we assume that the streaming of "Sad/Melancholic" songs was heightened during the pandemic and if our findings in the project conforms to be the same, the following will measure the success of our findings. The data we have has 5 songs for each day and these top 5 songs are extracted from the "Spotify Regional Charts" and we had to extract for each day.

We extracted these top 5 songs for each day and these songs extracted were stored in country specific csv files. The main aim of the project was to highlight the features of the regional usage of Spotify. Finding the trends on the shift of genre of music streamed during the pandemic and depicting the same is the crux of the project. We divided our approach in such a way that we used time-based segregation of the data, we split the date field in the extracted data frame into two parts: Lockdown phase and Post Lockdown phase. We have shown the difference between the two phases for each country and this comparison between the two phases gave us insights. We have visually shown the change in trends

2. **Data: -**

Data for any sort of analysis consist of three parts usually which are Data Extraction, Data Cleaning and Data Handling, almost every time each of the following methods are used except for cases where in the data extracted is in such a way that it requires minimal cleaning. We in the following project extracted our data based on the data available on "Spotify Regional Charts" when this extraction was done, we realized that we needed more data which then resulted in us using the Spotipy API. Spotipy is a lightweight Python library which is used for extracting feature elements of the song. Spotipy provides all the basic details of the songs along with insightful features which make the song the song it is. The Data Cleaning is the most important step in any form of data analysis, reason being that a clean data results in less redundancy and errors it also results in efficient insights with the data having no or very less outliers. Cleaning the data also helps us to remove the empty data points and have the extracted data in a meticulous manner. The data procured by us was therefore extracted in such a manner that we got the data in the cleanest way possible, the code developed was used for extraction in such a way to achieve high quality, non-redundant and clean data. In Data Handling we manage the extracted data and keep it in an orderly and systematic manner. The data obtained needed the additional fields for getting better analysis conforming to our project targets, features like danceability, loudness, valence, tempo, acousticness and instrumentalness were extracted and handled. The challenge to extract day to day feature for 3 different regions for a time frame of 180 days and having 17 rows was an exhaustive process as each song extracted needed to be extracted from the "Spotify Regional Charts" webpage and then matched to the Spotipy features.

In the end our dataset consisted of nearly 15,000 data points which was divided across 17 rows consisting of Song Name, Artist, Date, Streams, Rank, Country, Links, Danceability, Energy, Loudness, Speechiness, Acousticness, Instrumentalness, Liveness, Valence, Tempo and Genre. Each of these were there for countries like India, USA and UK respectively. The sample of our dataset with a head of 5 rows is shown in Figure 2.1

```
df_unitedstates.head(5)
```

	Song	Artist	Date	Streams	Rank	Country	Links	Danceability	Energy	Loudness	Speechiness	Acoustic
0	The Box	Roddy Ricch	3/1/20	2,145,340	1	us	https://open.spotify.com/track/0nbXyq5TXYPCO7p...	0.896	0.586	-6.687	0.0559	0.1
1	Say So	Doja Cat	3/1/20	1,116,529	2	us	https://open.spotify.com/track/3Dv1eDb0MEgF93G...	0.787	0.673	-4.577	0.1580	0.2
2	Blinding Lights	The Weeknd	3/1/20	1,106,280	3	us	https://open.spotify.com/track/0sf12qNH5qcw8qp...	0.513	0.796	-4.075	0.0629	0.0
3	Life Is Good (feat. Drake)	Future	3/1/20	1,048,449	4	us	https://open.spotify.com/track/5yY9lUy8nbvjM1U...	0.676	0.609	-5.831	0.4810	0.0
4	Blueberry Faygo	Lil Mosey	3/1/20	1,043,040	5	us	https://open.spotify.com/track/22LAwLoDA5b4AaG...	0.774	0.554	-7.909	0.0383	0.2

Figure 2.1

3.Analysis: -

Analysis of data is the process of obtaining a relevant subset of the entire dataset in order to get insights relevant to the outcome of the project, it helps in comparing various data points with one another and helps us understand the data based on particular parameters and constraints. Analysis of the dataset also enable us to provide graphical representation of the findings and insights gained. The project of ours has data analysis which provides us with vital statistical analysis and provides visual outlook for our data.

Our data analysis involved two parts one for Lockdown Phase and the other for Post Lockdown Phase. Each of this is done for India, USA and UK and is depicted as follows: -

INDIA

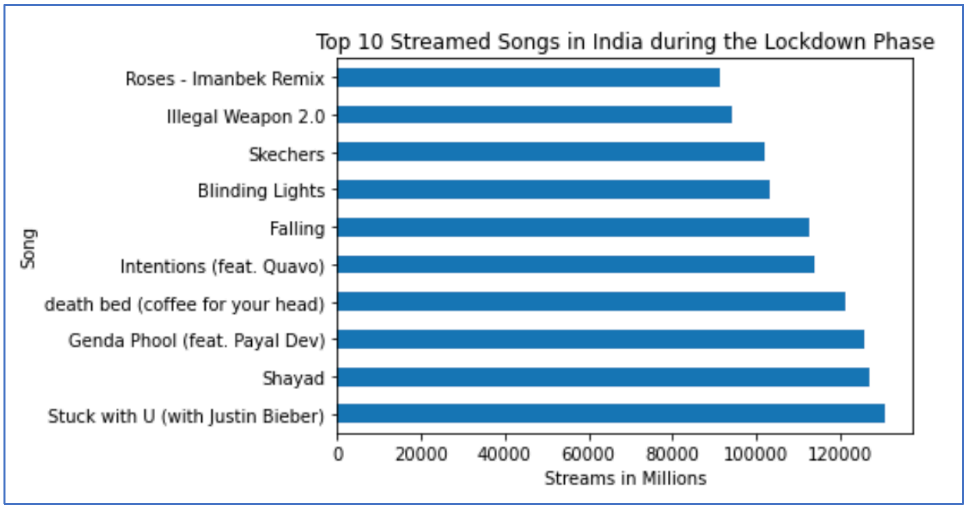


Figure 3.1.a

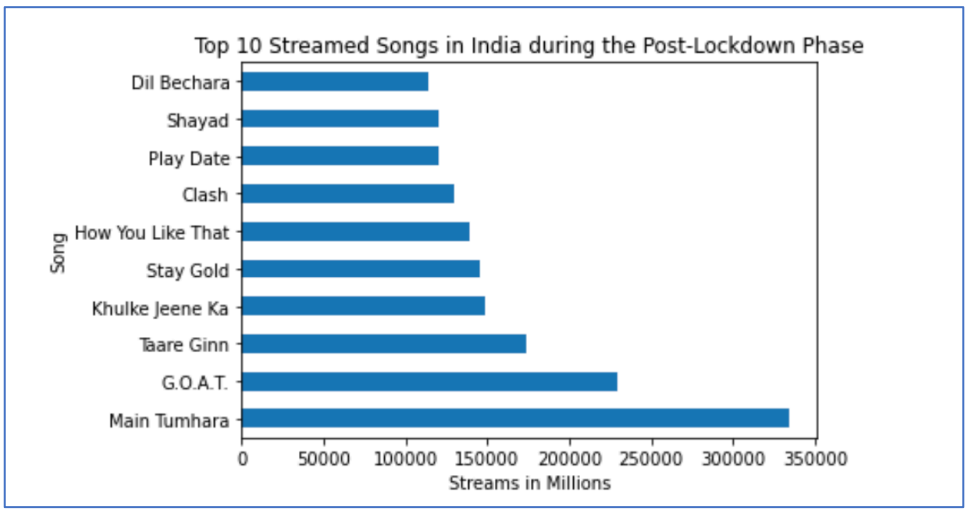


Figure 3.1.b

The **Figure 3.1.a** and **Figure 3.1.b** is a Bar Graph comparison between the “Top 10 Streamed Songs in India”. Figure 3.1.a depicts the graph for Lockdown phase and 3.1.b depicts the graph for Post-Lockdown Phase.

INDIA

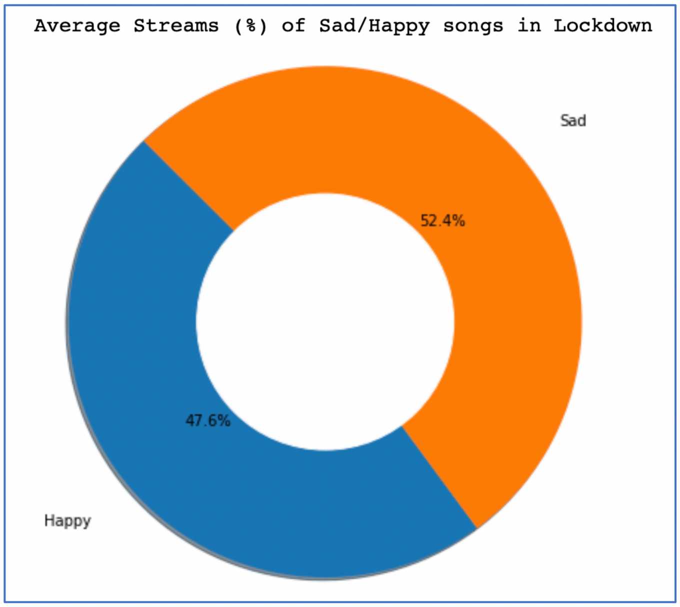


Figure 3.2.a

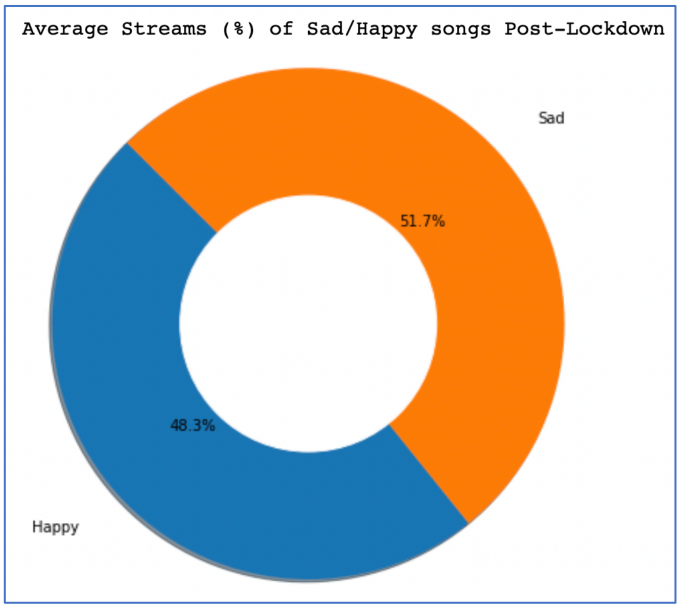


Figure 3.2.b

The **Figure 3.2.a** and **Figure 3.2.b is** a Pie Chart comparison between the "Stream %of Sad/Happy Songs in India". Figure 3.2.a depicts the graph for Lockdown phase and 3.2.b depicts the graph for Post-Lockdown Phase. Figure 3.2.a has 52.4% Sad Stream's and Figure 3.2.b has 51.7% Sad Stream's.

INDIA

Artist with Highest Sad Stream vs Artist with Highest Happy Stream Lockdown

<AxesSubplot:xlabel='Artist', ylabel='Streams'>

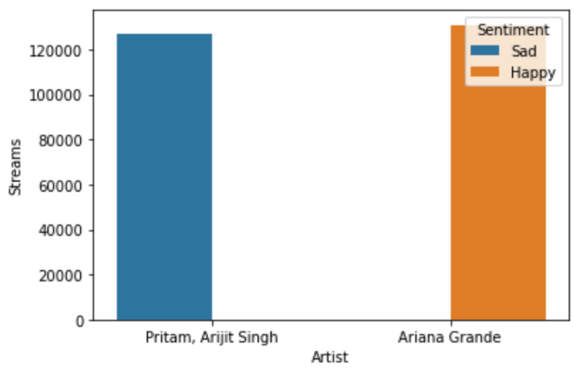


Figure 3.3.a

Artist with Highest Sad Stream vs Artist with Highest Happy Stream Post-Lockdown

<AxesSubplot:xlabel='Artist', ylabel='Streams'>

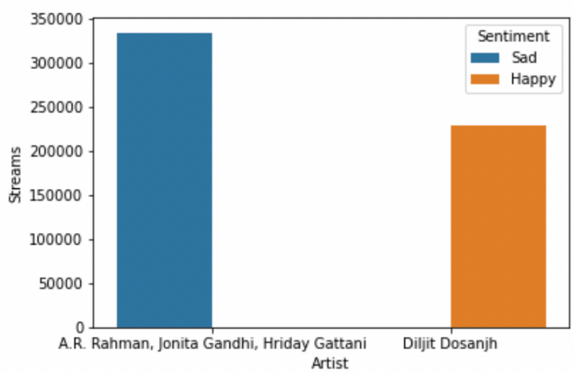


Figure 3.3a

The **Figure 3.3.a** and **Figure 3.3.b is** a Bar Graph comparison between the “Artist with the Highest Sad Stream vs Artist with the Highest Happy Stream in India”. Figure 3.3.a depicts the graph for Lockdown phase and 3.3.b depicts the graph for Post-Lockdown Phase. Figure 3.3.a has “Pritam, Arjit Singh” for Sad Song and “Ariana Grande” for Happy Song and Figure 3.3.b has “A.R. Rahman, Jonita Gandhi Hriday Gattani” for Sad Song and “Diljit Dosanjh” for Happy Song.

USA

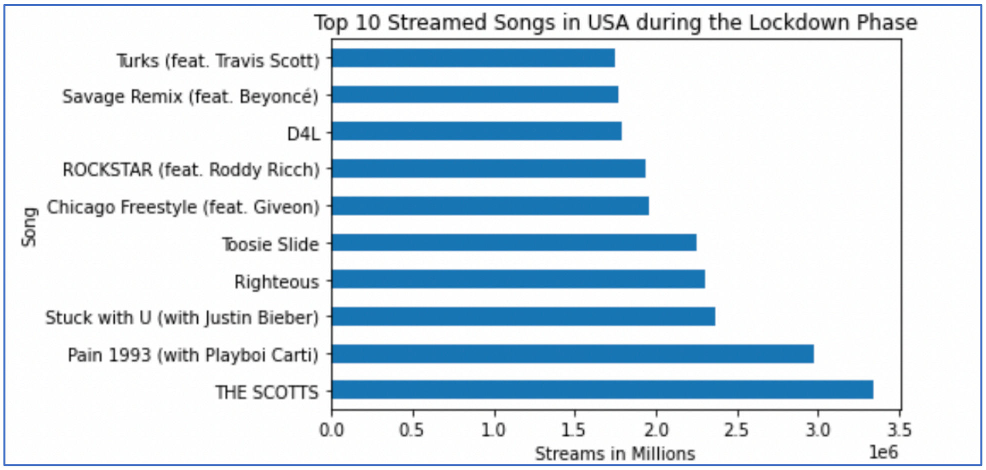


Figure 3.4.a

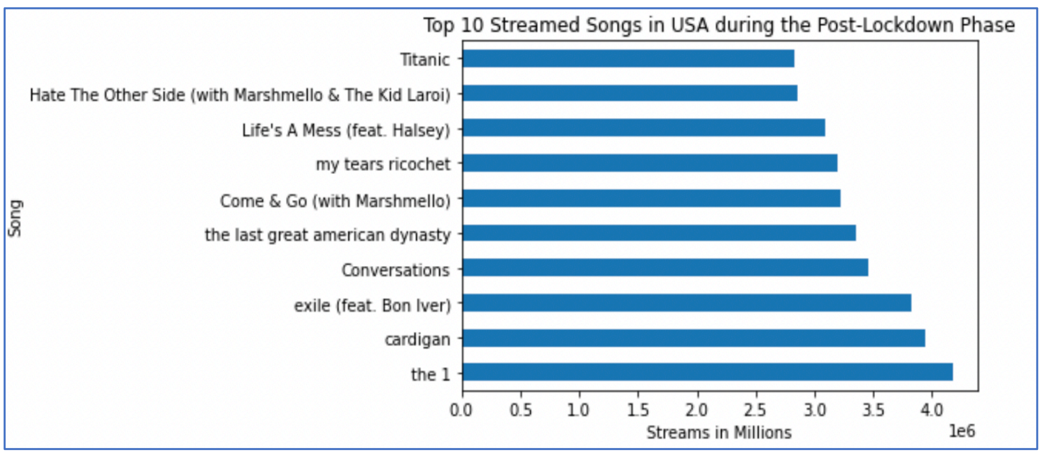


Figure 3.4.a

The **Figure 3.4.a** and **Figure 3.4.b** is a Bar Graph comparison between the "Top 10 Streamed Songs in USA". Figure 3.4.a depicts the graph for Lockdown phase and 3.4.b depicts the graph for Post-Lockdown Phase.

USA

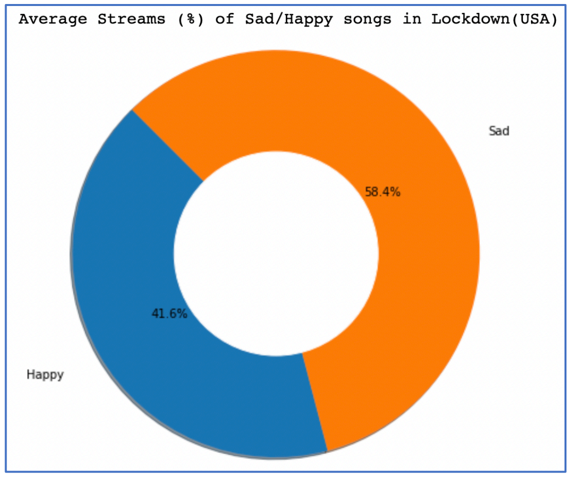


Figure 3.5.a

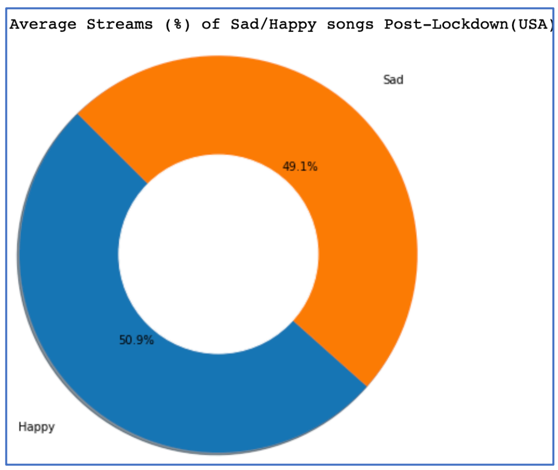


Figure 3.5.b

The **Figure 3.5.a** and **Figure 3.5.b is** a Pie Chart comparison between the "Stream %of Sad/Happy Songs in USA". Figure 3.5.a depicts the graph for Lockdown phase and 3.5.b depicts the graph for Post-Lockdown Phase. Figure 3.5.a has 58.4% Sad Stream's and Figure 3.5.b has 49.1% Sad Stream's.

USA

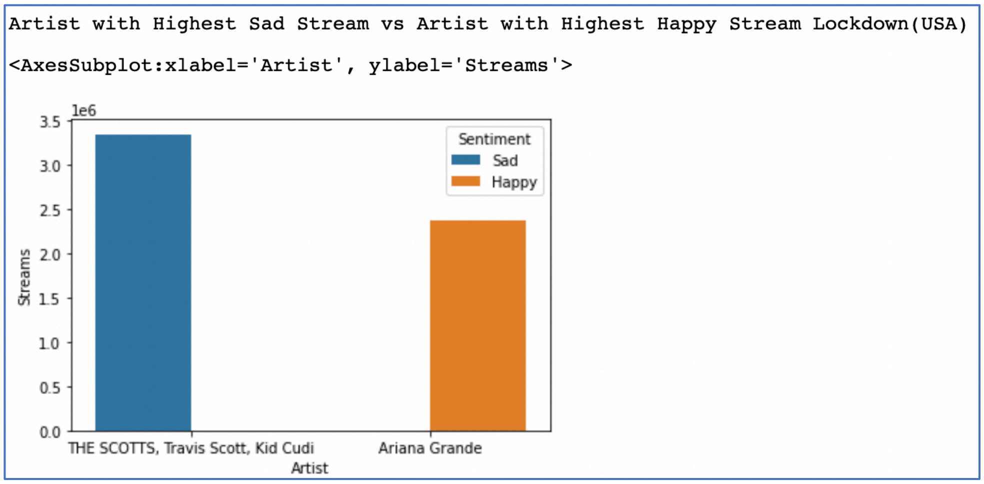


Figure 3.6.a

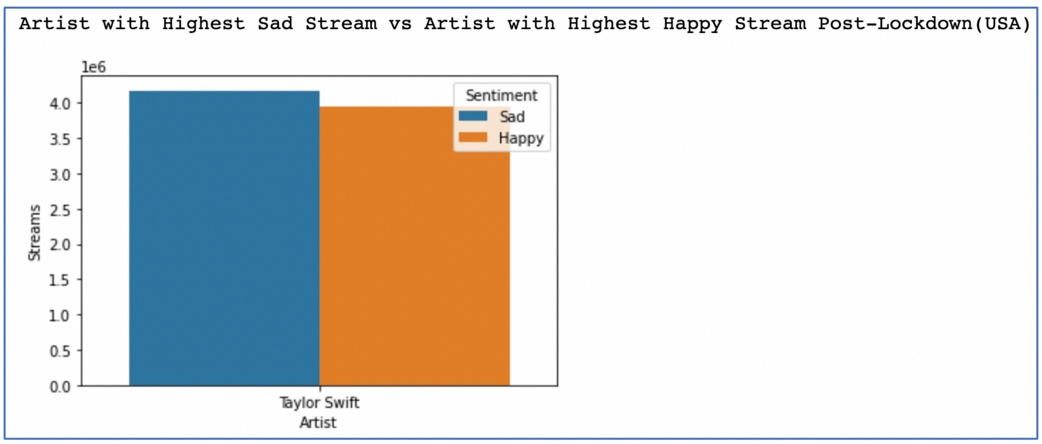
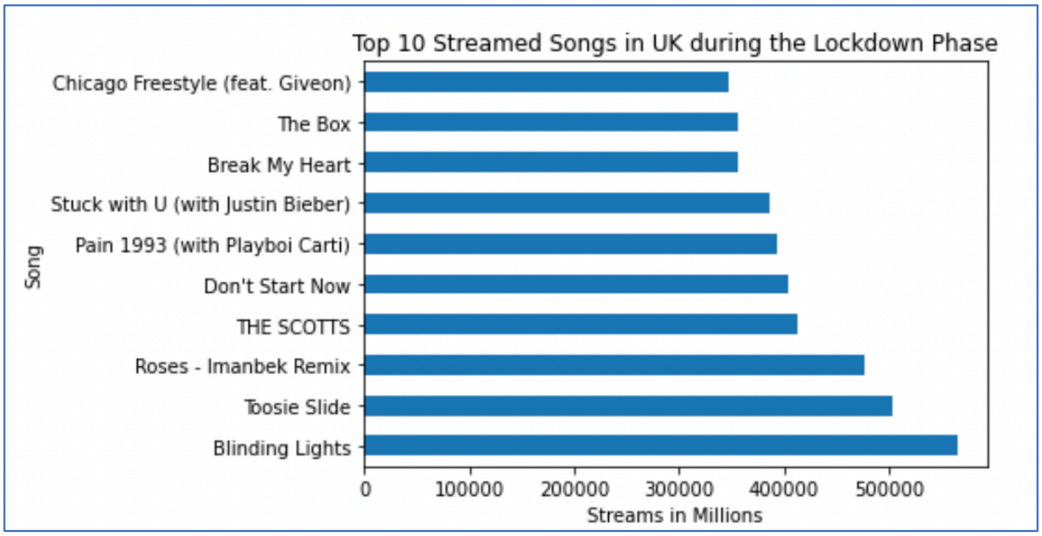


Figure 3.6.b

The **Figure 3.6.a** and **Figure 3.6.b is** a Bar Graph comparison between the "Artist with the Highest Sad Stream vs Artist with the Highest Happy Stream in USA". Figure 3.6.a depicts the graph for Lockdown phase and 3.6.b depicts the graph for Post-Lockdown Phase. Figure 3.6.a has "THE SCOTTS, Travis Scott, Kid Cudi" for Sad Song and "Ariana Grande" for Happy Song and Figure 3.6.b has "Taylor Swift" for Sad Song and "Taylor Swift" for Happy Song.

UK



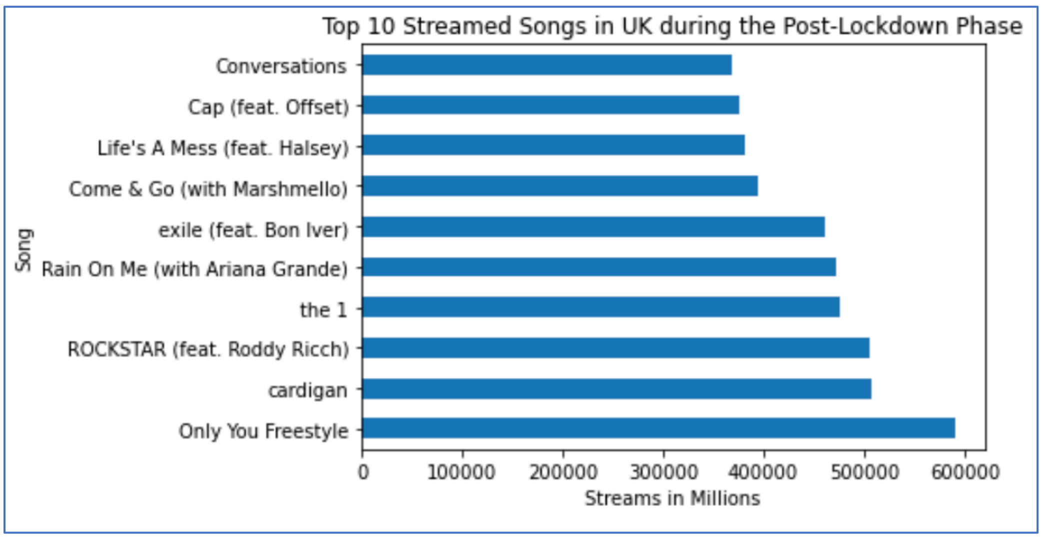


Figure 3.7.a

Figure 3.7.b

The **Figure 3.7.a** and Graph comparison Streamed Songs in UK". graph for Lockdown the graph for Post-

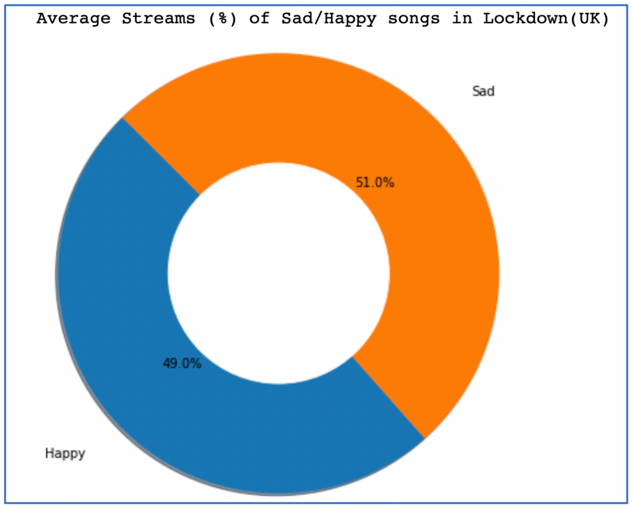


Figure 3.7.b is a Bar between the "Top 10 Figure 3.7.a depicts the phase and 3.7.b depicts Lockdown Phase.

UK

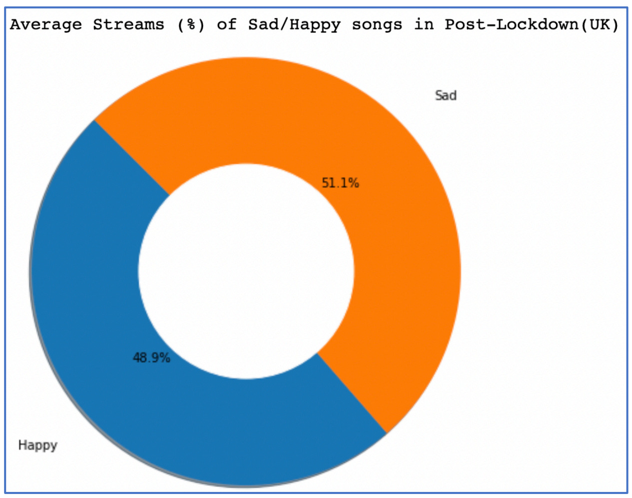


Figure 3.8.a

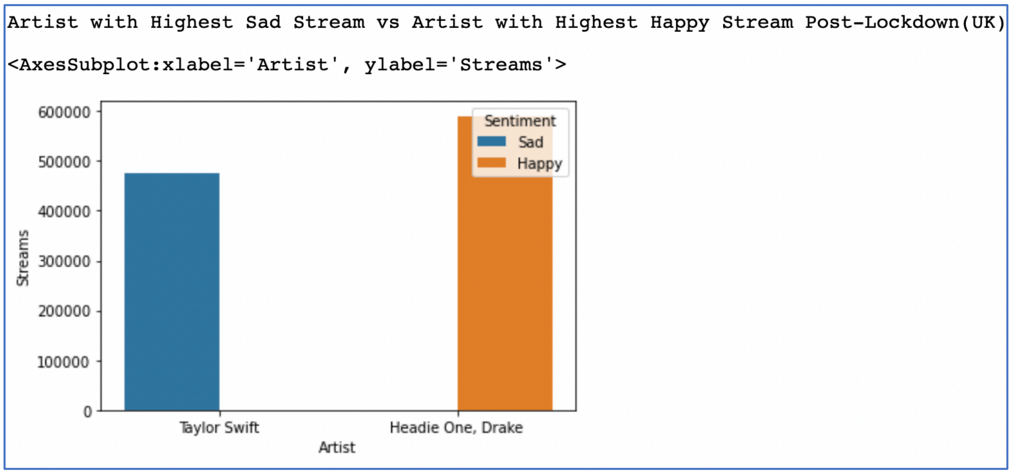


Figure 3.8.b

The **Figure 3.8.a** and **Figure 3.8.b is** a Pie Chart comparison between the "Stream %of Sad/Happy Songs in UK". Figure 3.8.a depicts the graph for Lockdown phase and 3.8.b depicts the graph for Post-Lockdown Phase. Figure 3.8.a has 51% Sad Stream's and Figure 3.8.b has 51.1% Sad Stream's.

UK

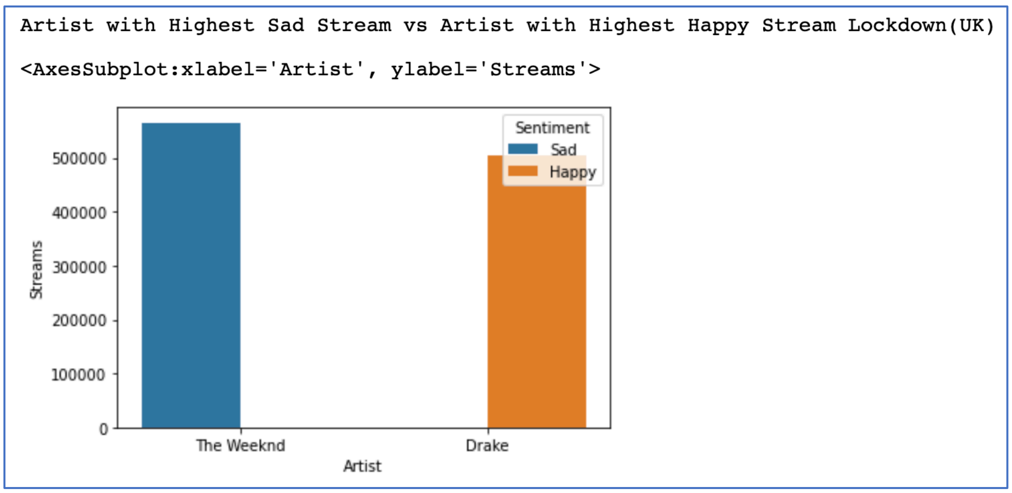


Figure 3.9.a

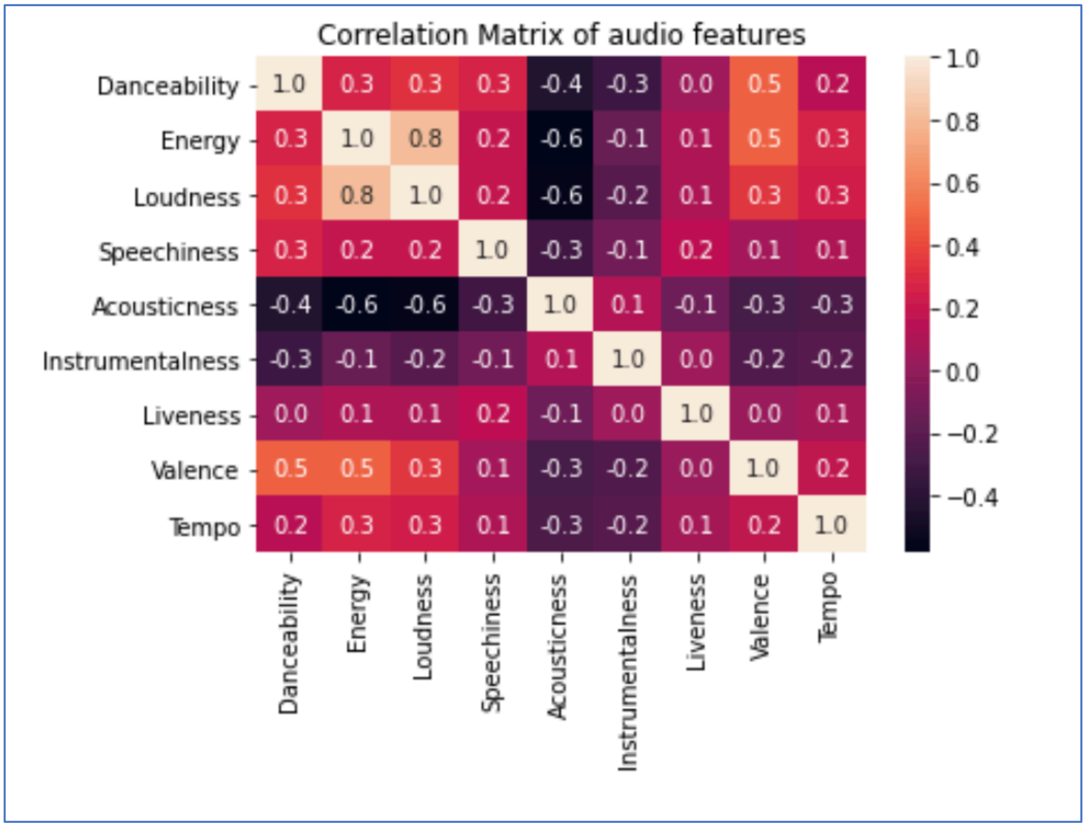


Figure 3.9.B

The **Figure 3.9.a** and **Figure 3.9.b is** a Bar Graph comparison between the "Artist with the Highest Sad Stream vs Artist with the Highest Happy Stream in UK". Figure 3.9.a depicts the graph for Lockdown phase and 3.9.b depicts the graph for Post-Lockdown Phase. Figure 3.9.a has "Taylor Swift" for Sad Song and "Headie One, Drake" for Happy Song and Figure 3.9.b has "The Weekend" for Sad Song and "Drake" for Happy Song

Figure 3.10

Figure 3.10 represents the Correlation Matrix of the Audio Features of each song in the dataset. Correlation Matrix is the same for each Country for which we are working.

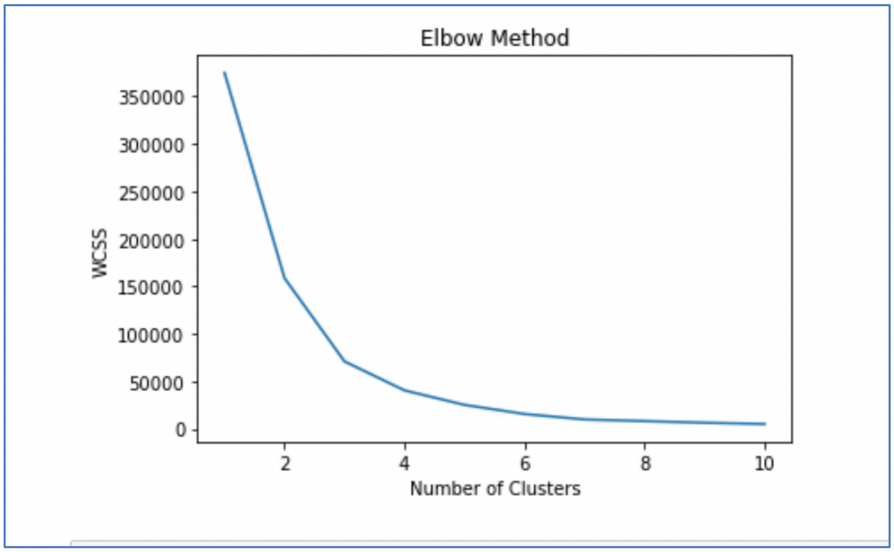


Figure 3.11

Elbow Method as shown in Figure 3.11 is a way for finding the number of clusters that should be there in K-Means the way we get the number is by analyzing the graph where we take the point at which the graph straightens relative to the X-Axis. We take the start point of the flattening trend as the k value of our K-Means algorithm.

4.Results: -

The project involved classification of songs into cluster's, and we did use K-Means Classifier to classify each song. To find the cluster's k value which is a value that tells us as to how many clusters does the classifier need to have, we used the Elbow Method which gave the k value as 5. The 5 clusters formed are as follows: -

Links	Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Genre	K-Means Cluster
spotify.com/track/4umlPjkehX1r7uh...	0.806	0.546	-6.637	0.0575	0.3000	0.000000	0.1020	0.874	147.986	['canadian pop', 'pop', 'post-teen pop']	0
tify.com/track/0WdbnNKO0Jt4BZA...	0.695	0.727	-6.274	0.0323	0.0744	0.000175	0.5330	0.864	118.034	['desi pop', 'filmi', 'modern bollywood']	0
.spotify.com/track/6q9XTgfWilsnyiF...	0.788	0.870	-5.217	0.1770	0.1230	0.000014	0.0692	0.884	109.974	['desi hip hop', 'desi pop', 'desi trap', 'fil...	0
otify.com/track/0gzu5mm36VJH2Zq...	0.955	0.538	-8.394	0.0734	0.1320	0.001460	0.0704	0.837	116.977	['desi hip hop', 'desi pop', 'desi trap', 'fil...	0
otify.com/track/127QTOFJsJQp5Lb...	0.834	0.454	-9.750	0.2010	0.3210	0.000006	0.1140	0.837	81.618	['canadian hip hop', 'canadian pop', 'hip hop'...	0

Figure 4.1 K-Means Cluster 0

Links	Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Genre	K-Means Cluster
.com/track/1smFN2CLqGROu0J...	0.483	0.468	-7.642	0.0341	0.785	0.000000	0.152	0.319	135.864	['desi pop', 'filmi', 'indian instrumental', '...	1
.com/track/4DpNNXFMMxQEKI7...	0.680	0.729	-5.077	0.0475	0.612	0.000000	0.224	0.446	123.970	['alt z', 'dance pop', 'electropop', 'pop']	1
otify.com/track/2Fv2injs4qAm8mJ...	0.427	0.396	-7.556	0.0366	0.736	0.000000	0.110	0.306	70.368	['desi pop', 'filmi', 'modern bollywood']	1
.com/track/5O932cZmzOZGOGZ...	0.534	0.481	-9.016	0.0412	0.697	0.000000	0.142	0.293	124.914	['desi pop', 'filmi', 'indian instrumental', '...	1
fy.com/track/4LEK9rD7TWlG4FC...	0.613	0.581	-8.588	0.0424	0.537	0.000345	0.250	0.551	130.033	['pop', 'post-teen pop']	1

Figure 4.2 K-Means Cluster 1

Out[30]:

Links	Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Genre	K-Means Cluster
open.spotify.com/track/7eJMfftS33KTjuF...	0.726	0.431	-8.765	0.135	0.731	0.0	0.696	0.348	144.026	['emo rap', 'sad rap']	2

Figure 4.3 K-Means Cluster 2

Links	Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Genre	K-Means Cluster
potify.com/track/7CY0CmCpSglfUKC...	0.805	0.919	-1.294	0.0938	0.1010	0.00343	0.0598	0.494	94.993	['desi pop', 'punjabi pop']	3
.spotify.com/track/2alc8VZAzDgdAsL...	0.903	0.327	-9.727	0.0877	0.2600	0.01100	0.1080	0.274	100.008	['viral rap']	3
.spotify.com/track/24Yi9hE78yPEbZ4...	0.770	0.724	-5.484	0.0495	0.0167	0.01070	0.3530	0.898	121.975	['melodic rap', 'rap', 'slap house']	3

Figure 4.4 K-Means Cluster 3

Links	Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Genre	K-Means Cluster
y.com/track/4TnjEaWOeW0eKTK...	0.785	0.431	-8.756	0.0364	0.12300	0.000000	0.0887	0.236	127.085	['pop', 'post-teen pop']	4
.com/track/25MPTnqXQB1H6Ok...	0.384	0.728	-6.503	0.0623	0.32900	0.000018	0.3290	0.311	156.396	['desi pop']	4
tify.com/track/0kPmcPPkjoyfLhU...	0.515	0.731	-5.934	0.0592	0.00146	0.000096	0.0897	0.336	171.004	['canadian contemporary r&b', 'canadian pop', ...	4
ify.com/track/4HBZA5flZLE435Q...	0.597	0.450	-6.658	0.0418	0.22300	0.000000	0.3820	0.537	178.765	['pop', 'post-teen pop']	4
/.com/track/0ZHILXmUaVSLEOC...	0.696	0.704	-7.876	0.0423	0.16700	0.000000	0.1550	0.426	124.972	['desi pop', 'filmi', 'modern bollywood']	4

Figure 4.5 K-Means Cluster 4

Each K-Mean Cluster formed has a specific property which is likely that the song in the cluster have similar features, now these features are Danceability, Energy, Loudness, Speechiness, Acousticness, Instrumentalness, Liveness, Valence and Tempo which help in classification of the song in an individual cluster.

Out[33]:

	Streams								Rank		...	Valence		Tempo		
	count	mean	std	min	25%	50%	75%	max	count	mean	...	75%	max	count	mean	std
K-Means Cluster																
0	173.0	124686.491329	30569.939429	84937.0	101639.00	119562.0	129592.00	229092.0	173.0	2.699422	...	0.845	0.884	173.0	129.514277	2.20037
1	317.0	123757.264984	26087.479885	82495.0	115044.00	122811.0	128653.00	334609.0	317.0	2.444795	...	0.358	0.551	317.0	122.971104	2.06958
2	78.0	104229.705128	13789.873931	87464.0	94303.75	100482.0	109198.75	136910.0	78.0	3.269231	...	0.348	0.348	78.0	144.026000	1.14422
3	62.0	105262.274194	13183.996769	79865.0	95283.75	107975.0	114026.00	128957.0	62.0	4.080645	...	0.494	0.898	62.0	101.833065	1.01936
4	135.0	107082.703704	13609.282087	81171.0	99070.00	105308.0	116865.50	145139.0	135.0	4.037037	...	0.334	0.548	135.0	141.452956	1.95801

Figure 4.6 K-Means Cluster Statistics

Now each K-Mean Cluster has statistical data based on each feature and showing the combined Mean, Standard Deviation, Min, Max, Q1, Q2 and Q3 based on the songs on the K-Mean Cluster.

```
In [34]: df_india_cluster.groupby("K-Means Cluster")["Valence"].describe()
```

Out[34]:

K-Means Cluster	count	mean	std	min	25%	50%	75%	max
0	173.0	0.821249	5.004000e-02	0.685	0.761	0.837	0.845	0.884
1	317.0	0.343965	7.053787e-02	0.123	0.306	0.319	0.358	0.551
2	78.0	0.348000	2.234818e-16	0.348	0.348	0.348	0.348	0.348
3	62.0	0.501226	2.189152e-01	0.274	0.274	0.494	0.494	0.898
4	135.0	0.304607	8.851133e-02	0.236	0.236	0.311	0.334	0.548

Figure 4.7 K-Means Cluster – Valence

Figure 4.7 shows us the statistical analysis of the K-Mean Cluster based on the feature Valence, Valence is the featural element of song that depicts the Mood of the song and its value is between 0 and 1. Valence nearer to the "0" is a "Sad" Song and Valence near to the "1" is a "Happy" Song. Song's Valence is categorized at 0.4 where "Valence <= 0.4" is "Sad" and "Valence > 0.4" is "Happy". Here, "K-Mean Cluster 0" has Valence Mean as 0.821 which categorizes the "K-Mean Cluster 0" as a cluster of "Happy Songs" and "K-Mean Cluster 1" has Valence Mean as 0.343 which categorizes the "K-Mean Cluster" as a cluster of "Sad Songs". Similarly, "K-Mean Cluster 2" is a cluster of "Sad Songs", "K-Mean Cluster 3" is a cluster of "Happy Songs" and "K-Mean Cluster 4" is a cluster of "Sad Songs".

5.Conclusion: -

This project enabled us to learn more about the real-life applications of data science and what can be done and understood using data. This project helped us put our skills into use and explore more dimensions of the data science domain.

The Spotify data set was something which intrigued us. The thought of the ongoing pandemic and the Spotify helped us come up with such an idea and we were deeply intrigued as to what our results would be. We wanted to this project because we wanted to see the songs people listened to during the pandemic and how they inclined towards digital media Streaming platforms like in our case Spotify.

We did our classification using K-Means Algorithm/Model generated clusters which were used to classify the songs based on feature elements (extracted using Spotipy), the feature element of valence gave us the insight of the song being Happy or Sad, now in the beginning the aim with which we started this project was that we wanted to visualize the mood of the Streamers during the pandemic. We made clusters of similar songs streamed and used the valence factor to understand what kind of clusters they were.

6.Appendix: -

6.1 Appendix A:

Extraction Code

```python
In [1]: import pandas as pd
import cloudscraper
import os
import requests
from bs4 import BeautifulSoup as bs
from datetime import timedelta, date
import spotipy
from spotipy.oauth2 import SpotifyOAuth
import sys
import spotipy
import spotipy.util as util
import time

scope = 'user-library-read'
username = '38aiox0njoaisv8ldippfpbyc'

token = util.prompt_for_user_token(username,scope,client_id='40a9fe14bfc7475ab1aa160efe7674f5',client_secret='c6d0449bf

if token:
    sp = spotipy.Spotify(auth=token)
    results = sp.current_user_saved_tracks()
    for item in results['items']:
        track = item['track']
        print(track['name'] + ' - ' + track['artists'][0]['name'])
else:
    print("Can't get token for", username)

# It reads the webpage.
def get_webpage(link):
    headers = {"User-Agent":"Mozilla/5.0 (Macintosh; Intel Mac OS X 10_15_4) AppleWebKit/537.36 (KHTML, like Gecko) Chr
    page = requests.get(link, headers = headers, timeout = 100)
    soup = bs(page.content, 'html.parser')
    return(soup)
```

Figure 6.1.a

```python
def daterange(start_date, end_date):
    for n in range(int ((end_date - start_date).days)):
        yield start_date + timedelta(n)

# It creates the list of page links we will get the data from.
def create_links(country):
    start_date = date(2020, 3, 1)
    end_date = date(2020, 8, 1)
    links = []
    dates = daterange(start_date, end_date)
    for single_date in daterange(start_date, end_date):
        links.append('https://spotifycharts.com/regional/' + country + '/daily/' + single_date.strftime("%Y-%m-%d"))
    return(links, dates)

# It collects the data for each country, and write them in a list.
# The entries are (in order): Song, Artist, Date, Play Count, Rank
def get_data(country):
    [links, dates] = create_links(country)
    rows = []
    for (link, date) in zip(links, dates):
        soup = get_webpage(link)
        songlinks = soup.find_all("td", class_="chart-table-image")
        entries = soup.find_all("td", class_ = "chart-table-track")
        streams = soup.find_all("td", class_="chart-table-streams")
        for i, (songlink,entry, stream) in enumerate(zip(songlinks,entries,streams)):
            if i > 4:
                break
            song_url = songlink.find('a',href=True)['href']
            song = entry.find('strong').get_text()
            artist = entry.find('span').get_text()[3:]
            play_count = stream.get_text()
            country_name = country
            result = sp.search(song)
            track = result['tracks']['items'][0]
            artist_data = sp.artist(track["artists"][0]["external_urls"]["spotify"])
```

Figure 6.1.b

```python
def save_data(country):
    if not os.path.exists('data'):
        os.makedirs('data')
    file_name = 'data/' + country[1].replace(" ", "_").lower() + '.csv'
    data = get_data(country[0])
    if(len(data)!= 0):
        data = pd.DataFrame(data, columns=['Song','Artist','Date', 'Streams','Rank', 'Country', 'Links', 'Danceability'
        data.to_csv(file_name, sep=',', float_format='%s', index = False)

# It generates a list of countries for which the data is provided.
def get_countries():
    headers = {"User-Agent":"Mozilla/5.0 (Macintosh; Intel Mac OS X 10_15_4) AppleWebKit/537.36 (KHTML, like Gecko) Chr
    page = requests.get('https://www.spotifycharts.com/regional', headers = headers)
    soup = bs(page.content, 'html.parser')
    countries = []
    ctys = soup.find('ul').findAll('li')
    for cty in ctys:
        if cty.get_text() == 'India':
            countries.append([cty["data-value"],cty.get_text()])

        if cty.get_text() == 'United States':
            countries.append([cty["data-value"],cty.get_text()])

        if cty.get_text() == 'United Kingdom':
            countries.append([cty["data-value"],cty.get_text()])
    return(countries)

# It runs the function save_data for each country.
# In other words, it creates the .csv data files for each country.
def scrape_data():
    countries = get_countries()
    print(countries)
    for country in countries:
        save_data(country)

scrape_data()
```

Figure 6.1.c

Figure 6.1.a, Figure 6.1.b and Figure 6.1.c show the code that was needed for extraction of songs from the Spotify Regional Charts and the implementation of Spotipy API.

6.2 Appendix B:

India CSV

india

Song	Artist	Date	Streams	Rank	Country	Links	Danceability	Energy	Loudness	Speechi
Shayad	Pritam, Arijit Singh	3/1/20	138,415	1	in	https://open.spotify.com/track/1smFN2CLqGROu0J0UyvDfL	0.483	0.468	-7.642	0.
Illegal Weapon 2.0	Jasmine Sandlas, Garry Sandhu	3/1/20	125,234	2	in	https://open.spotify.com/track/7CY0CmCpSglfUKCBOOiRfw	0.805	0.919	-1.294	0.
Intentions (feat. Quavo)	Justin Bieber	3/1/20	122,769	3	in	https://open.spotify.com/track/4umIPjkehX1r7uhmGvXiSV	0.806	0.546	-6.637	0.
Falling	Trevor Daniel	3/1/20	122,465	4	in	https://open.spotify.com/track/4TnjEaWOeW0eKTKIEvJyCa	0.785	0.431	-8.756	0.
Malang (Title Track) [From "Malang - Unleash The Madness"]	Ved Sharma	3/1/20	120,269	5	in	https://open.spotify.com/track/25MPTnqXQB1H6OkwSYUXWx	0.384	0.728	-6.503	0.
Shayad	Pritam, Arijit Singh	3/2/20	142,153	1	in	https://open.spotify.com/track/1smFN2CLqGROu0J0UyvDfL	0.483	0.468	-7.642	0.
Illegal Weapon 2.0	Jasmine Sandlas, Garry Sandhu	3/2/20	125,895	2	in	https://open.spotify.com/track/7CY0CmCpSglfUKCBOOiRfw	0.805	0.919	-1.294	0.
Falling	Trevor Daniel	3/2/20	125,187	3	in	https://open.spotify.com/track/4TnjEaWOeW0eKTKIEvJyCa	0.785	0.431	-8.756	0.
Intentions (feat. Quavo)	Justin Bieber	3/2/20	125,030	4	in	https://open.spotify.com/track/4umIPjkehX1r7uhmGvXiSV	0.806	0.546	-6.637	0.
Malang (Title Track) [From "Malang - Unleash The Madness"]	Ved Sharma	3/2/20	124,108	5	in	https://open.spotify.com/track/25MPTnqXQB1H6OkwSYUXWx	0.384	0.728	-6.503	0.
Shayad	Pritam, Arijit Singh	3/3/20	142,266	1	in	https://open.spotify.com/track/1smFN2CLqGROu0J0UyvDfL	0.483	0.468	-7.642	0.
Illegal Weapon 2.0	Jasmine Sandlas, Garry Sandhu	3/3/20	126,779	2	in	https://open.spotify.com/track/7CY0CmCpSglfUKCBOOiRfw	0.805	0.919	-1.294	0.
Intentions (feat. Quavo)	Justin Bieber	3/3/20	124,781	3	in	https://open.spotify.com/track/4umIPjkehX1r7uhmGvXiSV	0.806	0.546	-6.637	0.
Falling	Trevor Daniel	3/3/20	124,024	4	in	https://open.spotify.com/track/4TnjEaWOeW0eKTKIEvJyCa	0.785	0.431	-8.756	0.
Malang (Title Track) [From "Malang - Unleash The Madness"]	Ved Sharma	3/3/20	123,339	5	in	https://open.spotify.com/track/25MPTnqXQB1H6OkwSYUXWx	0.384	0.728	-6.503	0.
Shayad	Pritam, Arijit Singh	3/4/20	144,367	1	in	https://open.spotify.com/track/1smFN2CLqGROu0J0UyvDfL	0.483	0.468	-7.642	0.
Illegal Weapon 2.0	Jasmine Sandlas, Garry Sandhu	3/4/20	125,406	2	in	https://open.spotify.com/track/7CY0CmCpSglfUKCBOOiRfw	0.805	0.919	-1.294	0.
Falling	Trevor Daniel	3/4/20	123,685	3	in	https://open.spotify.com/track/4TnjEaWOeW0eKTKIEvJyCa	0.785	0.431	-8.756	0.
Intentions (feat. Quavo)	Justin Bieber	3/4/20	122,667	4	in	https://open.spotify.com/track/4umIPjkehX1r7uhmGvXiSV	0.806	0.546	-6.637	0.
Malang (Title Track) [From "Malang - Unleash The Madness"]	Ved Sharma	3/4/20	121,864	5	in	https://open.spotify.com/track/25MPTnqXQB1H6OkwSYUXWx	0.384	0.728	-6.503	0.
Shayad	Pritam, Arijit Singh	3/5/20	143,725	1	in	https://open.spotify.com/track/1smFN2CLqGROu0J0UyvDfL	0.483	0.468	-7.642	0.
Intentions (feat. Quavo)	Justin Bieber	3/5/20	128,945	2	in	https://open.spotify.com/track/4umIPjkehX1r7uhmGvXiSV	0.806	0.546	-6.637	0.
Illegal Weapon 2.0	Jasmine Sandlas, Garry Sandhu	3/5/20	124,417	3	in	https://open.spotify.com/track/7CY0CmCpSglfUKCBOOiRfw	0.805	0.919	-1.294	0.
Falling	Trevor Daniel	3/5/20	124,293	4	in	https://open.spotify.com/track/4TnjEaWOeW0eKTKIEvJyCa	0.785	0.431	-8.756	0.
Malang (Title Track) [From "Malang - Unleash The Madness"]	Ved Sharma	3/5/20	120,483	5	in	https://open.spotify.com/track/25MPTnqXQB1H6OkwSYUXWx	0.384	0.728	-6.503	0.
Shayad	Pritam, Arijit Singh	3/6/20	145,705	1	in	https://open.spotify.com/track/1smFN2CLqGROu0J0UyvDfL	0.483	0.468	-7.642	0.
Intentions (feat. Quavo)	Justin Bieber	3/6/20	134,088	2	in	https://open.spotify.com/track/4umIPjkehX1r7uhmGvXiSV	0.806	0.546	-6.637	0.

india

1		Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Genre
2	GROu0J0UyvDfL	0.483	0.468	-7.642	0.0341	0.785	0	0.152	0.319	135.864	['desi pop', 'filmi', 'indian instrumental', 'modern bollywood']
3	3glfUKCBOOiRfw	0.805	0.919	-1.294	0.0938	0.101	0.00343	0.0598	0.494	94.993	['desi pop', 'punjabi pop']
4	r7uhmGvXiSV	0.806	0.546	-6.637	0.0575	0.3	0	0.102	0.874	147.986	['canadian pop', 'pop', 'post-teen pop']
5	V0eKTKIEvJyCa	0.785	0.431	-8.756	0.0364	0.123	0	0.0887	0.236	127.085	['pop', 'post-teen pop']
6	B1H6OkwSYUXWx	0.384	0.728	-6.503	0.0623	0.329	1.85E-05	0.329	0.311	156.396	['desi pop']
7	GROu0J0UyvDfL	0.483	0.468	-7.642	0.0341	0.785	0	0.152	0.319	135.864	['desi pop', 'filmi', 'indian instrumental', 'modern bollywood']
8	3glfUKCBOOiRfw	0.805	0.919	-1.294	0.0938	0.101	0.00343	0.0598	0.494	94.993	['desi pop', 'punjabi pop']
9	V0eKTKIEvJyCa	0.785	0.431	-8.756	0.0364	0.123	0	0.0887	0.236	127.085	['pop', 'post-teen pop']
10	r7uhmGvXiSV	0.806	0.546	-6.637	0.0575	0.3	0	0.102	0.874	147.986	['canadian pop', 'pop', 'post-teen pop']
11	B1H6OkwSYUXWx	0.384	0.728	-6.503	0.0623	0.329	1.85E-05	0.329	0.311	156.396	['desi pop']
12	GROu0J0UyvDfL	0.483	0.468	-7.642	0.0341	0.785	0	0.152	0.319	135.864	['desi pop', 'filmi', 'indian instrumental', 'modern bollywood']
13	3glfUKCBOOiRfw	0.805	0.919	-1.294	0.0938	0.101	0.00343	0.0598	0.494	94.993	['desi pop', 'punjabi pop']
14	r7uhmGvXiSV	0.806	0.546	-6.637	0.0575	0.3	0	0.102	0.874	147.986	['canadian pop', 'pop', 'post-teen pop']
15	V0eKTKIEvJyCa	0.785	0.431	-8.756	0.0364	0.123	0	0.0887	0.236	127.085	['pop', 'post-teen pop']
16	B1H6OkwSYUXWx	0.384	0.728	-6.503	0.0623	0.329	1.85E-05	0.329	0.311	156.396	['desi pop']
17	GROu0J0UyvDfL	0.483	0.468	-7.642	0.0341	0.785	0	0.152	0.319	135.864	['desi pop', 'filmi', 'indian instrumental', 'modern bollywood']
18	3glfUKCBOOiRfw	0.805	0.919	-1.294	0.0938	0.101	0.00343	0.0598	0.494	94.993	['desi pop', 'punjabi pop']
19	V0eKTKIEvJyCa	0.785	0.431	-8.756	0.0364	0.123	0	0.0887	0.236	127.085	['pop', 'post-teen pop']
20	r7uhmGvXiSV	0.806	0.546	-6.637	0.0575	0.3	0	0.102	0.874	147.986	['canadian pop', 'pop', 'post-teen pop']
21	B1H6OkwSYUXWx	0.384	0.728	-6.503	0.0623	0.329	1.85E-05	0.329	0.311	156.396	['desi pop']
22	GROu0J0UyvDfL	0.483	0.468	-7.642	0.0341	0.785	0	0.152	0.319	135.864	['desi pop', 'filmi', 'indian instrumental', 'modern bollywood']
23	r7uhmGvXiSV	0.806	0.546	-6.637	0.0575	0.3	0	0.102	0.874	147.986	['canadian pop', 'pop', 'post-teen pop']
24	3glfUKCBOOiRfw	0.805	0.919	-1.294	0.0938	0.101	0.00343	0.0598	0.494	94.993	['desi pop', 'punjabi pop']
25	V0eKTKIEvJyCa	0.785	0.431	-8.756	0.0364	0.123	0	0.0887	0.236	127.085	['pop', 'post-teen pop']
26	B1H6OkwSYUXWx	0.384	0.728	-6.503	0.0623	0.329	1.85E-05	0.329	0.311	156.396	['desi pop']
27	GROu0J0UyvDfL	0.483	0.468	-7.642	0.0341	0.785	0	0.152	0.319	135.864	['desi pop', 'filmi', 'indian instrumental', 'modern bollywood']
28	r7uhmGvXiSV	0.806	0.546	-6.637	0.0575	0.3	0	0.102	0.874	147.986	['canadian pop', 'pop', 'post-teen pop']

Figure 6.2.a and Figure 6.2.b

Figure 6.2.a and Figure 6.2.b shows the CSV File of "India".

6.3 Appendix C:

UK CSV

united_kingdom

1	Song	Artist	Date	Streams	Rank	Country	Links	Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Live
2	**Blinding Lights**	The Weeknd	3/1/20	439,557	1	gb	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0
3	**The Box**	Roddy Ricch	3/1/20	401,034	2	gb	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	
4	**Roses - Imanbek Remix**	SAINt JHN	3/1/20	342,579	3	gb	https://open.spotify.com/track/24Yi9hE78yPEbZ4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	
5	**No Time To Die**	Billie Eilish	3/1/20	309,990	4	gb	https://open.spotify.com/track/73SpzrcaHk0RQPFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0
6	**Don't Start Now**	Dua Lipa	3/1/20	292,161	5	gb	https://open.spotify.com/track/6WrI0LAC5M1Rw2MnX2ZvEg	0.794	0.793	-4.521	0.0842	0.0125	0	0
7	**Blinding Lights**	The Weeknd	3/2/20	479,611	1	gb	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0
8	**The Box**	Roddy Ricch	3/2/20	419,792	2	gb	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	
9	**Roses - Imanbek Remix**	SAINt JHN	3/2/20	396,587	3	gb	https://open.spotify.com/track/24Yi9hE78yPEbZ4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	
10	**No Time To Die**	Billie Eilish	3/2/20	321,690	4	gb	https://open.spotify.com/track/73SpzrcaHk0RQPFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0
11	**Don't Start Now**	Dua Lipa	3/2/20	306,487	5	gb	https://open.spotify.com/track/6WrI0LAC5M1Rw2MnX2ZvEg	0.794	0.793	-4.521	0.0842	0.0125	0	0
12	**Blinding Lights**	The Weeknd	3/3/20	482,042	1	gb	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0
13	**The Box**	Roddy Ricch	3/3/20	419,587	2	gb	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	
14	**Roses - Imanbek Remix**	SAINt JHN	3/3/20	401,967	3	gb	https://open.spotify.com/track/24Yi9hE78yPEbZ4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	
15	**No Time To Die**	Billie Eilish	3/3/20	315,182	4	gb	https://open.spotify.com/track/73SpzrcaHk0RQPFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0
16	**Don't Start Now**	Dua Lipa	3/3/20	312,377	5	gb	https://open.spotify.com/track/6WrI0LAC5M1Rw2MnX2ZvEg	0.794	0.793	-4.521	0.0842	0.0125	0	0
17	**Blinding Lights**	The Weeknd	3/4/20	468,417	1	gb	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0
18	**The Box**	Roddy Ricch	3/4/20	416,911	2	gb	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	
19	**Roses - Imanbek Remix**	SAINt JHN	3/4/20	399,175	3	gb	https://open.spotify.com/track/24Yi9hE78yPEbZ4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	
20	**Don't Start Now**	Dua Lipa	3/4/20	302,956	4	gb	https://open.spotify.com/track/6WrI0LAC5M1Rw2MnX2ZvEg	0.794	0.793	-4.521	0.0842	0.0125	0	0
21	**No Time To Die**	Billie Eilish	3/4/20	302,891	5	gb	https://open.spotify.com/track/73SpzrcaHk0RQPFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0
22	**Blinding Lights**	The Weeknd	3/5/20	473,449	1	gb	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0
23	**The Box**	Roddy Ricch	3/5/20	413,665	2	gb	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	
24	**Roses - Imanbek Remix**	SAINt JHN	3/5/20	400,858	3	gb	https://open.spotify.com/track/24Yi9hE78yPEbZ4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	
25	**No Time To Die**	Billie Eilish	3/5/20	295,808	4	gb	https://open.spotify.com/track/73SpzrcaHk0RQPFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0
26	**Before You Go**	Lewis Capaldi	3/5/20	293,009	5	gb	https://open.spotify.com/track/2gMXnyrvIjhVBUZwvLZDMP	0.459	0.575	-4.858	0.0573	0.604	0	0
27	**Blinding Lights**	The Weeknd	3/6/20	513,868	1	gb	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0
28	**Rain**	Aitch, AJ Tracey, Tay Keith	3/6/20	497,950	2	gb	https://open.spotify.com/track/5LBikzSkad9yQ6RH87Gdrm	0.871	0.87	-4.797	0.202	0.0262	1.98E-06	

united_kingdom

		Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Genre
2	qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
3	O7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
4	Z4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	0.353	0.898	121.975	['melodic rap', 'rap', 'slap house']
5	PFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0.0827	0.0517	73.537	['electropop', 'pop']
6	w2MnX2ZvEg	0.794	0.793	-4.521	0.0842	0.0125	0	0.0952	0.677	123.941	['dance pop', 'pop', 'uk pop']
7	qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
8	O7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
9	Z4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	0.353	0.898	121.975	['melodic rap', 'rap', 'slap house']
10	PFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0.0827	0.0517	73.537	['electropop', 'pop']
11	w2MnX2ZvEg	0.794	0.793	-4.521	0.0842	0.0125	0	0.0952	0.677	123.941	['dance pop', 'pop', 'uk pop']
12	qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
13	O7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
14	Z4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	0.353	0.898	121.975	['melodic rap', 'rap', 'slap house']
15	PFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0.0827	0.0517	73.537	['electropop', 'pop']
16	w2MnX2ZvEg	0.794	0.793	-4.521	0.0842	0.0125	0	0.0952	0.677	123.941	['dance pop', 'pop', 'uk pop']
17	qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
18	O7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
19	Z4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	0.353	0.898	121.975	['melodic rap', 'rap', 'slap house']
20	w2MnX2ZvEg	0.794	0.793	-4.521	0.0842	0.0125	0	0.0952	0.677	123.941	['dance pop', 'pop', 'uk pop']
21	PFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0.0827	0.0517	73.537	['electropop', 'pop']
22	qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
23	O7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
24	Z4kxyoXAI	0.77	0.724	-5.484	0.0495	0.0167	0.0107	0.353	0.898	121.975	['melodic rap', 'rap', 'slap house']
25	PFP73vqVR	0.38	0.219	-13.273	0.0358	0.917	0.0104	0.0827	0.0517	73.537	['electropop', 'pop']
26	ZwvLZDMP	0.459	0.575	-4.858	0.0573	0.604	0	0.0885	0.183	111.881	['pop', 'uk pop']
27	qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
28	RH87Gdrm	0.871	0.87	-4.797	0.202	0.0262	1.98E-06	0.109	0.83	150.147	['dance pop', 'pop', 'post-teen pop']
29	O7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']

Figure 6.3.a and Figure 6.3.b

Figure 6.3.a and Figure 6.3.b shows the CSV File of "UK".

6.4 Appendix D:

USA CSV

Figure 6.4.a and Figure 6.4.b shown below is the CSV File of "USA".

united_states

	Song	Artist	Date	Streams	Rank	Country	Links	Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness
2	**The Box**	Roddy Ricch	3/1/20	2,145,340	1	us	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79
3	**Say So**	Doja Cat	3/1/20	1,116,529	2	us	https://open.spotify.com/track/3Dv1eDb0MEgF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904
4	**Blinding Lights**	The Weeknd	3/1/20	1,106,280	3	us	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938
5	**Life Is Good (feat. Drake)**	Future	3/1/20	1,048,449	4	us	https://open.spotify.com/track/5yY9lUy8nbvjM1Uyo1Uqoc	0.676	0.609	-5.831	0.481	0.0706	0	0.152
6	**Blueberry Faygo**	Lil Mosey	3/1/20	1,043,040	5	us	https://open.spotify.com/track/22LAwLoDA5b4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132
7	**The Box**	Roddy Ricch	3/2/20	1,994,274	1	us	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79
8	**That Way**	Lil Uzi Vert	3/2/20	1,751,164	2	us	https://open.spotify.com/track/5raTDhlbxFDnpn89bxArdH	0.719	0.611	-5.01	0.0403	0.0582	0	0.155
9	**Say So**	Doja Cat	3/2/20	1,172,448	3	us	https://open.spotify.com/track/3Dv1eDb0MEgF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904
10	**Blinding Lights**	The Weeknd	3/2/20	1,161,998	4	us	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938
11	**Blueberry Faygo**	Lil Mosey	3/2/20	1,108,917	5	us	https://open.spotify.com/track/22LAwLoDA5b4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132
12	**The Box**	Roddy Ricch	3/3/20	2,065,254	1	us	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79
13	**That Way**	Lil Uzi Vert	3/3/20	1,602,520	2	us	https://open.spotify.com/track/5raTDhlbxFDnpn89bxArdH	0.719	0.611	-5.01	0.0403	0.0582	0	0.155
14	**Blueberry Faygo**	Lil Mosey	3/3/20	1,198,391	3	us	https://open.spotify.com/track/22LAwLoDA5b4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132
15	**Blinding Lights**	The Weeknd	3/3/20	1,190,972	4	us	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938
16	**Say So**	Doja Cat	3/3/20	1,170,099	5	us	https://open.spotify.com/track/3Dv1eDb0MEgF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904
17	**The Box**	Roddy Ricch	3/4/20	2,048,884	1	us	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79
18	**That Way**	Lil Uzi Vert	3/4/20	1,502,100	2	us	https://open.spotify.com/track/5raTDhlbxFDnpn89bxArdH	0.719	0.611	-5.01	0.0403	0.0582	0	0.155
19	**Blueberry Faygo**	Lil Mosey	3/4/20	1,210,504	3	us	https://open.spotify.com/track/22LAwLoDA5b4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132
20	**Blinding Lights**	The Weeknd	3/4/20	1,176,120	4	us	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938
21	**Say So**	Doja Cat	3/4/20	1,139,915	5	us	https://open.spotify.com/track/3Dv1eDb0MEgF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904
22	**The Box**	Roddy Ricch	3/5/20	2,071,608	1	us	https://open.spotify.com/track/0nbXyq5TXYPCO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79
23	**That Way**	Lil Uzi Vert	3/5/20	1,389,297	2	us	https://open.spotify.com/track/5raTDhlbxFDnpn89bxArdH	0.719	0.611	-5.01	0.0403	0.0582	0	0.155
24	**Blueberry Faygo**	Lil Mosey	3/5/20	1,229,154	3	us	https://open.spotify.com/track/22LAwLoDA5b4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132
25	**Blinding Lights**	The Weeknd	3/5/20	1,204,391	4	us	https://open.spotify.com/track/0sf12qNH5qcw8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938
26	**Say So**	Doja Cat	3/5/20	1,153,997	5	us	https://open.spotify.com/track/3Dv1eDb0MEgF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904
27	**Baby Pluto**	Lil Uzi Vert	3/6/20	3,364,245	1	us	https://open.spotify.com/track/7hav1MHURQf5SAoPk0egqh	0.772	0.634	-6.101	0.212	0.135	0	0.432
28	**Lo Mein**	Lil Uzi Vert	3/6/20	2,839,950	2	us	https://open.spotify.com/track/6CUP2khYzdphXebxVTfPE3	0.855	0.676	-5.736	0.325	0.0888	0	0.144

Figure 6.4.a

united_states

		Danceability	Energy	Loudness	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	Tempo	Genre
2	CO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
3	gF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904	0.786	110.962	['dance pop', 'pop', 'pop rap']
4	w8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
5	M1Uyo1Uqoc	0.676	0.609	-5.831	0.481	0.0706	0	0.152	0.508	142.037	['atl hip hop', 'pop rap', 'rap', 'southern hip hop', 'trap']
6	4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132	0.349	99.034	['melodic rap', 'rap', 'rap conscient', 'trap', 'vapor trap']
7	CO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
8	pn89bxArdH	0.719	0.611	-5.01	0.0403	0.0582	0	0.155	0.489	129.962	['melodic rap', 'philly rap', 'rap', 'trap']
9	gF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904	0.786	110.962	['dance pop', 'pop', 'pop rap']
10	w8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
11	4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132	0.349	99.034	['melodic rap', 'rap', 'rap conscient', 'trap', 'vapor trap']
12	CO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
13	pn89bxArdH	0.719	0.611	-5.01	0.0403	0.0582	0	0.155	0.489	129.962	['melodic rap', 'philly rap', 'rap', 'trap']
14	4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132	0.349	99.034	['melodic rap', 'rap', 'rap conscient', 'trap', 'vapor trap']
15	w8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
16	gF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904	0.786	110.962	['dance pop', 'pop', 'pop rap']
17	CO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
18	pn89bxArdH	0.719	0.611	-5.01	0.0403	0.0582	0	0.155	0.489	129.962	['melodic rap', 'philly rap', 'rap', 'trap']
19	4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132	0.349	99.034	['melodic rap', 'rap', 'rap conscient', 'trap', 'vapor trap']
20	w8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
21	gF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904	0.786	110.962	['dance pop', 'pop', 'pop rap']
22	CO7pr3N8S4I	0.896	0.586	-6.687	0.0559	0.104	0	0.79	0.642	116.971	['melodic rap', 'rap', 'trap']
23	pn89bxArdH	0.719	0.611	-5.01	0.0403	0.0582	0	0.155	0.489	129.962	['melodic rap', 'philly rap', 'rap', 'trap']
24	4AaGSkg6bKW	0.774	0.554	-7.909	0.0383	0.207	0	0.132	0.349	99.034	['melodic rap', 'rap', 'rap conscient', 'trap', 'vapor trap']
25	w8qpgymFOqD	0.513	0.796	-4.075	0.0629	0.00147	0.000209	0.0938	0.345	171.017	['canadian contemporary r&b', 'canadian pop', 'pop']
26	gF93GpLXlucZ	0.787	0.673	-4.577	0.158	0.256	3.57E-06	0.0904	0.786	110.962	['dance pop', 'pop', 'pop rap']
27	f5SAoPk0egqh	0.772	0.634	-6.101	0.212	0.135	0	0.432	0.671	160.052	['melodic rap', 'philly rap', 'rap', 'trap']
28	hXebxVTfPE3	0.855	0.676	-5.736	0.325	0.0888	0	0.144	0.509	133.082	['melodic rap', 'philly rap', 'rap', 'trap']
29	dVO2fMo3Wbo	0.903	0.535	-6.238	0.286	0.0298	0	0.0851	0.157	130.117	['melodic rap', 'philly rap', 'rap', 'trap']

Figure 6.4.b