Final Project Submission

- Student name: Justin Grisanti
- Student pace: self-paced
- Scheduled project review date/time: 6/20/2022
- Instructor name: Claude Fried
- Blog post URL: https://justingrisanti.github.io/spotify_recommendation_system (https://justingrisanti.github.io/spotify_recommendation_system)

Section 1: Business Understanding

The purpose of this section is to define the business problem and understand the stakeholders for the work that I am performing. Spotify is an audio streaming and media services platfrom, created in 2006. It is one of the largest music streaming service providers with over 406 million monthly active users, including 180 million paying subscribers, as of December 2021.

Spotify offers digital copyright restricted recorded music and podcasts, including more than 82 million songs, from record labels and media companies. As a freemium service, basic features are free with advertisements and limited control, while additional features, such as offline listening and commercial-free listening, are offered via paid subscriptions. Spotify is currently available in 180+ countries as of October 2021. Users can search for music based on artist, album, or genre, and can create, edit, and share playlists.

Two of the most important aspects of Spotify that has led to its popularity are its music discovery functionalities, and playlist creation fostering a new social aspect to music listening. In a 2021 How-To Geek article called "6 Awesome Spotify Features You Should Be Using," 3 of the 6 features are related to playlists, and one speaks about music discovery. One of these features related to music discovery is called "Enhance." Enhance allows you to discover new tracks that might best fit one of your existing playlists. For example, if you have a playlist of a collection of 80s rock songs, Enhance might suggest that you add "Eye of the Tiger" by Survivor.

What I aim to perform is to create a recommendation system from scratch that can reperform the functionality of Enhance, which is to obtain a selection of songs and use content-based filtering to suggest a list of songs that are similar.

The stakeholders of this project are Spotify, music-listeners, DJs, and other music-related occupations.

The main purpose of this recommendation system is inferential, meaning that this model should be able infer information about songs from a given playlist and then to predict songs that a user will likely add to that same playlist.

Section 2: Data Understanding

Now that I have developed a overall business understanding, I will take a deeper dive into the data that I will be using for this project.

In [7]:
```
# Import relevant libraries

import pandas as pd
from numpy.random import seed
seed(123)
import numpy as np
import random
import shutil
import math
import statistics as stat
import os
import datetime
import seaborn as sns
from sklearn.metrics.pairwise import cosine_similarity as cos
from sklearn.impute import SimpleImputer
import matplotlib.pyplot as plt
import sklearn as sk
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.feature_extraction.text import TfidfVectorizer
import json
from pandas.io.json import json_normalize
import spotipy
from spotipy.oauth2 import SpotifyClientCredentials
import time
import config
sp = spotipy.Spotify(auth_manager=SpotifyClientCredentials(client_
                                                            client_
import sqlite3
conn = sqlite3.connect('music_recs.db')
cur = conn.cursor()
from pyspark import SparkContext
from pyspark.sql import SparkSession
import dataframe_image as dfi

import sys
import re
import collections
```

In [8]:
```
# Set input path for os functions

input_path = 'spotify_million_playlist_dataset/data/'
```

In [9]:
```
# Check how many items are in the data folder. There are 1000 file

list = os.listdir(input_path)
number_files = len(list)
print(number_files)
```

```
1000
```

In [10]:
```
# View a handful of files to see their types

os.listdir(input_path)[0:5]
```

Out[10]:
```
['mpd.slice.549000-549999.json',
 'mpd.slice.613000-613999.json',
 'mpd.slice.115000-115999.json',
 'mpd.slice.778000-778999.json',
 'mpd.slice.290000-290999.json']
```

As we can see above, it appears that we have 1000 json files in our data folder. Each file appears to have 1000 records each, which means there are 1 million songs in our dataset. After trying to load the first file, it was too large for my computer to handle. Instead, I will load the first playlist to see its contents.

In [11]:

```
# Open json file to see formatting

test = open(input_path+'mpd.slice.0-999.json')
data_0_999 = json.load(test)
data_0_999['playlists'][0]
```

Out[11]:


```
{'name': 'Throwbacks',
 'collaborative': 'false',
 'pid': 0,
 'modified_at': 1493424000,
 'num_tracks': 52,
 'num_albums': 47,
 'num_followers': 1,
 'tracks': [{'pos': 0,
   'artist_name': 'Missy Elliott',
   'track_uri': 'spotify:track:0UaMYEvWZi0ZqiDOoHU3YI',
   'artist_uri': 'spotify:artist:2wIVse2owClT7go1WT98tk',
   'track_name': 'Lose Control (feat. Ciara & Fat Man Scoop)',
   'album_uri': 'spotify:album:6vV5UrXcfyQD1wu4Qo2I9K',
   'duration_ms': 226863,
   'album_name': 'The Cookbook'},
  {'pos': 1,
   'artist_name': 'Britney Spears',
   'track_uri': 'spotify:track:6I9VzXrHxO9rA9A5euc8Ak',
   'artist_uri': 'spotify:artist:26dSoYclwsYLMAKD3tpOr4',
```

Looking at this playlist above, we can see that we have the following features:

> **Playlist Attributes**
>
> - Playlist Name
> - Playlist Type
> - Number of Tracks
> - Number of Unique Albums
> - Number of Followers
> - Number of Edits
> - Duration in Milliseconds
> - Number of Artists
>
> **Song Attributes**
>
> - Artist Name
> - Track URI
> - Artist URI
> - Track Name
> - Album URI
> - Duration in Milliseconds
> - Album Name

Some features that will be important to our model will be track name, artist name, album name, and their respective URIs. These will help us get more detail about a song from Spotipy. Another piece that could be helpful is the number of followers. This shows us interest in a given playlist. If a playlist has a jumble of random songs that don't form a cohesive playlist, it will probably have less followers than a well-crafted playlist.

Next, I will run code that was provided with the data, to get a better understanding on the population as a whole.

In [12]:
```
total_playlists = 0
total_tracks = 0
tracks = set()
artists = set()
albums = set()
titles = set()
total_descriptions = 0
ntitles = set()
title_histogram = collections.Counter()
artist_histogram = collections.Counter()
track_histogram = collections.Counter()
last_modified_histogram = collections.Counter()
num_edits_histogram = collections.Counter()
```

```
num_edits_histogram = collections.Counter()
playlist_length_histogram = collections.Counter()
num_followers_histogram = collections.Counter()

quick = False
max_files_for_quick_processing = 5


def process_mpd(path):
    count = 0
    filenames = os.listdir(input_path)
    for filename in sorted(filenames):
        if filename.startswith("mpd.slice.") and filename.endswit
            fullpath = os.sep.join((input_path, filename))
            f = open(fullpath)
            js = f.read()
            f.close()
            mpd_slice = json.loads(js)
            process_info(mpd_slice["info"])
            for playlist in mpd_slice["playlists"]:
                process_playlist(playlist)
            count += 1

            if quick and count > max_files_for_quick_processing:
                break

    show_summary()


def show_summary():
    print()
    print("number of playlists", total_playlists)
    print("number of tracks", total_tracks)
    print("number of unique tracks", len(tracks))
    print("number of unique albums", len(albums))
    print("number of unique artists", len(artists))
    print("number of unique titles", len(titles))
    print("number of playlists with descriptions", total_descript
    print("number of unique normalized titles", len(ntitles))
    print("avg playlist length", float(total_tracks) / total_play
    print()
    print("top playlist titles")
    for title, count in title_histogram.most_common(20):
        print("%7d %s" % (count, title))

    print()
    print("top tracks")
    for track, count in track_histogram.most_common(20):
        print("%7d %s" % (count, track))

    print()
```

```
    print("top artists")
    for artist, count in artist_histogram.most_common(20):
        print("%7d %s" % (count, artist))

    print()
    print("numedits histogram")
    for num_edits, count in num_edits_histogram.most_common(20):
        print("%7d %d" % (count, num_edits))

    print()
    print("last modified histogram")
    for ts, count in last_modified_histogram.most_common(20):
        print("%7d %s" % (count, to_date(ts)))

    print()
    print("playlist length histogram")
    for length, count in playlist_length_histogram.most_common(20
        print("%7d %d" % (count, length))

    print()
    print("num followers histogram")
    for followers, count in num_followers_histogram.most_common(2
        print("%7d %d" % (count, followers))


def normalize_name(name):
    name = name.lower()
    name = re.sub(r"[.,\/#!$%\^\*;:{}=\_`~()@]", " ", name)
    name = re.sub(r"\s+", " ", name).strip()
    return name


def to_date(epoch):
    return datetime.datetime.fromtimestamp(epoch).strftime("%Y-%m


def process_playlist(playlist):
    global total_playlists, total_tracks, total_descriptions

    total_playlists += 1
    # print playlist['playlist_id'], playlist['name']

    if "description" in playlist:
        total_descriptions += 1

    titles.add(playlist["name"])
    nname = normalize_name(playlist["name"])
    ntitles.add(nname)
    title_histogram[nname] += 1

    playlist_length_histogram[playlist["num_tracks"]] += 1
```

```
    playlist_length_histogram[playlist["num_tracks"]] += 1
    last_modified_histogram[playlist["modified_at"]] += 1
    num_edits_histogram[playlist["num_edits"]] += 1
    num_followers_histogram[playlist["num_followers"]] += 1

    for track in playlist["tracks"]:
        total_tracks += 1
        albums.add(track["album_uri"])
        tracks.add(track["track_uri"])
        artists.add(track["artist_uri"])

        full_name = track["track_name"] + " by " + track["artist_
        artist_histogram[track["artist_name"]] += 1
        track_histogram[full_name] += 1


def process_info(_):
    pass


if __name__ == "__main__":
    path = sys.argv[1]
    if len(sys.argv) > 2 and sys.argv[2] == "--quick":
        quick = True
    process_mpd(path)

```

```
number of playlists 1000000
number of tracks 66346428
number of unique tracks 2262292
number of unique albums 734684
number of unique artists 295860
number of unique titles 92944
number of playlists with descriptions 18760
number of unique normalized titles 17381
avg playlist length 66.346428

top playlist titles
  10000 country
  10000 chill
   8493 rap
   8481 workout
   8146 oldies
   8015 christmas
   6848 rock
   6157 party
```

As we see in the summary above, there are 1 million playlists with over 66 million songs. Within these playlists, there are 2.2 million unique songs, 734k unique albums, and 300k unique artists. There is a lot of data to work with here. The playlists are sorted into categories, with country and chill being the top, followed by rap and workout. Drake, Kanye West, and Kendrick Lamar are the 3 top artists. The next step in this process is to convert all of this json data to be compatible with python.

Section 3: Data Preparation

The first steps are to convert our JSON data to python and DataFrames. Once we have that, we need to unwrap our track data so it can be converted to a DataFrame, as well.

In [13]:
```
# This code was used to open 100 of the files in the dataset and a
# We then select the top 100 playlists according to number of foll
# cohesive playlists

## Start time to measure code execution length of time
# start_time = time.time()

## Generate DataFrame for playlist data
# spotify_playlist_data = pd.DataFrame()

## For Loop to open and append 100 json files to a DataFrame
# for item in range(0,100):
#     open_file = open(input_path+sorted(os.listdir(input_path))[i
#     load_file = json.load(open_file)
#     spotify_playlist_data = spotify_playlist_data.append(load_fi

## Send our DataFrame to a pickle file so we can call it instead o
# spotify_playlist_data.to_pickle('Spotipy Custom DataFrames/spoti

## Creating a top 100 playlist DataFrame to select the top 100 mos
# spotify_playlist_top_100 = spotify_playlist_data.sort_values(by=
# spotify_playlist_top_100 = spotify_playlist_top_100.set_index('p
# spotify_playlist_top_100.to_pickle('Spotipy Custom DataFrames/sp

# print("--- %s minutes ---" % ((time.time() - start_time)/60))

# Output: --- 0.7003742297490437 minutes ---
```

In [14]:
```
# Open pickle file with our top 100 playlist DataFrame
spd_top100 = pd.read_pickle('Spotipy Custom DataFrames/spotify_pla
spd_top100
```

Out[14]:

pid	name	collaborative	modified_at	num_tracks	num_albums	num_followers	
180831	My Little Pony	false	1478908800	85	9	31539	'arti 'App
159077	Rock Hits	false	1509408000	56	54	22102	'arti Figh
101121	Workout Playlist	false	1456531200	26	23	11745	'arti '
147486	J cole	false	1491523200	139	55	7912	'arti
17675	raggaeton	false	1501718400	107	71	2994	'arti K
...	...	...	...	...	...	...	
100819	Dance!	false	1440115200	10	6	74	'arti Má
127212	Demi Lovato	false	1470009600	84	23	72	'arti Lova
154640	Thankful.	false	1479168000	63	62	72	'arti '
143072	Dutch!	false	1490227200	216	197	68	'arti 'Di
147046	punk goes pop	false	1354147200	71	12	68	'arti M

100 rows × 11 columns

Now that we have aggregated our data, we can see that our track data is nested, which makes sense given we are using json data. In order to get this track data into a pandas dataframe, we will be using similar code to normalize our track data into its own dataframe. We will also pull in the playlist id so we know which track relates to which playlist for when we analyze or use SQL.

In [15]:

```
# pd.set_option('display.max_rows', 20)

## Creating DataFrame for the tracks column in our playlist data.
# unwrapped_track_data = pd.DataFrame()

## Adding playlist IDs to a list to be appended to the unwrapped t
# index_list = spd_top100.index.tolist()
# pid = []

## Using json_normalize to reformat the json data the DataFrame
# for item in range(0,len(spd_top100)):
#     unwrapped_track_data = unwrapped_track_data.append(pd.json_r

## Appending the playlist IDs to the pid list
# for row in range(0,len(spd_top100.index)):
#     track=0
#     while track<spd_top100['num_tracks'].iloc[row]:
#         track+=1
#         pid.append(index_list[row])

## Adding the playlist IDs to the unwrapped track data
# unwrapped_track_data['pid'] = pid

## Save the data as a pickle file
# unwrapped_track_data.to_pickle('Spotipy Custom DataFrames/unwrap
```

In [16]:
```
# Call the pickle file for data use
unwrapped_track_data = pd.read_pickle('Spotipy Custom DataFrames/u
unwrapped_track_data
```

Out[16]:

	pos	artist_name	track_uri	ar
0	0	Applebloom	spotify:track:527IbJxFcjjTix0ONdxDdS	spotify:artist:7ggsXdK95oJBkuZu
1	1	Apple Jack	spotify:track:1mOnMHXxt2vGI0b804eQsy	spotify:artist:1r0v3fdCiqrr9mYt
2	2	Twilight Sparkle	spotify:track:4GciJR91Tj8a7dLJ12WFvr	spotify:artist:53CQUfjaBNRwV2nF
3	3	Twilight Sparkle	spotify:track:68dC0K4xgIMF5Nhr44TevS	spotify:artist:53CQUfjaBNRwV2nF
4	4	Twilight Sparkle	spotify:track:0vhKFkvwgdPBrrNr9gUbVa	spotify:artist:53CQUfjaBNRwV2nF
...	...	...	...	
9318	66	Fake ID	spotify:track:3G0PWfSGIsUrl4El8u46EX	spotify:artist:4GwCpkFWajqx3KSm0
9319	67	Showoff	spotify:track:5qpQhP4hyjCKC95oRtTqni	spotify:artist:6IKhTkyp4EJ0ocid
9320	68	Thrice	spotify:track:7wwXG5FOebfhVBotX4vTXo	spotify:artist:3NChzMpu9exTlNPiq
9321	69	Nicotine	spotify:track:1Ibfp4HOrAS0fB8eIoEYko	spotify:artist:0p3U0uLx2oSf0yn
9322	70	Student Rick	spotify:track:6ktA174mwmCqcb9hfdL178	spotify:artist:6AluDNoFgmeUTnOc

9323 rows × 9 columns

In [17]:
```
# Ensure the sum of the number of tracks for each playlist equals
spd_top100['num_tracks'].sum() == unwrapped_track_data.shape[0]
```

Out[17]: True

In [18]:
```
# Stripping the URI fields to leave only the URI itself
unwrapped_track_data['track_uri'] = unwrapped_track_data['track_ur
unwrapped_track_data['artist_uri'] = unwrapped_track_data['artist_
unwrapped_track_data['album_uri'] = unwrapped_track_data['album_ur
```

In [19]:
```
unwrapped_track_data
```

Out[19]:

	pos	artist_name	track_uri	artist_uri	track_name	
0	0	Applebloom	527IbJxFcjjTix0ONdxDdS	7ggsXdK95oJBkuZu1txVjC	Hearts as Strong as Horses	6
1	1	Apple Jack	1mOnMHXxt2vGI0b804eQsy	1r0v3fdCiqrr9mYtvbCccT	Apples to the Core	6
2	2	Twilight Sparkle	4GciJR91Tj8a7dLJ12WFvr	53CQUfjaBNRwV2nFro1nac	Ballad of the Crystal Ponies	6
3	3	Twilight Sparkle	68dC0K4xgIMF5Nhr44TevS	53CQUfjaBNRwV2nFro1nac	Find a Way	6
4	4	Twilight Sparkle	0vhKFkvwgdPBrrNr9gUbVa	53CQUfjaBNRwV2nFro1nac	A True, True Friend	6
...	...	...	...	...	...	
9318	66	Fake ID	3G0PWfSGIsUrI4El8u46EX	4GwCpkFWajqx3KSm0MVh2a	All Or Nothing	
9319	67	Showoff	5qpQhP4hyjCKC95oRtTqni	6IKhTkyp4EJ0ocidcwafs6	Borderline	
9320	68	Thrice	7wwXG5FOebfhVBotX4vTXo	3NChzMpu9exTINPiqUQ2DE	Send Me An Angel	
9321	69	Nicotine	1Ibfp4HOrAS0fB8eIoEYko	0p3U0uLx2oSf0yn8i5XZki	Baby One More Time	
9322	70	Student Rick	6ktA174mwmCqcb9hfdL178	6AIuDNoFgmeUTnOc7DYXIN	Heaven Is A Place On Earth	

9323 rows × 9 columns

Now that our track data is unwrapped, we will remove duplicates to get a DataFrame of unique songs.

In [20]:
```
# Drop duplicates, reset index, and isolate important columns.
unique_track_data = unwrapped_track_data.drop_duplicates(subset='t
unique_track_data = unique_track_data.reset_index()
unique_track_data = unique_track_data[['track_uri','track_name','a
unique_track_data.to_sql('unique_track_data', con = conn, if_exist
unique_track_data
```

Out[20]:

	track_uri	track_name	artist_name	artist_uri	album_
0	527IbJxFcjjTix0ONdxDdS	Hearts as Strong as Horses	Applebloom	7ggsXdK95oJBkuZu1txVjC	Soı Poı (Musi the O
1	1mOnMHXxt2vGI0b804eQsy	Apples to the Core	Apple Jack	1r0v3fdCiqrr9mYtvbCccT	Soı Poı (Musi the O
2	4GciJR91Tj8a7dLJ12WFvr	Ballad of the Crystal Ponies	Twilight Sparkle	53CQUfjaBNRwV2nFro1nac	Soı Poı (Musi the O
3	68dC0K4xglMF5Nhr44TevS	Find a Way	Twilight Sparkle	53CQUfjaBNRwV2nFro1nac	Soı Poı (Musi the O
4	0vhKFkvwgdPBrrNr9gUbVa	A True, True Friend	Twilight Sparkle	53CQUfjaBNRwV2nFro1nac	Soı Poı (Musi the O
...	...	...	...	...	
8076	3G0PWfSGIsUrl4El8u46EX	All Or Nothing	Fake ID	4GwCpkFWajqx3KSm0MVh2a	Punk
8077	5qpQhP4hyjCKC95oRtTqni	Borderline	Showoff	6IKhTkyp4EJ0ocidcwafs6	Punk
8078	7wwXG5FOebfhVBotX4vTXo	Send Me An Angel	Thrice	3NChzMpu9exTINPiqUQ2DE	Punk
8079	1Ibfp4HOrAS0fB8eIoEYko	Baby One More Time	Nicotine	0p3U0uLx2oSf0yn8i5XZki	Punk
		Heaven Is A	Student		Punk

8080	6ktA174mwmCqcb9hfdL178	Place On Earth	Rick	6AIuDNoFgmeUTnOc7DYXIN

8081 rows × 6 columns

Now that I have my data prepared into tables, we will need to import some relevant features that describe the type of each song. While we have already have many features that describe the music, such as song name, length and artist, none of these describe the *charactaristics* of each song. To do this, I have imported the Spotipy library. Per Spotipy's website, this library is described as "a lightweight Python library for the Spotify Web API. With Spotipy you get full access to all of the music data provided by the Spotify platform."

We can use this library to get more information about each song, and therefore classify the type of playlist that we are listening to. The reason we have to do this is because the playlist names might not always have a good description of the type of playlist we have. For example, playlist 159077 above is labelled "Rock Hits!", but playlist 154640 is just labelled an arbitrary title, "Thankful.". We can name Rock songs, but "Thankful" songs can be more subjective, and it is harder to classify a sound or vibe from the title alone. Once we have the type of playlist that we are looking at, we can begin suggesting songs from a similar genre or "vibe".

We will be using the API to import thhe following:

1. Audio features that analyze the sound/vibe of the song
2. Genre for each song
3. Popularity of each song

3.1 Audio Features DataFrames

In [21]:
```
# Using the audio_features method to get characteristics of our sc
sp.audio_features('0UaMYEvWZi0ZqiDOoHU3YI')
```

Out[21]:
```
[{'danceability': 0.904,
  'energy': 0.813,
  'key': 4,
  'loudness': -7.105,
  'mode': 0,
  'speechiness': 0.121,
  'acousticness': 0.0311,
  'instrumentalness': 0.00697,
  'liveness': 0.0471,
  'valence': 0.81,
  'tempo': 125.461,
  'type': 'audio_features',
  'id': '0UaMYEvWZi0ZqiDOoHU3YI',
  'uri': 'spotify:track:0UaMYEvWZi0ZqiDOoHU3YI',
  'track_href': 'https://api.spotify.com/v1/tracks/0UaMYEvWZi0ZqiDOoH
U3YI',
  'analysis_url': 'https://api.spotify.com/v1/audio-analysis/0UaMYEvW
Zi0ZqiDOoHU3YI',
  'duration_ms': 226864,
  'time_signature': 4}]
```

Above, Spotipy gives us relevant audio features for each song:

- **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**: 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**: 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).

In [22]:

```
## Creating a DataFrame for all unique tracks and their audio feat
## file to save time. I also found I was getting rate limited from

# audio_features_df = pd.DataFrame()
# start_time = time.time()
# batch_record = 0

## For loop to append audio features for each track
# for track in range(0,len(unique_track_data)):
#     audio_features_df = audio_features_df.append(sp.audio_featur
#     batch_record +=1
#     if batch_record < 100:
#         pass
#     else:
#         time.sleep(2)
#         batch_record = 0

## Save to pickle to save loading time
# audio_features_df.to_pickle('Spotipy Custom DataFrames/audio_fea

# print("--- %s minutes ---" % ((time.time() - start_time)/60))

# Output time: --- 13.943817913532257 minutes ---
```

In [23]:

```
## Call file from pickle
audio_features_df = pd.read_pickle('Spotipy Custom DataFrames/audi
audio_features_df
```

Out[23]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalne
0	0.794	0.826	1	-4.384	1	0.0294	0.242000	0.0000
1	0.802	0.814	0	-2.489	1	0.0286	0.232000	0.0000
2	0.632	0.482	0	-7.480	1	0.0289	0.419000	0.0000
3	0.530	0.392	10	-8.648	1	0.0341	0.881000	0.0000
4	0.678	0.735	10	-6.135	1	0.0355	0.305000	0.0000
...	...	...	...	...	...	...	...	
8076	0.360	0.909	0	-4.105	1	0.0587	0.017700	0.0000

3.2 Genre DataFrames

Spotipy does not have a method to call genre for an individual song, so we will need to try our best in order to extract genre for an artist's music. I will create a function that gets the overall artist genre, which we can then apply to their songs. One possible downfall is if an artist goes across multiple genres, the songs might be mapped incorrectly.

In [24]:
```
unique_artist_data = unique_track_data.drop_duplicates(subset='art
unique_artist_data
```

Out[24]:

	track_uri	track_name	artist_name	artist_uri	album_
0	527IbJxFcjjTix0ONdxDdS	Hearts as Strong as Horses	Applebloom	7ggsXdK95oJBkuZu1txVjC	Sor Por (Music the O
1	1mOnMHXxt2vGI0b804eQsy	Apples to the Core	Apple Jack	1r0v3fdCiqrr9mYtvbCccT	Sor Por (Music the O
2	4GciJR91Tj8a7dLJ12WFvr	Ballad of the Crystal Ponies	Twilight Sparkle	53CQUfjaBNRwV2nFro1nac	Sor Por (Music the O
8	1rBQeB5zwAWf9mXL2HfMjt	Make a Wish - Extended Version	Pinkie Pie	7ExZeMNpyKhYSokWo9riU5	Sor Por (Music the O
11	3I4r9SZcAhEydPIS5eS5Sz	Becoming Popular	Rarity	6PqIHmHPCKrZoyLMf98era	Sor Frier and (Music
...	...	...	...	...	
8075	4krBGFZoDTDtjtGZC8rG9g	Sometimes	Reach The Sky	7masWBJicrrYn9G2iZezdv	Punk
8076	3G0PWfSGIsUrI4EI8u46EX	All Or Nothing	Fake ID	4GwCpkFWajqx3KSm0MVh2a	Punk
8077	5qpQhP4hyjCKC95oRtTqni	Borderline	Showoff	6IKhTkyp4EJ0ocidcwafs6	Punk
8079	1Ibfp4HOrAS0fB8eIoEYko	Baby One More Time	Nicotine	0p3U0uLx2oSf0yn8i5XZki	Punk
8080	6ktA174mwmCqcb9hfdL178	Heaven Is A Place On Earth	Student Rick	6AIuDNoFgmeUTnOc7DYXIN	Punk

3148 rows × 6 columns

In [25]:
```
# Extract artist data from spotipy using the search method and loc

def genre_extract(artist):
    extract = pd.DataFrame()
    result = sp.search(artist)
    if len(result['tracks']['items']) != 0:
        track = result['tracks']['items'][0]
        artist = sp.artist(track["artists"][0]["external_urls"]["s
        extract['genres'] = artist["genres"]
        extract['artist_id'] = artist["id"]
        return extract
    else:
        pass
```

In [26]:
```
genre_extract('Taylor Swift')
```

Out[26]:

	genres	artist_id
0	pop	06HL4z0CvFAxyc27GXpf02

We will now create a DataFrame with the genres for each artist.

In [27]:
```
## Creating DataFrame for genre data

# unique_genre_data = pd.DataFrame()
# start_time = time.time()
# batch_record = 0

## Using function created above to append the genre data to the Da
# for artist in unique_artist_data['artist_name']:
#     unique_genre_data = unique_genre_data.append(genre_extract(a
#     batch_record +=1
#     if batch_record < 100:
#         pass
#     else:
#         time.sleep(2)
#         batch_record = 0
# print("--- %s minutes ---" % ((time.time() - start_time)/60))

## Save to pickle to save runtime
# unique_genre_data.to_pickle('Spotipy Custom DataFrames/unique_ge

# Output Time: --- 14.149477303028107 minutes ---
```

In [28]:
```
# Call data from pickle
unique_genre_data = pd.read_pickle('Spotipy Custom DataFrames/uniq
unique_genre_data
```

Out[28]:

	genres	artist_id
0	pony	7ggsXdK95oJBkuZu1txVjC
0	trap queen	1ziRj7e5Tm72Qf2ag6jHed
0	pony	53CQUfjaBNRwV2nFro1nac
0	pony	53CQUfjaBNRwV2nFro1nac
0	alternative emo	2ElhbnEc2cvYIAsXXbo9tg
...	...	...
4	tropical house	7i9j813KFoSBMIdGqlh2Z1
5	uk dance	7i9j813KFoSBMIdGqlh2Z1
0	bow pop	4zeHJ3kiJyjYXIIOcG4MA7
1	pop violin	4zeHJ3kiJyjYXIIOcG4MA7
0	modern rock	20JZFwl6HVl6yg8a4H3ZqK

11796 rows × 2 columns

In [29]:

```
# Set index and group data by artist ID
unique_genre_data = unique_genre_data.set_index('artist_id')
unique_genre_data = unique_genre_data.groupby('artist_id').agg({'g
unique_genre_data
```

Out[29]:

	genres
artist_id	
001aJOc7CSQVo3XzoLG4DK	[classic soul, disco, electro, funk, post-disc...
00FQb4jTyendYWaN8pK0wa	[art pop, pop]
00RJAkLnjGx4kVWVJbOJx1	[opm]
00TKPo9MxwZ0j4ooveIxWZ	[alt z, dance pop, electropop, indie poptimism...
00Z3UDoAQwzvGu13HoAM7J	[indie pop rap, pop rap, underground hip hop, ...
...	...
7z55f4aJkaPR4EF2BXqsq7	[gaming edm]
7z5WFjZAIYejWy0NI5lv4T	[contemporary country, country, pop]
7zICaxnDB9ZprDSiFpvbbW	[dirty south rap, gangster rap, hip hop, houst...
7zmk5lkmCMVvfvwF3H8FWC	[hip pop, neo soul, pop r&b, r&b, urban contem...
7zsin6IgVsR1rqSRCNYDwq	[stomp and holler]

2499 rows × 1 columns

In [30]:

```
# Create new column reformatting data from list to string
unique_genre_data['genres_string'] = [','.join(map(str, l)) for l
unique_genre_data
```

Out[30]:

	genres	genres_string
artist_id		
001aJOc7CSQVo3XzoLG4DK	[classic soul, disco, electro, funk, post-disc...	classic soul,disco,electro,funk,post-disco,qui...
00FQb4jTyendYWaN8pK0wa	[art pop, pop]	art pop,pop
00RJAkLnjGx4kVWVJbOJx1	[opm]	opm
00TKPo9MxwZ0j4ooveIxWZ	[alt z, dance pop, electropop, indie poptimism...	alt z,dance pop,electropop,indie poptimism,nyc...
00Z3UDoAQwzvGu13HoAM7J	[indie pop rap, pop rap, underground hip hop, ...	indie pop rap,pop rap,underground hip hop,indi...
...	...	...
7z55f4aJkaPR4EF2BXqsq7	[gaming edm]	gaming edm
7z5WFjZAIYejWy0NI5lv4T	[contemporary country, country, pop]	contemporary country,country,pop
7zICaxnDB9ZprDSiFpvbbW	[dirty south rap, gangster rap, hip hop, houst...	dirty south rap,gangster rap,hip hop,houston r...
7zmk5lkmCMVvfvwF3H8FWC	[hip pop, neo soul, pop r&b, r&b, urban contem...	hip pop,neo soul,pop r&b,r&b,urban contemporary
7zsin6IgVsR1rqSRCNYDwq	[stomp and holler]	stomp and holler

2499 rows × 2 columns

In [31]:
```
# Split string column to explode it across all columns
unique_genre_data = unique_genre_data['genres_string'].str.split(p
unique_genre_data
```

Out[31]:

	0	1	2	3	4	
artist_id						
001aJOc7CSQVo3XzoLG4DK	classic soul	disco	electro	funk	post-disco	qı
00FQb4jTyendYWaN8pK0wa	art pop	pop	None	None	None	
00RJAkLnjGx4kVWVJbOJx1	opm	None	None	None	None	
00TKPo9MxwZ0j4ooveIxWZ	alt z	dance pop	electropop	indie poptimism	nyc pop	
00Z3UDoAQwzvGu13HoAM7J	indie pop rap	pop rap	underground hip hop	indie pop rap	pop rap	unc
...	...	...	...	...	...	
7z55f4aJkaPR4EF2BXqsq7	gaming edm	None	None	None	None	
7z5WFjZAIYejWy0NI5lv4T	contemporary country	country	pop	None	None	
7zICaxnDB9ZprDSiFpvbbW	dirty south rap	gangster rap	hip hop	houston rap	new orleans rap	
7zmk5lkmCMVvfvwF3H8FWC	hip pop	neo soul	pop r&b	r&b	urban contemporary	
7zsin6IgVsR1rqSRCNYDwq	stomp and holler	None	None	None	None	

2499 rows × 42 columns

In [32]:

```
# Strip columns to remove any unwanted characters

for column in range(0,41):
    unique_genre_data[column] = unique_genre_data[column].apply(la

unique_genre_data
```

Out[32]:

	0	1	2	3	4	
artist_id						
001aJOc7CSQVo3XzoLG4DK	classic soul	disco	electro	funk	post-disco	qu
00FQb4jTyendYWaN8pK0wa	art pop	pop	None	None	None	
00RJAkLnjGx4kVWVJbOJx1	opm	None	None	None	None	
00TKPo9MxwZ0j4ooveIxWZ	alt z	dance pop	electropop	indie poptimism	nyc pop	
00Z3UDoAQwzvGu13HoAM7J	indie pop rap	pop rap	underground hip hop	indie pop rap	pop rap	unc
...	...	...	...	...	...	
7z55f4aJkaPR4EF2BXqsq7	gaming edm	None	None	None	None	
7z5WFjZAIYejWy0NI5lv4T	contemporary country	country	pop	None	None	
7zICaxnDB9ZprDSiFpvbbW	dirty south rap	gangster rap	hip hop	houston rap	new orleans rap	
7zmk5lkmCMVvfvwF3H8FWC	hip pop	neo soul	pop r&b	r&b	urban contemporary	
7zsin6IgVsR1rqSRCNYDwq	stomp and holler	None	None	None	None	

2499 rows × 42 columns

3.3 Popularity DataFrames

In [33]:
```
# We can get popularity of a track from the track method
sp.track('0KKkJNfGyhkQ5aFogxQAPU')
```

Out[33]:

```
{'album': {'album_type': 'album',
  'artists': [{'external_urls': {'spotify': 'https://open.spotify.c
om/artist/0du5cEVh5yTK9QJze8zA0C'},
    'href': 'https://api.spotify.com/v1/artists/0du5cEVh5yTK9QJze8z
A0C',
    'id': '0du5cEVh5yTK9QJze8zA0C',
    'name': 'Bruno Mars',
    'type': 'artist',
    'uri': 'spotify:artist:0du5cEVh5yTK9QJze8zA0C'}],
  'available_markets': ['AD',
   'AE',
   'AG',
   'AL',
   'AM',
   'AO',
   'AR',
   'AT',
   'AU',
   'AZ',
```


In [34]:
```
sp.track('0KKkJNfGyhkQ5aFogxQAPU')['popularity']
```

Out[34]: 83

In [35]:
```
# Define function to extract the popularity from a given track. Pa
# don't break the function

def popularity_extract(track):
    extract = pd.DataFrame()
    pop_list = []
    try:
        result = sp.track(track)
        track = result['id']
        popularity = result['popularity']
        pop_list.append(int(popularity))
        extract['popularity'] = pop_list
        extract['track_id'] = result['id']
        return extract
    except Exception:
        pass
```

In [36]:

```
# Test function
popularity_extract('0KKkJNfGyhkQ5aFogxQAPU')
```

Out[36]:

	popularity	track_id
0	83	0KKkJNfGyhkQ5aFogxQAPU

In [37]:

```
# Test function if track_id doesn't exist
popularity_extract('example_error')
```

HTTP Error for GET to https://api.spotify.com/v1/tracks/example_error (https://api.spotify.com/v1/tracks/example_error) with Params: {'market': None} returned 400 due to invalid id

In [38]:

```
## Creating DataFrame for track popularity
# unique_track_popularity = pd.DataFrame()
# start_time = time.time()
# batch_record = 0

## Iterating over track data to apply function and append it to Da
# for track in range(0,len(unique_track_data)):
#     track_id = unique_track_data['track_uri'][track]
#     unique_track_popularity = unique_track_popularity.append(pop
#     batch_record +=1
#     if batch_record < 100:
#         pass
#     else:
#         time.sleep(2)
#         batch_record = 0

# print("--- %s minutes ---" % ((time.time() - start_time)/60))

## Save time by exporting DataFrame to pickle
# unique_track_popularity.to_pickle('Spotipy Custom DataFrames/uni

# Output time: --- 17.975244084994 minutes ---
```

In [39]:
```
# Call pickle file and remove 0 popularity songs
unique_track_popularity = pd.read_pickle('Spotipy Custom DataFrame
unique_track_popularity.drop(unique_track_popularity[unique_track_
unique_track_popularity
```

Out[39]:

	popularity	track_id
82	64	3kdMzXOcrDIdSWLdONHNK5
83	69	7aOor99o8NNLZYEIOXIBG1
86	60	45HAjqRWiNv6mMPw4NvZrU
87	56	5y1jgbDNgTfxoWXv3FhH2Q
90	67	2UZtI2HUyLRzqBjodvcUmY
...	...	...
8007	30	76ictxnZf8a4MAmaeNqvbU
8009	39	0MHJ3Obkdl3EN29A8nv6uz
8042	43	4POJUFV0qevJyeAX0j2mxR
8061	46	34ccBqL3xNaCzPxr0UqoEw
8069	33	6HcSRCF0R0DYRNY6vG0448

Next I am going to create an overall track_features file that combines all of our tables together.

In [40]:
```
# Send DataFrames to SQL
audio_features_df.to_sql('audio_features_df', con = conn, if_exist
unique_track_data.to_sql('unique_track_data', con = conn, if_exist
unwrapped_track_data.to_sql('unwrapped_track_data', con = conn, if
spd_top100 = spd_top100.applymap(str)
spd_top100.to_sql('spd_top100', con = conn, if_exists='replace')
unique_genre_data.to_sql('unique_genre_data', con = conn, if_exist
unique_track_popularity.to_sql('unique_track_popularity', con = cc
```

In [41]:
```
# Query and join all of our relevant DataFrames

track_features = """SELECT *
                    FROM unique_track_data as utd
                    LEFT JOIN audio_features_df as af
                        ON utd.track_uri = af.id
                    LEFT JOIN unique_genre_data as ugd
                        ON utd.artist_uri = ugd.artist_id
                    LEFT JOIN unique_track_popularity as utp
                        ON utd.track_uri = utp.track_id"""
```

In [42]:
```
# Convert it to a DataFrame

track_features = pd.read_sql(track_features, con = conn)
```

In [43]:

```
# Reformat the DataFrame, dropping columns, removing duplicates, k

track_features = track_features.drop(columns=['index','type','id',
track_features = track_features.loc[:,~track_features.columns.dupl
track_features = track_features.drop(track_features.iloc[:, 21:62]
track_features = track_features.rename(columns={'pid':'playlist_ic
track_features = track_features.set_index('playlist_id')


scaler = MinMaxScaler()
minmax_columns = track_features.columns.tolist()[5:18] + ['popular
track_features[minmax_columns]=scaler.fit_transform(track_features
track_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8081 entries, 180831 to 147046
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   track_uri         8081 non-null   object
 1   track_name        8081 non-null   object
 2   artist_name       8081 non-null   object
 3   artist_uri        8081 non-null   object
 4   album_name        8081 non-null   object
 5   danceability      8081 non-null   float64
 6   energy            8081 non-null   float64
 7   key               8081 non-null   float64
 8   loudness          8081 non-null   float64
 9   mode              8081 non-null   float64
 10  speechiness       8081 non-null   float64
 11  acousticness      8081 non-null   float64
 12  instrumentalness  8081 non-null   float64
 13  liveness          8081 non-null   float64
```

In [44]:
```
track_features
```

Out[44]:

playlist_id	track_uri	track_name	artist_name	artist_uri	al
180831	527IbJxFcjjTix0ONdxDdS	Hearts as Strong as Horses	Applebloom	7ggsXdK95oJBkuZu1txVjC	
180831	1mOnMHXxt2vGI0b804eQsy	Apples to the Core	Apple Jack	1r0v3fdCiqrr9mYtvbCccT	
180831	4GciJR91Tj8a7dLJ12WFvr	Ballad of the Crystal Ponies	Twilight Sparkle	53CQUfjaBNRwV2nFro1nac	
180831	68dC0K4xgIMF5Nhr44TevS	Find a Way	Twilight Sparkle	53CQUfjaBNRwV2nFro1nac	
180831	0vhKFkvwgdPBrrNr9gUbVa	A True, True Friend	Twilight Sparkle	53CQUfjaBNRwV2nFro1nac	
...	...	...	...	...	
147046	3G0PWfSGIsUrI4EI8u46EX	All Or Nothing	Fake ID	4GwCpkFWajqx3KSm0MVh2a	
147046	5qpQhP4hyjCKC95oRtTqni	Borderline	Showoff	6IKhTkyp4EJ0ocidcwafs6	
147046	7wwXG5FOebfhVBotX4vTXo	Send Me An Angel	Thrice	3NChzMpu9exTINPiqUQ2DE	
147046	1Ibfp4HOrAS0fB8eIoEYko	Baby One More Time	Nicotine	0p3U0uLx2oSf0yn8i5XZki	
147046	6ktA174mwmCqcb9hfdL178	Heaven Is A Place On Earth	Student Rick	6AIuDNoFgmeUTnOc7DYXIN	

8081 rows × 21 columns

In [45]:
```
# Send it to SQL

track_features.to_sql('track_features', con = conn, if_exists='rep
```

3.4 Create Playlist/Track Vectors for Modeling

Now that we have our general information tables, it is time to createe our vectors for our recommendation system. We will make a Features, popularity, and genre vector for both our track data, and then we will use spark to aggregate the data and group it by playlist. All columns will be numeric.

3.4.1.1 Track Features Vector

In [46]:
```
# Combine track features with base list to get track_uri

playlist_features_by_track = """SELECT *
                    FROM track_features as tf
                    LEFT JOIN spd_top100 as spd
                        ON tf.playlist_id = spd.pid"""
```

In [47]:
```
# Convert to DataFrame
playlist_features_by_track = pd.read_sql(playlist_features_by_trac
```

In [48]:
```
# View DataFrame to determine columns to drop
playlist_features_by_track
```

Out[48]:

	playlist_id	track_uri	track_name	artist_name	artist_
0	180831	527IbJxFcjjTix0ONdxDdS	Hearts as Strong as Horses	Applebloom	7ggsXdK95oJBkuZu1tx\
1	180831	1mOnMHXxt2vGI0b804eQsy	Apples to the Core	Apple Jack	1r0v3fdCiqrr9mYtvbCc
2	180831	4GciJR91Tj8a7dLJ12WFvr	Ballad of the Crystal Ponies	Twilight Sparkle	53CQUfjaBNRwV2nFro1r

3	180831	68dC0K4xglMF5Nhr44TevS	Find a Way	Twilight Sparkle	53CQUfjaBNRwV2nFro1r
4	180831	0vhKFkvwgdPBrrNr9gUbVa	A True, True Friend	Twilight Sparkle	53CQUfjaBNRwV2nFro1r
...	...	...	...	...	
8076	147046	3G0PWfSGIsUrl4El8u46EX	All Or Nothing	Fake ID	4GwCpkFWajqx3KSm0MVr
8077	147046	5qpQhP4hyjCKC95oRtTqni	Borderline	Showoff	6IKhTkyp4EJ0ocidcwa
8078	147046	7wwXG5FOebfhVBotX4vTXo	Send Me An Angel	Thrice	3NChzMpu9exTINPiqUQ2
8079	147046	1Ibfp4HOrAS0fB8eIoEYko	Baby One More Time	Nicotine	0p3U0uLx2oSf0yn8i5X
8080	147046	6ktA174mwmCqcb9hfdL178	Heaven Is A Place On Earth	Student Rick	6AIuDNoFgmeUTnOc7DY

8081 rows × 34 columns

In [49]:
```
# Drop irrelevant columns that we will not use
playlist_features_by_track = playlist_features_by_track.drop(colum
```

In [50]:
```
# Create Master Vector for Audio Features (1/6)

master_track_audio_features = playlist_features_by_track
master_track_audio_features = master_track_audio_features.set_inde
master_track_audio_features = master_track_audio_features.iloc[:,5
master_track_audio_features
```

Out[50]:

track_uri	danceability	energy	key	loudness	mode	speechiness
527IbJxFcjjTix0ONdxDdS	0.811861	0.827313	0.090909	0.905208	1.0	0.033832
1mOnMHXxt2vGI0b804eQsy	0.820041	0.815265	0.000000	0.951044	1.0	0.032911
4GciJR91Tj8a7dLJ12WFvr	0.646217	0.481938	0.000000	0.830322	1.0	0.033257
68dC0K4xgIMF5Nhr44TevS	0.541922	0.391578	0.909091	0.802070	1.0	0.039241
0vhKFkvwgdPBrrNr9gUbVa	0.693252	0.735949	0.909091	0.862855	1.0	0.040852
...	...	...	...	...	...	...
3G0PWfSGIsUrI4EI8u46EX	0.368098	0.910644	0.000000	0.911956	1.0	0.067549
5qpQhP4hyjCKC95oRtTqni	0.561350	0.902612	0.363636	0.882834	1.0	0.053970
7wwXG5FOebfhVBotX4vTXo	0.267894	0.943776	0.545455	0.920809	1.0	0.059839

3.4.1.2 Playlist Features Vector

In [51]:
```
# Create Spark Session
spark = SparkSession.builder.master('local').getOrCreate()
```

In [52]:
```
# Create first spark DataFrame
spark_df = spark.createDataFrame(playlist_features_by_track)
```

In [53]:
```
# Assign aggregate type to the columns. We will be using mean

aggregate_features = {'danceability': 'mean',
                      'energy' : 'mean',
                      'key' : 'mean',
                      'loudness' : 'mean',
                      'mode' : 'mean',
                      'speechiness' : 'mean',
                      'acousticness' : 'mean',
                      'instrumentalness' : 'mean',
                      'liveness' : 'mean',
                      'valence' : 'mean',
                      'tempo' : 'mean',
                      'time_signature' : 'mean'}

# Create aggreate DataFrame for playlist
playlist_features_aggregate_spark = spark_df.groupBy('playlist_id'
```

In [54]:

```
# Convert Spark DF to DataFrame in Pandas
playlist_features_aggregate = playlist_features_aggregate_spark.tc
playlist_features_aggregate = playlist_features_aggregate.set_inde

# Scale our data
scaler.fit(playlist_features_aggregate)
playlist_features_aggregate[['avg(tempo)', 'avg(valence)', 'avg(er
        'avg(speechiness)', 'avg(acousticness)', 'avg(key)',
        'avg(time_signature)', 'avg(danceability)', 'avg(mode)',
        'avg(loudness)', 'avg(instrumentalness)']] = scaler.fit_tra
        'avg(speechiness)', 'avg(acousticness)', 'avg(key)',
        'avg(time_signature)', 'avg(danceability)', 'avg(mode)',
        'avg(loudness)', 'avg(instrumentalness)']])
# Final Master playlist audio features (2/6)
playlist_features_aggregate
```

Out[54]:

	avg(tempo)	avg(valence)	avg(energy)	avg(liveness)	avg(speechiness)	avg(acousticr
playlist_id						
161637	0.694524	0.497423	0.709771	0.157685	0.107528	0.14
102585	0.823791	0.548295	0.865645	0.120445	0.216264	0.11
108597	0.739989	0.148843	0.579360	0.200743	0.014312	0.20
108807	0.258784	0.779182	0.657603	0.060408	0.127342	0.41
154640	0.467288	0.488090	0.565782	0.200535	0.092561	0.33
...	...	...	...	...	...	
184707	0.618714	0.488399	0.828643	0.118603	0.052562	0.08
101224	0.776221	0.779233	0.882427	0.174811	0.137989	0.08
182403	0.966172	0.715060	0.634357	0.047950	0.031668	0.27
17675	0.446490	0.952899	0.841984	0.155741	0.218703	0.19
147261	0.458375	0.501439	0.493811	0.076724	0.033469	0.26

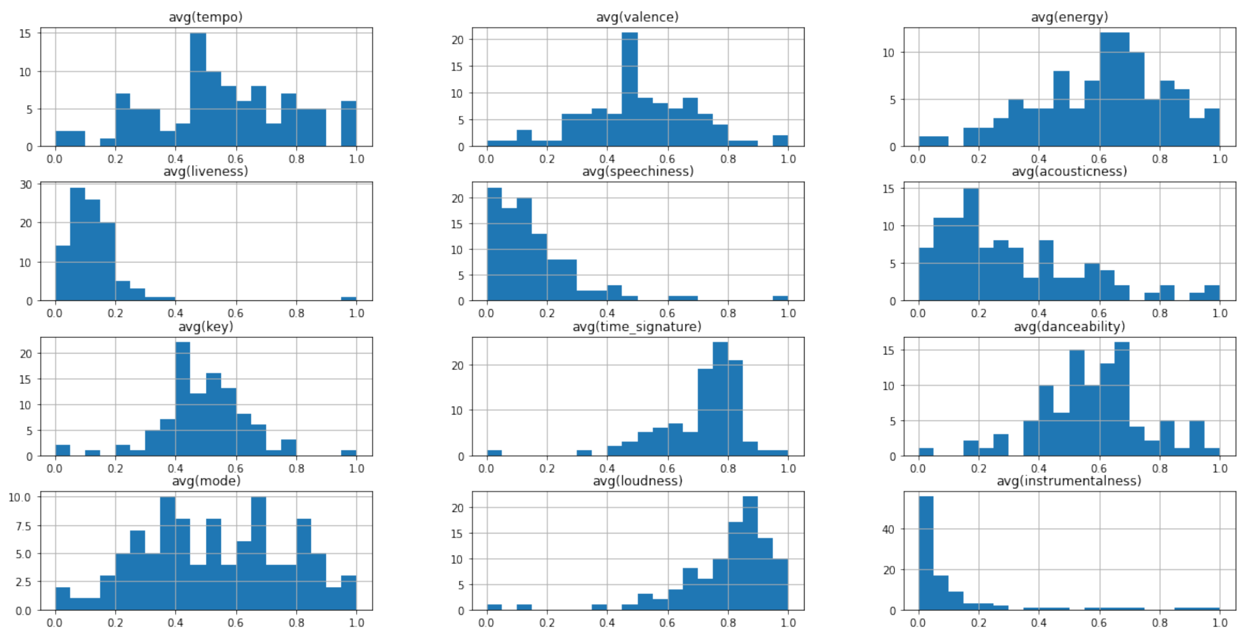
100 rows × 12 columns

In [55]:

```
# Create Visualization for each feature type

fig, axes = plt.subplots(len(playlist_features_aggregate.columns)/

i = 0
for triaxis in axes:
    for axis in triaxis:
        playlist_features_aggregate.hist(column = playlist_feature
        i = i+1
```



3.4.2.1 Popularity Track Vector

In [56]:

```
# Create df for all popularity data that have no nulls, set index
playlist_popularity_no_nulls = playlist_features_by_track.dropna(a
master_track_popularity_data = playlist_popularity_no_nulls[['trac
master_track_popularity_data = master_track_popularity_data.set_ir
```

In [57]:
```python
# Master Popularity data for Tracks (3/6)
master_track_popularity_data
```

Out[57]:

track_uri	popularity
3kdMzXOcrDIdSWLdONHNK5	0.724138
7aOor99o8NNLZYElOXIBG1	0.781609
45HAjqRWiNv6mMPw4NvZrU	0.678161
5y1jgbDNgTfxoWXv3FhH2Q	0.632184
2UZtI2HUyLRzqBjodvcUmY	0.758621
...	...
76ictxnZf8a4MAmaeNqvbU	0.333333
0MHJ3ObkdI3EN29A8nv6uz	0.436782
4POJUFV0qevJyeAX0j2mxR	0.482759
34ccBqL3xNaCzPxr0UqoEw	0.517241

3.4.2.2 Popularity Playlist Vector

In [58]:
```python
# Create second Spark df for popularity dataset
spark_df2 = spark.createDataFrame(playlist_popularity_no_nulls)
```

In [59]:
```python
# Group our popularity data by playlist
playlist_popularity_aggregate_spark = spark_df2.groupBy('playlist_
```

In [60]:

```
# Send our spark df to Pandas and set index to playlist id (4/6)
playlist_popularity_aggregate = playlist_popularity_aggregate_spar
playlist_popularity_aggregate = playlist_popularity_aggregate.set_
playlist_popularity_aggregate
```

Out[60]:

	avg(popularity)
playlist_id	
161637	0.326230
102585	0.634261
108597	0.466595
108807	0.445680
154640	0.218391
...	...
184707	0.431965
101224	0.518953
182403	0.678161
17675	0.625248
147261	0.517241

99 rows × 1 columns

3.4.3.1 Genre Track Vector

In [61]:

```
# Prepare dataframe for genre for tracks

playlist_features_by_track[playlist_features_by_track['genre_1'].r
```

Out[61]:

	playlist_id	track_uri	track_name	artist_name	artist_
0	180831	527IbJxFcjjTix0ONdxDdS	Hearts as Strong as Horses	Applebloom	7ggsXdK95oJBkuZu1tx\
2	180831	4GciJR91Tj8a7dLJ12WFvr	Ballad of the Crystal Ponies	Twilight Sparkle	53CQUfjaBNRwV2nFro1r
3	180831	68dC0K4xgIMF5Nhr44TevS	Find a Way	Twilight Sparkle	53CQUfjaBNRwV2nFro1r
4	180831	0vhKFkvwgdPBrrNr9gUbVa	A True, True Friend	Twilight Sparkle	53CQUfjaBNRwV2nFro1r
6	180831	1XBQVELMITpvMal5Pn1UpO	Babs Seed	Applebloom	7ggsXdK95oJBkuZu1tx\
...	...	...	...	...	
8068	147046	2jbupzHNwz0VgORg1uJb3D	Like A Prayer	Rufio	0HjoyITAvSVktTCjXUa4
8069	147046	6HcSRCF0R0DYRNY6vG0448	Bye, Bye, Bye	Further Seems Forever	1Enp9WKfk0aI9CFi2YGE
8071	147046	57uO0ogaSWb7t20CY85CfD	I'm Like A Bird	Element 101	6pndtpE63q5pHaGhDko
8073	147046	5AI3VJyLLmB8hEIoCAVCIm	I'm Real	The Starting Line	3E3xrZtBU5ORqcmX78v5
8078	147046	7wwXG5FOebfhVBotX4vTXo	Send Me An Angel	Thrice	3NChzMpu9exTINPiqUQ2

6135 rows × 21 columns

In [62]:
```
# Select genre data and set index to track_uri
genre_data_no_nulls = playlist_features_by_track[playlist_features

# OneHotEncode our data so it can be read by our model
ohe = OneHotEncoder()
X = ohe.fit_transform(genre_data_no_nulls['genre_1'].values.reshap
y = ohe.get_feature_names(['genre_1'])
master_track_genre_data = pd.DataFrame(X, columns = y)
master_track_genre_data.index = genre_data_no_nulls.index

# Final master genre data by track (5/6)
master_track_genre_data['genre_1_a cappella'].value_counts()
```

Out[62]:
```
0.0    6120
1.0      15
Name: genre_1_a cappella, dtype: int64
```

3.4.3.2 Genre Playlist Vector

In [63]:
```
# Prep our track genre data
playlist_genre_prep = master_track_genre_data.join(genre_data_no_r
```

In [64]:
```
# Create our third spark dataframe
spark_df3 = spark.createDataFrame(playlist_genre_prep)
```

In [65]:
```
# Aggregate our genre data by sum

genre_keys = playlist_genre_prep.columns.to_list()
genre_values = ['sum'] * 500
aggregate = dict(zip(genre_keys,genre_values))

playlist_genre_aggregate_spark = spark_df3.groupBy('playlist_id').
```

In [66]:
```
# MinMax scale our sums to weight our most common genres on a scal
playlist_genre_aggregate = playlist_genre_aggregate_spark.toPandas
playlist_genre_aggregate = playlist_genre_aggregate.set_index('pla
playlist_pie_chart = playlist_genre_aggregate.copy()
minmax_columns2 = playlist_genre_aggregate.columns.tolist()
playlist_genre_aggregate[minmax_columns2] = scaler.fit_transform(p

# Final Master playlist data for genre (6/6)
playlist_genre_aggregate.index.get_loc(102585)
```

Out[66]:
```
1
```

In [67]:
```
playlist_genre_aggregate.iloc[1:2]
```

Out[67]:

playlist_id	sum(genre_1_la pop)	sum(genre_1_lovers rock)	sum(genre_1_lo-fi beats)	sum(genre_1_french shoegaze)	sum(genr classic
102585	0.0	0.0	0.0	0.0	

1 rows × 500 columns

In [68]:
```
# End Spark Session
SparkSession.stop(spark)
```

3.5 Final Vectors

Track Vector

In [69]:
```
# Send master track vectors to SQL

master_track_audio_features.to_sql('master_track_audio_features',
master_track_popularity_data.to_sql('master_track_popularity_data'
master_track_genre_data.to_sql('master_track_genre_data', con = co
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/pandas/core
/generic.py:2615: UserWarning: The spaces in these column names will
not be changed. In pandas versions < 0.14, spaces were converted to u
nderscores.
  method=method,
```

In [70]:
```
# Join track vectors using SQL

final_track_join = """SELECT *
                    FROM master_track_audio_features as taf
                    LEFT JOIN master_track_popularity_data as mtp
                        ON taf.track_uri = mtp.track_uri
                    LEFT JOIN master_track_genre_data as mtg
                        ON taf.track_uri = mtg.track_uri"""
# Read into Pandas and set index, impute values for most frequent
final_track_vector = pd.read_sql(final_track_join, con = conn)
final_track_vector = final_track_vector.set_index('track_uri')
impute = SimpleImputer(missing_values=np.nan, strategy='most_frequ
final_track_vector[final_track_vector.columns.to_list()] = impute.

```

```
# Fix index (formatting was strange)
new_index = []

for item in range(0,len(final_track_vector.index)):
    new_index.append(final_track_vector.index[item][0])

final_track_vector['track_uri_fix'] = new_index
final_track_vector = final_track_vector.set_index('track_uri_fix')
final_track_vector.index = final_track_vector.index.rename(name =

# Final track vector ready for modelling shape is (8081 x 513)
final_track_vector
```

Out[70]:

	danceability	energy	key	loudness	mode	speechiness	ac
track_uri							
527IbJxFcjjTix0ONdxDdS	0.811861	0.827313	0.090909	0.905208	1.0	0.033832	
1mOnMHXxt2vGI0b804eQsy	0.820041	0.815265	0.000000	0.951044	1.0	0.032911	
4GciJR91Tj8a7dLJ12WFvr	0.646217	0.481938	0.000000	0.830322	1.0	0.033257	
68dC0K4xgIMF5Nhr44TevS	0.541922	0.391578	0.909091	0.802070	1.0	0.039241	
0vhKFkvwgdPBrrNr9gUbVa	0.693252	0.735949	0.909091	0.862855	1.0	0.040852	
...	...	...	...	...	...	...	
3G0PWfSGIsUrI4EI8u46EX	0.368098	0.910644	0.000000	0.911956	1.0	0.067549	
5qpQhP4hyjCKC95oRtTqni	0.561350	0.902612	0.363636	0.882834	1.0	0.053970	
7wwXG5FOebfhVBotX4vTXo	0.267894	0.943776	0.545455	0.920809	1.0	0.059839	
1Ibfp4HOrAS0fB8eIoEYko	0.601227	0.886548	0.818182	0.884164	0.0	0.038780	
6ktA174mwmCqcb9hfdL178	0.627812	0.794181	0.818182	0.895920	1.0	0.035328	

8081 rows × 513 columns

Playlist Vector

In [71]:
```
# Send playlist vectors to SQL
playlist_features_aggregate.to_sql('playlist_features_aggregate',
playlist_popularity_aggregate.to_sql('playlist_popularity_aggregat
playlist_genre_aggregate.to_sql('playlist_genre_aggregate', con =
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/pandas/core
/generic.py:2615: UserWarning: The spaces in these column names will
not be changed. In pandas versions < 0.14, spaces were converted to u
nderscores.
  method=method,
```

In [72]:
```
# Join playlist vectors using SQL
final_playlist_join = """SELECT *
                    FROM playlist_features_aggregate as pfa
                    LEFT JOIN playlist_popularity_aggregate as ppa
                        ON pfa.playlist_id = ppa.playlist_id
                    LEFT JOIN playlist_genre_aggregate as pga
                        ON pfa.playlist_id = pga.playlist_id"""

# Bring vector into pandas and set index/reformat
final_playlist_vector = pd.read_sql(final_playlist_join, con = cor
final_playlist_vector = final_playlist_vector.T.groupby(level=0).f
final_playlist_vector = final_playlist_vector.set_index('playlist_
final_playlist_vector.index = final_playlist_vector.index.astype('

# Impute missing values by mean
impute = SimpleImputer(missing_values=np.nan, strategy='mean')
final_playlist_vector[final_playlist_vector.columns.to_list()] = i
final_playlist_vector.columns = final_playlist_vector.columns.str[

# Final playlist vector ready for modelling shape is (100 x 513)
final_playlist_vector
```

Out[72]:

playlist_id	acousticness	danceability	energy	instrumentalness	key	liveness	loudnes
161637	0.148188	0.445153	0.709771	0.018887	0.552636	0.157685	0.86673(
102585	0.114856	0.546310	0.865645	0.028130	0.248950	0.120445	0.93704:
108597	0.201619	0.272096	0.579360	0.000185	0.507042	0.200743	0.84735!
108807	0.412638	0.676090	0.657603	0.018128	0.485424	0.060408	0.78530'
154640	0.334549	0.492089	0.565782	0.021793	0.443580	0.200535	0.77675:
...	...	...	...	...	...	...	..
184707	0.085384	0.512558	0.828643	0.083441	0.517708	0.118603	0.91529(
101224	0.080236	0.617600	0.882427	0.024309	0.541906	0.174811	0.96093:
182403	0.270722	0.675093	0.634357	0.044887	0.479767	0.047950	0.74812'
17675	0.192292	0.903091	0.841984	0.001929	0.613870	0.155741	0.93619·
147261	0.268973	0.532730	0.493811	0.092371	0.418482	0.076724	0.75109:

100 rows × 513 columns

Section 4: Modeling

Content-Based Filtering using Cosine Similarity

Now that we have our vectors with our audio features, popularity, and genre data, I will use cosine similarity to build our recommendation system. Here is how it will work:

- Step 1: Our model will take a look at a selected playlist id and its vector to analyze the overall features of the songs within.
- Step 2: Our model will then compare the playlist's vector to our unique track data vector (audio feaures, popularity, and genre) to generate a list of x number of songs (user-inputted) that are closely comparable to the playlist vectors, using cosine similarity. The greater the cosine similarity, the more similar the vectors are related.
- Step 3: We will then analyze the features of the top song generated for reasonableness.

In [100]:

```
# Recommenders
def song_recommender(playlist_id,num_recs):
    # This function serves as the recommendation system behind ou
    # Inputs pulled from spotify_recommendation function below:

    # playlist_id: spotify playlist id from top 100 popular playl
    # num_recs: number of recomendations desired

    # Remove songs from track vector that appear in the selected 
    playlist_key = unique_track_data[['pid','track_uri']].set_ind
    new_final_track_vector_no_playlist_tracks = pd.merge(playlist
    new_final_track_vector_no_playlist_tracks = new_final_track_v


    # Create consine similarity model between unique tracks and p
    row_number = final_playlist_vector.index.get_loc(playlist_id)
    playlist_selection_vector = final_playlist_vector.iloc[row_nu
    playlist_feature_cos = pd.DataFrame(cos(new_final_track_vecto
    playlist_feature_cos.index = new_final_track_vector_no_playli

    # Reformat and sort based on strongest cosine similarity valu
    playlist_feature_cos = playlist_feature_cos.rename(columns = 
    playlist_feature_cos = playlist_feature_cos.sort_values(playl

    # Use SQL to bring in track name, artist name and album name
    playlist_feature_cos.to_sql('playlist_feature_cos', con = con
    clean_recommendations = """SELECT *
                    FROM playlist_feature_cos as pfc
                    LEFT JOIN unique_track_data as utd
                        ON pfc.track_uri = utd.track_uri"""
```

```
                              ON plc.track_uri = utd.track_uri

    # Send to Pandas and reformat
    clean_recommendations_df = pd.read_sql(clean_recommendations,
    clean_recommendations_df = clean_recommendations_df.drop(colu
    clean_recommendations_df = clean_recommendations_df.iloc[:,2:
    return clean_recommendations_df

def spotify_recommendation(playlist_id,num_recs):
    # This function provides us with our general interface for ou

    # Inputs:
    # playlist_id: spotify playlist id from top 100 popular playl
    # num_recs: number of recomendations desired

    playlist_info = unwrapped_track_data[unwrapped_track_data['pi
    playlist_info = playlist_info[['track_uri','track_name','arti
    dfi.export(playlist_info.head(10), 'Visualizations/playlistsn
    dfi.export(song_recommender(playlist_id,num_recs), 'Visualiza
    return print('\nThank you for inputting your playlist. Please


# Comparisons
def song_vs_playlist_comparison(playlist_id, track_uri):

    # This function gives us the sample variance between our sele
    rnum = final_playlist_vector.index.get_loc(playlist_id)
    playlist_snapshot = final_playlist_vector.iloc[rnum:rnum+1].r
    track_snapshot = final_track_vector[final_track_vector.index=

    # Manually calculated variance
    variance_df = np.power((playlist_snapshot - track_snapshot),2
    variance_df['average variance'] = variance_df.mean(axis=1)
    return variance_df

def song_vs_playlist_visual_comparison(playlist_id, track_uri):

    # This function is for creating a cluster barchart that will

    # Get track data formatted for bar graph
    track_snapshot_bar = final_track_vector[final_track_vector.in
    track_snapshot_bar = track_snapshot_bar.loc[:, (track_snapsho
    size_track = len(track_snapshot_bar.columns)
    track_snapshot_bar_values = track_snapshot_bar.values.reshape
    track_snapshot_bar_columns = track_snapshot_bar.columns.tolis

    # Get playlist data formatted for bar graph
    rnum = final_playlist_vector.index.get_loc(playlist_id)
    playlist_snapshot_bar = final_playlist_vector.iloc[rnum:rnum+
    playlist_snapshot_bar = playlist_snapshot_bar.loc[:, (playlis
    common_columns = [col for col in set(track_snapshot_bar.colum
```

```
    playlist_snapshot_bar = playlist_snapshot_bar[common_columns]
    size_playlist = len(playlist_snapshot_bar.columns)
    playlist_snapshot_bar_values = playlist_snapshot_bar.values.r
    playlist_snapshot_bar_columns = playlist_snapshot_bar.columns

    x = np.arange(len(track_snapshot_bar_columns))  # the label l
    width = 0.35  # the width of the bars

    # Create plot for clustered bar graph
    fig, ax = plt.subplots(figsize=(30,15),facecolor='white')
    ax.bar(x - width/2, playlist_snapshot_bar_values,width, label
    ax.bar(x + width/2, track_snapshot_bar_values, width,label='t
    sns.set_context('poster')
    ax.set_xlabel('Feature', fontsize=30)
    ax.set_ylabel('Feature Score', fontsize=20)
    ax.set_title('Features Comparison: Top Recommended Track vs.
    ax.set_xticklabels(playlist_snapshot_bar_columns, fontsize=20
    ax.legend(fontsize=20)
    ax.set_xticks(x)
    plt.savefig('Visualizations/songvsplaylist'+str(playlist_id)+
    return plt.show()

# Genre population breakdown by playlist

def playlist_genre_breakdown(playlist_id):
    playlist_pie_chart_df = playlist_pie_chart
    row_number = playlist_pie_chart_df.index.get_loc(playlist_id)
    playlist_pie_chart_df = playlist_pie_chart_df.iloc[row_number
    playlist_pie_chart_df = playlist_pie_chart_df.loc[:, (playlis
    playlist_pie_chart_df = playlist_pie_chart_df.loc[:, ~(playli
    rows = playlist_pie_chart_df.shape[1]
    playlist_pie_chart_values = np.reshape(playlist_pie_chart_df.
    playlist_pie_chart_labels = playlist_pie_chart_df.columns.tol
    playlist_pie_chart_labels = [label.title() for label in playl
    fig, ax = plt.subplots(figsize=(20,10),facecolor='white')
    sns.set_context('poster')
    ax.pie(playlist_pie_chart_values,labels=playlist_pie_chart_la
    ax.set_title('Playlist Genre Breakdown (>2 records)',fontsize
    plt.savefig('Visualizations/PlaylistGenreBreakdown'+str(playl
    return fig, ax
```

How can I review results when there aren't many metrics available for content-based filtering? First, I will review the overall features for our selected playlist and compare them to the top track selected by our recommendation system for reasonableness. Second, I will plot the feature scores against each other to visualize the magnitude of difference between the average playlist scores and the top recommended song. Lastly, I will listen to a selection of 3 songs on each playlist, and then I will listen to and analyze the tracks provided by our recommendation system to subjectively determine whether I think they could belong on the playlist.

Playlist #102585 Reasonableness Test

In [74]:

```
# Call function for recommender

spotify_recommendation(102585,5)
```

```
Thank you for inputting your playlist. Please see playlist tracks bel
ow:
```

pos	track_uri	track_name	artist_name	album_name
0	67WTwafOMgegV6ABnBQxcE	Some Nights	fun.	Some Nights
1	6Ep6BzIOB9tz3P4sWqiiAB	Radioactive	Imagine Dragons	Night Visions
2	4wCmqSrbyCgxEXROQE6vtV	Somebody That I Used To Know	Gotye	Making Mirrors
3	5j9iuo3tMmQIfnEEQOOjxh	Best Day Of My Life	American Authors	Oh, What A Life
4	6cpk00i5TxCqSeqNi2HuIe	One More Night	Maroon 5	Overexposed Track By Track
...	...	...	...	...
137	1YGvv0iH1TEjMrp0oRPB5a	Louder Than Your Love	Andy Black	The Shadow Side
138	1DtLI0k0zMrFqcW0pquxpf	Broken Pieces	Andy Black	The Shadow Side
139	4WTesnTwFAtRtC6fhXuX31	The Void	Andy Black	The Shadow Side
140	0NWQTyapmz4GuDTSN9xTB7	Candyman	Zedd	Candyman
141	2qPUnoasNe4Ep43emVXEig	Billionaire (feat. Bruno Mars)	Travie McCoy	Lazarus

142 rows × 4 columns

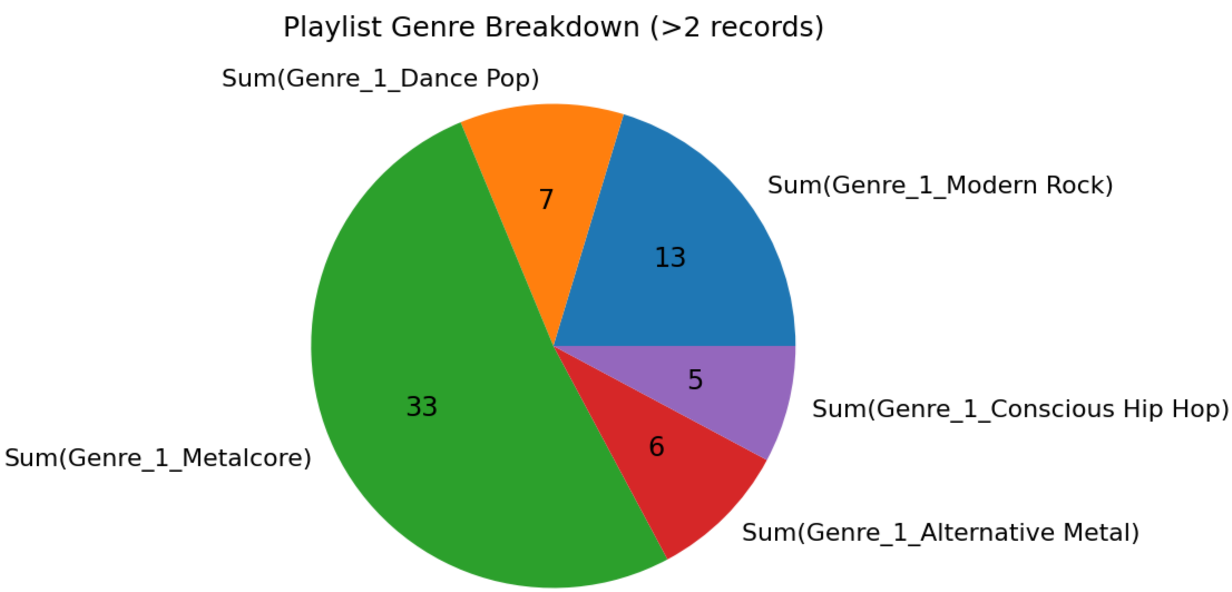
```
Here are 5 tracks that might fit this playlist:
```

	track_uri	track_name	artist_name	album_name
0	5zT5cMnMKoyruPj13TQXGx	I Found	Amber Run	5AM (Deluxe)
1	4GlTtbZtRCQXhWLMXrWXHt	Roots	Imagine Dragons	Roots
2	673WCjn0SxKJD4qRKczaCk	She Had The World	Panic! At The Disco	Pretty. Odd.
3	0z8yrlXSjnl29Rv30RssNI	Shots - Broiler Remix	Imagine Dragons	Smoke + Mirrors
4	2AObzKd3JYIWQqQ067Z0YI	Release	Imagine Dragons	Smoke + Mirrors

Out[74]:
```
(None, None, None, None)
```

In [88]:
```
playlist_genre_breakdown(102585)
```

Out[88]:
```
(<Figure size 1440x720 with 1 Axes>,
 <AxesSubplot:title={'center':'Playlist Genre Breakdown (>2 records)'
}>)
```

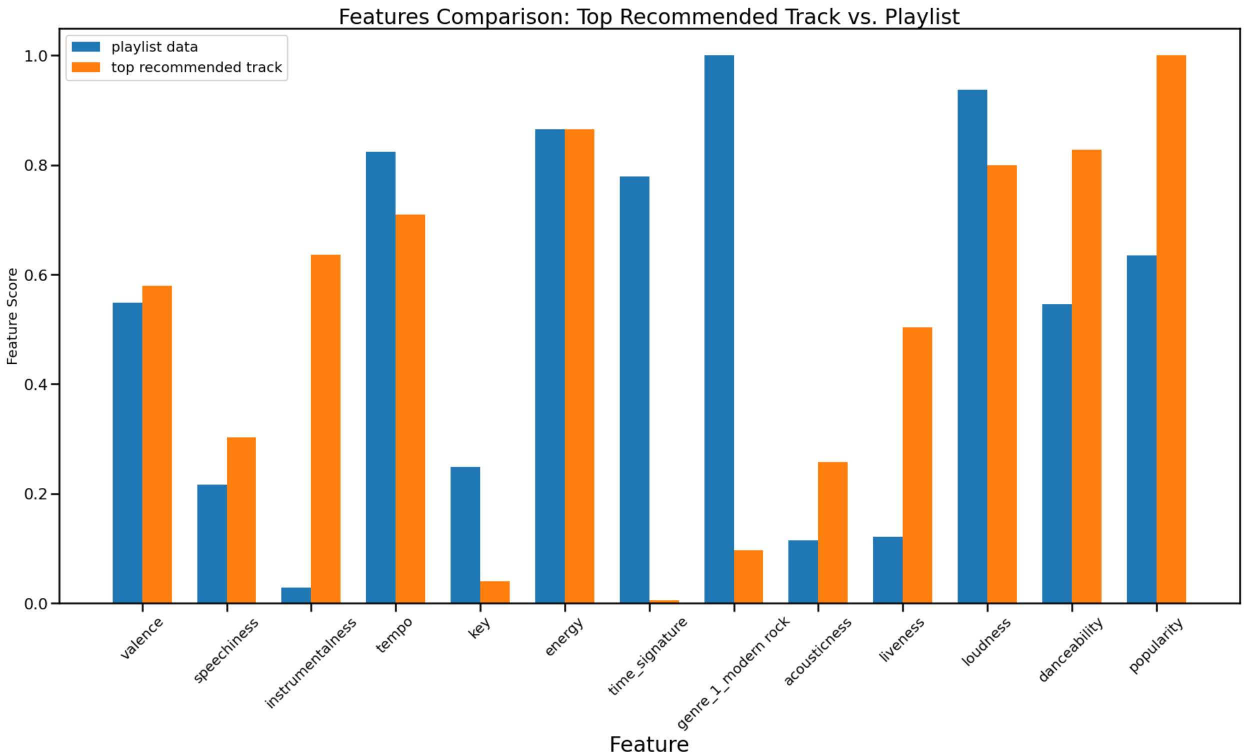


In [101]:

```
# Call function for graphical comparison

song_vs_playlist_visual_comparison(102585,'5zT5cMnMKoyruPj13TQXGx'
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_l
auncher.py:97: UserWarning: FixedFormatter should only be used togeth
er with FixedLocator
```



In [77]:

```
# Call function for variance

song_vs_playlist_comparison(102585,'5zT5cMnMKoyruPj13TQXGx')
```

Out[77]:

	acousticness	danceability	energy	genre_1_21st century classical	genre_1_a cappella	genre_1_abstract beats	genre_1_ab h
0	0.563409	0.001119	0.317444	0.0	0.027778	0.0	

1 rows × 514 columns

As we can see above, the sample variance between our recommended song and our playlist average seems to be very low, driven mainly by the genre data. While it can be argued that our genre data is so specific that it is dominating our model, I personally think the specificity of the genre helps us narrow our recommendations down to suggest more accurate songs.

Looking at our visualization, for the most part it appears most of the features are comparable, except for time signature, acousticness, liveness, and key. As a musician, I would argue that key and time signature does not matter too much in terms my enjoyment for music, so at first glance, I would not say that our recommendation is that far off.

Now for the sound test. I will document my subjective findings below:

Some Nights, Radioactive, and Somebody That I Used to Know were all hits around 2013, and I personally have listened to these songs already. My description of Radioactive is an arena rock, bass thumping anthem that brings a high level of intensity. Some Nights and Somebody That I Used to Know are more chill and have a very nostaglic sound to them.

For our recommendations, we have 3 songs by Imagine Dragons, 1 song by Panic at the Disco and our top song was Amber Run. I already know all of the songs except for the one made by Amber Run, and I would say that it is reasonable that these songs would be suggested, seeing the selection of songs on the playlist. I had to listen to the Amber Run song, and it definitely is a slower song that is lesser known to me than the others. It is definitely more acoustic and I wouldn't necessarily classify it as modern rock.

Overall, I would deem that these 5 recommended songs pass the reasonableness test.

Playlist #765 Reasonableness Test

In [78]:
```python
spotify_recommendation(765,10)
```

```
Thank you for inputting your playlist. Please see playlist tracks bel
ow:
```

pos	track_uri	track_name	artist_name	album_name
0	03xWMkKEbeO4SnylA53ipj	When Will My Life Begin - From "Tangled"/Sound...	Mandy Moore	Tangled
1	1IOSxJNCLvWm2bYaTcTSmK	Mother Knows Best - From "Tangled"/Soundtrack ...	Donna Murphy	Tangled
		I've Got a Dream - From		

2	0TCt7OFRdD8PQ6vTRQxNgQ	"Tangled"/Soundtrack V...	Mandy Moore	Tangled
3	6klpXs2uAjagnZMFkt4qkl	I See the Light - From "Tangled"/Soundtrack Ve...	Mandy Moore	Tangled
4	75VVIB2x1h6BfxD2PqOO57	Healing Incantation - From "Tangled"/Soundtrac...	Mandy Moore	Tangled
...	...	...	...	...
76	6FHUBs8P5qcjpj7C2QHdEq	Tulou Tagaloa	Olivia Foa'i	Moana
77	3ZJnc1eGicPxRitBoC7eWZ	An Innocent Warrior	Vai Mahina	Moana
78	2bwSCIuNtVrQPVddCi8sOW	Where You Are	Christopher Jackson	Moana
79	3C4WmF4klgfmb6GzW8DEdX	We Know The Way - From "Moana"	Opetaia Foa'i	We Know The Way
80	2wCRJwiL1WSrW0Dwfco7Nj	Know Who You Are	Auli'i Cravalho	Moana

81 rows × 4 columns

```
Here are 10 tracks that might fit this playlist:
```

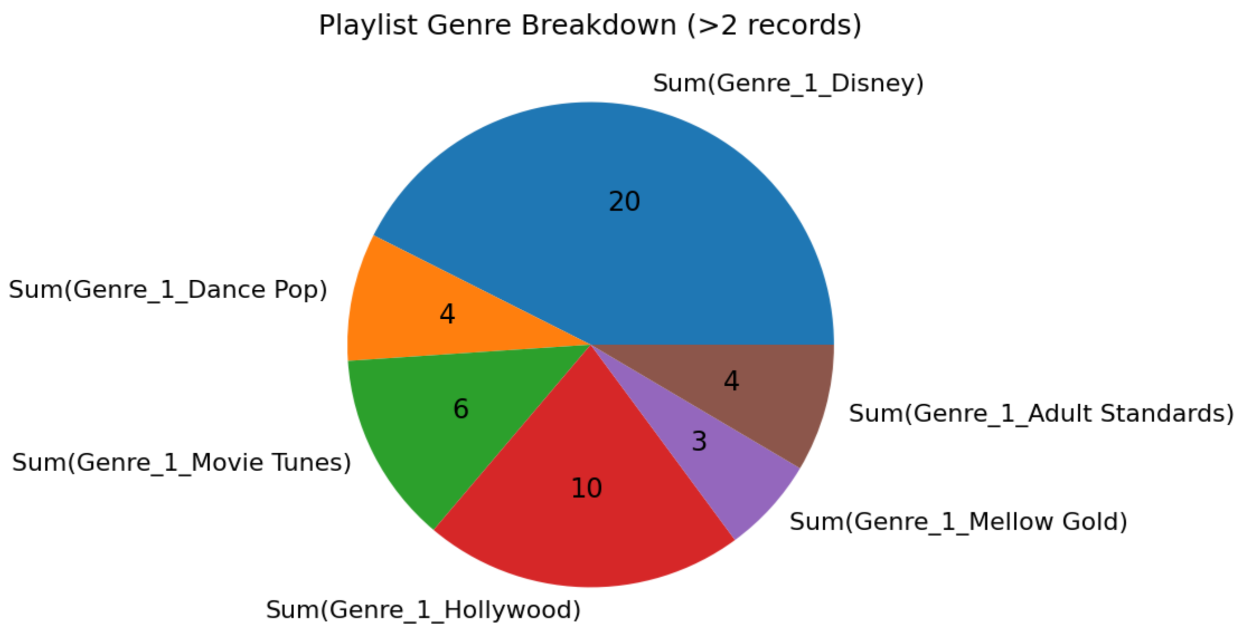
	track_uri	track_name	artist_name	album_name
0	2stkLJ0JNcXklRDNF3ld6c	You've Got A Friend In Me - From "Toy Story"/ ...	Randy Newman	Toy Story
1	7G061Oqw7NXFr1NDTpXol4	Happy Working Song - From "Enchanted"/Soundtra...	Amy Adams	Enchanted
2	7wjiMdiSgsL9Vkrwb10Num	On My Way	Phil Collins	Brother Bea
3	6mDxu0xwhv5tn1oMTNUypu	Something There	Robby Benson	Beauty and the Beas
4	6ZgigeSB0XUMqc0jjzaq6d	You're A Mean One, Mr. Grinch	Thurl Ravenscroft	How The Grinch Stole Christmas
5	2dlxN435ZY9ruxGYND2Hq0	Almost There	Anika Noni Rose	The Princess and the Frog
6	2s6wCS3vDZFPY9NOTIPXJZ	Take Me Home - 2016 Remastered	Phil Collins	No Jacket Required (Remastered
7	0jkGkwy510cvhy0jYPFme4	Kingdom Dance - From "Tangled"/Score	Alan Menken	Tangled
8	4qKDjmz094Bu2wMepNuwVN	Main Title / Once Upon A Dream / Prologue - Fr...	Chorus - Sleeping	Sleeping Beauty

		Dream / Prologue - Fi...	Beauty	
9	0QKHM0vKGZcgRpryeqtYkG	The Chipmunk Song	Alvin & The Chipmunks	Alvin & The Chipmunks / OST

Out[78]:
```
(None, None, None, None)
```

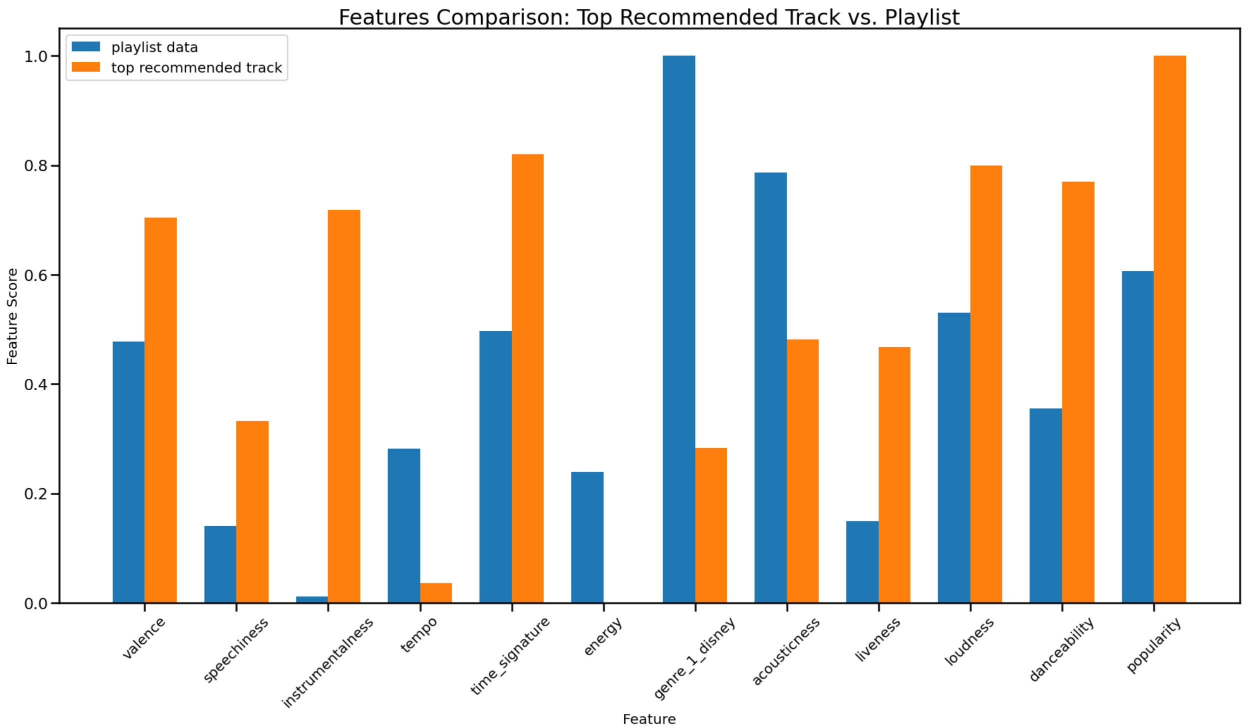
In [90]:
```
playlist_genre_breakdown(765)
```

Out[90]:
```
(<Figure size 1440x720 with 1 Axes>,
 <AxesSubplot:title={'center':'Playlist Genre Breakdown (>2 records)'
}>)
```



In [96]:
```
song_vs_playlist_visual_comparison(765,'2stkLJ0JNcXkIRDNF3ld6c')
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_l
auncher.py:97: UserWarning: FixedFormatter should only be used togeth
er with FixedLocator
```



In [81]:
```
song_vs_playlist_comparison(765,'2stkLJ0JNcXkIRDNF3ld6c')
```

Out[81]:

	acousticness	danceability	energy	genre_1_21st century classical	genre_1_a cappella	genre_1_abstract beats	genre_1_ab h
0	0.001126	0.122204	0.008676	0.0	0.0	0.0	

1 rows × 514 columns

In [82]:

```
unwrapped_track_data[unwrapped_track_data['pid']==765].head(50)
```

Out[82]:

	pos	artist_name	track_uri	artist_uri	t
1791	0	Mandy Moore	03xWMkKEbeO4SnylA53ipj	2LJxr7Pt3JnP60eLxwbDOu	When E "Tangl
1792	1	Donna Murphy	1lOSxJNCLvWm2bYaTcTSmK	5BuTOT6mPoNZ5EmaPheBI9	Mother K "Tangled".
1793	2	Mandy Moore	0TCt7OFRdD8PQ6vTRQxNgQ	2LJxr7Pt3JnP60eLxwbDOu	I've Go "Tangled".
1794	3	Mandy Moore	6klpXs2uAjagnZMFkt4qkl	2LJxr7Pt3JnP60eLxwbDOu	I See the "Tangled".
1795	4	Mandy	75VVIB2x1h6BfxD2PqOO57	2LJxr7Pt3JnP60eLxwbDOu	Healing I

As we can see above, the sample variance between our recommended song and our playlist average is very low, driven mainly by the genre data.

Looking at our visualization, for the most part it appears most of the features are comparable, except for the instrumentalness and energy. Seeing that the general theme of this playlist seems to be soundtrack for childrens movies, again, I believe that genre is the most important driver of the recommender here. Our most common genre, disney, seems a little off, but that can be explained because not all childrens movies are necessarily Disney movies.

Now for the sound test. I will document my subjective findings below:

As we can see from our selection of songs, they all seem to be Disney songs from Moana and Tangled. I would expect that our recommendation system would suggest other kids songs accross childrens movies. After pulling more songs from the unwrapped track data, I can confirm that there are some songs that are not Disney.

For our recommendations, all 10 songs appear to be soundtrack songs, which is great, and they are all mainly from beloved kids movies. Because it seems like kids movie is the main category for this playlist, I will not review the other audio features.

Overall, I would deem that these 10 recommended songs pass the reasonableness test.

Playlist #160101 Reasonableness Test

In [83]:
```
spotify_recommendation(160101,5)
```

```
Thank you for inputting your playlist. Please see playlist tracks bel
ow:
```

pos	track_uri	track_name	artist_name	album_name
0	4w3dm0pGQ9otu7cG5uWy88	Not Just a Girl	She Wants Revenge	Valleyheart
1	37r6i0GTqgR05rGe5wNhmp	When They Fight, They Fight	Generationals	Con Law
2	0grFc6kIR3hxoHLcgCYsF4	Howlin' For You	The Black Keys	Brothers
3	6M23RkYPbVR91c4iWVNkcl	Changing	The Airborne Toxic Event	All At Once
4	5nHRIKsXDwUpse9gzrAxLR	Oxford Comma	Vampire Weekend	Vampire Weekend
...	...	...	...	...
202	6T9ZJ2cJbtF4eDapnRHCux	Death Valley	My Jerusalem	Preachers
203	2QVmiA93GVhWNTWQctyY1K	Outro	M83	Hurry Up, We're Dreaming
204	7raMTVKDjLfTAyfDXKlfrz	Beneath The Surface	Demons Of Ruby Mae	Beneath The Surface
205	6y88SnrCoqRDZs1WTjKlZc	You're Loved & I'm Hated	Christopher Tyng	Suits (Original Television Soundtrack)
206	3uvsVUrAaGQJCTEUR1S3Sx	Bare	WILDES	Bare

207 rows × 4 columns

```
Here are 5 tracks that might fit this playlist:
```

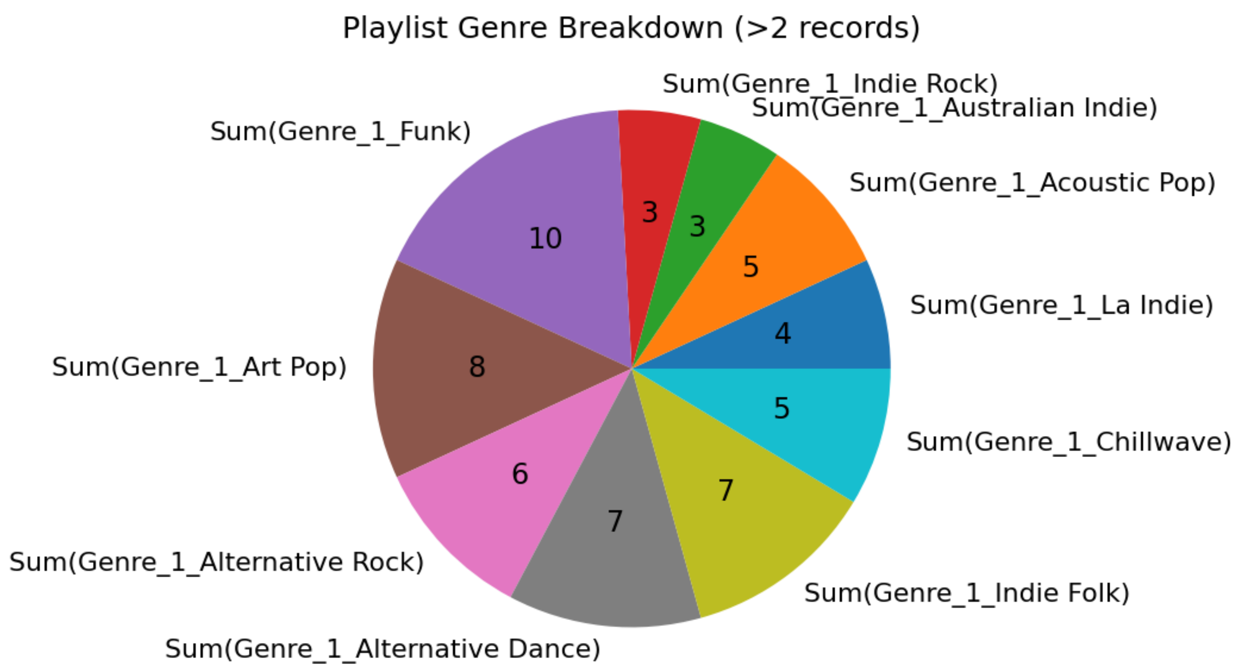
	track_uri	track_name	artist_name	album_name
0	54KFQB6N4pn926IUUYZGzK	To Build A Home	The Cinematic Orchestra	Ma Fleur
1	13PUJCvdTSCT1dn70tlGdm	Welcome Home, Son	Radical Face	Ghost

2	2gZNwCpx5Twi1fQO94AY3G	The Lakes	James Vincent McMorrow	Post Tropical
3	5dulWCZyRqio1YhzwCc4P4	King Of Spain	The Tallest Man On Earth	The Wild Hunt
4	3iTi975Q6qnoRKrBL1FNsl	Gold	Matt Hartke	Gold

Out[83]:
```
(None, None, None, None)
```

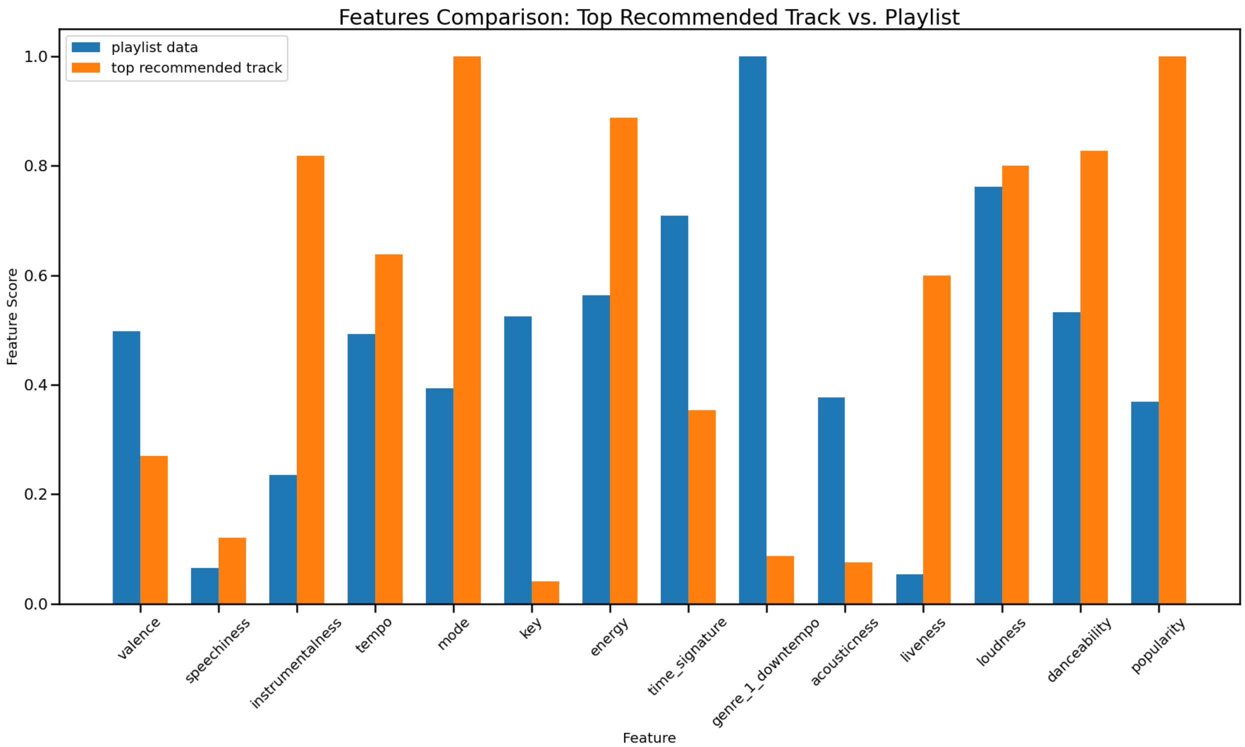
In [92]:
```
playlist_genre_breakdown(160101)
```

Out[92]:
```
(<Figure size 1440x720 with 1 Axes>,
 <AxesSubplot:title={'center':'Playlist Genre Breakdown (>2 records)'
}>)
```



In [97]:
```
song_vs_playlist_visual_comparison(160101,'54KFQB6N4pn926IUUYZGzK'
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_l
auncher.py:97: UserWarning: FixedFormatter should only be used togeth
er with FixedLocator
```



In [86]:
```
song_vs_playlist_comparison(160101,'54KFQB6N4pn926IUUYZGzK')
```

Out[86]:

	acousticness	danceability	energy	genre_1_21st century classical	genre_1_a cappella	genre_1_abstract beats	genre_1_ab h
0	0.261405	0.06918	0.195705	0.0	0.0	0.0	

1 rows × 514 columns

As we can see above, the sample variance between our recommended song and our playlist average is very low, driven mainly by the genre data.

According to our visualization, our top song features appear to be a little more variable, with most feautres having a large distance. I think this once again proves that our specific genre data is the driver for our model.

Now for the sound test. I will document my subjective findings below:

From our playlist, I already recognize M83, the Black Keys and Vampire Weekend. Outro by M83 is very spacy and slow, whereas Howlin' For You is more uptempo and rock themed. Oxford Comma is also uptempo and kind of spaced out, but overall sounds chill. Not Just a Girl is slower paced, but also sounds like alt-rock overall. For our recommendations, I would expect chiller alt-rock that is slower in pace and has mostly fleshed out instrumentals.

For our recommendations, I recognize none of the songs. To Build a Home is definitely a very slow song, and I would argue it sounds more like pop than alt-rock, but if our main genre for our playlist is "Downtempo," I would say it fits. Welcome Home, Son by Radical Face sounds like chill folk-rock, comparable to the Lumineers. Based on the type of playlist, I think this is a decent recommendation. King of Spain also sounds like folk, similar to Welcome Home, Son. The Lakes and Gold give me a similar feeling to To Build a Home, they are very slow and sound more like chill pop.

This playlist seems like there is more variety between the genres, and as such, my recommendations also seem varied. The thing in common does appear to be the style of songs being acoustic and instrumental and downtempo overall. I would say that these recommendations are adequate.

Section 5: Results

To summarize: using cosine similarity, I was able to successfully create a recommendation system using a selection of data from the Spotify Million Playlist Dataset. Overall, I have identified 3 potential drawbacks that might affect this model: 1. Suggesting songs from the same basket that the machine is learning from may create bias, 2. There are few metrics to assess our system, which makes it harder to determine the broader success of the model, 3. I analyzed the model using subjectivity. Tastes can be very different and subjectivity begets bias, as well. With these in mind, however, I beleive that this recommendation system is adequate at suggesting similar songs based on our tests in the results section.

As shown in the results section, our music recommendations seem to be driven mainly by the genre. Extracting Genre data from Spotipy provided us with very specific genre data that might've been able to isolate our list to a very select handful of songs. It then used the audio features and popularity vectors to differentiate the songs when it came to using cosine similarity.

I believe some good improvements to this project would be to source more general genre data if it is eventually made available as an export from Spotipy. As I had to manually export the data from Spotipy usng different means, it is hard to tell how accurate the genre data actually is. I would also like to include information on the year released, in case a playlist is related to a certain year, for example, 2013s hits. I would also like user-review data that shows how much a user liked a song, so I could try a collaborative-based filtering approach. Another thing I would like to do is research other forms of content-based recommendation systems, perhaps some form of clustering. Lastly, if I had a faster computer I would include all of the playlists in my analysis to capture more songs for my recommendation system.