Spotify Music Mood Classification

Soumya Mahavadi

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Abstract

This paper investigates the extent to which a k-nearest-neighbors (KNN) algorithm can accurately classify songs based on their associated mood and the "vibes" they emit, with reference to and comparison with Spotify's classification. The selected dataset for this investigation provides the values of nine audio features for each song, which were used to individually classify each song as one of four moods: energetic, happy, sad, or calm.

Two particular techniques were applied to the original dataset to modify and mold it to be suitable for this project. These techniques are data normalization, in order to improve the integrity of the data and reduce redundancy, and weighting the parameters—or audio features—which was accomplished by means of the Euclidean distance formula. In terms of the KNN algorithm, the dataset was further split into two sets, where 80% of the data was utilized to train the algorithm, and the remaining 20% was used to test the accuracy of the algorithm.

Ultimately, the KNN algorithm that was implemented in this investigation was found to be 75% successful in comparison with Spotify's respective classification. Errors in the algorithm can possibly allude to the fact that moods can overlap for particular songs, whereas the algorithm only identifies one mood for each respective song. Further suggestions of this investigation would be to identify at least two moods per musical track to potentially reduce the error rate and subsequently improve the success rate of the KNN algorithm.

Introduction

Spotify is a global and popular audio streaming service. Since the software was founded in 2006, Spotify has compiled over 70 million individual musical tracks to date.[1] The software

[1] "Company Info." Spotify, 16 Mar. 2021, newsroom.spotify.com/company-info/#:~:text=Discover, manage and share over,and ad-free listening experience.

has taken the extra step of organizing the musical tracks into different categories based on features like artists, genres, and even mood, which is particularly the focus of this investigation.

Growing up, music has always played a large role in my life. I personally tend to associate particular songs with specific moods that I listen to depending on how I feel at a certain point of time. This has further led me to create personalized playlists on Spotify that associate with moods I frequently experience. In particular, when nearing the end of my playlists, I often find myself astonished to encounter ten additional songs that are recommended by Spotify that match my mood and emotions perfectly. This experience has led me to become intrigued by how a computer determines what songs are considered to be similar with respect to mood.

In order to investigate this concept, a k-nearest-neighbors (KNN) algorithm, which is a type of machine learning algorithm, is implemented to label songs as one of four moods—energy, happy, calm, and sad—based on their respective audio features. This algorithm is ideal for this project since the purpose of machine learning is to train a computer to think like a human, and more specifically in this scenario, to classify moods as a human would.

Technical Approach

The dataset was normalized in order to manage any potential outliers that could skew the algorithm itself. This process of normalization also modified the ranges of the values under each parameter in order to keep the dataset uniform. The formula that was utilized to normalize the data is as follows: $X_{normalized} = \frac{(X - X_{minimum})}{(X_{maximum} - X_{minimum})}$.

As stated before, a KNN algorithm is implemented in this investigation to classify the moods of songs. This algorithm assumes that the smaller the distance between two points, from the training data and the test data, the more similar they are. The k value is set to the odd number of 5, where the algorithm compares the test data point with the 5 closest training data points, in order to avoid a tie that may result from an even number of comparison points. Using this method, the algorithm is able to group songs with similar moods, which are recognized based on their audio features.

In particular, this investigation uses the Euclidean distance formula to determine the width between data points. The formula is as follows: $\sqrt{(x_1 - x_2)^2 + (y_1 - y_2) + ...}$ In this formula, each variable represents a parameter in the dataset. The chosen parameters for this dataset are the same audio features that Spotify uses to categorize songs: danceability, acousticness, energy, instrumentalness (the presence of vocals), liveness (the presence of a live audience), valence (musical positivity), loudness, speechiness (the presence of spoken words), and tempo. The parameters are further weighted with respect to this investigation based on their significance in determining mood. The designated weights of the parameters are as follows:

Parameter	**Weight**
Danceability	1.5
Acousticness	1
Energy	1.5
Instrumentalness	1
Liveness	0.5
Valence	2
Loudness	1.5
Speechiness	1
Tempo	1.5

The weight of liveness was decreased since the presence of a live audience in a recording file was not considered to be a significant factor of mood. On the other hand, danceability, energy, valence, loudness, and tempo were all increased as they could significantly separate the happy and energetic moods from the calm and sad moods—higher values of these parameters would associate with a more positive, upbeat song. Acousticness, instrumentalness, and speechiness were left the standard weight of 1 as they were not considered unimportant, but also not as important as features like valence and energy.

Therefore, when taking these weighted parameters into account, the Euclidean distance formula can be rewritten as: $\sqrt{1.5(x_1 - x_2)^2 + (y_1 - y_2) + 1.5(z_1 - z_2)...}$ where x represents danceability, y represents acousticness, z represents energy, and so forth.

Experimental Methodology

The original dataset consisted of nearly 700 songs with respective features, which were previously extracted through a Python library called *Spotipy*.[2] However, the dataset was modified in multiple ways for this investigation. The first modification involved removing parameters including artist, popularity, and key signature, as they were deemed unnecessary for classifying moods. The data for the nine chosen parameters, or the Spotify audio features, that were previously outlined were normalized, while the mood of each song remained a qualitative value. In addition, the normalized data was rounded to a maximum of six decimal places to ensure consistency, and the dataset as a whole was cut down to a total of only 100 songs for efficiency purposes. Finally, the dataset was split by means of a 80:20 ratio, where 80% of the data, or 80 songs, was used to train the KNN algorithm, and 20%, or simply 20 songs, was used to test it.

Findings & Analysis

Test Case	Song Name	Actual Mood	Algorithm-Predicted Mood
1	Dragula	Energetic	Energetic
2	Dreams Tonite	Sad	Energetic
3	Drifting	Calm	Calm
4	Driver’s Seat	Happy	Energetic
5	Duality	Energetic	Energetic
6	Duck and Run	Energetic	Energetic
7	Dust on The Ground	Sad	Sad
8	EDM Sux	Energetic	Energetic

[2] “Welcome to Spotipy!¶.” Welcome to Spotipy! - Spotipy 2.0 Documentation, spotipy.readthedocs.io/en/2.13.0/.

9	Eagle	Calm	Calm
10	Easily	Sad	Happy
11	Easy Lover	Happy	Happy
12	Eden - Hunted Version	Sad	Sad
13	Edge of Seventeen	Happy	Energetic
14	Eidolon	Calm	Calm
15	Electronic Memories	Energetic	Energetic
16	Emotions in Motion	Sad	Sad
17	Empty Street at Night	Calm	Calm
18	Enemy	Energetic	Energetic
19	Escaping Time	Calm	Sad
20	Essential Attitudes	Calm	Calm

Table 1: Comparison of Actual and Predicted Moods From KNN Algorithm of Test Data

Table 1 depicts the actual moods of the musical test cases compared to the predicted moods that were generated by means of the KNN algorithm. The name of the song respective to each test case was also included for reference, although the parameter was *not* factored into the actual algorithm. The table is further color-coded, in which the moods of the test cases that are highlighted in green match up with the KNN algorithm's prediction, whereas the test cases in red do not match. Out of the 20 test cases, it is clear that 15 of the predictions were accurate; this translates to a 75% success rate, of the algorithm applied to this dataset.

Looking at the findings of the test cases, it is possible to observe small trends in the data. Out of the five errors, two of them reflected the algorithm classifying the songs as "energetic" instead of "happy." Likewise, the algorithm classified one case as "sad" instead of "calm." This could be because, sometimes, songs can overlap between similar moods. For example, the song "Rain On Me" by Ariana Grande and Lady Gaga is featured in both the Spotify playlists "Happy

Hits!"[3] as well as "Pop Party,"[4] which is more energetic. From this information, it is possible that test cases 4, 13, and 19 can be classified as both the actual and predicted mood, as "happy" and "energetic" can be recognized as overlapping moods, as well as "sad" and "calm." If one were to take these mood similarities into account, then they could argue that the algorithm actually has a 90% success rate, with 18 accurate predictions out of 20 test cases; however, this interpretation of the findings of the data is subjective to the analyst.

Conclusion

Overall, this project investigation did not result in an *exact* replication of Spotify's algorithm for classifying songs based on their associated moods. Mood is definitely a subjective feature; however, even without this consideration of subjectivity, the KNN algorithm for this Spotify dataset can still be deemed as fairly successful since it has a 75% accuracy rate. Moving forward, if one were to complete this project again, a suggestion would be for the algorithm to classify a musical track as the top two moods rather than just one mood in order to depict the variation and overlapping of moods. This could potentially make the algorithm even more accurate for the dataset.

[3] "Happy Hits!" Spotify, open.spotify.com/playlist/37i9dQZF1DXdPec7aLTmlC.
[4] "Pop Party." Spotify, open.spotify.com/playlist/37i9dQZF1DWXti3N4Wp5xy.

Works Cited

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