

Spotify Clarifies

An Analysis of Music Popularity over Time

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Abstract

Write something

Introduction

REWRITE TO DESCRIBE QUESTION OF INTEREST

We analyze a database of Spotify tracks that have had attributes assigned to them algorithmically by Spotify. These attributes act as descriptors for each track and allow us to group similar tracks and identify potentially interesting information and trends in the data. We have used this to analyze the songs in the Spotify database for what we found to be the most interesting questions. In the following sections we will cover the data more in depth, describe our methodology for exploring the data, and present our final analyses.

Data Description

We conducted our analysis using a dataset compiling various music features for songs found on Spotify's Web API[1]. This data was obtained by sampling two different subsets of songs, hits and flops, from 1960-2019. Hits are defined as any song that made a top 100 'hit' list any week in a given decade. Flops are defined as the opposite, with additional requirements such as belonging to a genre considered non-mainstream or avant-garde. While the original purpose of this dataset was to predict whether or not a song will be successful, we will be utilizing the musical attributes to analyze the change in music over time. Since this dataset is stratified at the track level, each track acts as a unique unit of observation. With over 40,000 unique songs spread evenly across six decades, it provides plenty of information to analyze the changes in musical attributes across the last several years.

The majority of these variables are generated by Spotify's music analytic algorithm, which is unknown to the general public. Therefore, we have provided documentation to get a fairly robust understanding of the variables. The definitions for all our variables can be found in the attached JSON file as well as in the dataDictionary table when connected to the database instance.

Methodology

This analysis will use a variety of investigative techniques to explore the data and understand music on a deeper level; answering intriguing questions about the songs we listen to but never question. We will begin by exploring the top producing artists of each decade to get a better understanding of the production of tracks over time. Just because the world's population is growing, will the number of tracks produced by artists also increase across each decade?

We will then shift into an analysis of song titles and what terms appear most frequently. Nowadays, it is common practice to use certain pictures and words in social media and online videos to attract wider audiences. This same logic applies to song titles. However, instead of simply displaying the most common words, we will first "clean" the song titles using the tm[2] package and tidytext[3] to gain insight on the bigger picture. This cleaning process involves converting every word into lowercase then removing non-alphabetical characters, punctuation, and stop words that exist simply as determiners to mark nouns like "the", coordinating conjunctions like "but", or prepositions like "in". While these terms help to form a language, they do not hold any meaning for our song titles and were removed to decrease clutter in the text portion of the analysis. The final step of our cleaning process was to stem the text. This process alters words to return them to their root meaning. An example in our data was changing the words "remastered", "remaster", and "remastering" into their root: "remast". This allows us to interpret all these separate terms as the same term. With a clean text corpus, we then created a word cloud as a method to understand the frequent concepts in song titles.

The next method of our analysis involves a deeper dive into three main music theory attributes: tempo, time signature, and key signature. Any musician can look at sheet music, recognize these features, and immediately know exactly how to play the song. Besides the actual notes of the melody, these are the characteristics that define how a song should sound. But we will take it one step further and see how these three features effect the popularity of a song.

Analysis

QUICK DESCRIPTION OF ANALYSIS

Top Artists

We begin our exploratory data analysis by creating a table of the top 5 artists or bands of each decade. For the purpose of this analysis, the top artists are defined in terms of their production output, or in other words, their total amount of songs created per decade. One interesting thing this table shows is the decreasing trend in the number of tracks from top artists over each decade. In the 1960s, the top artists/bands produced over 100 tracks per decade while artists in the 2010s produced 50 or less. This indicates a potential focus on quality rather than quantity as the music industry evolves with time.

Table 1: Top 5 Artist/Bands with the Most Songs per Decade

Artist	Decade	Total Number of Songs
Traditional	60s	145
P. Susheela	60s	130
Jerry Goldsmith	60s	118
Harry Belafonte	60s	114
Ennio Morricone	60s	96
MPB4	70s	59
Buzzcocks	70s	50
kalapana	70s	49
John Coltrane	70s	44
Vicente Fernández	70s	44
The Cleaners From Venus	80s	47
Malcolm Arnold	80s	45
Nobuo Uematsu	80s	33
Skinny Puppy	80s	33
Running Wild	80s	32
Luis Miguel	90s	28
Madonna	90s	25
Iggy Pop	90s	22
Nobuo Uematsu	90s	19
El Gran Combo De Puerto Rico	90s	17
Toby Keith	00s	27
Tim McGraw	00s	24
Rascal Flatts	00s	24
Iron Maiden	00s	23
Kenny Chesney	00s	23
Drake	10s	50
Glee Cast	10s	41
Taylor Swift	10s	35
Luke Bryan	10s	25
The Weeknd	10s	24

Song Titles

Like music itself, our analysis is multifaceted, so we will transition our analysis from artists to song titles. As discussed in the Methodology section above, we extracted terms from the dataset and are now able to use the wordcloud2[4] package to create the following word cloud in the shape of a star, to resemble the talented artists we just explored.



There are a number of key takeaways from the above plot, but we will start by asking the very question Tina Turner asked in 1984, “What’s love got to do with it?” Well it appears love has a lot to do with it, with “it” being song titles. This word appears over 2000 times, which is much more than any other common word found in song titles from 1960-2019. The abundance of this makes absolute sense, since love is one of the most powerful emotions humans have put into words. So powerful, that love songs are commonly seen as more than emotion, but a genre. In addition, we see that love songs are not the only emotional genre listed in our dataset. The blues, heavily prevalent in the 1960s, also appears in the word cloud, leading us to believe that more emotive phrases are popular in song titles.

Besides emotions and feelings, another topic arises as a common theme in song titles: people. More accurately, descriptions of who these people are to the artists of each song. This is reflected by the size the word “man”, “girl”, “baby”, or “boy” have in the word cloud, indicating a higher frequency in our data’s song titles. Often times, people seem to talk about themselves and the people in their lives, which seems to hold true for music as well. Therefore, using just the title of the songs, we have established two significant themes in music: emotions and relationships.

Music Theory Attributes

Now that we've explored the artists and song titles, we will examine some of the musical attributes themselves. We will begin with three very important music theory concepts that every musician lives and breathes: tempo, time signature, and key signature.

Tempo

Tempo describes the speed/pace of a song. In general, fast tempos evoke more positive emotions such as happiness and delight while slow tempos evoke negative emotions such as sadness and depression. To get an idea of the artists that tend to convey positive emotions compared to those that channel negative emotions, we will take a look at the top 10 artists with the fastest average tempos as well as the top 10 with the slowest.

Table 2: Top 10 Artist/Bands with the Fastest Average Tempos

Artist	Average Song Tempo	Total Number of Songs
Crass	172.8562	15
Angerfist	157.4122	13
The Lurkers	156.5629	19
Allison	156.0839	10
The Vibrators	150.0379	10
The Dickies	149.5186	19
Avril Lavigne	147.3464	15
Foo Fighters	147.1191	10
Trifonic	146.2458	11
The Nashville Bluegrass Band	145.9536	10

Time Signature

Time signature indicates the rhythm of the song in terms of a beat's duration and the number of beats per measure. While it can get fairly technical, it is important to know that the most common time signature is 4 beats per measure (and is hence referred to as 'common time'). In fact, 88% of our dataset is made up of songs with common time. Compared to the other time signatures, common time has higher averages for danceability and energy but lower averages for acousticness. This time signature also has the highest success rate for hit songs with 43% of common time songs getting classified as a hit. As seen from the average rates in the table below, the success behind this time signature can be attributed to these songs being easier for people to dance to. Therefore, this table indicates that successful hit songs tend to higher levels of dancibility and energy.

Table 3: Summary of Time Signature Characteristics

Time Signature	4.000000e+00	3.000000	5.000000	1.000000	0.000000
Average Danceability	5.579703e-01	0.4049516	0.3993724	0.4014569	0.1334000
Average Acousticness	3.308935e-01	0.6177392	0.6153970	0.6211903	0.5906667
Average Energy	6.058251e-01	0.3784532	0.3824055	0.3927565	0.4109940
Number of Tracks	0.000000e+00	0.0000000	0.0000000	0.0000000	0.0000000
Number of Hits	1.569300e+04	973.000000	117.0000000	61.0000000	1.0000000
Percentage of Hit Tracks	4.345000e-01	0.2555000	0.1993000	0.1644000	0.3333000

Key Signature

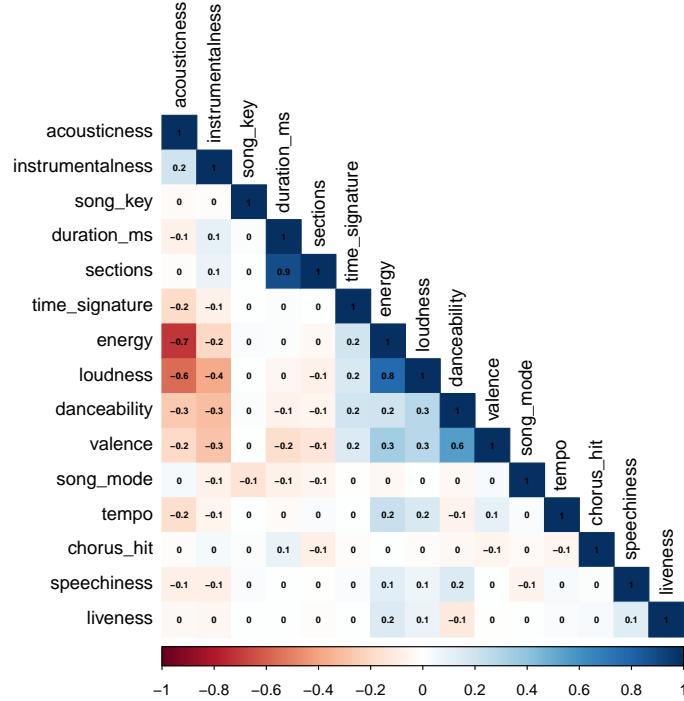
Key signature describes the combination of sharps and flats that determine the scale of a piece of music. In general, most songs shift from key to key to add variance and intrigue but this dataset simply estimates the overall key. As the table below indicates, the estimated key does not have a large effect on the success rate of songs since the ‘Percentage of Hit Tracks’ varies around 40% for each key.

Table 4: Summary of Key Signature Characteristics

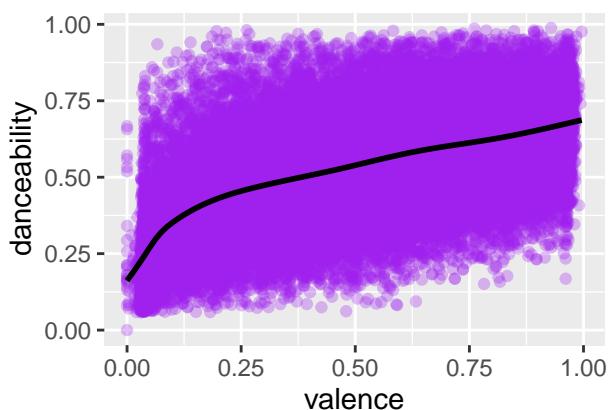
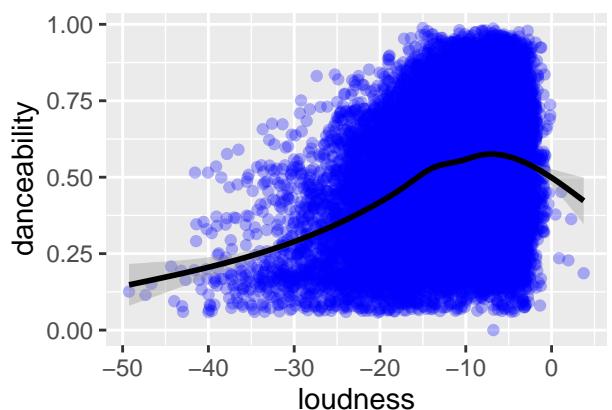
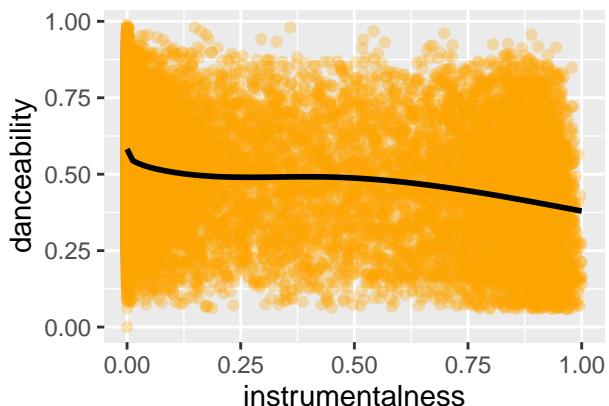
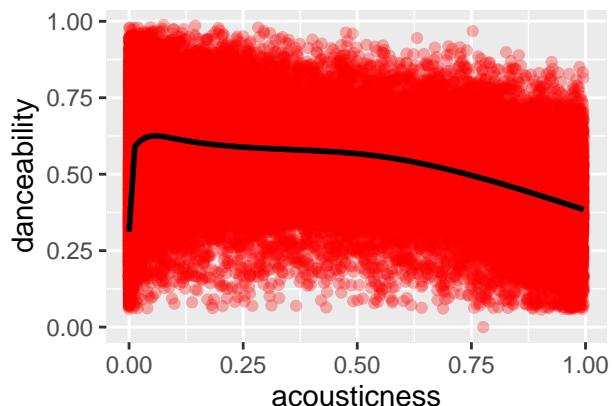
Key Signature	Average Danceability	Average Acousticness	Average Energy	Percentage of Hit Tracks
C	0.5391916	0.3912941	0.5613325	0.4078
C#/Db	0.5757106	0.2853243	0.6194482	0.4621
D	0.5225773	0.3628475	0.5817457	0.3876
D#/Eb	0.5051904	0.4968816	0.5100628	0.3822
E	0.5217508	0.3590309	0.5866685	0.3873
F	0.5329451	0.4307504	0.5385227	0.4084
F#/Gb	0.5568206	0.2918481	0.6267238	0.4417
G	0.5399274	0.3730568	0.5711438	0.4018
G#/Ab	0.5477378	0.3751159	0.5693247	0.4398
A	0.5261597	0.3525814	0.5924012	0.3834
A#/Bb	0.5593870	0.3920532	0.5595066	0.4569
B	0.5607593	0.2833212	0.6295437	0.4240

Danceability

Through our analysis of the music theory features, we discovered the importance of danceability. This attribute is defined by Spotify as a way to describe 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 close to 0 indicates a song difficult to dance to while 1 represents dance-friendly songs. However, since we do not know the specifics of Spotify’s algorithm, we will explore the correlation of this feature with other variables in our dataset.



TEXT TEXT TEXT

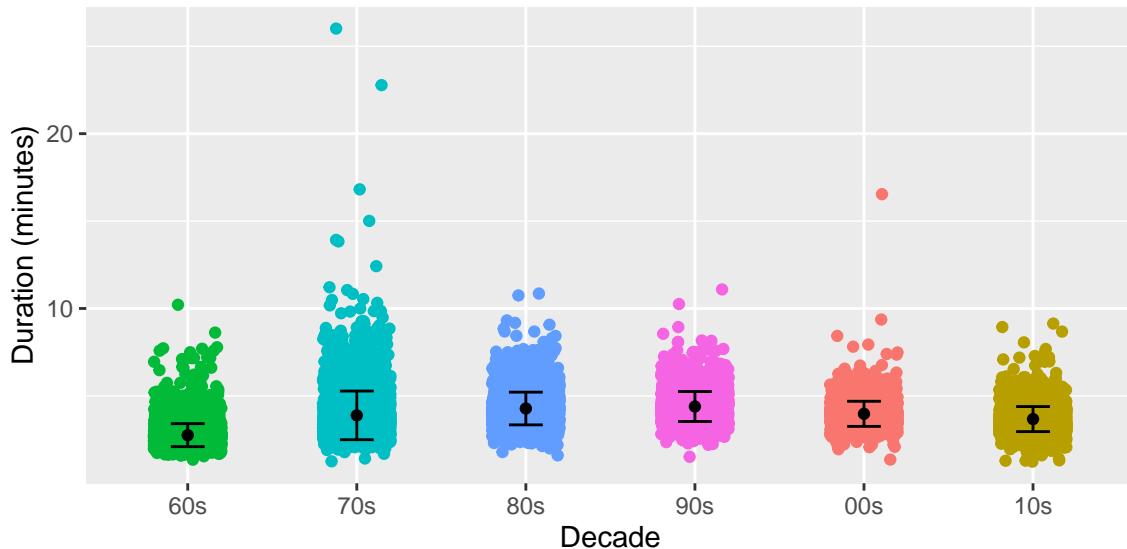


Attributes by Decade

TEXT TEXT TEXT

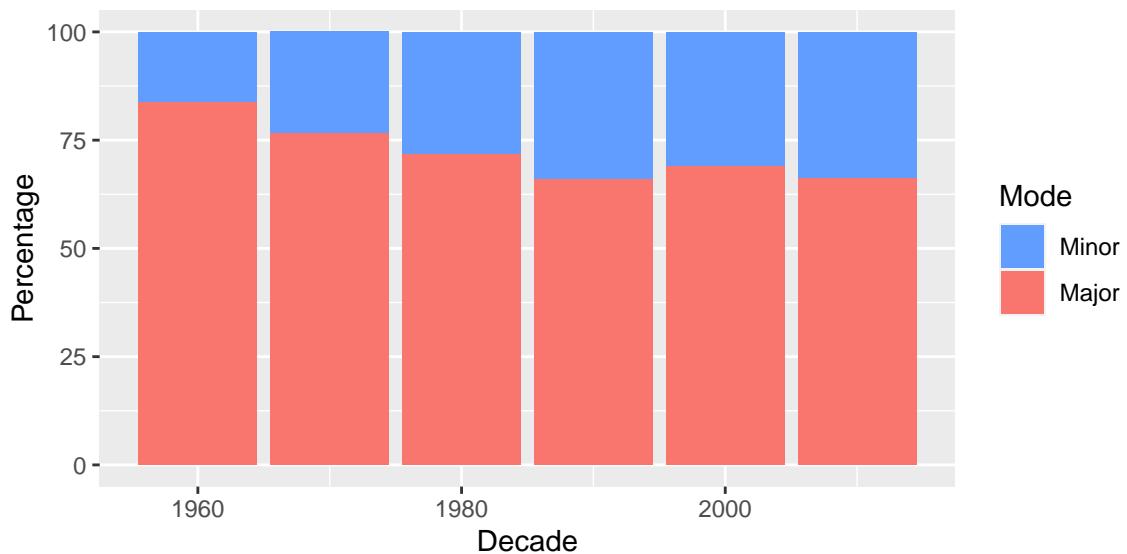
Duration of Hit Tracks

The duration of hit tracks is generally under 10 minutes with an average closer to 4 minutes across the decades. One notable exception is in the 1970s, possibly due to the popularity of Progressive Rock during those years with the blending of Rock and Jazz Fusion into long, drawn-out concept albums and longer-winded tracks.



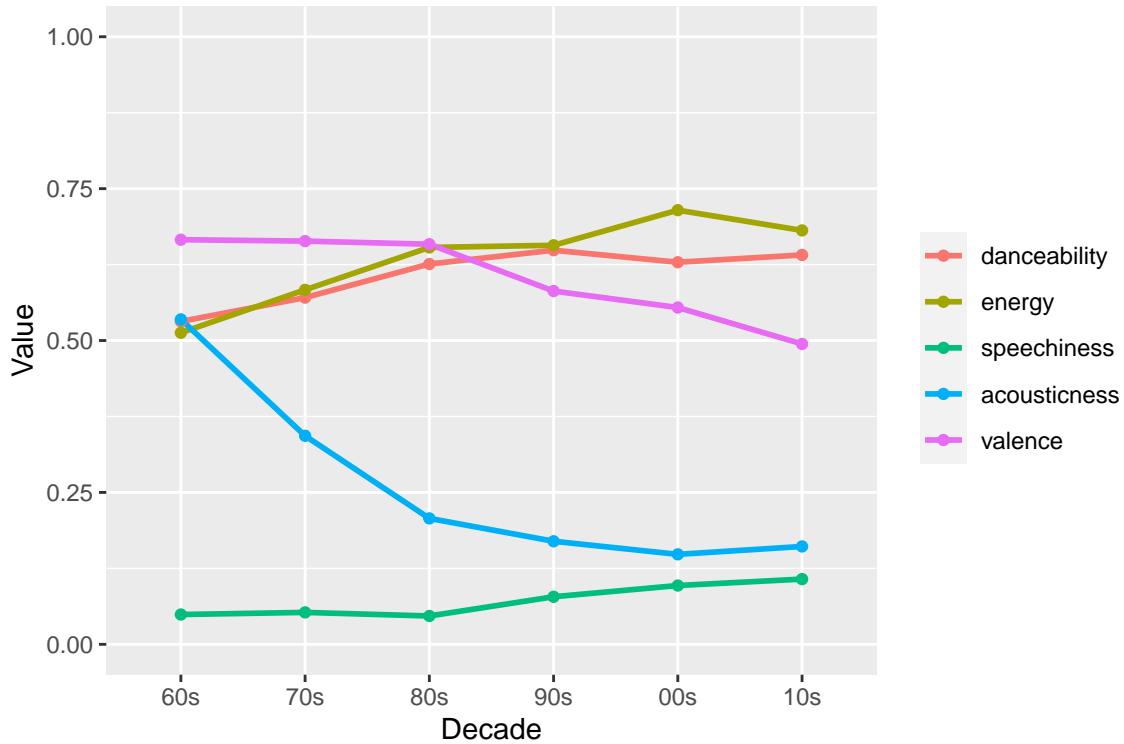
Proportion of Major/Minor Hit Tracks

The proportion of hit songs in the minor mode has increased from about 15% in the 1960s to almost 30% in the 2010s. The minor mode is associated with sadness, while the major has a happier sound. This signifies a potential trend that people have developed a taste for more depressing, saddening popular music over the last couple of decades.



Traits of Hit Tracks

In addition to the duration and mode of songs, there are also a few noticeable trends in the Spotify qualities of hit music across the decades. Danceability, energy, and speechiness (the use of vocals) all saw a general upward trend over time, leveling out or decreasing slightly in the 2010s. On the other hand, we see the use of acousticness, as opposed to electric instruments, in tracks decline significantly from the 60's onward. This downward trend is align with the historical development of more electronic instruments and their widespread use. Finally, valence, which describes the musical positiveness conveyed by a track, has also been trending downward since the 80's. This decrease agrees with our finding in the previous section that indicates people prefer sadder songs in recent years.



Conclusions

Bibliography

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