Analysis of The Most recent 399 Songs in My spotify

**most recent songs**

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Abstract:

For my final project, I did an analysis on the attributes recent songs added into my Spotify, so this would give insight on my current taste. Since music is a crucial aspect in my life, I wanted to do some analysis on the topic as I am a big fan of dubstep and lo-fi. Music is a huge part of daily life and streaming is a major part of our economy, so it attracts data scientists. I used bootstrap computations in order to find correlations between variables related to musical attributes.

Materials and Methods:

I used a website to organize Spotify, so I created an excel sheet from the last 399 songs I added to my music. Of these songs, Spotify created various parameters for the songs in the form of musical attributes. The following descriptions of the attributes Spotify computed are sourced from Spotify.

* **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.
* **Energy** – Represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
* **Loudness** - The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typical range between -60 and 0 db.
* **Speechiness** - Speechiness detects the presence of spoken words in a track.
* **Acousticness** - A confidence measure of whether the track is acoustic.
* **Liveness** - Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.
* **Valence** - A measure 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).
* **BPM** - 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.
* **Duration** - The duration of the track in seconds.

Analysis

**BPM Bar Graph**

I graphed my songs by the tempo due to the relative pacing of the song. Around 75% of the music I listened to have a bpm that would fall under the Allegro or andante tempo. Allegro is generally described as quick and bright while andante is a slower and calmer pace. The temp of allegro is categorized as dubstep in EDM so my hypothesized interest seems to be true.

A screenshot of a computer

Description automatically generated

**Correlation of Musical Attributes**

I wanted to see if there was any correlation between the key factors for EDM music that subsequently lead to it being a song I liked recently. To do all the attributes against ach o0ther would inefficient so I picked crucial attributes that I thought may correlate.

Danceability vs Energy: As seen below is there is not really a correlation between the attributes. The data does not seem to fit the line.

A picture containing text, map

Description automatically generated

Danceability vs Loudness: As seen below is there is not really a correlation between the attributes. The data does not seem to fit the line. A picture containing text, map

Description automatically generated

Danceability vs Acousticness: As seen below is there is a negative correlation as the songs that I like decrease in danceability, they increase in acousticness.

A picture containing text, map

Description automatically generated

Danceability vs Valence: As seen below is there is a positive correlation, therefore as the songs that I like increase in danceability, they increase in valence.

A close up of a map

Description automatically generated

Danceability vs BPM: As seen below is there is not really a correlation between the attributes. The data does not seem to fit the line.

A picture containing text, map

Description automatically generated

Loudness vs Energy: As seen below is there is a strong positive correlation, therefore as the songs that I like increase in loudness, they increase in energy.

A close up of a map

Description automatically generated

Loudness vs Liveness: As seen below is there is not really a correlation between the attributes. The data does not seem to fit the line.

A close up of a map

Description automatically generated  
Loudness vs Valence: As seen below is there is not really a correlation between the attributes. The data does not seem to fit the line.

A close up of a map

Description automatically generated

Energy vs Acousticness: As seen below is there is a negative correlation as the songs that I like decrease in energy, they increase in acousticness.

A picture containing text, map

Description automatically generated

Energy vs Valence: As seen below is there is not really a correlation between the attributes. The data does not seem to fit the line.

A picture containing text, map

Description automatically generated

Energy vs BPM: As seen below is there is not really a correlation between the attributes. The data does not seem to fit the line.

A picture containing text, map

Description automatically generated

Summary and Conclusion:

The analysis of the 399 most recent songs I liked in Spotify afforded some insight into my recent music taste. The BPM of the music sampled fell mainly into two categories which include the main genres I listen. It was interesting to see the various correlations as many things I thought would correlate had no correlation. The positive correlations between loudness and energy and danceability and valence were expected as were the negative correlations seen with acousticness. If Spotify included stream counts in order to allow for a weighted average of how much you listened to something in order to better categorize the data. This same analysis can be used to0 see trends in overall consumer taste if applied on top song lists for regions or countries which could help predict future hits.

**Literature cited:**

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