**Spotify Tracks Dataset**

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**Introduction**

**Content**

This is a dataset of Spotify tracks over a range of 125 different genres. Each track has some audio features associated with it. The data is in CSV format which is tabular and can be loaded quickly.

**Usage:**

The dataset is being used for observing the relationship between traditional music theory metrics (Key, Tempo, Time Signature, Duration, Tempo, Energy, Explicit, Mode) and a song’s streaming popularity on Spotify and find out which factors contribute more towards a song be more popular.

**Column Description:**

* **track\_id:** The Spotify ID for the track
* **artists:** The artists' names who performed the track. If there is more than one artist, they are separated by a;
* **album\_name:** The album name in which the track appears.
* **track\_name:** Name of the track.
* **popularity:** The popularity of a track is a value between 0 and 100, with 100 being the most popular. The popularity is calculated by algorithm and is based, in the most part, on the total number of plays the track has had and how recent those plays are. Generally speaking, songs that are being played a lot now will have a higher popularity than songs that were played a lot in the past. Duplicate tracks (e.g. the same track from a single and an album) are rated independently. Artist and album popularity is derived mathematically from track popularity.
* **duration\_ms:** The track length in milliseconds.
* **explicit:** Whether the track has explicit lyrics (true = yes it does; false = no it does not OR unknown).
* **danceability:** 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.
* **energy:** Energy is 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. For example, death metal has high energy, while a Bach prelude scores low on the scale.
* **key:** The key the track is in. Integers map to pitches using standard Pitch Class notation. E.g. 0 = C, 1 = C♯/D♭, 2 = D, and so on. If no key was detected, the value is -1.
* **loudness:** The overall loudness of a track in decibels (dB).
* **mode:** Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0 **speechiness**: 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. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.
* **acousticness:** A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
* **instrumentalness:** Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". 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. A value above 0.8 provides a strong likelihood that the track is live.
* **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).
* **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.
* **time\_signature:** An estimated time signature. The time signature (meter) is a notational convention to specify how many beats are in each bar (or measure). The time signature ranges from 3 to 7 indicating time signatures of 3/4, to 7/4.
* **track\_genre:** The genre in which the track belongs.

**Overview and SMART Questions:**

We choose this dataset mainly because we are all avid music listeners and one of us has subject matter expertise in the field of music creation and this dataset offered potential insight into certain questions. Since we had interest in the field of making music, we wondered, “What makes a song popular?”. We wanted to pursue the hypothetical “magic song”; a song that will become popular purely based on its base musical qualities. This brought us to our first of 3 SMART questions:

1. **“Can we use regression modeling on musical data about a given song to predict its popularity?”**

Our Subject Matter Expert did not think our models would be that successful because popularity in music, as shown in other similar studies[[1]](#footnote-1), has more to do with the musical and cultural landscape around it as opposed to the song itself. It makes intuitive sense, imagine a popular song from today being released in 1955. The cultural attitudes towards music would not be ready for it yet and it would probably not be very popular. Yet because we were deeply curious, we still wanted to see how well we could predict popularity based on a song’s musical qualities.

During dataset analysis, our team Subject Matter Expert noticed that there were two kinds of variables that were used to describe music: traditional, and algorithmic. Meaning some of the variables such as key, mode, tempo, time signature, explicitness, and duration are classical metrics for music (or in the case of explicitness, has become widely accepted over the last forty years[[2]](#footnote-2)). These metrics are widely understood with exact definitions in the realm of music. The algorithmic metrics, such as danceability, valence, energy, speechiness etc. reference qualities that are often talked about, but have no exact definition. This means that these values in the data were completely assigned by Spotify’s algorithm and are beholden only to Spotify’s definitions, rather than the musical community. This creates an interesting inquiry of whether Spotify’s metrics for describing music are more effective for predicting popularity than traditional metrics. This leads to our second SMART question:

1. “**Do Regression Models predicting popularity do better using traditional music metrics as predictor variables or Spotify’s Algorithmic Musical Metrics ?”**

Our Subject Matter Expert did not know whether or not the Spotify Metric Models would outperform the Traditional Metric Models, but there is a reason to believe the biggest music streaming company would develop effective metrics to describe streamed music.

Our third SMART question started more as a side inquiry and became a larger project as we started to see success. We were curious what would make a song positive and danceable per Spotify’s algorithmic “valence” and “danceability” metrics. Would traditional or algorithmic metrics do better ? We made our third SMART question about predicting the combination variable of valence and danceability:

1. “**Can we predict what makes a positive danceable song using regression modeling? Will it be best predicted by traditional metrics, algorithmic metrics, or a combination of the two ?”**

We also did some modeling of the “durability variable”, but that was more out of pure curiosity and did not have any SMART Question driving it.

**Data Manipulation**

**Cleaning the Data:**

This is a very clean dataset with no null values, so no null value handling was required.

FOR MODELING PHASE:

**Dropping Non-Interesting Variables:**

Since our SMART question was more focused on the inherent qualities of the music in regression, before building our models, we dropped all non-numerical data: such as ‘track\_id’, ‘artists’, ‘album\_name’, and ‘track\_name’

*Note:*

The artist variable would have been interesting to use, but sadly it was coded in a way that listed artist collaborations as separate artists and had no way to account for different artists with the same name. This would have required a lot of work to clean into a useable state that was outside the scope of our initial SMART question but would be great for future inquiry.

**Encoding:**

We encoded the binary variables as float type 0 or 1 variable, for regression and upcoming VIF tests

**Multicollinearity:**

Because of the results of our correlation matrix, as you’ll see below, we decided to run a VIF test on the data before modeling. After running a VIF test on our dataset we found deep multicollinearity concerns with VIF scores exceeding 50. In order to control this, we took 3 steps to strip the concerns from our data:

1. We removed ‘loudness’ and ‘energy’ as they were both too heavily correlated with other variables
2. We merged ‘Valence’ and ‘Danceability’ as they were heavily correlated with each other and describe similar concepts. The new variable is simply called (‘valence+danceability). We did the same with ‘Tempo’ and ‘Time\_Signature’, with similar logic we created (time\_signature+tempo).
3. We centered our data by subtracting the mean from each one of our variables. This handled any structural multicollinearity in our new combination variables

After these changes, all our variables showed satisfactory VIF scores, and we were ready to model.

**EDA Summary**

**Data VisualizationChart, scatter chart

Description automatically generated**

Chart, scatter chart

Description automatically generated

**Correlation Plot (Pre-Modeling Cleaning)**

**Chart, treemap chart

Description automatically generated**

**Modelling Summary**

**Conclusion**

1. Noah Askin and Michael Mauskapf, “What Makes Popular Culture Popular? Product Features and Optimal Differentiation in Music,” *American Sociological Review* 82, no. 5 (June 2017): pp. 910-944, https://doi.org/10.1177/0003122417728662. [↑](#footnote-ref-1)
2. Cole, Tom. “You Ask, WE ANSWER: 'Parental Advisory' Labels - the Criteria and the History.” NPR. NPR, October 29, 2010. https://www.npr.org/sections/therecord/2010/10/29/130905176/you-ask-we-answer-parental-advisory---why-when-how. [↑](#footnote-ref-2)