PHS 650: Final Project

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Contents

# Introduction

In the music industry, there is a consideration of what song will be popular or a ‘hit,’ as song popularity is associated with more revenue (Pham, Kyauk, and Park 2015). Thus, predicting the popularity of a song, referred to as the Hit Song Science, can be useful in determining which songs should receive the most investment from musicians and their labels. Random forests have been found to accurately predict which songs will be popular and determined that songs that ‘made it’ to the top charts were found to be ‘happier’ and more ‘party-like’ (Interiano et al. 2018; Middlebrook and Sheik 2019). Additionally, artist familiarity, loudness, year of release, and number of genres were also found to accurately predict the popularity of songs (Pham, Kyauk, and Park 2015). In Billboard Top 100 and the Spotify Global Top 50 songs, the length of songs has been decreasing since the 90’s, while changes in energy and danceability, although tending to increase, have been inconsistent. (van der Heide et al. 2019)

The goal of our project is to contribute to the field of Hit Song Science and examine how song elements, specifically the duration and intensity, are associated with a song’s popularity. We hypothesize that shorter songs are more likely to be popular. We also hypothesize that more intense songs are more likely to be popular.

# Methods

The following analysis will use data from the Tidy Tuesday Spotify Songs dataset (Thompson et al. 2020). The dataset contains 32833 songs in the genres of EDM, Latin, Pop, R&B, Rap, & Rock and 23 variables describing characteristics of the songs and the playlists they were found in. The data dictionary can be found [here](https://github.com/rfordatascience/tidytuesday/blob/master/data/2020/2020-01-21/readme.md#data-dictionary). We will be using all the songs in the Tidy Tuesday Spotify datasets. The only exclusion criteria we will apply is to remove duplicate songs, indicated by track\_id. The data was originally accessed 4/5/2023.

The R code to import the dataset can be found below:

spotify\_songs <- readr::read\_csv('https://raw.githubusercontent.com/rfordatascience/tidytuesday/master/data/2020/2020-01-21/spotify\_songs.csv', show\_col\_types = FALSE)

Applying the exclusion criterion reduces the sample size from 32833 songs to 28356 songs.

To complete the present analysis, 5 new variables were created. [Table 1](#tbl-newvars) describes these variables, norm.loudness, norm.tempo, itensity, duration\_mins, popularity created from original loundness, tempo, and popularity variables from the Spotify dataset. The table provides the class, range, and description of each new variable.

Table 1: Spotify Data variables

| Variable | Class | Range | Description |
| --- | --- | --- | --- |
| loudness | double | -46.448 to 1.275 | The overall loudness of a track in decibels (dB) averaged across the entire track. |
| tempo | double | 0-239.44 | estimated track tempo in beats per minute (bpm) |
| norm.loudness | double | 0-1 | a min-max normalized spotify\_songs$loudness |
| norm.tempo | double | 0-1 | a min-max normalized spotify\_songs$tempo |
| intensity | double | 0-1 | the average of energy, normalized tempo, and 1- normalized loudness, where higher scores imply higher intensity |
| minutes | double | 0.07-8.6 minutes | The duration of song in minutes, converted from milliseconds (duration\_ms) |
| popularity | double | 1, 2, 3 | Song popularity characterized into three tertiles. 1 represents low 0-33, 2 represents medium 34-66, and 3 represents high 64-100 ranges from the numeric track\_popularity variable. |

# Results

|  |  |  |  |
| --- | --- | --- | --- |
| |  | | --- | | (a) Duration | | |  | | --- | | (b) Intensity | |

Figure 1: Duration and Intensity by Popularity Level

From [Figure 1](#fig-plots) we see that the distributions of intensity and duration are visibly skewed within popularity classes. As a result, we used a Spearman rank correlation to test each hypothesis. In [Table 2](#tbl-cor) we see that both p-values are well below our pre-established cutoff of 0.05. Since we are doing multiple statistical tests, we could adjust the p-values to account for this. However, since there are only two tests and the p-values are several orders of magnitude smaller than our cutoff, this is unnecessary and would not change the conclusions drawn from this analysis. Both duration and intensity were weakly negatively correlated with popularity; neither coefficient was on the expected scale or in the expected direction. Since intensity was a composite measure, exploration of how the individual components, including energy, tempo, and loudness, relate to popularity could explain why the direction of correlation was unexpected.

Table 2: Spearman Rank Correlation Results

| Factor | p-value | Coefficient |
| --- | --- | --- |
| Duration | 5.3257883^{-96} | -0.1143639 |
| Intensity | 2.9352496^{-100} | -0.1169066 |

# References

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