Music Analysis via Spotify

WANG YANHAO
A0113742N

Overview

As a music lover and an amateur bass player, I listen to music on a daily basis, and Spotify is one of the top tier music streaming softwares in the market.

In this project, some visualizations will be done to give the reader more insights on what makes a song commercially successful -- there are many ways to define success, for simplicity, we define it as being popular among the majorities.

Dataset

The dataset is crawled from Spotify and provided by:
https://www.kaggle.com/yamaerenay/spotify-dataset-19212020-160k-tracks

There are 19 fields present in the dataset, many of them have music specific meanings which we will explore in the visualizations below.

Some fields such as artists name and data entry id are less important to the analysis due to their high cardinality. Fields like release date are also not that meaningful to the overall visualizations because similar information is encompassed inside the coarse grained category such as release year of the track.

Some interesting fields are listed in the table below:

Name	Range	Description
acousticness	0 to 1	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
danceability	0 to 1	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	0 to 1	Represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy.
duration_ms	200k to 300k	The duration of the track in milliseconds.
instrumentalness	0 to 1	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. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.
valence	0 to 1	Describes 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).
popularity	0 to 100	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.
tempo	50 to 150	Tempo is the speed or pace of a given piece and derives directly from the average beat duration.
liveness	0 to 1	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.
loudness	-60 to 0	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).
speechiness	0 to 1	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.
year	1921 to 2020	The release year of track.
mode	0 or 1	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.
explicit	0 or 1	An explicit track is one that has curse words or language or art that is sexual, violent, or offensive in nature. 0 = No explicit content, 1 = Explicit content

key	0 to 11	Octave encoded as values ranging from 0 to 11, starting on C as 0, C# as 1 and so on…

Visualizations

Visualization is done via D3JS, and it can be found and downloaded from the github link below:
https://github.com/WYHNUS/CS5346-OTOT-Type-A-D3-01

If you are a musician and would like to write a song to be popular among the majorities, some of the questions you might ask are:

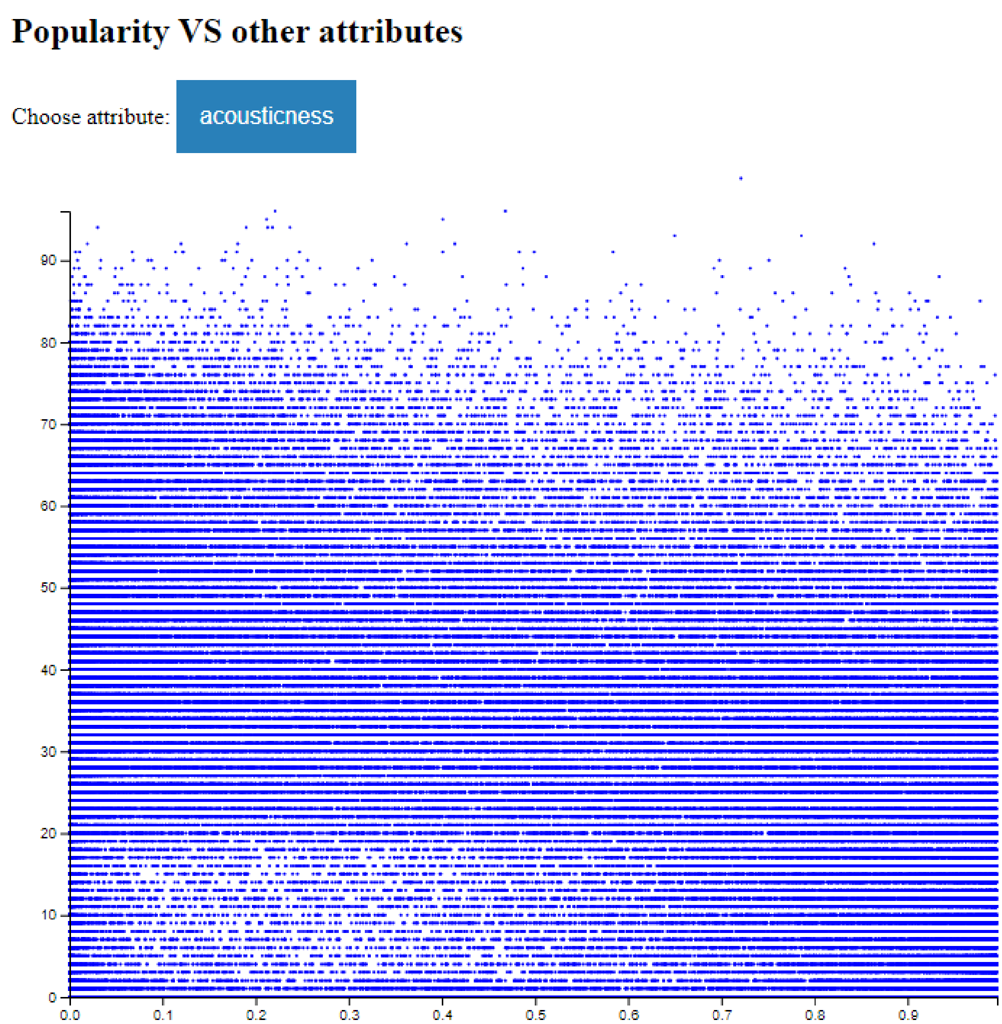
- Should I write a song the old way (more acoustic) or should I add more modern elements (EDM, autotune, synthesizers, ...)?
- Would it be better if I record the song in the studio or use the live version?
- The song I wrote is already 5 mins long, are there any benefits if I remove one repetitive chorus to make it shorter?
- I'm a musician who has written an instrumental track, should I find a singer who can blend in with some audio tracks?

All of those questions are concentrated on the popularity, hence we can create graphs with x axis being the attributes present in the dataset and y axis to be the popularity. Below are some screenshots of various graphs that can hopefully address those questions:

Popularity VS Acousticness

Based on the scatter plot below, it seems when the song is acoustic, there is a lower chance for it to be unpopular (based on the sparse region when acousticness is between 0.1 and 0.5, and popularity is between 0 and 20). However, this could be due to the fact that there aren't that many acoustic songs produced recently compared to songs with modern components (will be analysed in the later sections).

On the other hand, there isn't any obvious relationship (e.g. linear relationship) between acousticness and popularity of the music.



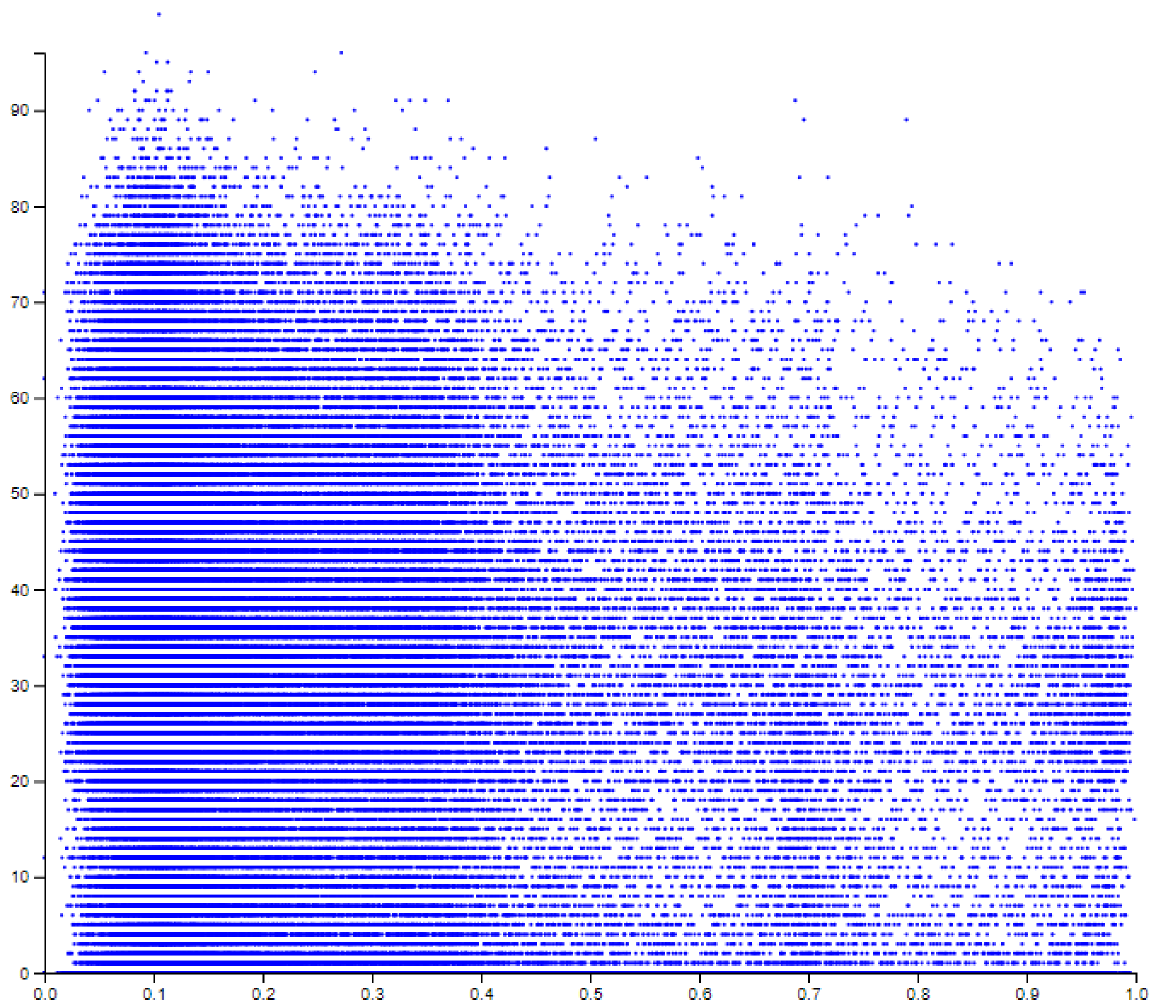
Popularity VS Liveness

Based on the scatter plot between popularity and liveness, we can conclude there are more songs in the dataset which are recorded in the studio instead of live (i.e. a score above 0.8).

Although it seems there are higher chances for the studio versions to be more popular (maybe because of the better sound quality), the relationship is not conclusive.

Popularity VS other attributes

Choose attribute: liveness



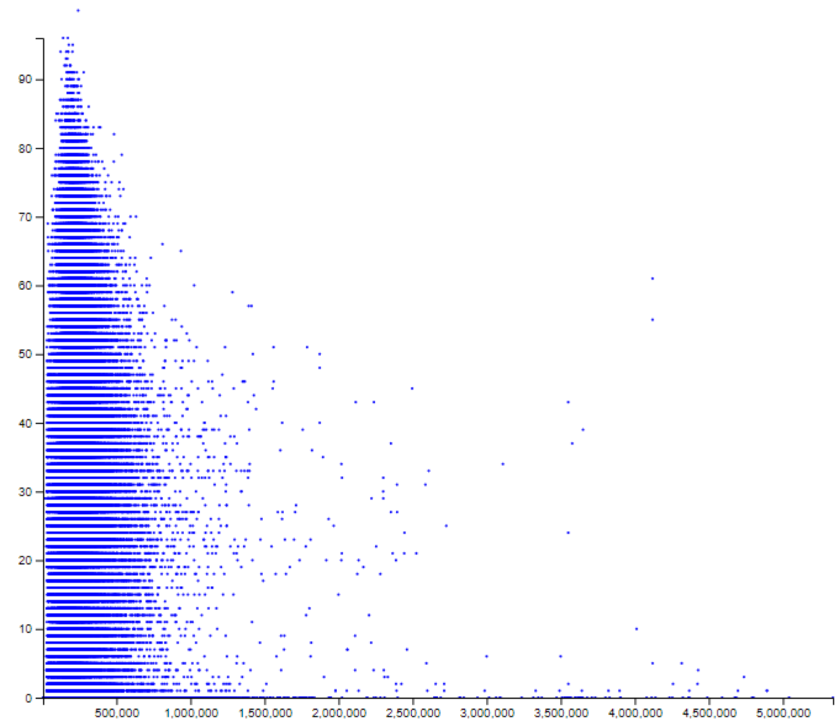
Popularity VS Duration

Although there are songs which are excessively long (more than one hour), most songs are within 600 seconds (second graph below), with most popular songs with length around 210 seconds (3:30 mins).

Hence, although there is no relationship between sound duration and popularity, it might be beneficial to trim unnecessarily long songs to a shorter version.

Choose attribute: duration_ms

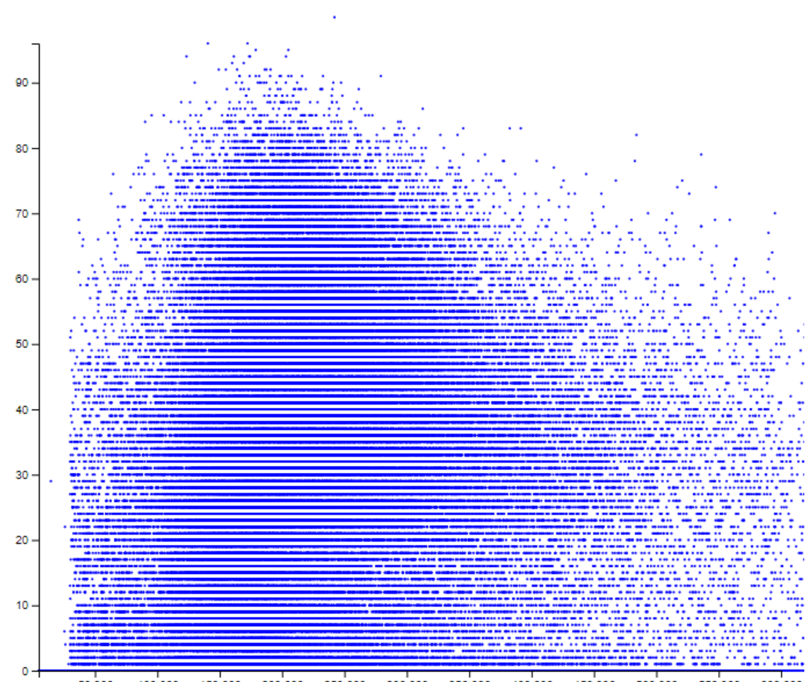
Set max: Update



Popularity VS other attributes

Choose attribute: duration_ms

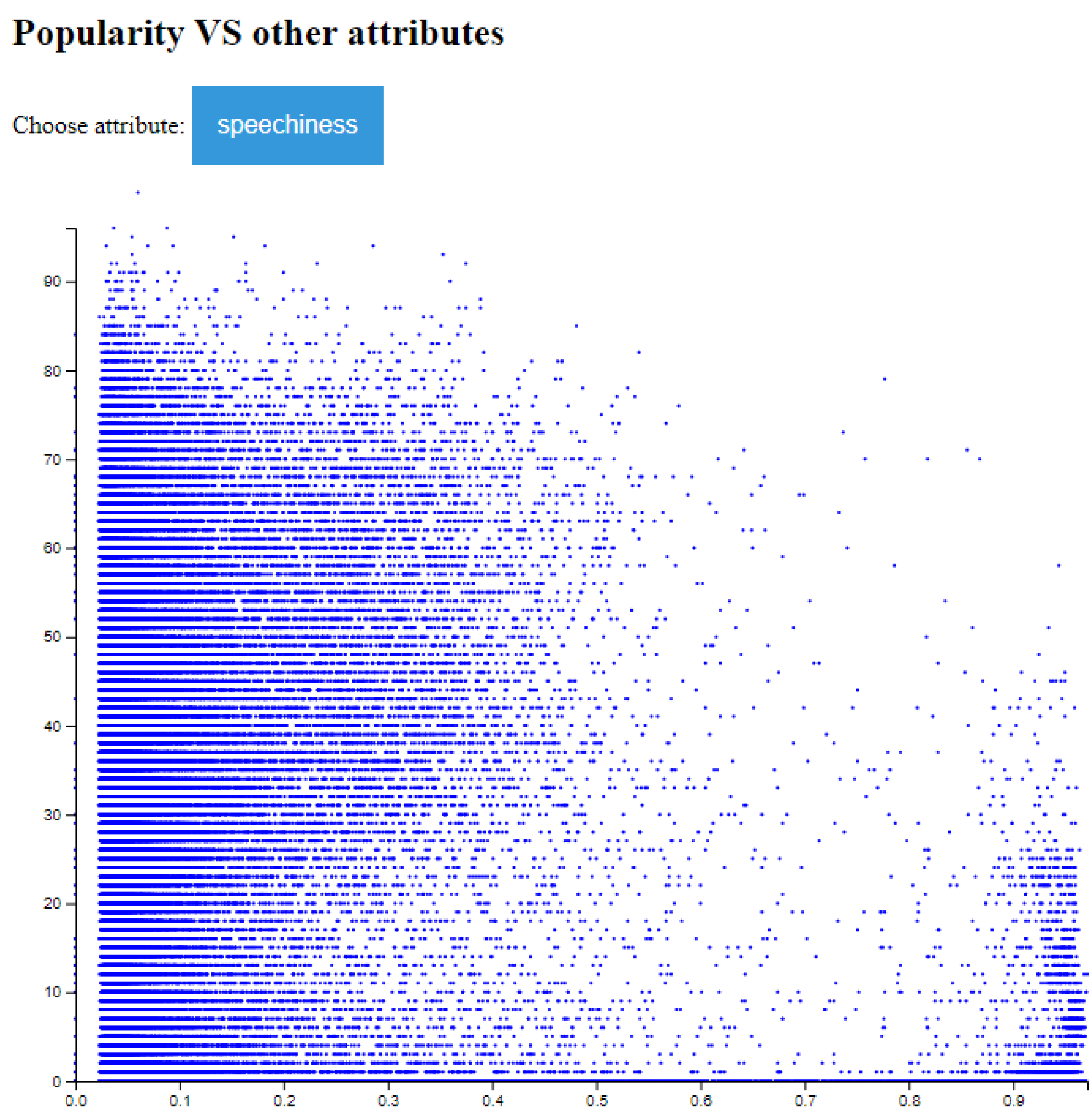
Set max: 600000 Update



Popularity VS Speechiness

This is one of the most inaccurate fields in the dataset where from the scatterplot, it seems most songs are pure music without any human voice over, however, based on randomly selecting a few songs from the dataset with low speechiness value (less than 0.3), many contains singer’s voice.
Hence, it would be hard to answer the question on whether it is necessary to find a singer for a written instrumental track.

On the other hand, most of the tracks with pure human voice (larger than 0.9 for speechiness) are not music, but audio books, which also explains the low popularity (since Spotify is famous for the music streaming service instead of the audio books.).



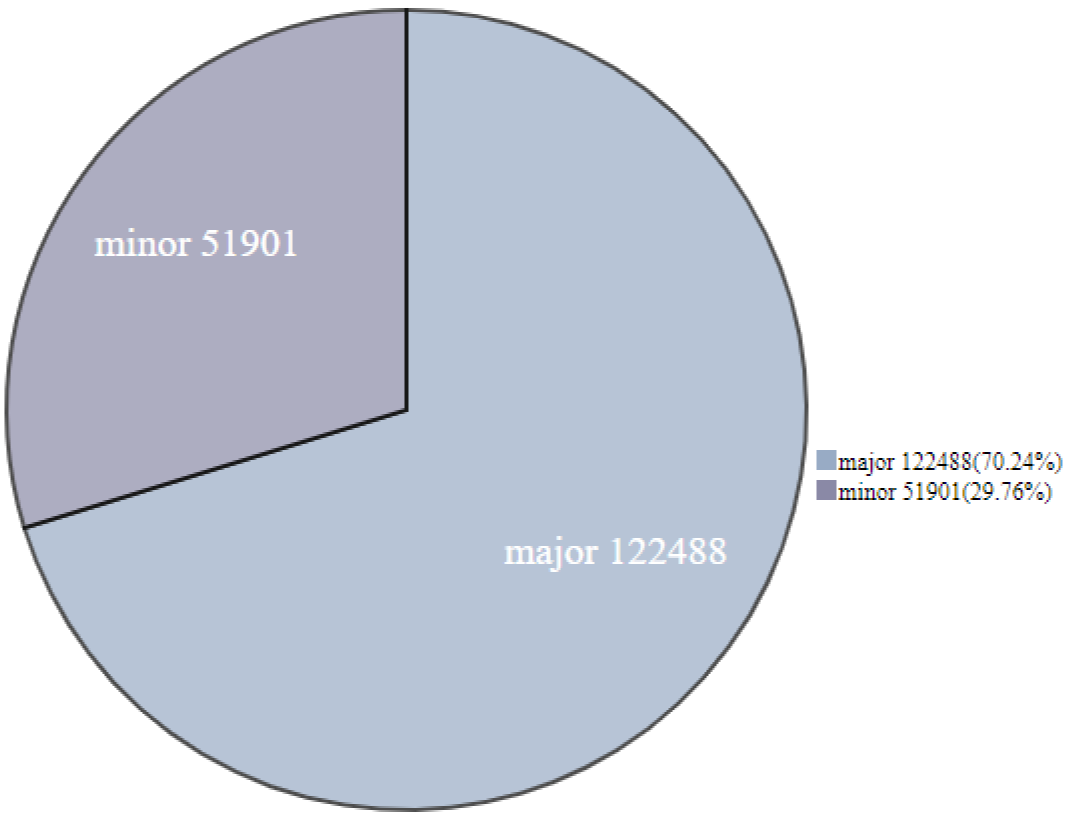
Key VS Mode

There are several data that are not best represented using scatterplot (e.g. Popularity VS Mode), and they could be better represented via other encodings.

In the sections below, we will investigate one interesting question:

- If I want to write a more emotional song (minor scale), which key should I use?

Since Minor and Major are the only two binary categories inside mode, we can use a bar plot or a pie chart to have a clear visualization on the percentage of tracks in each mode.

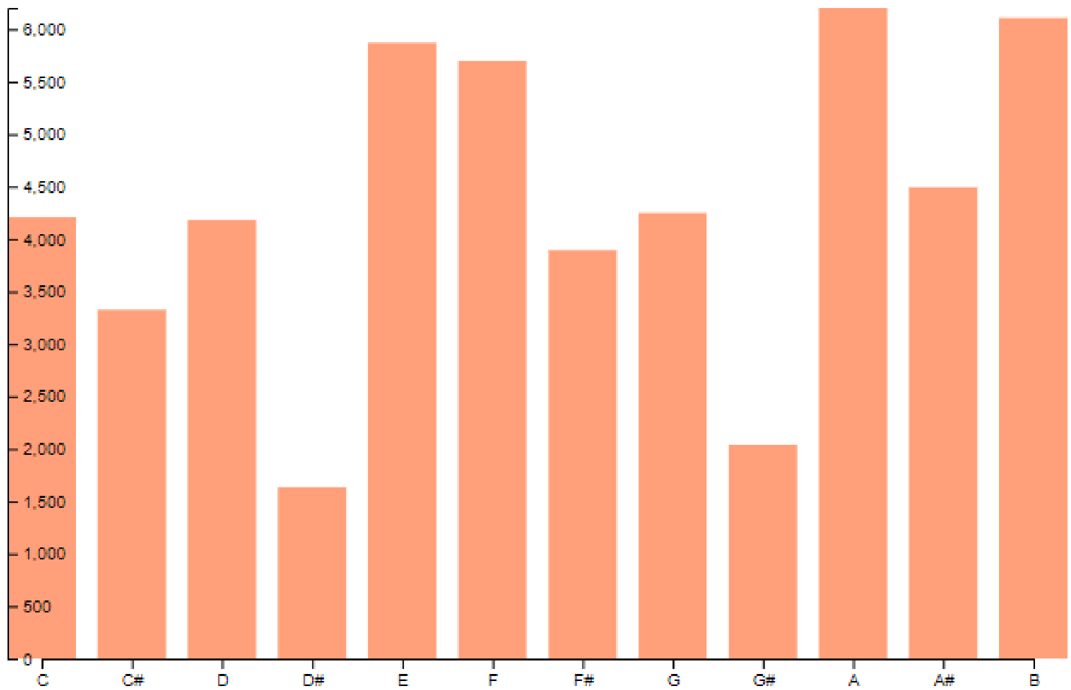


As can be seen from the pie chart above, most of the tracks in the dataset have a major scale, and if one chooses to write a minor scale song, it will be from the minority (30%) of all tracks.

Distribution of keys based on mode is shown in the graph below:

Key VS Mode

Major Minor



As seen from the graph, when minor key is used, the mostly used keys are A, B, E and F whereas D# and G# are rarely used in comparison -- this helps us to answer the question on “If I want to write a more emotional song (minor scale), which key should I use?”. =D

This is very different from the keys used for songs with major scale (shown in the graph below), where the mostly used keys are C, G and D.

This could mean that there are some characteristics in each key which makes them suitable for a certain scale. However, my music knowledge is too limited to comment further.

Key VS Mode

Major Minor