Characteristics of Top Songs Has Changed from Pandemic Brain*

An analysis of songs on Billboard's Year-End Hot 100 list (2014 to 2023)

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Music often reflects the current climate of society and there is a growing interest in how hit songs as seen on Billboard's Year-End Hot 100 singles has changed after the COVID-19 pandemic. This paper looks at music characteristics such as tempo, song duration, loudness, and modality of songs from Billboard's Year-End Hot 100 singles list from 2014 to 2023 to reveal patterns and relationships to explain the difference between top songs before 2020 and 2020 onwards. The results show that hit songs from 2020 onwards had become on average shorter, quieter, but slightly faster with the melody of songs being in a major key. These results can support the evaluation of the emotional state of different populations and improve treatments such as music therapy, however further investigation is needed on the influence of lyrics on different music characteristics.

Table of contents

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*Code and data are available at: https://github.com/moonsdust/top-songs.

1 Introduction

During the COVID-19 pandemic, viral songs on social media sites such as TikTok were met
with thousands of listens on streaming platforms such as Spotify and at times go onto being
on lists like the Billboard Year-End Hot 100. These songs often accompany thousands of short
clips of people talking about their lives, challenges, etc. Ghaffari et al in their study, "The
impact of COVID-19 on online music listening behaviors in light of listeners' social interactions"
noted that other studies have found that people used music as a way to cope and regulate their
thoughts and emotions during the pandemic and the lockdowns that came with it (Ghaffari
et al. 2023). We can see this translated through the short-form videos where users don't talk
and instead have the song play out to convey how they are feeling or thinking. Ghaffari et
al's findings are similar to how music therapy works. As defined by the Canadian Association
of Music Therapists, music therapy is the use of music to support an individual's health,
social development, and well-being and some of the techniques used include listening to music
(Canadian Association of Music Therapists 2020). Hurwitz and Krumhansl conducted a study
into how people's listening habits throughout the pandemic and they found that the songs they
listened to often were linked to an emotion such as sadness and/or invoking memories from
the past (Hurwitz and Krumhansl 2021). However, this raises the following question, which
we explored in our analysis: how are top songs prior to 2020 or the start of the pandemic
different from the top songs during and after 2020?

In this paper, to investigate patterns and trends in music, we analyzed data from the Billboard
Year-End Hot 100 singles list from 2014 to 2023 on music characteristics such as its modality

(major or minor key), track duration, loudness, and tempo. Our estimand is the song characteristics from the Billboard Year-End Hot 100 singles such as its modality (major or minor), track duration, loudness, and tempo if a song was created before 2020 or during and after 2020. The list allowed us to gauge how preference in music characteristics has changed overall during and after the pandemic. Current studies give us a sense of how currently people are feeling based on surveys done. However, there is currently a lack of understanding and focus on the difference in musical characteristics of popular songs with the general population before the pandemic and during and after it. In our findings, our data showed that songs in a major key made up the majority of top songs before, during, and after 2020 and top songs were on average quieter, shorter, and had slightly faster tempos during and after 2020. [TODO: ADD RESULTS FROM MODEL]. Music can reflect the climate of society and understanding trends in music characteristics of hit songs can help provide insight on the overall feelings of different populations during and after the pandemic as well as before it. This can aid in improving treatments such as music therapy.

In the rest of this paper, the data section (Section 2) will cover the dataset used, how it was obtained, define the variables of interest that are used by our tables and graphs, and briefly explain the data cleaning process. The model section (Section 3) will explain our proposed causal model, which would explain potential relationships in our data, the setup of our model to understand these relationships, and justification for our model. In the results section (Section 4), we will reveal tables and graphs made on our datasets, explain what they show, and show our results from our model. In the discussion section (Section 5), we will connect back to the real world and explain what the results could mean, the implications of our results, potential areas of improvement for the paper, and suggestions for future works. Finally, the appendix section (Section A) will extra tables and graphs from our results as well, as additional information about the model, and a link to a Shiny application featuring an interactive graph of some of the results.

2 Data

2.1 Methodology

The dataset used in this paper was retrieved, simulated, cleaned, analyzed, and tested using the R programming language (R Core Team 2023), tidyverse (Wickham et al. 2019), knitr (Xie 2014), janitor (Firke 2023), dplyr (Wickham et al. 2023), ggplot2 (Wickham 2016), spotifyr (Thompson et al. 2022), usethis (Wickham et al. 2024), arrow (Richardson et al. 2024), ggcorrplot (Kassambara 2023), testthat (Wickham 2011), and lintr (Hester et al. 2024). The packages that were used for the model-related sections or used for the model itself are DiagrammeR (Iannone and Roy 2024), rsvg (Ooms 2023), magrittr (Bache and Wickham 2022), DiagrammeRsvg (Iannone 2016), png (Urbanek 2022), rstanarm (Goodrich et al. 2024), and modelsummary (Arel-Bundock 2022).

2.2 Data Source and Measurements

The data used for the model and analysis comes from the `playlists_analysis_data` dataset. This dataset was constructed by using an R wrapper for Spotify's API called spotifyr (Thompson et al. 2022) to scrape playlists complied by Spotify users antoniomendoza and wickeddreamer96 of songs from the Billboard Year-End Hot 100 singles from 2014 to 2023. User antoniomendoza created playlists for the years 2018 to 2023, inclusive, while user wickeddreamer96 created playlists for the years 2014 to 2017, inclusive. The latest version of the data used was scraped on Tuesday March 26, 2024 at 9:46pm EDT. The Billboard Year-End Hot 100 singles list for the year 2014 onward was created based on data from Nielsen SoundScan [Add citation].

Initially, we had scraped playlists created by Spotify that they have compiled of the top songs on the app. However, we had an insufficient amount of observations from these playlists for our dataset since each only had around 50 songs and there were years where Spotify had not created a top song playlist for such as 2021 and 2022.

Each observation in the dataset belongs to a song from the Spotify playlist that we scraped compiled by antoniomendoza and wickeddreamer96 for songs on the Billboard Year-End Hot 100 singles. For the duplicate songs that showed up in different years, they were kept as we wanted to analyze song characteristics.

In total, there are 1000 observations in the `playlists_analysis_data` dataset, which equals to the number of songs on the Billboard Year-End Hot 100 singles lists from 2014 to 2023.

Table 1: Preview of dataset on Billboard Year-End Hot 100 singles from 2014 to 2023 provided by Spotify

hit_year	track_duration_ms	tempo	loudness	mode_name	key_mode	period
2014	232720	160.019	-4.662	minor	F minor	Before Pandemic
2014	215672	131.931	-6.122	major	F# major	Before Pandemic
2014	269560	119.930	-7.064	major	G# major	Before Pandemic
2014	199938	94.981	-4.141	minor	A# minor	Before Pandemic
2014	257840	122.017	-4.972	minor	C# minor	Before Pandemic
2014	177685	100.315	-7.321	major	F# major	Before Pandemic

Not seen in Table 1, before_pandemic, major, and minor are numerical versions of the

4

mode_name and period columns. The variables that were originally the raw dataset that was scraped are track_duration_ms, tempo, loudness, mode_name, and key_mode.

The variables constructed from the raw dataset are before_pandemic, period, hit_year, major, and minor. How these variables were constructed was that hit_year was obtained from check the name of the playlist and it represents the hit. From hit_year, the period column was constructed, which indicates whatever or not the hit year of the song was before 2020, which was when the COVID-19 pandemic started, or during 2020 onwards. Reading from the period column, the before_pandemic column was created, where 1 represents that the song was a hit song before the pandemic and 0 otherwise. The major and minor columns represents whatever or not the melody of the song is in a major or minor key and the value would be 1 if it's that key and 0 otherwise. These columns were constructed from checking mode_name when it would indicate either "major" or "minor".

2.3 Variables of Interest

As seen in Table 1, there are multiple columns however our main variables of interests are

3 Model

From our analysis of the data, we observed that there were trends between a song's duration, loudness, tempo, and modality for top songs prior 2020 and 2020 onwards. We are interested in investigating if a song is likely to be a top song prior to 2020 or not based on what we know about the duration, loudness, tempo, and modality of a top song. We will do this by creating a model.

3.1 Model set-up

In order to predict a top song was a hit prior to 2020, we will make the assumption that there is a relationship between the outcome variable, if the song is a top song prior to 2020 and our variables of interests: duration, loudness, tempo, and modality. Our variables of interests will be the predictor variables for the model. We will define our model as a logistic regression

model with a Bayesian approach as follows:

$$y_i | \pi_i \sim \text{Bern}(\pi_i)$$
$$\text{logit}(\pi_i) = \beta_0 + \beta_1 \times \text{duration}_i + \beta_2 \times \text{loudness}_i + \beta_3 \times \text{tempo}_i + \beta_4 \times \text{modality}_i$$
$$\beta_0 \sim \text{Normal}(0, 2.5)$$
$$\beta_1 \sim \text{Normal}(0, 2.5)$$
$$\beta_2 \sim \text{Normal}(0, 2.5)$$
$$\beta_3 \sim \text{Normal}(0, 2.5)$$
$$\beta_4 \sim \text{Normal}(0, 2.5)$$

We define y_i to be a top song, which if it is 1 represents a top song prior to 2020 and 0 if it is a top song from 2020 onwards. π_i is the probability that a top song i is a top song prior to 2020. Let duration_i be the duration of the top song in milliseconds (ms) and loudness_i to be the mean loudness of a top song in decibels (dB). Set tempo_i to be the mean beats per minutes (BPM) of a top song and modality_i to be the modality of the top song, where 1 means the melody of the song is in a minor key and 0 if it is in a major key.

We ran the model using the rstanarm package (Goodrich et al. 2024) with the default priors from the package. Diagnostics related to the model such as a trace plot, Rhat plot, and posterior predictive check can be found at Section A.

3.1.1 Model justification

A logistic regression model was chosen because our outcome variable, if the song is a top song prior to 2020, is a binary outcome. However, alternative models were considered such as a multiple linear regression model since the model has multiple predictor variables. Other regressions models like negative binomial regressions were also considered but they were not chosen since we are not deleting with discrete counts for the outcome. Our logistic regression model describes the following causal relationship (Figure 1) where song characteristics predicts whatever a hit song was made prior to 2020, excluding a confounder, lyrics. The assumption we make is that there is a relationship between song characteristics and a top song being a hit prior to 2020. In Figure 1, the reason lyrics is a confounder is because lyrics can affect not only if the song was a hit prior to 2020 but also song characteristics. However, we are unable to observe the effects of lyrics directly with our data. Weakness and further improvments to the model are discussed in Section 5.
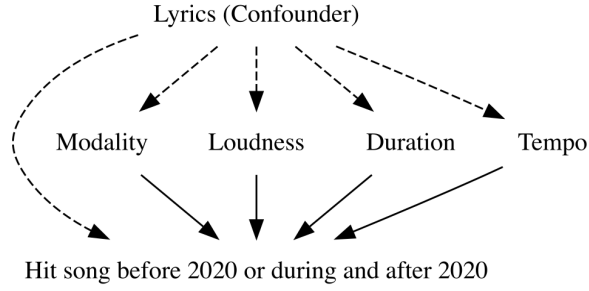
4 Results

[To Finish]

Figure 1: Causal relationship between song characteristics and hit song (before 2020 or during and after 2020)

4.1 Difference in song characteristics before 2020 (the pandemic) and during and after 2020 (the pandemic) of songs from the Billboard Year-End Hot 100 singles
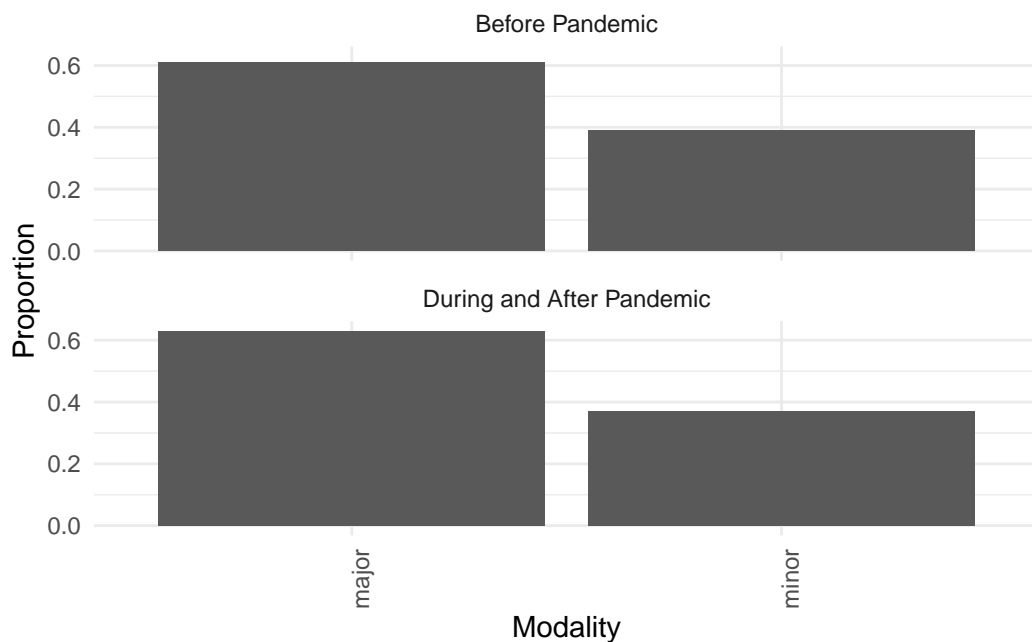
4.1.1 Scale and Modality

Table 2: Proportion of songs whose modality is in a major or minor key before 2020 versus during and after 2020

Period	Modality	Count of each mode	Proportion of each mode
Before Pandemic	major	368	0.61
Before Pandemic	minor	232	0.39
During and After Pandemic	major	251	0.63
During and After Pandemic	minor	149	0.37

Figure 2: Proportion of songs whose modality is in a major or minor key before 2020 versus during and after 2020
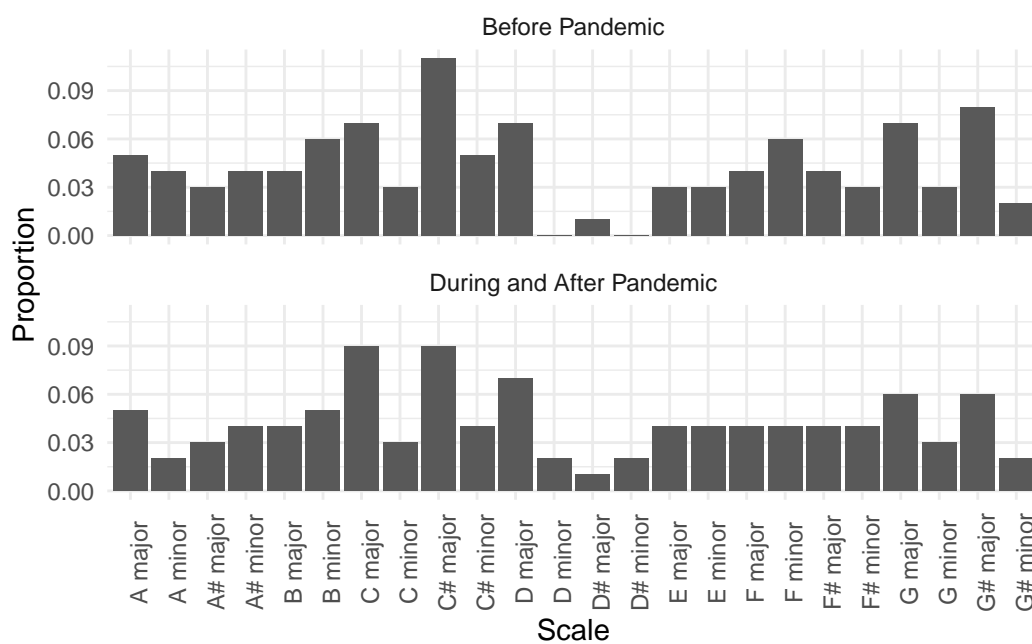

Figure 3: Proportion of songs in different scales before 2020 versus during and after 2020
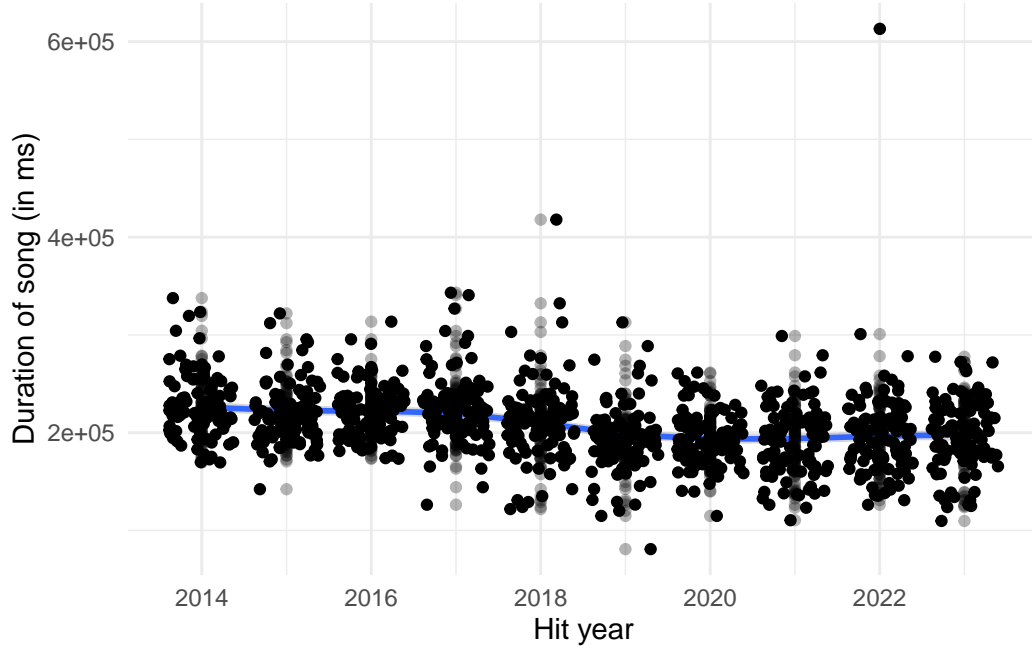
4.1.2 Track Duration

Figure 4: Relationship between the hit year and track duration of a song

Table 3: Minimum, quartiles, median, and maximum of track duration (in ms) before 2020

Duration of song (in ms)
Min. : 80927
1st Qu.:194600
Median :214070
Mean :216286
3rd Qu.:233087
Max. :417920

Table 4: Minimum, quartiles, median, and maximum of track duration (in ms) during and after 2020

Duration of song (in ms)
Min. :109750
1st Qu.:173369
Median :195120

Table 4: Minimum, quartiles, median, and maximum of track duration (in ms) during and after 2020

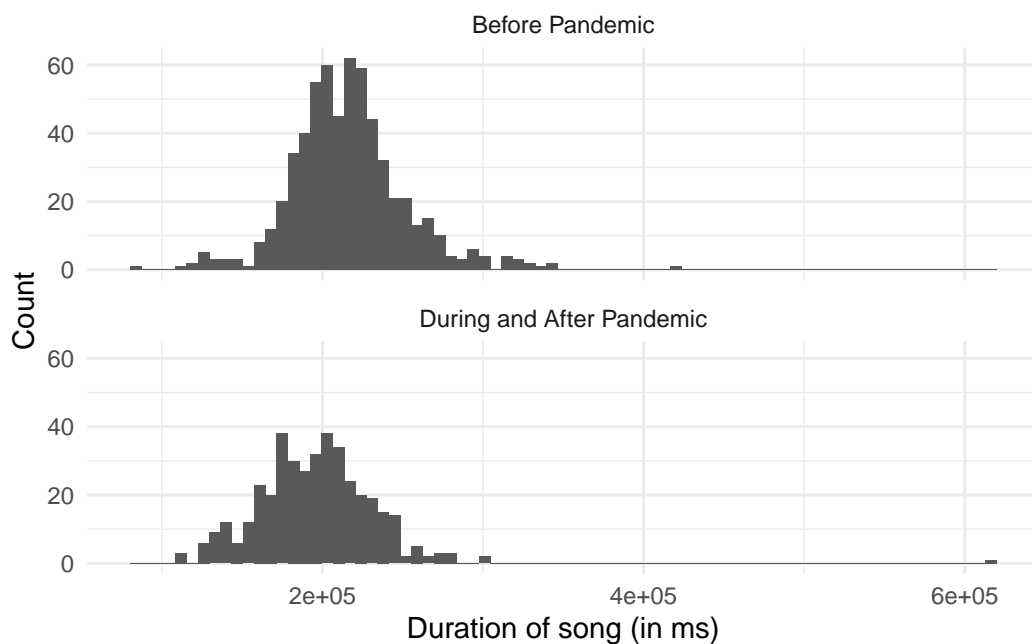| Duration of song (in ms) |
| --- |
| Mean :195999 |
| 3rd Qu.:215336 |
| Max. :613026 |

Figure 5: Distribution of track duration (in ms) before 2020 versus during and after 2020
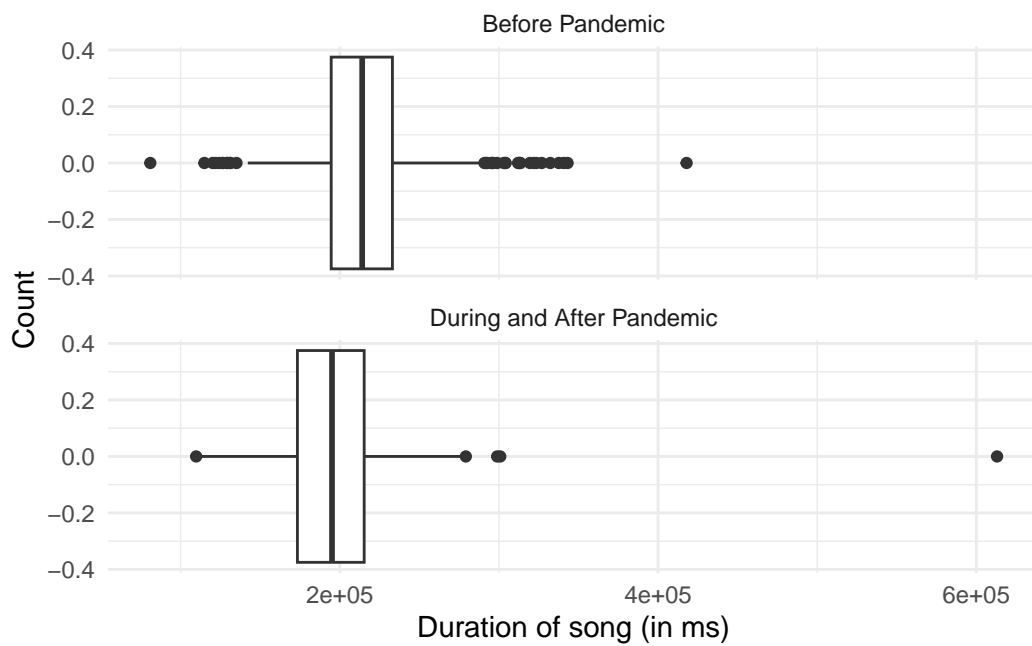

Figure 6: Track duration (in ms) before 2020 versus during and after 2020
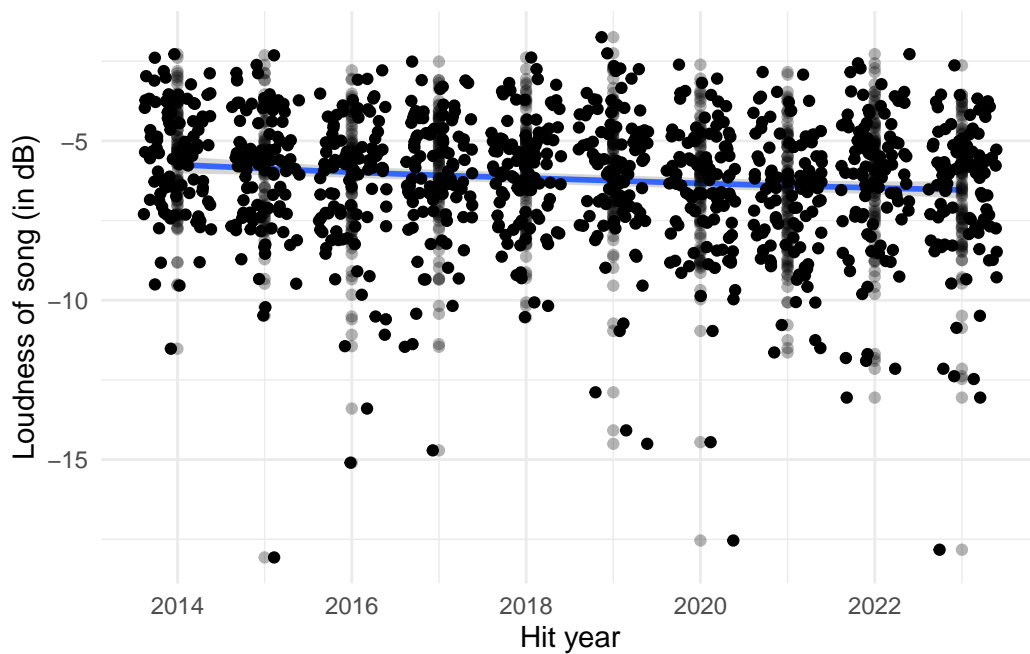
4.1.3 Loudness

Figure 7: Relationship between the hit year and loudness of a song

Table 5: Minimum, quartiles, median, and maximum of loudness of song (in dB) before 2020

Loudness of song (in dB)
Min. :-18.071
1st Qu.: -7.051
Median : -5.700
Mean : -5.964
3rd Qu.: -4.705
Max. : -1.746

Table 6: Minimum, quartiles, median, and maximum of loudness of song (in dB) during and after 2020

Loudness of song (in dB)
Min. :-17.829
1st Qu.: -7.604
Median : -6.151

Table 6: Minimum, quartiles, median, and maximum of loudness of song (in dB) during and after 2020

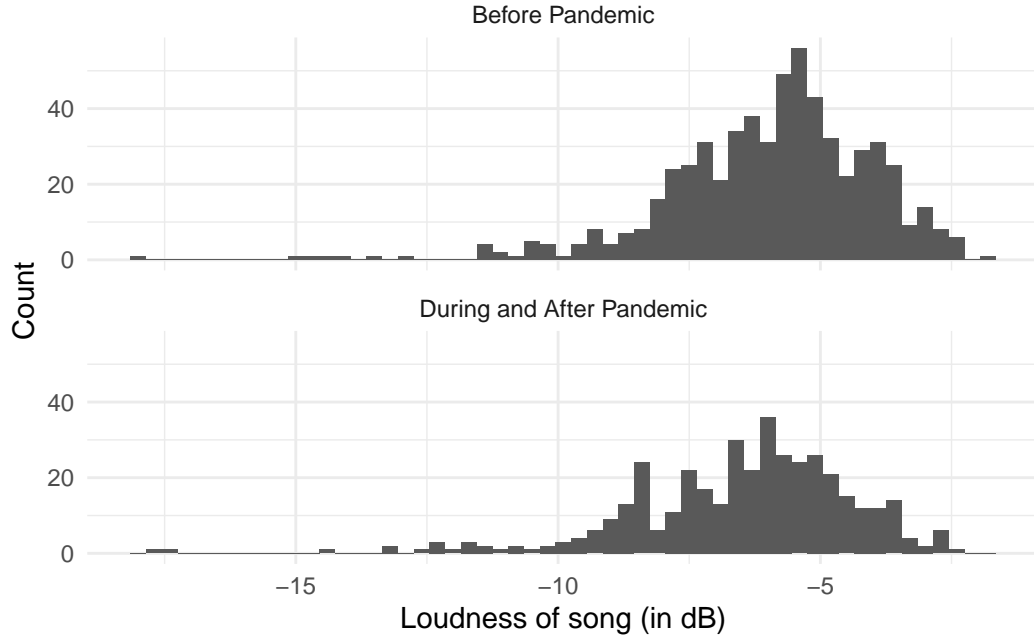| Loudness of song (in dB) |
|---|
| Mean : -6.516 |
| 3rd Qu.: -5.109 |
| Max. : -2.278 |

Figure 8: Distribution of loudness (in dB) before 2020 versus during and after 2020

4.1.4 Tempo

Table 7: Minimum, quartiles, median, and maximum of tempo of a song (BPM) before 2020

Tempo of song (BPM)
Min. : 53.86
1st Qu.: 98.03
Median :119.98
Mean :121.11
3rd Qu.:140.00
Max. :205.97

Table 8: Minimum, quartiles, median, and maximum of tempo of a song (BPM) during and after 2020

Tempo of song (BPM)
Min. : 67.03
1st Qu.: 98.02
Median :120.03

Table 8: Minimum, quartiles, median, and maximum of tempo of a song (BPM) during and after 2020

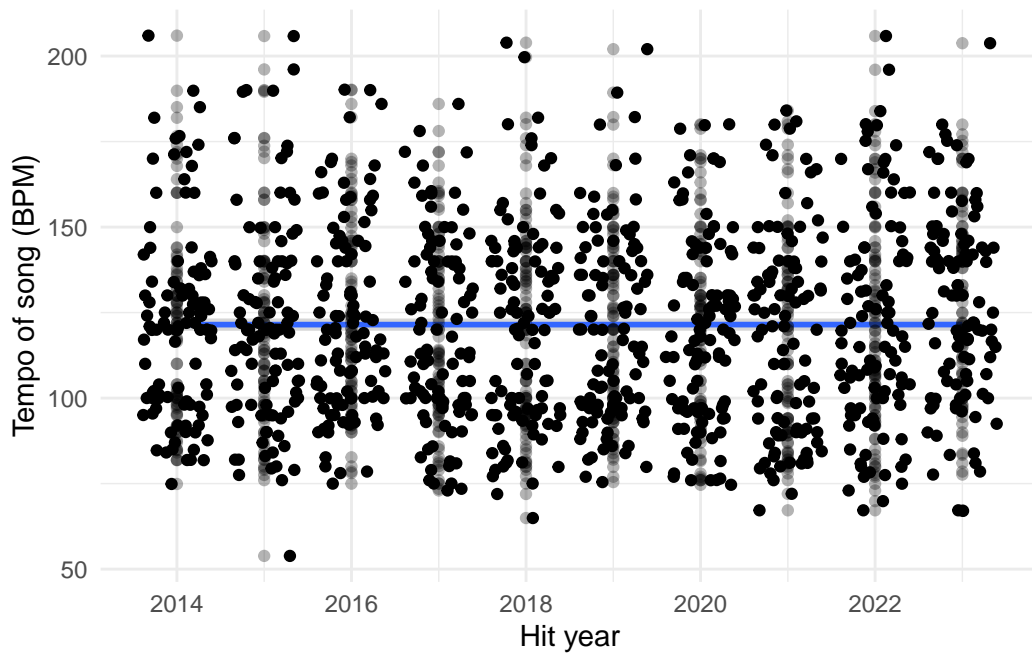| Tempo of song (BPM) |
| --- |
| Mean :122.06 |
| 3rd Qu.:142.31 |
| Max. :205.86 |

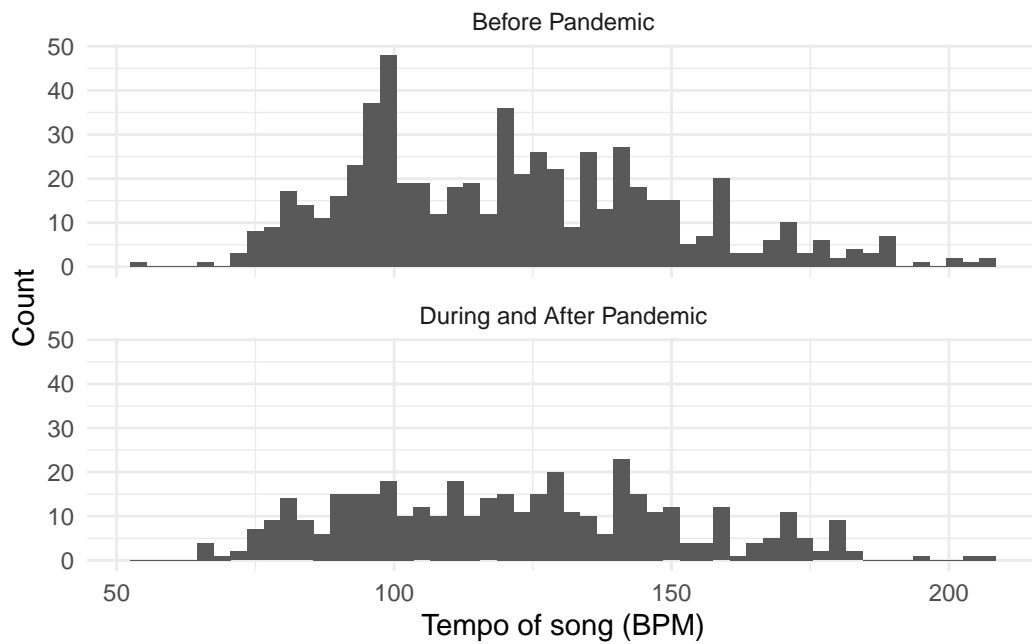Figure 9: Relationship between the hit year and tempo of a song

Figure 10: Distribution of tempo (BPM) before 2020 versus during and after 2020

16

Table 9: How likely a hit song is a hit before 2020 / the pandemic based on its tempo, song duration, loudness, and modality

	A hit song before 2020
(Intercept)	−2.002
	(0.550)
track_duration_ms	0.000
	(0.000)
loudness	0.148
	(0.033)
tempo	−0.002
	(0.002)
mode_nameminor	0.095
	(0.139)
Num.Obs.	1000
R2	0.096
Log.Lik.	−624.867
ELPD	−630.3
ELPD s.e.	12.9
LOOIC	1260.6
LOOIC s.e.	25.7
WAIC	1260.6
RMSE	0.46

4.2 Model Results

Table 9 and Figure 11 shows the results of our logistic regression model. Table 9 indicates that the y-intercept is -2.002, this however has no meaning in this situation since we only have two outcomes, 0 and 1 to represent a hit song from 2020 onwards and a hit song prior to 2020, respectively. Table 9 and Figure 11 reveal that the coefficient of track duration is 0.000 when tempo, mode, and loudness are constant and its credible interval contains 0. [The credible interval means…….] This indicates there is no relationship between a song being a hit before 2020 and the duration of the song. Since its credible interval is narrow,
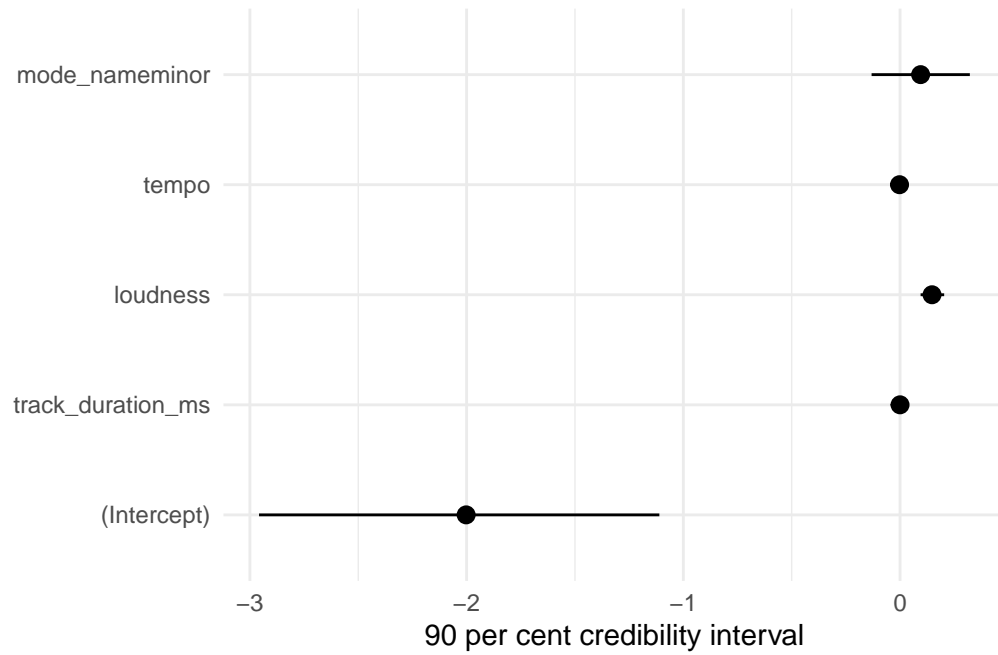
Figure 11: The credible intervals for predictors of a hit song before 2020

5 Discussion

[To Do]

A Appendix

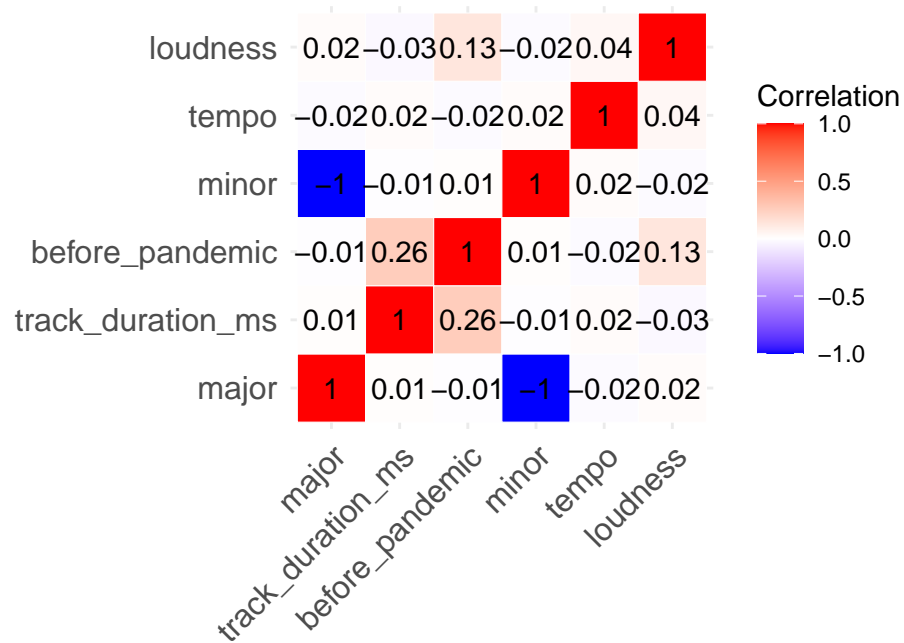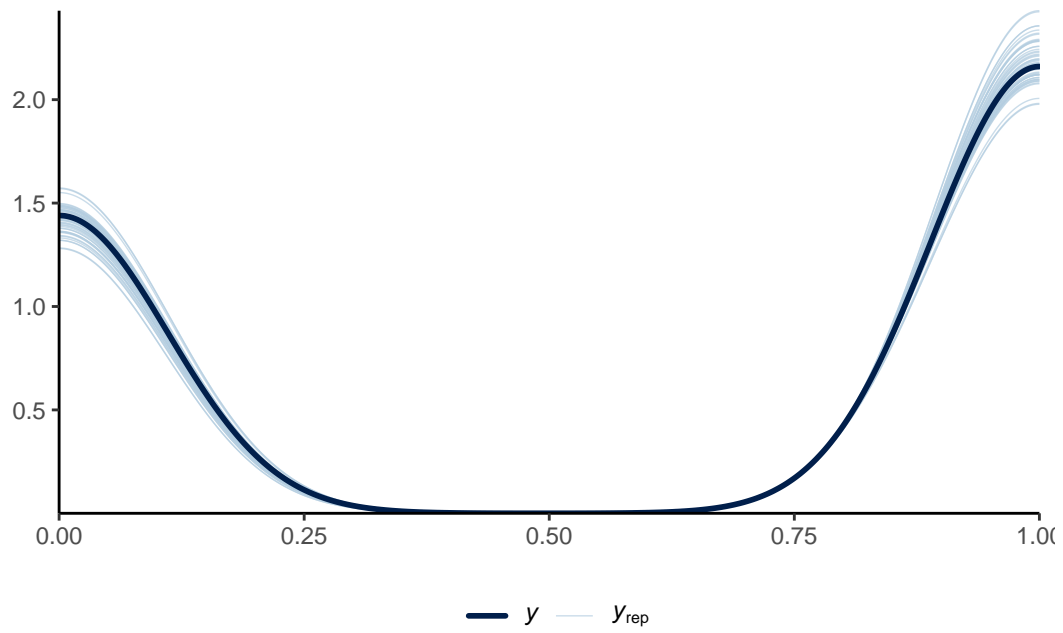## A.1 Additional Figures and Tables

Figure 12: Correlation between numerical characteristics of songs from Billboard Year-End Hot 100 single and if song was a hit before 2020/the pandemic

A.2 Posterior predictive check for model

(a) Posterior prediction check for the model

Figure 13: How the data impacts how the model fits
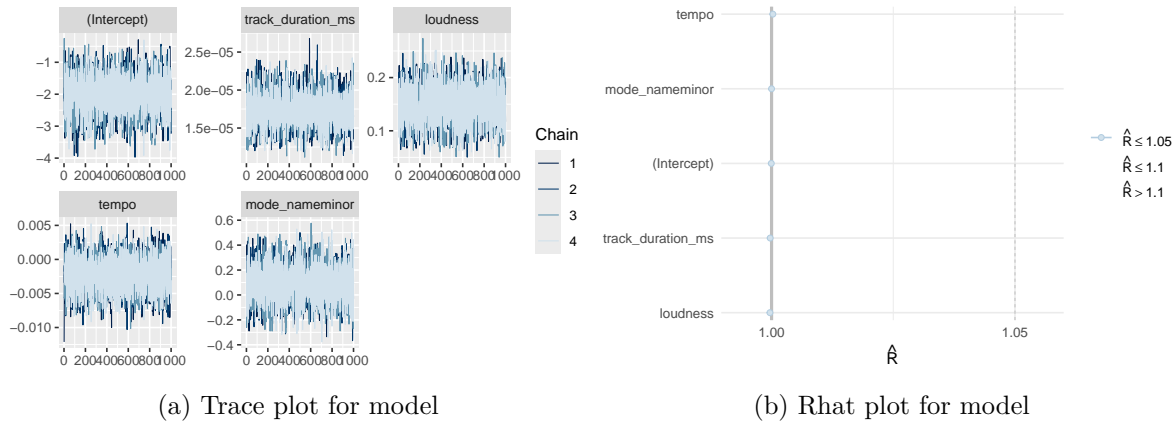
A.3 Diagnostics for model

(a) Trace plot for model

(b) Rhat plot for model

Figure 14: Checking the convergence of the MCMC algorithm for hit song model

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