Do Major Historical Events Affect the Mood of Music We Listen To?

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Abstract: The study explores the relationship between different characteristics in popular music and impactful events in U.S. history. The authors draw on data from the Spotify API, the billboard charts Python API, and record of historical events in American history. Every week since March 4, 1958 the Billboard Hot 100 was pulled for said week. The songs from the hot 100 were then cross referenced with the Spotify API to retrieve Spotify's analysis of each song. The study orbits around the song characteristics of: danceability and valence. Historical events vary from violent events like the JFK assassination to more peaceful trends like the Summer of Love. Trends of these song characteristics are then analyzed for the following two weeks surrounding an event.

1. Introduction

Where American culture is today is quite different than where (or what) it was 50 years ago. Part of what reflects and constructs culture is music. As culture has changed and adapted to world events, increasing knowledge, and countless other factors; music has changed along with it. How does one measure the change of such a complex system with intricate and endless composition? Many fields attempt to answer this question through many different means (political science, psychology, etc.). However, music is an artform that can capture some essence of an artist's human experience and the culture that influenced it. Through examining music, a microcosm of culture can be diagnosed and show symptoms of the whole culture and collective experience. Instead of examining every genre, part, and created piece of music, our study focuses on the majority—the popular music. By looking at the top billboard charts one can see what the majority of people found worth in and were attracted to. Further, our aim was to see how certain historical events affected culture through the lenses of music. For example, did large, violent events produce sadder, less danceable music? Some events showed an intriguing correlation, others produced few notable results. From our tests one of the most marked findings was the drop in danceability after 9/11. Looking from a larger perspective, our findings are not groundbreaking. Rather they provide a solid fodder and foundation for further investigation in a fairly new and unexplored field of popular music.

2. Literature review

Music is an element of the human experience that casts a culture umbrella: enveloping, creating, and distributing what each artist discerns from their life. Music is now a part of many people's everyday lives. However, music has not always commanded such a prominent presence. Just as the accessibility to music has greatly changed overtime, so has music itself. Music is a centrifuge of many different factors and has thus garnered the attention of scholars for centuries. Such interest created the field of musicology which explores the complex nature of music. Musicology has many subfields, such as music: theory, history, anthropology, etc. Each field focuses on different aspects. For example, music theory in its basest form is the study of "notes, chords, and so on" with notes and chords making "the building blocks of the language of music" (Miller, 2016). Music theory is built around analyzing these building blocks. There has been copious amounts of work done in established sub-fields. However, a fairly new field is the study of popular music.

As Allan Moore reflects in 2003 in his book *Analyzing Popular Music*, "Twenty years ago, it was difficult to find any institution where popular music (as a field distinct from 'classical' or 'non-Western' musics or jazz) could be found being taught to prospective musicians at undergraduate level" (Moore, 1). The field gained traction in the 80s and stemmed from other fields like "sociology, literary, and cultural studies" (Moore, Scott, Hawkins, 2). Moore continues to lament that "'music analysis' and 'popular music', is an undertaking that has been addressed a number of times but not yet, to my mind, at sufficient length and in sufficient detail" (Moore, Scott, & Hawkins, 3). With the field in its infancy and barely any ground broken, there are ample options to adding to the pool of knowledge.

Hawkins argues that popular music "functions primarily as an internalised condition of experience within its own social environment" (Hawkins, 17). Seeing music as a part of the whole of society rather than separate is crucial. Moore, Scott, and Hawkins argue that popular music is put together "always with an ear to a particular listening public" (Moore, Scott, Hawkins, 3). Most likely this characteristic of popular music is due to that artists "will only attract that public if they can resonate with potential listeners" (Moore, Scott, Hawkins, 3). Society and music are strongly intertwined and reflect off one another. Listening to music is an experience that can having varying effects, "it may evoke anything from mere arousal and basic emotions such as happiness and sadness to complex emotions such as nostalgia" (Juslin, Harmat, & Eerola, 599). Just as it provokes different responses, music can be created in the context of different emotions and factors; some of these from societal forces outside an individual's control. Hawkins points out that "traditionally, music has been analysed as an abstract form with limited reference to its social and cultural function" (Hawkins, 18). The trained methods of analyzing concert music are "not adequate to the discussion of popular song" (Moore, Scott, Hawkins, 3).

The goal of this study is to close this gap between old and new methods in the recent field of popular music—to look at popular music in proper context. Specifically, the study will conduct an examination of popular music throughout its changes in time. Starting from mid 20th century to within the last decade, an analysis of song structure/music theory will be cross referenced with historical events. In doing so the study seeks to find if there is a correlation between historical events and features/qualities of song (such as danceability and valence).

3. Method

Data Collection

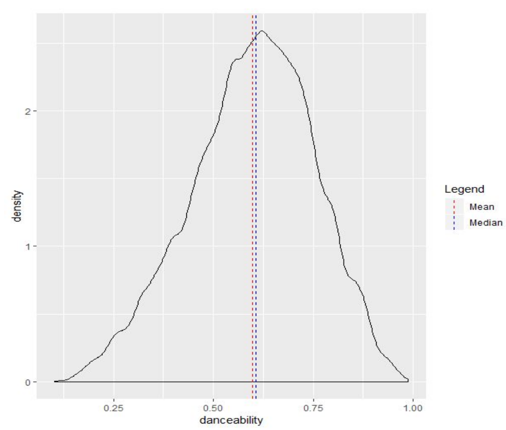
Our dataset was constructed with data from the Billboard API as well as the Spotify API. Using Python, we wrote a function that takes date as a parameter and returns the 100 songs from the Billboard Hot 100 for that week. For each song, a request is made to the Spotify API, posting a search query with the artist and title from the Billboard API. This request returns a search query from which we pulled the SpotifyID for the song to allow for more API calls for the particular song. In the process of getting the Spotify ID, another functions retrieves the top genre for the artist and adds that to the row as well. Using the newly retrieved SpotifyID for each song, we use the Spotify endpoint for retrieving track features. From this endpoint, we downloaded the valence, energy, tempo, danceability, key, and mode for each song for use in our analysis. This function returns a pandas dataframe of 100 songs for the inputted week. This function was run iteratively, incrementing every other week starting with August 4, 1958, and ending with December 26, 2009. Every other week was stored instead of every single week, because during exploratory data analysis, it was found that the number of new songs (songs not previously on the chart) each week was around 4.5. This leads us to believe the chart does not change much from one week to the next. For each year, the top 100 songs for each of the 52 weeks were appended to a dataframe for that specific decade. For example, “sixties” contains 52,000 rows, some are duplicates as songs often remained on the chart for multiple weeks. Each decade's dataframe was written to a csv and transferred to another script in R.

Data Cleaning

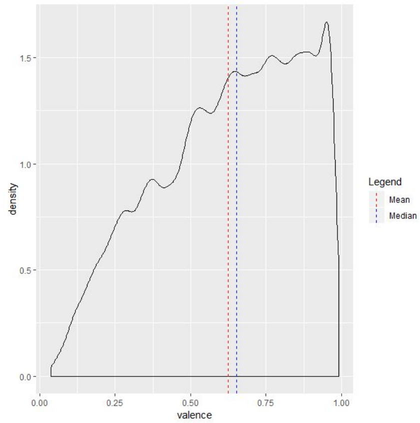
In R, each decade's csv was read in as a data.frame then combined, resulting in a data.frame with around 140,000 rows representing pop music from 1958 to 2010. The data.frame was cleaned, removing NA values where SpotifyIDs were unavailable. The resulting data.frame contained around 137,000 rows. Summary statistics for each variable are as follows:

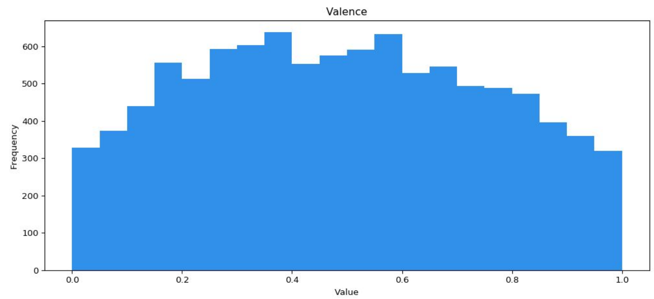
```
      X                     artist        danceability          date                  energy               featuring
 Min.   : 0.00   Madonna       :   604   Min.   :0.1030   Min.   :1958-08-05   Min.   :0.0181   none           :124473
 1st Qu.:22.00   Elton John    :   599   1st Qu.:0.4960   1st Qu.:1968-03-02   1st Qu.:0.4560   The Gang       :   229
 Median :46.00   The Beatles   :   527   Median :0.6070   Median :1983-04-02   Median :0.6140   The Vandellas:   193
 Mean   :47.48   Mariah Carey  :   464   Mean   :0.5976   Mean   :1982-04-29   Mean   :0.6041   Fire           :   193
 3rd Qu.:72.00   Connie Francis:   442   3rd Qu.:0.7080   3rd Qu.:1994-11-05   3rd Qu.:0.7640   Dean           :   175
 Max.   :99.00   Stevie Wonder :   423   Max.   :0.9880   Max.   :2009-12-26   Max.   :0.9970   The News       :   174
                 (Other)       :134498                                                          (Other)        : 12120
```

Distributions of key variables



Danceability is a measure of how well suited a song is for dancing based on tempo, beat strength, and overall regularity. Danceability is the most normal distributed of the "audio features" columns and a good indicator of the general mood of a song, so it was selected for further analysis in examining our research question.





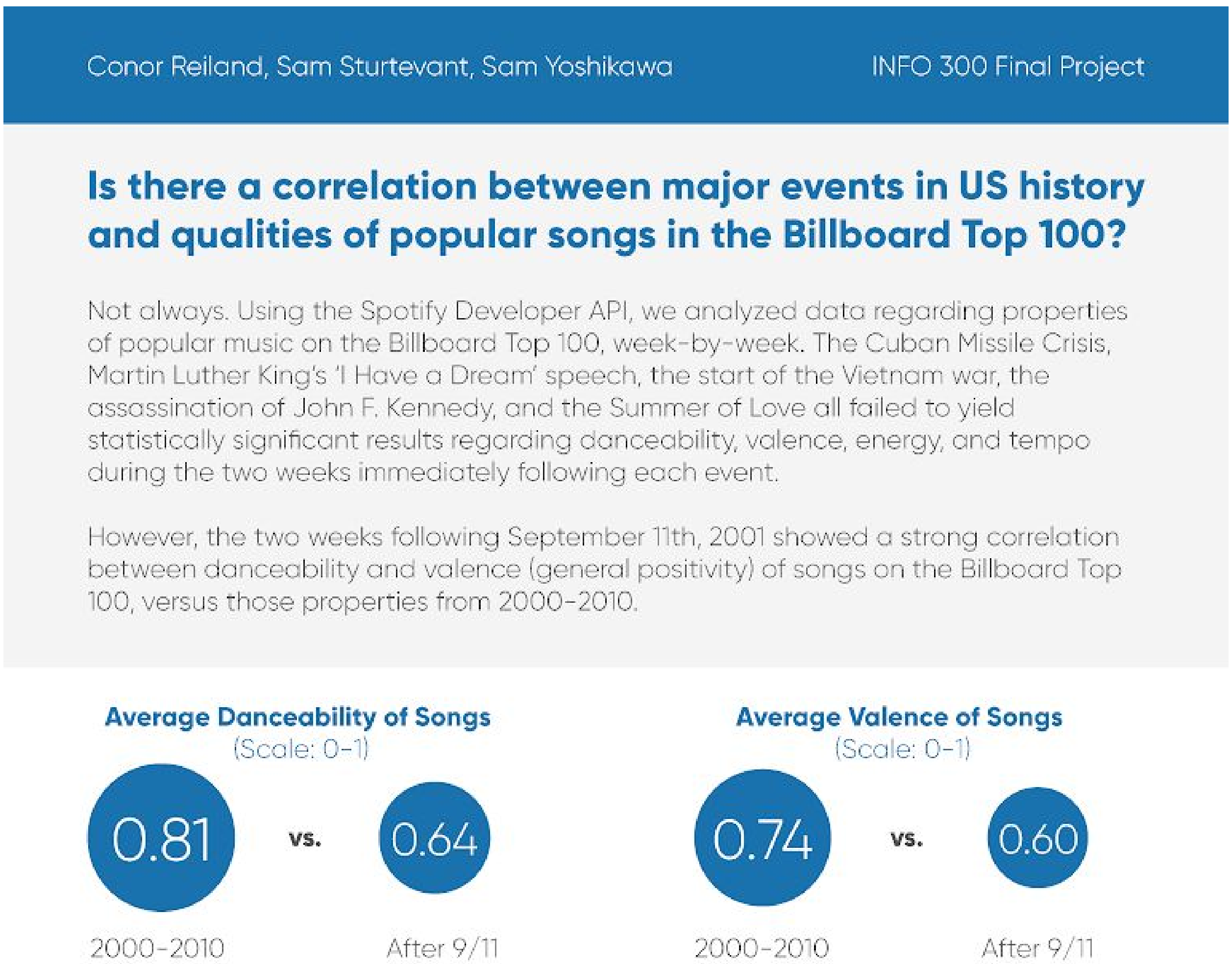
Valence is a measure of the positivity of a song, 1.0 being 100% positive and 0.0 being entirely negative. The density plot for our data, on the left, is much less normally distributed. It is rather left skewed, yet still very dense between 0.0 and 1.0 with no real outliers.. The graph on the left shows the distribution of valence values of every song on Spotify. This shows that music in the Billboard Hot 100 is generally more positive than the songs on the rest of spotify. The skewed distribution is slightly concerning but unsurprising, and is normal enough for analysis considering the skew can be explained by our dataset's relation to the larger spotify dataset.

Statistical Analysis

In order to answer our research question, regarding correlations between major historical events and popular music features, we looked at both danceability and valence of tracks in the Hot 100 for the two weeks following the event. We identified, 3-5 events per decade to examine, ranging from the Cuban Missile Crisis, to the Summer of Love, to the 9/11 terrorist attacks. To analyze changes in music during those two weeks, we first remove the two weeks following from the dataframe containing songs for the decade in which the event happened. With these two subsets, we ran a two sample t-test with an alpha value of 0.05 to determine if the subpopulation mean is significantly different than the mean of the subset of the overall population. For example, the two weeks following September 11, 2001 were removed from the data for 2000-2009, then a t-test was run to compare the mean for the weeks of September 11 - September 26 to the rest of 2000-2009. If the t-test shows a significant difference in means with a p-value below 0.05, then the event had an effect on popular music.

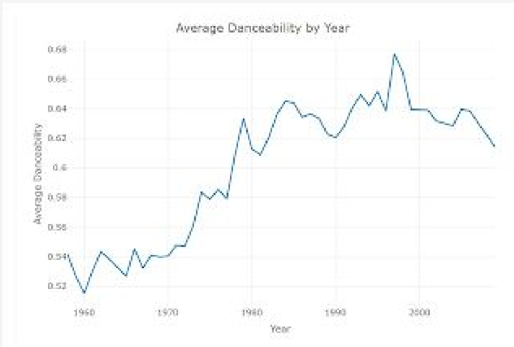
4. Results

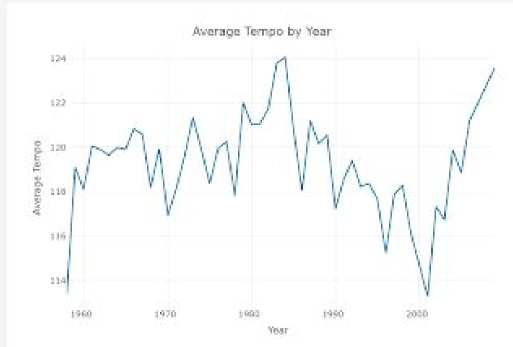
Our results are neatly summarized in the following infographic:

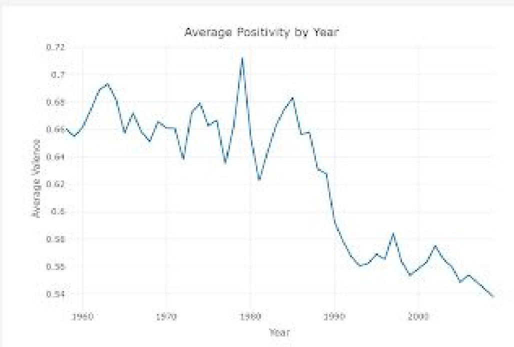


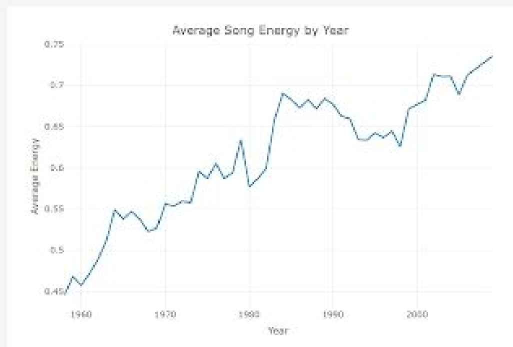
(Charts generated by ggplot)

Properties of Songs by Year

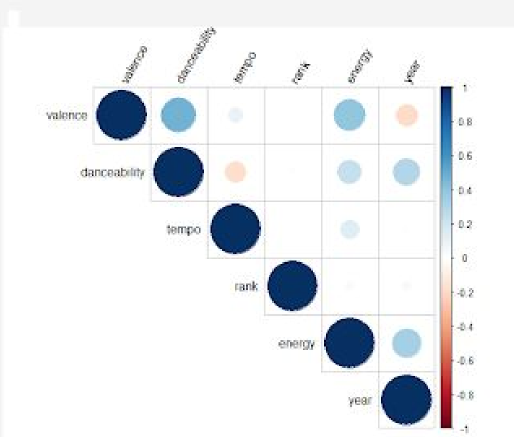








Correlation of Song Properties by Year



This chart shows the strength of correlations between different song properties. There exists co-linearity between some song properties based on how Spotify calculates them; for example energy and danceability are closely tied. We can see the correlation between valence, danceability, energy, and year supports the data presented in the above graphs.

We did not find significant enough results to reject the null hypothesis according to the multitude of t-tests run on various events (Appendix Figure 1). Most tests showed a p-value well above the alpha value of 0.05 as well as a difference in means less than 1%. The data following 9/11 was the only data that showed a statistically significant difference, which is interesting and leads us to believe this may warrant further, more complete research. We did however identify some interesting trends in popular music over time. Danceability steadily rose from the fifties to the eighties, peaking in the mid eighties when disco music was dominating the charts, then declining again. The positivity of music in the Hot 100 has steadily declined since 1958, dropping sharply after the 80s as well. Energy, a measure of the intensity of a song, has steadily risen throughout the years, even after the drop in danceability following the 80s. Additionally, we looked at top genres by decade (Appendix Figure 2), which shows an interesting trend in the adoption of new genres by popular culture. In the 50s, 60s, and 70s, Adult Standards ("sophisticated music" intended for those above 50) dominated the top charts. The final years of the 70s and the decade of the 80s were dominated by Album Rock, while the 90s and 00s were dominated by Dance Pop indicating a possible shift in the age of listeners.

5. Discussion

Results

Our research sought to find notable differences in music that were caused by impactful historical events. The results showed that few events triggered changes in the makeup of popular music. The work done is on a large, macro scale. Looking at events and music trends over a long period and focusing on what was most popular. Much of the work previously done has been on a smaller, micro scale. For example, Hawkins looked at just one song—'Money Can't Buy it' by Annie Lennox. Hawkins wanted to look at how her gender, style, and performance iconography influenced the song and how the song might have conversely influenced those said factors. The focus was around the closed musical text of the song and looking at it through different cultural lenses. Much of the work in the popular music field is somewhat similar. Studies have been investigating the song in comparison to aligning social theories. Our study is comparable in the sense that songs and music are compared with the social forces that made them. However, using more quantitative data rather than qualitative theory as a means to further consider where factors in songs are coming from, as well as looking at larger sets of data is an approach seen more rarely. Although we were not able to reject the null hypothesis some key findings do provide basis for further research. Further exploring how and why some events seemed to trigger changes in music rather than others would largely flush out remaining questions. Moving studies somewhere in between the larger macro scale that our study used and the more micro scale other work has done would advance answering the question of how historical events affect music.

Limitations

Our study relies primarily on data from the Spotify API to determine the characteristics and mood of songs. We are unsure of the method Spotify uses to codify these “track features” as the algorithms used to do so are unavailable to the public. As the features are related conceptually, they are probably also related in terms of calculation, which may cause collinearity that skews data. Additionally, many assumptions were made to analyze the data such as using the two weeks following an event as well as removing every other week from the overall dataset. Although these assumptions were carefully considered, they may have slightly skewed some of the results. We tried to control for confounding variables by comparing events to their decade, but there are obviously many variables that could cause changes in the composition of the Hot

100. For example, if the Beatles release an album shortly before a major event, chances are their music will dominate the chart regardless of differences in the rest of the chart due to the event. Finally, we were limited by time and computing power, which limited the avenues through which we can examine our research question. Machine learning could be used to create complex models and find more robust patterns over time which could be trained and referenced against events in a test set.

6. Reference list

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7. Appendix

```
        Two Sample t-test

data:  zeros$danceability and nine$danceability
t = 4.4524, df = 41659, p-value = 8.514e-06
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.09080884 0.23363505
sample estimates:
mean of x mean of y
0.8055822 0.6433602
```

```
        Two Sample t-test

data:  eighties$danceability and berlin$danceability
t = 2.4445, df = 23487, p-value = 0.01451
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.005263868 0.047857418
sample estimates:
mean of x mean of y
0.6301253 0.6035647
```

```
        Two Sample t-test

data:  eighties$valence and berlin$valence
t = 2.4185, df = 23487, p-value = 0.01559
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.008368748 0.079931871
sample estimates:
mean of x mean of y
0.6537444 0.6095941
```

```
        Two Sample t-test

data:  eighties$valence and black$valence
t = -2.6462, df = 23483, p-value = 0.008145
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.08511017 -0.01267808
sample estimates:
mean of x mean of y
0.6537444 0.7026386
```

```
        Two Sample t-test

data:  sixties$danceability and mlk$danceability
t = -0.26534, df = 37538, p-value = 0.7908
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.02647419  0.02016098
sample estimates:
mean of x mean of y
0.5348302 0.5379868
```

```
        Two Sample t-test

data:  sixties$danceability and summer$danceability
t = 1.227, df = 38649, p-value = 0.2198
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.003074308  0.013366617
sample estimates:
mean of x mean of y
0.5348302 0.5296841
```

```
        Two Sample t-test

data:  zeros$valence and nine$valence
t = 3.4772, df = 41659, p-value = 0.0005072
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.06128366 0.21962556
sample estimates:
mean of x mean of y
0.7400372 0.5995826
```

Figure 1: T-tests

decade	genre
1950	adult standards
1960	adult standards
1970	adult standards
1980	album rock
1990	dance pop
2000	dance pop

Figure 2: Most Popular Genre by Decade