Sentiment Analysis of Top 100 Songs Over Past 14 Years and Different Genres

1 Introduction

The analysis of Billboard Top 100 song lyrics from 2011 to 2023 offers a unique opportunity to explore the evolving emotional landscape of popular music. This study aims to examine the trajectory of sentiments over time, uncovering shifts in emotional expression and identifying commonly used lexicons associated with these emotions. Furthermore, by dissecting lyrical content across different music genres, I seek to elucidate genre-specific emotional motifs and discern variations in emotional expression and vocabulary usage. Through this comparative analysis, I aim to illuminate the diverse emotional landscapes traversed by various music genres and unravel the underlying sociocultural factors contributing to these differences. By undertaking a comprehensive sentiment analysis of Billboard Top 100 song lyrics, this research not only sheds light on the evolving emotional tapestry of popular music but also provides valuable insights into the linguistic markers of emotional expression and the nuanced interrelationships between music, emotion, and culture, thereby deepening our understanding of the intricate dynamics that shape our emotional experiences through music and paving the way for further interdisciplinary inquiries into the realms of music psychology, sociolinguistics, and cultural studies.

To conduct the study, I gathered the top 100 songs' data, including lyrics, release year, and genre information. After data preprocessing, I did the sentiment analysis over different years and different genres, showing an overall upper trend that is possibly related to recent years' social events, especially COVID-19. All code and data, as well as this pdf file, can be found on GitHub.

2 Data

To get the data from 2011 to 2023, including the genre information, song name, artist, and lyrics. Several different APIs and resources were used. I first used billboard.py, a Python API for accessing music charts from Billboard.com, which helped generate the top 100 songs' names, the artists' names, and the year. Then, I used the Genius API to extract the lyrics data for each song. I also needed the genre data, for this purpose, I used Spotify API to get the genre of the artist and the album in which the song was included. After extracting all the data, some simple data processing needs to be done.

Missing data. I couldn't find some of the songs' lyrics or genres. And because I have a relatively large dataset, I deleted songs with missing information. For this study, I only want to include English songs. So, I used a Python library langdetect to detect the language of the music. By now, I can exclude all the non-English songs.

Lyrics processing. In the extracted lyrics data, there are many noises that can have a bad influence on our sentiment analysis and also visualization. Below is a sample of data before processing the lyrics.

Lyrics before processing
88 ContributorsTranslationsPolskiOnly Girl (In The World) Lyrics[Intro] La-la-la-la La-la-la-la La-la-la-la

(Uh, yeah) La-la-la-la [Verse 1] I want you to love me Like I'm a hot ride (Uh, yeah) Be thinking of me (Uh) Doing what you like (Haha) So, boy, forget about the world 'Cause it's gon' be me and you tonight (Yeah) I wanna make you beg for it Then I'ma make you swallow your pride, oh (Uh, uh) [Chorus] Want you to make me feel Like I'm the only girl in the world Like I'm the only one that you'll ever love

Table 1 Lyrics Sample

I implemented several steps to clean up the text for analysis to minimize the noise. Firstly, I removed special characters using regular expressions. Then, I removed stopwords using NLTK's stopwords list to eliminate common words that do not contribute to the overall sentiment of the lyrics. Next, I used SpaCy for lemmatization, which helped reduce words to their base forms, making it easier to analyze the text. Additionally, I removed certain words that appeared to be contributors' information or other noises in the lyrics, such as 'verse,' 'bridge,' 'chorus,' and some vocal sounds.

Genres aggregating. In the process of aggregating genres from the Spotify API data, I encountered a challenge where the API only provides genre information at the artist level rather than the song level. To address this limitation, I made the assumption that an artist's genre reflects the predominant style of their music and, therefore, assigned each song the first genre listed for its respective artist. Initially, there were over 100 different genres identified in the dataset. However, upon closer examination, I found that many of these genres could be grouped into broader categories, such as 'pop' and 'country'. I manually merged some of these similar genres, focusing on those that belonged to larger, more encompassing categories. This process resulted in a final set of 51 distinct genres. After aggregating the genres, I analyzed the distribution of genres among the top songs. Among these, there were 283 pop songs, 210 country songs, 178 hip-hop songs, 45 rock songs, and 35 R&B songs.
After all the data processing work, the dataset has 1245 rows and 8 columns, and we can start the sentiment analysis.

3 Sentiment Analysis and Result

In the study of lyrics, previous researchers have used different methods to conduct sentiment analysis. Cano(2005) investigates the use of NLP tools for the analysis of music lyrics, arguing that lyrics using Naïve Bayes and Cosine Distance Measure. Malheiro(2013) used SVM, KNN, and Naïve Bayes to study and test music emotion classifiers. Sharma(2016) used SentiWordNet, an online lexical resource containing sentiment scores of each word, to study lyrics. In this study, sentiment analysis is conducted using TextBlob. TextBlob is a Python library that offers simple API access to perform various natural language processing tasks, including sentiment analysis. TextBlob allows users to determine the polarity and subjectivity of text. The polarity score ranges from -1 (very negative) to 1 (very positive), and the subjectivity score ranges from 0 (very objective) to 1 (very subjective). Here, polarity is used to help analyze text and classify text into positive, negative, or neutral, thus enabling deeper insights into the emotional content of the Billboard Top 100 song lyrics from the past 13 years. Its ease of use and effectiveness make it a valuable tool for uncovering the emotional nuances present in the lyrics over the years and across different music genres.

3.1 Sentiment description

The sentiment score we got here is the sentiment score of the lyrics in each song. The sentiment analysis of song lyrics from top songs between 2010 and 2023 includes 1,245 entries, with an average sentiment score of approximately 0.0875, indicating a slightly positive overall sentiment. The data shows considerable variability, as evidenced by a standard deviation of 0.1864. The sentiment scores range from a minimum of -0.6714, indicating very negative sentiment, to a maximum of 0.7929, which reflects highly positive sentiment. For other statistics, see below.

Metrics	**Value**
Mean	0.087494
std	0.186421
min	-0.671429
25%	-0.035422
50%	0.076282
75%	0.196104
max	0.792857

Table 2 polarity statistics

3.2 Overall Trend and Top 15 Trend

The analysis was conducted to explore the trends in the emotional tone of song lyrics over time, specifically from 2010 to 2023. While the top 100 songs can reflect certain information of current culture or emotion in society, the top 15 can show stronger information since they are the most popular songs. By analyzing the average sentiment of all songs and specifically the top 15 songs for each year, we aim to understand how popular music reflects changing societal moods, trends, and possibly events that might influence lyrical content.

To make the trend more clear, here are two line charts of the average sentiment of those songs across the past years.

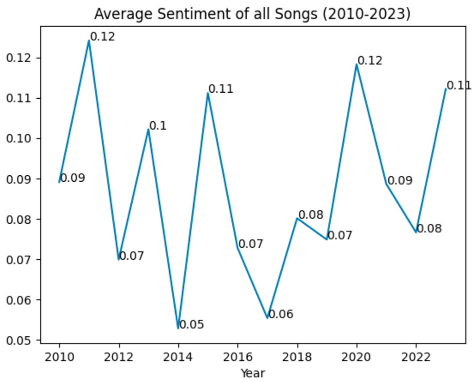

Fig 1 sentiment for all

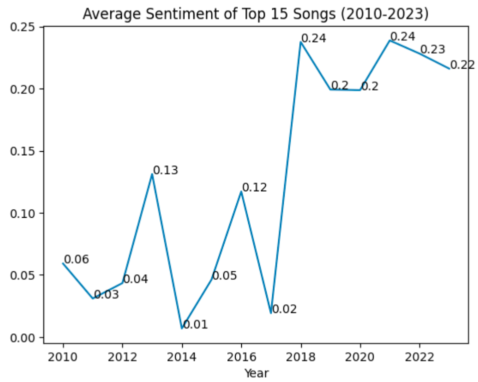

Fig 2 sentiment for top 15

The sentiment trend for all songs fluctuates over the years, starting relatively higher in 2010, dipping towards 2014, and then showing an inconsistent pattern up to 2023. But overall, all the songs maintain approximately the same level of sentiment scores.

On the other hand, the top 15 songs exhibit more pronounced fluctuations in sentiment. Starting from a lower point in 2010, there was a significant peak in 2013, followed by dramatic drops and rises. The sentiment reached its highest in the later years (2018, 2021), suggesting that the most popular songs in these years might have been more positive or uplifting. One thing interesting here is that the top 15 songs have a significant upper trend. From the year 2018 to 2020, there was a light decline, but after 2020, the sentiment scores increased again, maintaining a high in the following 3 years. An implication of this is that during Covid, there were more needs for positive songs, thus showing an upper trend of sentiment scores.

3.3 Word frequency without genres

Now let's look into what words are most frequently used in those positive, neutral, and negative songs. Below are the word clouds of three different types of songs and a table of the 20 most frequent words in those songs.

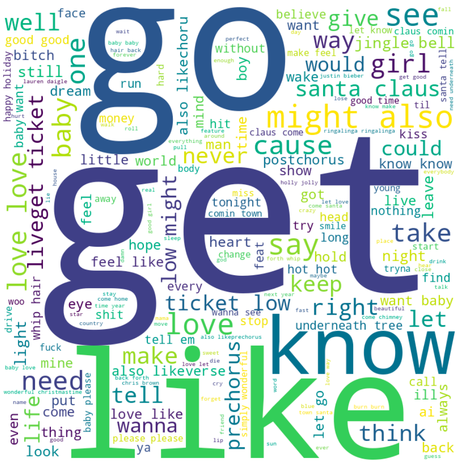

Fig 3 positive word cloud

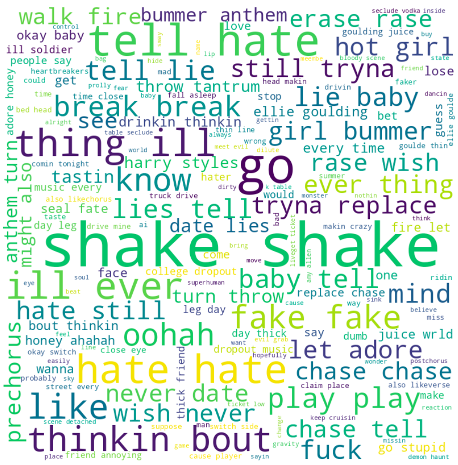

Fig 4 negative word cloud

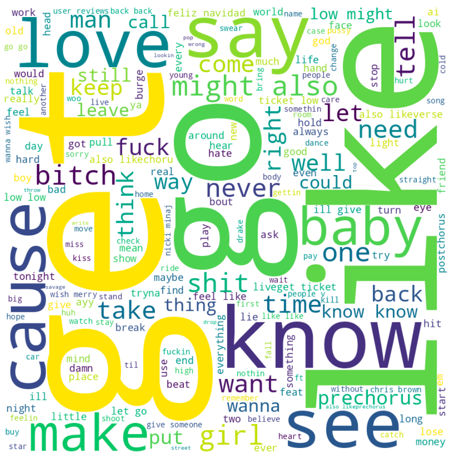

Fig 5 neutral word cloud

	pos_word	count	neg_word	count	neu_word	count
0	not	3090	hate	77	not	5460
1	i	2373	shake	70	i	4879
2	love	1981	tell	53	get	4012
3	get	1826	go	43	like	2866
4	do	1593	i	38	do	2730
5	go	1362	not	36	know	2728
6	like	1343	you	30	go	2378
7	know	1331	baby	28	say	1445
8	baby	1007	ill	27	baby	1373

9	you	950	to	23	make	1354
10	come	889	ever	22	you	1354
11	good	874	thing	22	see	1273
12	see	841	do	20	back	1193
13	let	829	chase	18	let	1140
14	make	755	bout	18	want	1137
15	time	735	fake	18	love	1134
16	want	705	thinkin	17	take	1072
17	one	701	break	17	wanna	1066
18	girl	683	like	17	be	1051
19	say	631	play	16	one	1048

Table 3 Word frequency of 3 types of songs

The positive word cloud is dominated by words like "like," "baby," and "know," which often reflect themes of affection, personal relationships, and introspection. The most frequent word is "not," which might seem counterintuitive but often appears in contexts that negate negative situations, thus contributing to a positive sentiment. Other common words include "love" and "good," reinforcing the positive tone.

The negative word cloud features words such as "hate," "lie," and "break," clearly illustrating themes of anger, deceit, and separation. The word "hate" tops the chart in negative lyrics, followed by words like "shake" and "tell," which can convey even aggressive situations.

Neutral sentiments are represented by more varied vocabulary or verbs, including "think," "know," and "see," which may relate to everyday situations or abstract thoughts that don't convey strong emotions.

3.3 Trend with genres

We have got the genre data in the data processing step. Now let's find out if there is a trend in sentiment and differences in different genres. I first draw a line chart for these main genres: pop, country, hip-hop, rock, and R&B. There are significant signs showing that only Rock and R&B songs showed an upper trend, while other genres' sentiments didn't change a lot. So, here we are to study these two genres in the years 2010 and 2023 since there are major differences when comparing these two years.

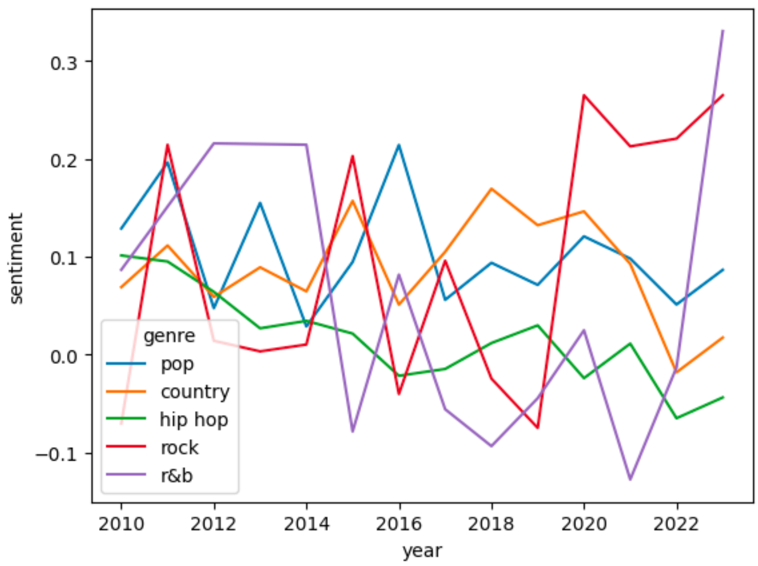

Fig 6 Genre trend

Fig 7 2010-R&B

Fig 8 2023-R&B

The 2010 R&B word cloud features words like "feel," "got," "like," and "tonight," which suggest a focus on personal experiences, emotions, and nightlife. By 2023, the R&B word cloud shows a shift with words like "look," "good," "like," and "fly," indicating a continued emphasis on personal and relational narratives but with a fresher, possibly more reflective and happier vocabulary.

Fig 9 2010-Rock

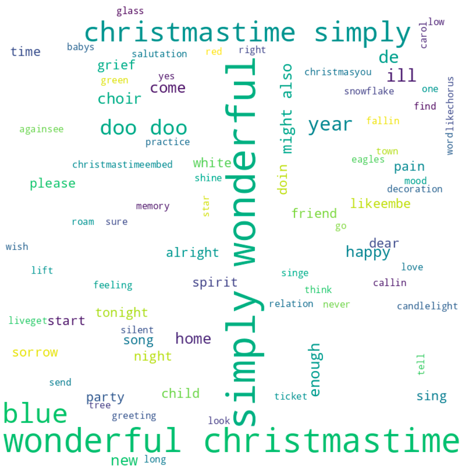

Fig 10 2023-Rock

The 2010 Rock genre is represented by words such as "want," "give," "secret," and "away," reflecting themes of desire, intimacy, and possibly escapism. In 2023, the Rock word cloud transformed to include "wonderful," "Christmastime," and "simply," which could suggest a turn towards more positive, festive, and possibly nostalgic themes.

The lexical shifts in R&B and Rock genres not only reflect changes in musical themes but also potentially point to broader cultural shifts. As sentiment scores have increased, the positivity in the language used has also increased, suggesting that recent listeners may prefer more optimism.

4 Discussion

There are several limitations in this study. I only studied one language, but the top 100 songs not only include English songs, but more languages could also be studied. Moreover, I've only used one model

to get the sentiment scores, a comparison study based on different models can also be studied.
On top of that, with the recommender system more advanced and more users relying on recommendations from those systems, this study could be used to generate playlists that have certain topics by the sentiment analysis result and the frequency of words contained in those songs.

Reference

[1] Mahedero, Jose & Martinez, Alvaro & Cano, Pedro & Koppenberger, Markus & Gouyon, Fabien. (2005). Natural language processing of lyrics. 475-478. 10.1145/1101149.1101255.
[2]Yang, Dan & Lee, Won-Sook. (2010). Music Emotion Identification from Lyrics. 624 - 629. 10.1109/ISM.2009.123.
[3] Malheiro, Ricardo & Panda, Renato & Gomes, Paulo & Paiva, Rui Pedro. (2013). Music Emotion Recognition from Lyrics: A Comparative Study.
[4] Choi, Jinhyuck & Song, Jin-Hee & Yanggon, Kim. (2018). An Analysis of Music Lyrics by Measuring the Distance of Emotion and Sentiment. 176-181. 10.1109/SNPD.2018.8441085.
[5] Sharma, Vivek & Agarwal, Apoorv & Dhir, Renu & Sikka, Geeta. (2016). Sentiments mining and classification of music lyrics using SentiWordNet. 1-6. 10.1109/CDAN.2016.7570965.
[6]Çano, Erion. (2017). MoodyLyrics: A Sentiment Annotated Lyrics Dataset. 118-124. 10.1145/3059336.3059340.
[7] Chen, Xituo(Vito) & Tang, Tiffany. (2018). Combining Content and Sentiment Analysis on Lyrics for a Lightweight Emotion-Aware Chinese Song Recommendation System. 85-89. 10.1145/3195106.3195148.

Disclaimer
I used ChatGPT to make the word choices in this paper more appropriate.