Success in Music Production: Analysis of Hot 100 Songs Over Time

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ABSTRACT

Music is an essential part of our daily life, and with the booming music business and an enormous amount of data, there are various options for investigation. The goal of this master's project is to investigate and contrast successful songs with unsuccessful songs in the field of music data analysis. Using the Billboard Hot 100 chart as the basis for success, feature, sentiment, and keyword analysis is conducted on hit songs and those that have never appeared on the chart.

The results show that a majority of hit songs only appear once on the list, while a select few enjoy an extended stay on the ranking. Furthermore, we find that most Billboard songs exhibit high danceability and low speechiness, contributing to their commercial success. On average, the sentiment of songs has experienced a gradual annual decrease from 1958 to 2019. Finally, a logistic regression analysis is employed on a dataset encompassing all songs, both successful and unsuccessful, to assess the impact of different variables, such as sentiment, on the likelihood of a song becoming a hit. The findings provide essential knowledge for musicians, producers, and industry professionals, and they exemplify the potential of data-driven approaches in understanding and predicting musical trends.

KEYWORDS

Billboard Hot 100, feature analysis, sentiment analysis, keyword analysis, hit songs, data-driven

Introduction

The Billboard Hot 100 is a famous popular music ranking chart that is widely known and and many musicians aim to reach its highest positions. Furthermore, data has shown that Billboard Hot 100 ranking also correlates with song popularity, since the calculation of rank includes listens from music streaming services, album sales, radio plays. The Billboard Hot 100 rank is a great thing to try and predict based on song attributes, and successfully doing this would have natural appeal to those trying to make a 'chart-topping' hit song. I am interested to know which songs made it into the Billboard 100 Hot songs over the years from 1958 to 2019, which artists were most popular and what trends I could identify for sentiment of the songs and what are most common keywords used in the lyrics.

1.1 Research Framework

The research is structured across four distinct stages. In Stage 1, the foundation is laid with a research proposal, delineating clear research objectives and formulating research questions. Proceeding to Stage 2, a robust data collection process is initiated, encompassing the extraction of lyrics through the Genius API. This stage is complemented by data preprocessing and cleansing, ensuring the integrity of the subsequent analyses. Advancing to Stage 3, the core of the research unfolds. Here, a multi-faceted examination of successful songs takes place, encompassing sentiment analysis, as well as top keyword analysis within the lyrics. This stage involves the comparative analysis between songs that achieved Billboard Hot 100 success and those that did not. In Stage 4, where the outcomes, insights, and conclusions are synthesized and visualized (Figure 1).

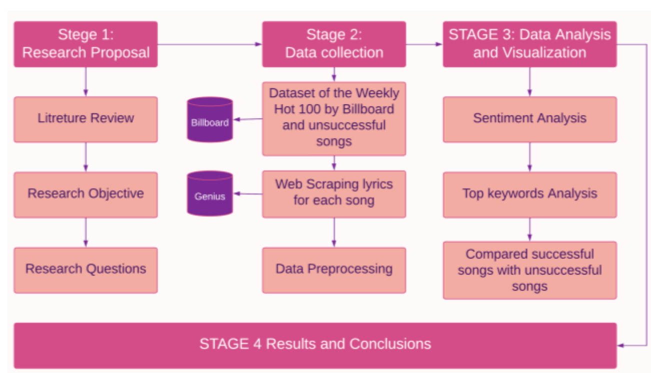

Figure 1: Research Framework

1.2 Research Questions

The goal of this study is to find answers to the following research questions:

(1) What is the number of top hits on Billboard over time?

(2) What are patterns of repeated success among the artists?

(3) What is the temporal trend of the audio features? (e.g., Do tracks become more danceable?)

(4) Is there a seasonal mood change in the successful songs?

(5) What is mood of successful songs over the years?

(6) How has the sentiment of lyrics in music industry changed over time?

(7) What are the top keywords in songs over time?

DATA

The dataset employed in this study draws from Billboard Hot 100. Serving as the preeminent record chart in the United States, the Billboard Hot 100 is published on a weekly basis by Billboard magazine. Its rankings are systematically computed, encompassing various metrics such as sales (both physical and digital), radio airplay, and online streaming within the United States. The data set containing all Billboard Hot 100 entries from 1958 to 2019, offers a representative sample of the musical landscape and serves as a comprehensive resource for unraveling the dynamics and trends of charting songs over the decades.

2.1 Billboard Lyrics Extraction

Genius.com stands as an interactive online platform that combines music, lyrics, and annotations, offering users a comprehensive resource for exploring the intricacies of songs. Functioning as a collaborative hub for music enthusiasts, the website thrives on crowdsourced annotations and interpretations, creating an insightful fusion of musical content and contextual insights. Genius.com offers a free Application Programming Interface (API) that enables individuals to programmatically access a wealth of song and artist data from their comprehensive repository [1]. However, while the Genius API provides valuable metadata, it does not directly offer a means to download the actual song lyrics. Addressing this gap, a solution emerged through the application of Beautiful Soup, a powerful web scraping library. This method allows for the extraction of song lyrics, complementing the Genius API's capabilities. Remarkably, the process has been further streamlined by the creation of LyricsGenius [2], a Python API client that covers these functionalities. In the context of this research, the song lyrics were adeptly scraped from the Genius.com platform using the LyricsGenius Python API client, enhancing the study's breadth and depth by tapping into the textual essence that underlies each song's narrative.

The process of scraping lyrics from Genius.com involves several steps. Initiated by logging into the Genius API site (Figure 2), the journey proceeds by navigating to the Genius API Client management page, where the creation of an API client for the intended application occurs. This action culminates in the generation of a client_id and a client_secret, pivotal in establishing the application's identity within the Genius ecosystem. Following this registration phase, the subsequent step involves setting up a connection to the Genius API, effectively establishing the bridge between the application and the platform's data. To get song lyrics, I used a function I created called "get_lyrics()". I needed to provide the song name and artist as inputs. I then went through all the songs, one by one, using a loop. For each song, I used the "get_lyrics()" function to collect and store the lyrics in a new column called "Lyrics" in the dataset. I made sure to follow the same process for both successful and unsuccessful songs, ensuring that all song lyrics were included and organized for further analysis.

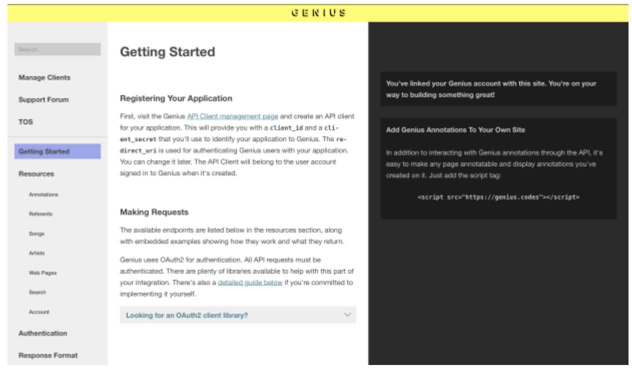

Figure 2: Genius API website

2.2 Data Description

The successful songs dataset granted us access to valuable information spanning the weekly Hot 100 singles chart on Billboard.com from 1958 to 2019, which we found on data.world website [3]. After refining the data, we were left with a total of 21,741 successful songs that met our criteria. On the other hand, the unsuccessful songs dataset encompassed songs that hadn't made an appearance on the Billboard Hot 100 chart and was sourced from Kaggle.com [4]. This dataset, after conducting data preprocessing, contains 23,671 songs. The datasets also included audio features such as acousticness, danceability, energy, instrumentalness, loudness, and valence. A detailed breakdown of these audio features can be found in Appendix A - Audio Features at the end of the study.

TOP ARTISTS AND TRACKES

3.1 What is the number of top hits on Billboard over time?

Over time, it's quite evident that the number of top hits on the Billboard chart has changed, going down. But interestingly, there have been moments when the count of these top hits surged considerably. Figure 3 shows the number of top 3 hit songs per year. These noticeable spikes can be traced back to advancements in technology within the recorded music market [5]. It is pointed out that specific turning points: the first happened when CDs brought digital audio to the forefront, the second as MP3s and file sharing became significant, and the third with the rise of legal digital downloads, linked to the debut of a major music downloading service like iTunes. These technological leaps have left distinct marks on the music industry's landscape, shaping the popularity of Billboard hits across different eras.

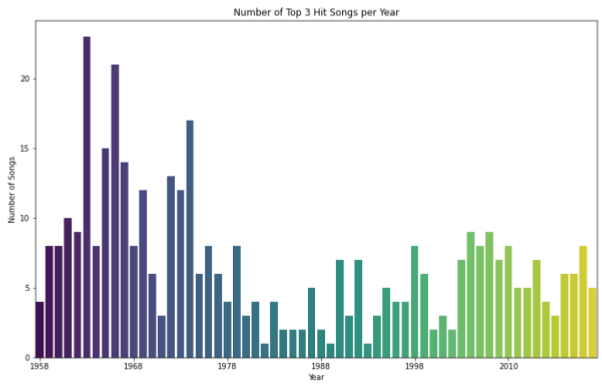

Figure 3: Number of top 3 hit songs per year.

In an unexpected turn, the average time that hits spent on the Billboard chart increased from 1958 to 2007 (Figure 4). A possible reason behind the decrease in the number of unique artists, songs, and top-1 songs over time, despite the substantial rise in the average time songs spent on Billboard, could be explained through something called the "superstar effect" [6]. This effect talks about a small group of individuals who earn a lot of money and dominate their field, like superstars. Building upon this, there's also the "winner-take-all effect" where a few songs capture a large part of the market and become huge hits. This effect suggests that the digital music market, being incredibly efficient, leads to fewer very popular songs (blockbusters) and fewer artists (superstars) performing them. However, what's interesting is that after a certain point, we notice a decrease in this trend.

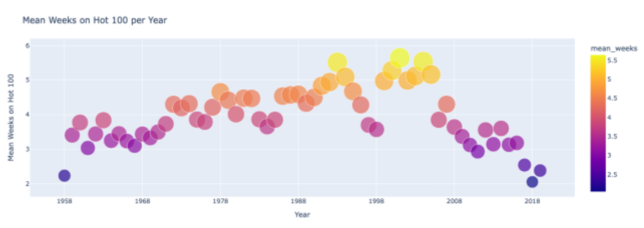

Figure 4: Mean Weeks on Hot 100 per Year

3.2 What are patterns of repeated success among the artists?

Over time, the number of different artists breaking into the top 100 on Billboard's chart is getting smaller. This basically means that each year, there are about three fewer new pop stars competing for a spot in the Hot 100 (you can see this in Figure 5). This change creates a kind of stage where superstars can release more of their songs, and since there are fewer other artists around, their songs have less competition. It's like they have more space to shine and stand out in the crowd. This shift in the music market sets the scene for superstars to bring out their music and have it grab more attention, as there's a bit more room for them to do so.

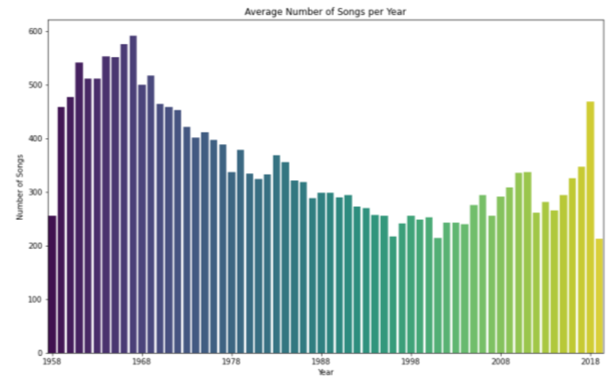

Figure 5: Average number of songs per year.

In Figure 6, the findings paint an interesting picture – the majority of hit songs tend to make just one appearance on the chart, but there's also a group that manages to stay there for a longer period. If we take a closer look, we see that approximately 4,600 out of 7,500 artists (around 62%) who appeared on a year-end chart didn't manage to secure a second hit.

These successful songs also differ a lot from one another. Around 1,2000 songs were only on the chart for just one week (that's about 56.33% of the total), while some songs keep their spot for much longer. What's interesting is the song that holds the record for the longest time spent on the chart during this observation period. It's "Even Though I'm Leaving" by Luke Combs, which managed to stay on the list for 19 weeks (Figure 7). This showcases how some songs have that special something that keeps them riding high for an extended period of time, while others may shine brightly for a shorter duration.

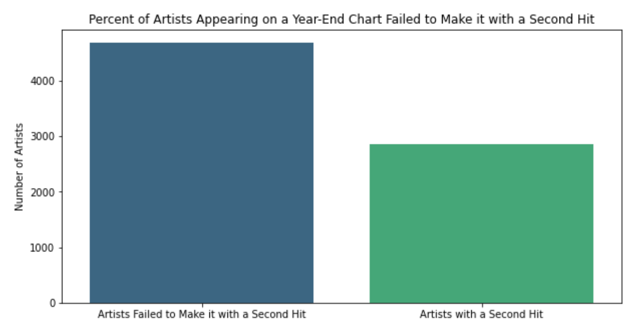

Figure 6: Percent of Artists Appearing on a Year-End Chart Failed to Make it with a Second Hit.

Looking at Figure 8, we can observe the number of songs attributed to each artist. Notably, Drake leads the pack with an impressive count of over 70 songs. Following closely are Glee Cast, the Beatles, and Taylor Swift, making their mark on the list with their substantial contributions.

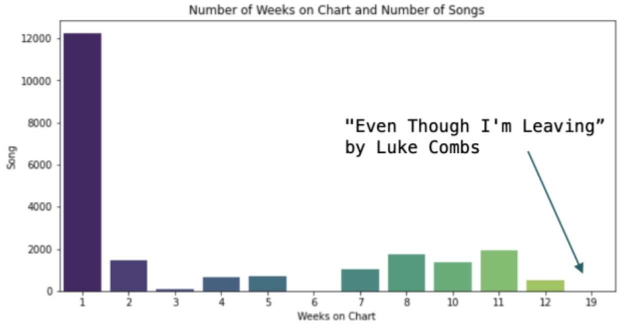

Figure 7: Number of Weeks on Chart and Number of Songs.

When delving into the career spans of the top 10 artists boasting the highest song counts on the chart (as seen in Figure 9), some interesting observations emerge. It's actually quite surprising to note the relatively short durations of the careers of several of these heavily-charted artists. For instance, Glee Cast managed to accumulate more than 60 charted songs within just 5 years. This spurred me to explore the connection between the length of an artist's career and their average count of songs charted per year. Interestingly, this investigation revealed a negative relationship, implying that generally, shorter careers correlated with a higher average of charted songs per year – except for Drake.

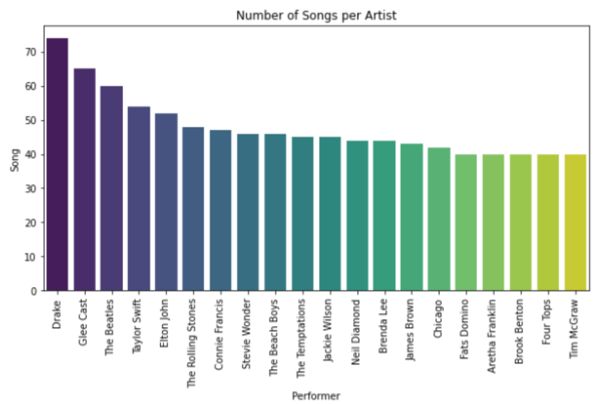

Figure 8: Number of Songs per Artist.

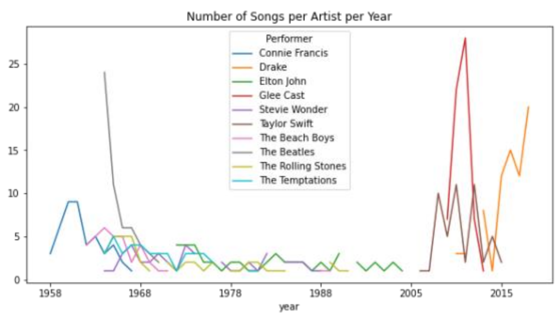

Figure 9: Career span of top 10 artists with the highest number of songs.

As depicted in Figure 10, a notable trend emerges that there's a substantial increase in the number of songs featuring two or more artists over the years. This trend signifies a growing prevalence of collaborations within the music industry. The sharp rise in the count of such collaborative songs underlines a shift in artists' creative endeavors, as more and more musicians are joining forces to create unique musical fusions. This could enriches the diversity of the musical landscape and reflects an evolving synergy among artists from various genre.

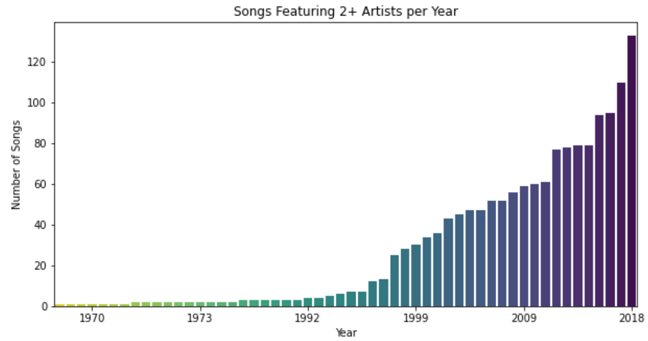

Figure 10: Number of songs Featuring 2+ Artists per year.

FEATURE ANALYSIS

4.1 What is the temporal trend of the audio features?

The study of temporal changes in the audio aspects of Billboard Hot 100 songs offers fascinating insights into the changing musical context. Upon closer inspection of Figures 11 and 12, several noteworthy observations emerge.

Firstly, a distinct pattern emerges in the danceability of the songs. Most tracks exhibit a notably high danceability, often falling within the range of 0.5 to 0.75. This trend underscores the preference for energetic rhythms and dynamic musical elements that encourage movement and engagement among listeners. Additionally, the distribution of energy levels across the songs showcases a remarkable trait. This distribution forms an almost normal curve, indicating a wide range of musical energy encompassed by the Billboard Hot 100. The songs span the spectrum from spirited and up-tempo compositions to mellower, more tranquil offerings. This diversity underscores the versatility and broad appeal of the songs that earn a coveted spot on this influential chart. Moreover, a significant and prevailing trend is apparent in terms of speechiness, a measure of lyrical content in the songs. The majority of tracks exhibit speechiness values ranging from 0 to 0.1, pointing towards an abundance of songs with minimal lyrics. This suggests a considerable emphasis on the musical and instrumental dimensions of the tracks, as opposed to extensive vocal content (Figure 11).

As the analysis goes deeper into the comparison between successful and unsuccessful songs, no discernible differences in the distributions of danceability, energy, and speechiness emerge (Figure 12). The result suggests that these unique auditory qualities do not serve as differentiating criteria between successful and unsuccessful songs. This realization highlights the complicated interaction of different components that contribute to a song's chart performance, indicating that the path to chart-topping success is multilayered and includes a plethora of influences beyond these specific auditory properties.

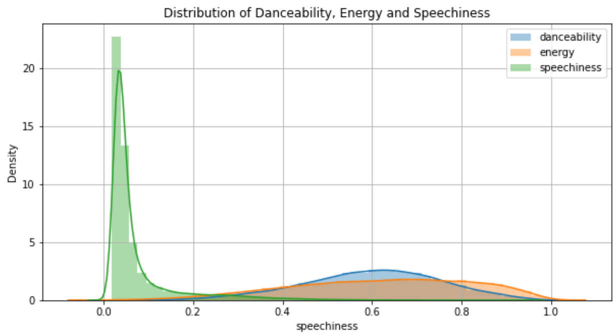

Figure 11: Distribution of Danceability, Energy and speechiness for Successful Songs

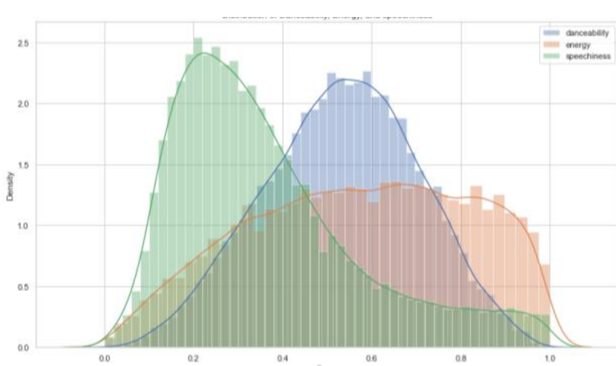

Figure 12: Distribution of Danceability, Energy and speechiness for Unsuccessful Songs

Notably, the danceability of songs demonstrates a compelling pattern that reflects the changing interests of music listeners. It's remarkable to see how the danceability score has risen over time (Figure 13), increasing from an average of 0.55 in 1958 to almost 0.67 in 2019. This trend represents a significant shift in the style of music that connects with listeners, demonstrating a collective preference for more danceable songs. This improvement in danceability does not apply only to successful or unsuccessful songs. Both categories have shown a comparable increase in danceability throughout the years, indicating a larger shift in the musical environment rather than a differentiation between hit and non-hit recordings. This suggests that the trend towards danceable music is a shared phenomenon that transcends the traditional boundary of song success.

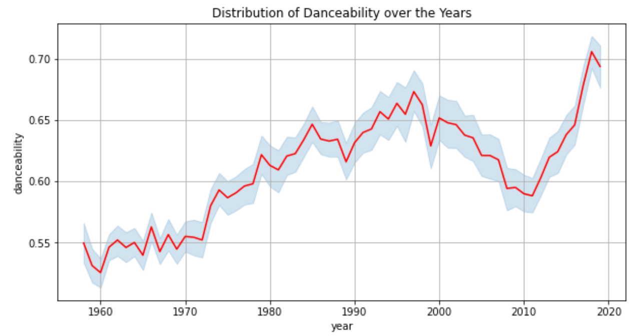

Figure 13: Distribution of Danceability over the Years.

4.2 Is there a seasonal mood change in the successful songs?

The distribution of energy in Billboard singles reveals an enlightening shift in the musical environment throughout time. Figure 14 depicts the growth of this auditory element, which shows a considerable rise in the vitality of songs. This tendency has effects for music's tempo, pace, and general mood, indicating a clear move towards quicker and more upbeat compositions. This dramatic shift in energy distribution through time reflects a larger shift in musical preferences, showing an increasing preference for songs that demonstrate dynamism and strength.

Figure 15 shows how these adjustments in energy distribution present themselves in the context of different months. The data demonstrates clear seasonal changes in music consumption habits. Listeners incline towards songs with lower energy levels throughout the winter months, particularly December, indicating a preference for more gentle and less frenetic tracks. In contrast, when temperatures rise and summer arrives, there is a noticeable increase in the desire for songs that convey stronger energy, corresponding with the season's mood. The month of July, in particular, has the greatest energy levels for songs, indicating a significant peak in the taste for dynamic and intense musical compositions.

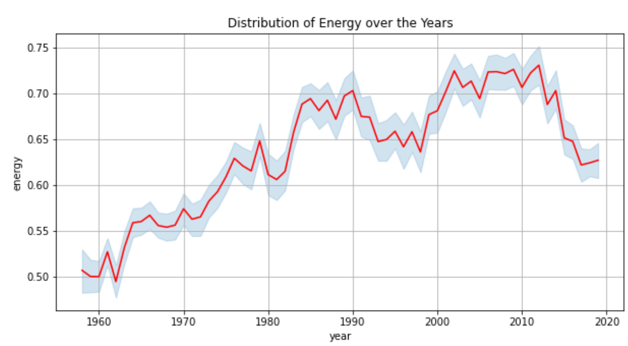

Figure 14: Distribution of Energy Over the Years

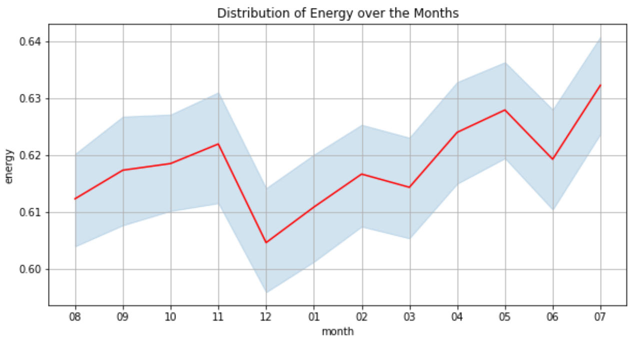

Figure 15: Distribution of Energy Over the Months

4.3 What is the mood of successful songs over the years? (Happy, sad, excited, or Peaceful)

Exploring the emotional landscape of popular songs over time reveals a comprehensive journey identified by valence and arousal. These two dimensions serve as key anchors in various emotional music systems, establishing the foundation for interpreting the emotional nuances of musical works. The valence axis indicates how pleasant or negative an emotion is, whereas the arousal axis measures the strength of physical and emotional response that an emotion elicits [7].

For this purpose, the four quadrants were determined:

1. “happy”: valence > 0.5, arousal (energy) > 0.5
2. “excited”: valence <= 0.5, arousal (energy) > 0.5
3. “sad”: valence <= 0.5, arousal (energy) <= 0.5
4. “peaceful”: valence > 0.5, arousal (energy) <= 0.5

Applying this framework to successful songs across the years, as depicted in Figure 16, unveils distinctive trends. The majority of Billboard hits can be classified as evoking a "happy" mood, with a notable portion encompassing “sad” track. Notably, songs exuding a "peaceful" mood form the smallest segment over the span of 1958 to 2019. This investigation explores the complex emotional palette that underpins Billboard singles, emphasizing the resonant impact of valence and arousal on the musical environment.

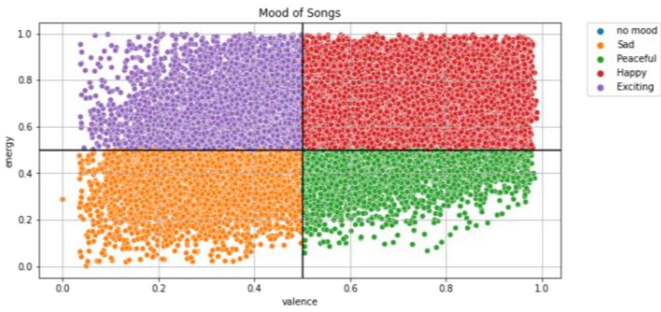

Figure 16: Mood of successful songs over the Years.

5 SENTIMENT ANALYSIS

In the following description, I outline the step-by-step process I followed to compute the sentiment of songs. Firstly, I began by installing and importing essential Python libraries for text manipulation, namely ‘nltk’ and ‘spacy’. These libraries are well-known in the field of natural language processing. Moving on, I proceeded to define the necessary functions. One particular function was crafted to extract sentiment from song lyrics, which were sourced from the 'Lyrics' column within the dataset. To perform the sentiment analysis, I used the the TextBlob library [9]. This Python library serves as a versatile tool for various natural language processing tasks, including sentiment analysis, part-of-speech tagging, and more. Once the libraries were integrated and functions were established, I applied them to the dataset, accordingly, generating the outcomes of my sentiment analysis.

5.1 How has the sentiment of lyrics in music industry changed over time?

The sentiment analysis results, depicted in Figure 17, reveal several noteworthy trends. Firstly, when examining successful songs making it to the Billboard Hot 100, it becomes evident that their lyrics tend to exhibit a proximity to neutral sentiment. The dataset's mean sentiment polarity stands at 0.125, denoting a relatively neutral sentiment overall, where -1 signifies complete negativity and 1 signifies utmost positivity. Second, when looking at specific years, 2019 comes out as having the most negative recorded lyrics, while 1979 had the most positive lyrics. The negativity of lyrics in 2019 outnumbers that of 1979 by a factor of four. Finally, a longitudinal study from 1958 to 2019 reveals a progressive fall in lyric feeling, with an annual average decline of 1.3%.

The sentiment analysis outcomes for unsuccessful songs, depicted in Figure 18. Notably, unsuccessful songs also exhibit a gradual decline in sentiment over time. Specifically for unsuccessful songs, 2018 emerges with the highest recorded negativity in lyrics, whereas the year 1953 presents the most positive lyric sentiment. The results underscore a significant trend shared by both categories: a gradual shift towards more negative sentiment over time. Such a phenomena emphasizes the changing nature of artistic expression in the music industry and opens up new areas for research into the cultural and socioeconomic elements that influence these variations in lyrical sentiment.

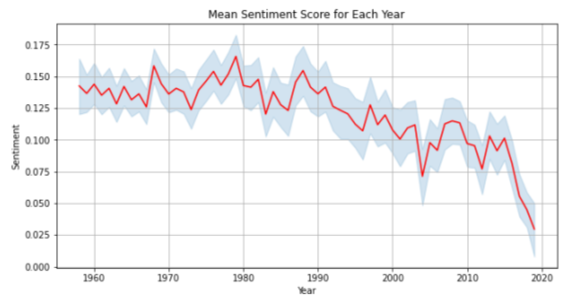

Figure 17: Successful songs’ mean sentiment for each year.

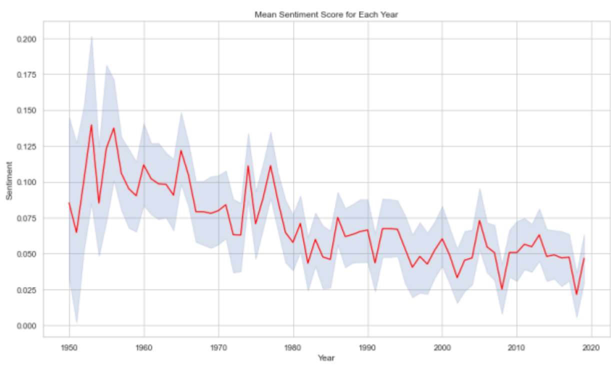

Figure 18: Unsuccessful songs' mean sentiment for each year.

6 TOP KEYWORD ANALYSIS

Conducting a keyword analysis on song lyrics can reveal crucial themes and topics that characterize the essence of the music. To achieve this, I employed the Rapid Automatic Keyword Extraction (RAKE) algorithm, a text mining technique available through the NLTK toolkit, known as rake-nltk [8]. RAKE is designed to identify significant keywords within a body of text by assessing word co-occurrence and frequency. By using rake-nltk, I efficiently extracted keywords from the lyrics of each song under scrutiny. This approach allowed for a comprehensive understanding of the lyrical content and facilitated the exploration of dominant motifs across various songs.

6.1 What are the top keywords in songs over time?

The study of the most common words used in song lyrics offers a fascinating look at how the linguistic and cultural landscape of popular music has changed through time. The most popular search terms between 1958 and 2019 reveal a notable shift in lyrical themes and phrases. In 1958, a sense of positivity and connection emerges from keywords such as "like," "come," "good," and "jump like". These words reflect a prevailing sense of innocence and optimism that characterized the era. Fast-forward to 2019, and a stark transformation is evident, with keywords like "yeah," "niggas," "bitches," and " lil bitch" occupying prominent positions. This shift underscores the changing social dynamics and language norms that have influenced contemporary music.

Figure 19 provides a visual representation of the most common words in lyrics for top songs. Certain phrases stand out as being repeated and embedded in the music despite the number of lyrics. The phrases "one," "like," "know," and "love" stand out as being the most often used terms. This comprehension reveals the concepts that endure throughout generations and genres. While "know" and "love" reflect enduring human feelings and experiences, terms such as "one" and "like" are frequently used to denote universal concepts.

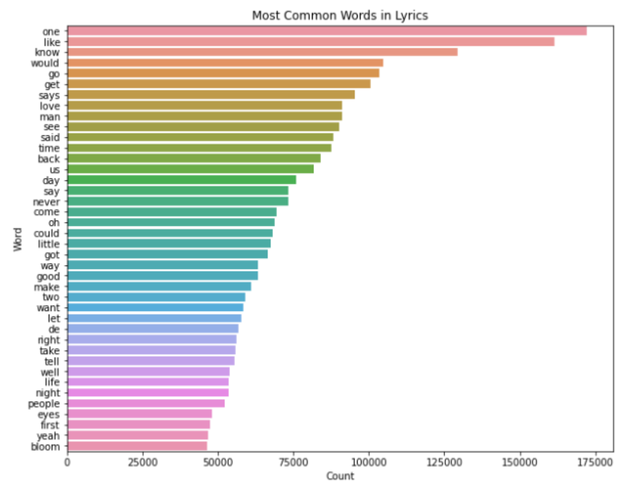

Figure 19: Successful songs' mean sentiment for each year.

7 REFLECTION

Logistic regression is a widely used statistical method that serves as a fundamental tool in predictive modeling and classification tasks. It is particularly effective when the outcome of interest is binary, meaning it can take one of two possible outcomes. In essence, logistic regression helps to understand the relationship between one or more independent variables and the probability of a specific outcome occurring.

In my analysis, I employed logistic regression to delve into the intricate dynamics between various factors and the likelihood of a song achieving hit status. This comprehensive examination included both successful and unsuccessful songs, offering a holistic view of the factors contributing to a song's success. Results of the logistic regression analysis provide valuable insights. The accuracy of the model stands at 0.617, indicating the proportion of correctly predicted outcomes. Precision, measuring the proportion of true positive predictions among all positive predictions, stands at 0.612. Recall, which gauges the proportion of true positive predictions among actual positive cases, mirrors this precision at 0.617. The F1-score, a composite metric of precision and recall, stands at 0.6111. These metrics collectively reflect the model's ability to effectively capture and predict the nuanced relationship between various variables and a song's hit potential. The logistic regression analysis underscores the multifaceted nature of predicting hit songs. While the model's performance indicates a reasonable level of predictive power, the dynamic and often unpredictable nature of music success suggests that a variety of complex factors, beyond those captured in the model, contribute to a song's success.

In logistic regression, coefficients represent the estimated impact of each independent variable on the log odds of the dependent variable, thereby indicating the strength and direction of their influence on the outcome. In the context of this analysis, I selected sentiment, danceability, energy, loudness, acousticness, instrumentalness, and valence as independent variables, while considering "success" as the dependent variable. As depicted in Figure 20, the coefficient results reveal intriguing insights. Notably, all features exhibit positive coefficients, indicating a general positive association with the likelihood of song success. Instrumentalness stands out with a negative coefficient of approximately -1.5, suggesting a negative impact on success. Among the positive coefficients, danceability and sentiment emerge as significant contributors, boasting the highest numerical values. Valence and acousticness, on the other hand, showcase coefficients near zero, implying a comparatively weaker influence.

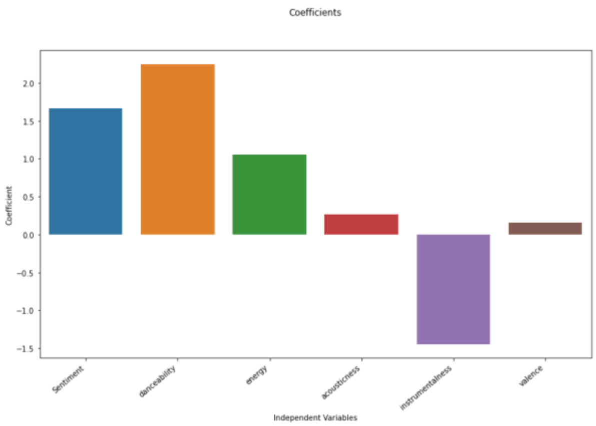

Figure 20: coefficients of logistic regression

8 CONCLOUSION

Finally, the purpose of the study was to provide significant insights into the subtle dynamics of song success in the music industry. We have obtained a better knowledge of the components that lead to a song's appeal by researching into many characteristics of both successful and unsuccessful songs. We discovered significant patterns and trends in the successful songs by examining top songs, top artists, audio features, sentiment, and top keywords.

However, it is essential to acknowledge the limitations of this study. The exclusion of recent songs from the dataset due to period constraints may affect the generalizability of our findings. Furthermore, the research outcomes are primarily applicable to the Billboard Hot 100 chart and the U.S. music market, potentially limiting the broader applicability of our insights. The absence of explicit theoretical frameworks for guiding the research questions also highlights the need for deeper theoretical engagement in future studies.

There are several promising avenues for further exploration. Expanding the dataset to include a more diverse range of songs beyond the Billboard Hot 100 chart would enhance the comprehensiveness of our analysis. A cross-cultural approach would enable us to uncover variations in success factors and trends across different cultural contexts, enriching our understanding of global music preferences. Additionally, the development of machine learning-based predictive models presents an exciting opportunity to forecast song success based on a combination of features, sentiment analysis, and keyword extraction. In essence, while this analysis provides valuable insights into the factors influencing song success, it also serves as a stepping stone for future research endeavors that hold the potential to refine our understanding and prediction of music industry dynamics.

ACKNOWLEDGMENTS

I wish to thank Professor Jürgen Lerner for giving support and guidance.

The codes and data sets used to the project can be found here: https://git.rwth-aachen.de/Sayedmahdi.raghib/success-in-music-production

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A AUDIO FEATURES

Table 1: Audio Features

Features	Description
Acousticness	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	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	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
Instrumentalness	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.
Loudness	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). Values typically range between -60 and 0 db.
Valence	A measure from 0.0 to 1.0 describing 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).