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Sentiment analysis of popular song lyrics in the US from the 1990s and 2010s

BA thesis

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ABSTRACT

Popular music is significant in today's society, reflecting our emotions and cultural trends. While nowadays listeners often focus mostly on melodies and rhythms of a song, they do not pay attention to the messages that these songs are trying to convey. From a linguistic point of view, analyzing the sentiments in popular music offers valuable insights into societal values, cultural shifts, and music preferences. This study aims to conduct a quantitative corpus study in order to even further broaden the field of using sentiment analysis to study song lyrics by looking at the popular songs in the United States from the 1990s and 2010s. In order to do so, the SentiStrength software was used with the goal of highlighting its capabilities in this field. A specialized corpus consisting of songs that had reached the number one spot on the Billboard Hot 100 during those decades was compiled for analysis of these sentiments. The research question for this study intended to understand how the results of the sentiments of both decades differed.

The BA thesis is divided into three sections: the introduction, literature review, and empirical analysis. It begins with an introductory section that defines the term "popular music", discusses the reasons for conducting this study, and provides an overview of the upcoming sections. The literature review focuses on defining sentiment analysis alongside its classifications and limitations, the importance of song lyrics and popular music, and discusses previous works on similar topics. The empirical analysis section focuses on the compilation of the song corpus, explains the nature and functionality of SentiStrength, followed by a presentation of the results of the study and finally a discussion section. The entire thesis ends with a conclusion which summarizes the key points brought out in the course of the study.

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INTRODUCTION

Popular music holds significant importance in today's society as it is not just only something we hear but it also reflects our feelings and provides an insight into what is going on within our culture. DeWall et al. (2011: 1) have argued that popular song lyrics serve as a window through which it is possible to understand cultural changes in psychological states. Music itself possesses a powerful ability to create a deep connection between the sound and the listener, influencing the way people might feel at certain times or even how they see the world around them. For some people, music might even be their first connection to a foreign language and act as a gateway into learning new vocabulary. Additionally, the widespread availability of music streaming platforms like Spotify or Apple Music and the accessibility of charts like the Billboard Hot 100 have made it easier than ever before for individuals to discover the latest popular songs. Nevertheless, the focus of many listeners tends to be on the captivating melodies and infectious rhythms of a song, often overshadowing the importance of its lyrical content and thus leading to a lack of attention towards the song's deeper emotional messages conveyed. By analyzing the sentiments expressed in popular music, researchers can gain valuable insights into societal values and cultural shifts, as well as see the type of music that people prefer listening to. Within the context of this study, popular music is referred to music with worldwide appeal and not just the pop music genre, as other genres of music can also fall under popular music (Brand et al. 2019: 1).

The selection of the topic of the thesis stems from various personal and academic factors. Music has always played a big part of my everyday life. Regular engagement with music, a habit of exploring song lyrics to unravel their hidden meanings, and most importantly, music being one of my initial encounters to the English language, collectively influenced this choice on a personal level. From an academic perspective, there has yet to be a qualitative sentiment analysis specifically focusing on the popular song lyrics of the 1990s and 2010s with the goal of examining the evolving sentiments expressed across these two decades. The study closest to this in terms of topic and methods used is that of Kathleen Napier and Lior Shamir (2018), who conducted a sentiment analysis of popular song lyrics spanning from 1951 to 2016. This research gap opens up the possibility of conducting this analysis, and determining whether these findings align with or diverge from previous studies on similar subjects. From a methodological perspective, this study also tests how effectively sentiment analysis works on song lyrics.

The United States was chosen as the focus of this thesis because of the US having a significant impact on global music trends and the kind of songs that are played on the radios around the world. Because of this global reach, American popular music can often influence the cultures of people living in other countries as well. The US also has a wide range of different popular music genres, from pop and rock to hip-hop and country, which provides a comprehensive analysis of the sentiments expressed in a diverse pool of popular song lyrics. Another reason for choosing the United States was the fact that the US has well-documented official music charts and databases, like the Billboard Hot 100 chart, which provide sufficient information of the songs that are the most popular on a weekly basis. With the US being an English-speaking country, it is naturally assumed that most of the popular songs in that country would be in English, which makes analysing lyrical content and the sentiments expressed in them much easier if the focus is on the English language. This also eliminates the need for translating song lyrics, lowering the risk of losing the original sentiments conveyed in the song’s native language.

The main aim of this thesis is to carry out a quantitative corpus study using sentiment analysis to study the lyrics of top-charting popular songs in the United States from the 1990s and 2010s. Specifically, this thesis would be looking at the lyrics of number one songs from 1990 to 1999 and 2010 to 2019. As a result, this study intends to explore how the sentiments of popular song lyrics of the two decades differ and whether they have become more positive or negative over time. In order to find this out, a corpus of song lyrics from 197 popular songs from the 1990s and 2010s was compiled. SentiStrength version 2.3 was used to calculate the scores of positive and negative sentiments expressed in the chosen song lyrics. The software itself was created by Professor Mike Thelwall and it is free to use for the purpose of academic research. Another goal of this study is to evaluate the effectiveness of SentiStrength as a research tool for analyzing the sentiments expressed in various popular song lyrics. This is done by manually inspecting the sentiments expressed in the song lyrics that were assigned either the maximum positive or maximum negative sentiment score.

The research question for this thesis is: "How do the sentiment scores of the lyrics of popular songs in the US from the 1990s differ from the ones from the 2010s?". Based on previous findings, the hypothesis for this study was that the results of this analysis would also show that the sentiments expressed in the song lyrics of the 2010s would be more negative than the ones from the 1990s. This suggests that the songs of the 2010s would have a lower positive mean score and a higher negative mean score.

The thesis itself is divided into two main sections. The first section provides background information on sentiment analysis, discussing its various classifications and limitations. It also addresses the importance of song lyrics, highlighting their value within the lives of youth and culture in general. This section concludes with a discussion of previous studies that have utilized similar methods or focused on sentiment analysis. The second section begins with an explanation of the steps taken to compile the corpus of popular songs from the 1990s and 2010s for this study. This is followed by a subsection on the SentiStrength software, aiming to enhance the understanding of how it operates and calculates negative and positive scores for every line of a song. The next subsection examines the results of the study and delves further into a few selected songs with conflicting sentiment scores. The thesis concludes with a discussion section, which explains the results of the research, and addresses the strengths and limitations of using SentiStrength as a tool to conduct sentiment analysis. Additionally, it proposes potential other avenues for further research within this field.

1. LITERATURE REVIEW

The section starts with a discussion regarding the definition of sentiment analysis alongside its main objectives according to various researchers. The first subsection also sheds light on the classifications of sentiment analysis and sentiments. It also addresses the limitations of sentiment analysis, such as positive or negative words that can have the opposite meaning in certain contexts or the difficulty in detecting sarcasm. The following subsection touches upon the importance song lyrics have and why they should be studied. The last subsection brings attention to previous research related to sentiment analysis and the studying of song lyrics.

1.1. Sentiment analysis, its classifications, and limitations

Sentiment analysis, also known as opinion mining, is a field of research focused on examining people's opinions, sentiments, attitudes, and emotions towards various entities such as products, services, issues, topics, and their attributes (Liu 2012: 7). This is mostly done through programs that use Natural Language Processing (NLP) in order to analyze whether the given digital text's emotional tone is positive, negative, or neutral. It aims to determine the sentiment polarity of sentences by using certain words from the sentence's context (Pang and Lee 2004: 1). One of the main objectives in sentiment analysis is to have enough information, so when a new text requires processing, its features could be extracted to determine whether it contains positive or negative sentiment based on pre-existing information (Taboada 2016: 327). Pang and Lee (2008: 5) refer to sentiment analysis as "the computational treatment of opinion, sentiment, and subjectivity in text." There are other names that have been used in relation with sentiment analysis that all describe aspects of what it is capable of, such as opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, or review mining (Liu 2012: 7). The term *sentiment*, which was used in relation to the automatic analysis of text and tracking of the predictive judgments used within these texts, was first introduced in research papers written by Das and Chen (2001) and Tong (2001), in which the authors analyzed market sentiment (Pang and Lee 2008: 6). The term *sentiment analysis* in all probability first appeared in the research article by Nasukawa and Yi (2003, cited in Liu 2012: 7), while the term *opinion mining* was first mentioned in Dave et al.'s (2003, cited in Liu 2012: 7) research paper.

According to Medhat et al. (2014: 1), sentiment analysis aims to locate opinions, identify the sentiments they express and classify their polarity, which is why sentiment analysis could be regarded as a classification process. In the case of sentiment analysis, classification process means that sentiments would be regarded as either negative or positive. The authors provide three primary classification levels for sentiment analysis: document-level, sentence-level, and aspect-level. Document-level sentiment analysis determines whether an opinion document expresses either a positive or negative sentiment, while considering that the entire document is focused on a single topic. Sentence-level sentiment analysis classifies the sentiments expressed in each sentence. At first it determines whether the sentence is subjective or objective, and if it is subjective the analysis will further evaluate whether the sentence expresses positive or negative opinions (Medhat et al. 2014: 1). It should be noted that subjectivity is different from sentiment, as numerous objective sentences can convey implicit opinions (Liu 2012: 11). Nevertheless, document and sentence-level classifications do not have a clear distinction, as sentences are basically short documents (Medhat et al. 2014: 2).

According to Napier and Lier (2018: 4-5), aspect-level analysis identifies distinct characteristics of an entity, who is the main subject of the document, and makes use of the writer's opinion of those features to classify the sentiment related to the entity in question. Neither document-level nor sentence-level analyses discover the specific aspects that people liked or disliked, while a more detailed analysis can be performed at the aspect-level. In contrast to document and sentence-level, aspect-level can provide a more detailed analysis. Rather than focusing on language constructs like documents, paragraphs, sentences, clauses, or phrases, aspect-level directly looks at the opinions themselves. It operates on the premise that an opinion consists of both a sentiment, which can be either positive or negative, and a target, typically the subject of the opinion (Liu 2012: 11).

The primary indicators of sentiment are sentiment words, also referred to as opinion words, and they are crucial components in sentiment analysis. The terms *opinion* and *sentiment* can be used interchangeably due to both of them being subjective. The former can serve as a comprehensive idea that covers sentiment, evaluation, appraisal, or attitude associated with an opinion target and the latter can convey the underlying positive or negative feelings associated with an opinion (Liu 2015: 16-17). Sentiments can be classified in several ways. There are linguistic-based, psychology-based, and consumer research-based classifications. Consumer research-based classifications can be separated into two categories, namely rational sentiment and emotional sentiment (Liu 2015: 20). Rational sentiments originate from logical thinking, concrete convictions, and utilitarian attitudes and these sentences are devoid of emotions, as exemplified by sentences like “This car is worth the price.” Emotional sentiments are stronger than rational sentiments as they convey the actual emotions of the subject. Two examples of emotional sentiments occurring in sentences are “This is the best car ever,” and “I am so angry with their service people” (Liu 2015: 20-21).

As these sentences demonstrate, the polarity of sentiments can be categorized as neutral, positive, or negative. Neutral typically means that there is no clear sentiment expressed. Sentiments have various levels of positive or negative intensity, and these could be measured in two different ways. One way would be to use sentiment words or phrases with appropriate strengths. For example, *good* is weaker than *great*, and *dislike* is weaker than *hate*. The second way would be to use various intensifiers and diminishers to increase or decrease the intensity of the sentiment. Some of the most common sentiment intensifiers are *very*, *so*, and *extremely*, while some of the most common sentiment diminishers are *slightly, pretty,* and *a little bit* (Liu 2015: 21).

While sentiment analysis is a valuable tool for understanding textual sentiment, it is not without its limitations. Since sentiment words like *good*, *great*, *bad*, *horrible*, are the main indicators of sentiments, it is important for the tool to properly understand how they are used in a sentence. However, this can be a much bigger problem for sentiment analysis. One issue is that a word usually expressing positive or negative sentiment may have opposite meanings across various ways of being used in sentences (Liu 2015: 10). For example, while the word *kill* usually carries a negative meaning like in the sentence “He threatened to kill his opponent,” it can also have a positive one, like in the idiom “You killed it,” which means that the person being referred to did something very well. In order to give accurate feedback, the sentiment analysis tool needs to understand the context these sentiment words are used in. However, that can be harder than it might seem at first.

As a result of a majority of research in the field of sentiment analysis focusing on detecting the sentiment of the speaker, there can be several instances in which it is unclear whether the sentiment of the sentence is the same as the speaker’s intended sentiment. For example, in the sentence “The pop star suffered a fatal overdose of heroine,” it is ambiguous whether the person stating this is personally affected by this or not (Mohammad 2017: 3). The same issue applies to sentences containing sentiment words that may not express the speaker’s true feelings. This usually occurs in interrogative or conditional sentences (Liu 2015: 11). For example, although both the sentences “Is the movie Titanic good?” and “If Molly thinks the movie Titanic is good, I will watch it,” include the positive sentiment word *good,* they do not express a positive opinion about the movie itself.

Detecting sarcasm in sentences can be challenging in the context of sentiment analysis as positive words or phrases can actually have a negative meaning and vice versa (Liu 2012: 52). Maynard and Greenwood (2014: 6) discuss how one of the reasons machines have difficulties in understanding sarcasm is because people tend to combine words with opposite polarity together in order to show that they are being sarcastic. Adding a swear word to a positive sentiment word also heightens the probability of sarcasm. Sentences that contain phrases or words with opposite meanings are hard to deal with as common knowledge and discourse analysis skills are often required to identify them (Liu 2015: 82).

Associating the presence of strong opinion with specific keywords or phrases in sentences can also prove to be demanding for sentiment analysis (Pang and Lee 2008: 11). Pang and Lee (2008: 11-12) illustrate this issue by using the sentence "Jane Austen's books madden me so that I can't conceal my frenzy from the reader". They explain that while the sentence does indicate a negative opinion through words such as *madden* and *frenzy*, it is still difficult for sentiment analysis to link that strong opinion to certain keywords or phrases in the sentence.

1.2. The importance of song lyrics

It is a general consensus that many people overlook the depth and significance of song lyrics when listening to music. Nowadays listeners prioritize paying attention to the melody, rhythm, and overall sound of the song over the meaning of its lyrics. David West (2019: 3) has pointed out how song lyrics have not been paid much attention to in literary studies. He highlights how this field of study started getting more recognition after Bob Dylan won the Nobel Prize for Literature in 2016, challenging what falls under literature and raising the question of value. In West's (2019: 4) own opinion, song lyrics play a crucial role within popular music, also defined as a realm of human experience that holds immense importance. When the melodies of songs are paired with lyrics, they are able to convey emotions, narrate stories, as well as express opinions or attitudes (Pettijohn and Sacco 2009: 297).

From its debut through revolutionary media in the early 20th century to its widespread accessibility in the late 1950s, popular music has arguably become the most influential cultural form ever created, in the sense that it can be experienced everywhere (West 2019: 4). With its omnipresence, popular music profoundly shapes the lives of the younger generation, influencing their attitudes, behaviors, and identities. Ter Bogt et al. (2011: 148-149) argue that music serves as a way for young people to acquire information about the outside world and that listening to music serves as a way to construct one's identity through various elements such as the lyrics and imagery of the artists they listen to. According to them, young people claim that music is a "crucial medium", which helps them deal with their internal problems, such as depression and anxiety, or cope with feelings of alienation and anger (Ter Bogt et al. 2011: 148). If popular music serves as an expression of the thoughts of the youth who produce and listen to it, the lyrics in these songs should also reflect the interests, concerns, and aspirations of those who listen to it. However, these song lyrics should not be taken as a entirely true representation of youth culture and its values, but instead as a "funhouse mirror", which provides a rather distorted image of how life for the younger generation really is like (Christenson et al. 2019: 195).

1.3. Previous research related to sentiment analysis and popular song lyrics

In recent years, there has been a noticeable growth in studies employing methodologies involving sentiment analysis, particularly within the field of analysing popular song lyrics. Many of these involve building a large corpus of songs in order to conduct sentiment analysis or explore other aspects within song lyrics. Brand et al. (2019) examined two large datasets containing song lyrics from popular songs from 1965 to 2015 and found out that the frequency of negative sentiments in song lyrics increased over time, while the frequency of positive sentiments in song lyrics decreased. In their research, they used cultural evolutionary theory, a field that examines the transmission of cultural variation from one person to another through social learning mechanisms such as imitation, as well as the processes that alter this transmitted variation over time, in order to explain patterns observed in music production.

Kathleen Napier and Lior Shamir (2018) implemented a digital humanities and data science approach in their research by using Tone Analyzer to examine how the sentiments expressed in the lyrics of 6,150 popular songs from the Billboard Hot 100 chart have changed from 1951 to 2016. Through their analysis they found that there was a notable shift towards a more negative tone in the sentiments expressed, with feelings such as anger, disgust, fear, and sadness occurring more, while feelings such as joy, confidence, and openness appearing less.

DeWall et al. (2011) focused on the importance of popular song lyrics as cultural products that can influence the emotions and behavior of individuals. The study investigates whether changes in word use of popular song lyrics over time correspond with shifts in generational personality traits. In order to do so, they used the Linguistic Inquiry Word Count program to analyze the 10 most popular US songs per each year from 1980 to 2007. The result of the study revealed a rise in the usage of words associated with negative and antisocial behavior alongside a decline in the occurrence of words related to positive emotions.

Both Varnum et al. (2021) and Parada-Cabaleiro et al. (2024) have investigated the increasing trend of song lyrics becoming simpler in recent times. However, both authors have taken different approaches when looking into this trend. Varnum et al. (2021) looked at how lyrical simplicity is connected to the quantity of novel song choices by analyzing the ecological and cultural factors that may be linked to it, such as resource availability or rising individualism. The authors gathered data from 14,661 songs that have entered the Billboard Hot 100 chart from its year of creation, 1958, until 2016. In their research, they used various measures of correlation or partial correlation, including Kendall's test, to explore how the selection of new songs over time relates to the average simplicity of lyrics in popular songs. The results of the study indicate a growing simplification of popular music lyrics over time, potentially correlated with shifts in the popularity of various musical genres.

Parada-Cabaleiro et al. (2024) investigated the various dynamics of the English language found in popular music from 1970 to 2020 across the five most favored music genres according to the music streaming platform last.fm. The authors created a dataset containing 353,320 English song lyrics obtained from the Genius online platform in order to look into lyrical descriptors such as complexity, structure, emotion, and popularity. The study included two distinct analyses. In their first analysis, the authors investigated the evolution of popular music lyrics and identified the predictors most effective for modeling a linear trend in a regression task based on release years. The following analysis examined the correlation between the view count of lyrics, descriptors, and the release year of corresponding songs by using a multiple linear regression analysis. The main findings of their research revealed a simplification and enhanced clarity of popular music lyrics over time. They point out a decline in lexical complexity, as evidenced by reduced vocabulary richness and increased readability, and a decrease in structural complexity, such as lyric repetitiveness. Their analysis also confirms previous findings indicating a shift towards song lyrics containing more negative emotions and becoming more personal over the past five decades.

At the University of Tartu, there have been previous studies that have also explored song lyrics or other texts by utilizing methodologies involving sentiment analysis. Mehar Abbas Ali Habibi (2023) examined sentiments expressed in the top-5 charting songs in the

US and the UK for the first two years of the pandemic from March 2020 to March 2022 from a corpus of 1,055 songs. The research aimed to provide further insights into how the emotional tone of popular song lyrics can influence individuals during periods of turmoil. The author used the software SentiStrength to quantitatively assess the positive and negative sentiments expressed in the song lyrics. The findings of the study showed that in the cases of both the US and UK, songs became more positive and less negative, and song lyrics were used as a way to express shared emotions such as loneliness or talk about struggles with mental health that affected people in the wake of the pandemic.

Lotte Parksepp (2019) chose 10 classic American novels and analyzed their Goodreads reviews with the goal of understanding the intensity of the sentiments present in them. In order to do so, the author used the software SentiStrength and found out that both positive and negative sentiments expressed were stronger in 5-star reviews, which, on average, were 63% longer than 1-star reviews. The analysis also revealed that the book "Lolita" by Vladimir Nabokov had the highest overall sentiment in both positive and negative reviews.

Ronald Rae (2020) investigated the potential of sentiment analysis through an examination of five literary works by Mark Twain. The books were analyzed using the programming language R and the RStudio program. Given that sentiment analysis within RStudio lacks full automation, the author had to write a script to achieve the desired objective. They had the goal of wanting to find out the most commonly used sentiment words, examine shifts in sentiment from the start of a book to its finish, and measure the general positive and negative sentiment of the selected works. The main findings of the study were that the most common sentiment word was *pretty*, the usage of positive sentiment words increasing by the end in all of the selected books, and that the examination of sentiment word frequency revealed certain patterns related to the general theme of each of the selected book's narratives.

While the previously mentioned works all utilized sentiment analysis, Mark Aaron Levin (2023) analyzed the frequency of multi-word verbs in hip-hop music from the 1990s and 2010s using the freeware corpus analysis toolkit AntConc. In his analysis, the author gathered the lyrics of the five most popular rap singles from each year spanning 1990 to 1999 and from 2010 to 2019, investigating potential changes in the usage of multi-word verbs within the genre. Additionally, they also conducted a type-token ratio analysis to assess the lexical diversity of hip-hop songs and compare the two decades. It was found that while the 2010s displayed more multi-word verbs, the 1990s displayed a higher lexical diversity of multi-word verbs.

All of these previous works share a common focus of analyzing some aspect of language use or sentiment expression within popular song lyrics or other forms of text. Utilizing various methodologies, including corpus analysis tools like SentiStrength and AntConc, these studies investigate changes in emotional tone, lexical complexity, and thematic content over time. Common findings from these studies indicate a trend towards more negative sentiments in lyrics, increased simplicity, and decreased lexical richness. Additionally, these works highlight the influence of cultural and economic factors on music, emphasizing the importance of using sentiment analysis to understand societal and psychological changes.

2. EMPIRICAL ANALYSIS

The empirical section begins with an explanation of the custom corpus, detailing its manual compilation for this thesis and its contents. Afterwards, the process of gathering and saving the data is discussed. The next subsection elaborates on the nature and functionality of the SentiStrength software. This is followed by a comprehensive description of the entire methodology employed in this thesis. In the subsection discussing the findings of the study, the minimum and maximum scores as well as the average scores and the range of the data of both decades are discussed. Additionally, the sentiment scores provided by the software are compared with the meaning of a few selected songs with the goal of assessing SentiStrength's capability in accurately understanding the sentiments expressed in popular song lyrics. The final subsection briefly highlights the importance of song lyrics as scholarly sources to understand cultural shifts and trends. The research question and hypothesis are discussed in the context of the results of the quantitative sentiment analysis study, as well as suggesting possible reasons for this trend. Furthermore, the subsection explores the capabilities and limitations of the SentiStrength software in analyzing popular song lyrics. Finally, it offers suggestions for possible follow-up studies to further investigate this area.

2.1. The compilation of the corpus of popular song lyrics

For the purpose of this analysis, a custom corpus consisting of the songs that have reached the number one spot on the Billboard Hot 100 chart during the 1990s and 2010s had to be created. This means that all songs that reached that position between 1990 and 1999 alongside 2010 and 2019 were all eligible to be chosen into this corpus. The process involved reviewing the weekly updated Billboard Hot 100 charts from both decades and deciding which songs to include in it. It has to be mentioned that the songs were chosen based on the year they reached the top spot, not the year the song was originally released in. The corpus was initially planned to include 10 songs from each year. However, neither 2014 and 2015 had the intended quantity of hit songs that had reached the number one spot on the chart. As a result, the corpus consists of 197 songs instead of 200.

All songs were manually added into the corpus as there was no already existing corpus of top-charting songs for only those two decades. It is also worth mentioning that three popular songs had to be left out of the corpus, namely the massively popular “Macarena” by Los del Rio, “Harlem Shake” by Baauer, and “Despacito” by Luis Fonsi featuring Daddy Yankee. The viral song “Harlem Shake” from 2013 was left out due to a lack of lyrical content variety, and the other two were left out because the song lyrics were in Spanish and not English. The songs in the corpus were selected based on the duration of each number one song’s consecutive stay in that position, with priority given to those that remained on the top spot for at least three weeks. The longer a song stayed at the number one position, the more it demonstrated its influence over various listeners, showing its strong resonance with them and indicating the extent to which people listened to or purchased the song.

The lyrics of the popular songs from the two decades in this corpus were obtained from the online lyrics databases AZlyrics and Genius, both of which are freely accessible to everyone. Since AZlyrics is deemed a more reliable source for obtaining highly accurate song lyrics, the majority of the lyrics in this corpus are acquired from there, while any unavailable lyrics are retrieved from Genius. Citing two sources for the corpus provides an opportunity to cross-check the accuracy of the lyrics, mitigating the risk of any potential errors. The song lyrics were copied from both online lyric databases and pasted into .txt files through the free and open-source text editor Notepad++. All songs were saved as separate .txt files and organized into separate folders according to the years they occupied the top spot on the Billboard chart. This allowed the SentiStrength software to properly assign positive and negative sentiment scores to all songs within the same year simultaneously.

2.2. SentiStrength

SentiStrength is a software that was developed by Mike Thelwall, who is a data science professor at the University of Wolverhampton in the United Kingdom. SentiStrength is a lexicon-based program that uses nonlexical linguistic information and rules to detect positive and negative sentiments in short informal texts (Thelwall et al. 2012: 166). One of SentiStrength's key features is that it provides human-level accuracy when identifying the strength of sentiments present in social web texts with the exception of political texts (SentiStrength n.d.). After providing the software with a sample text, it reports two sentiment strengths: varying from -1 (not negative) to -5 (extremely negative) and from 1 (not positive) to 5 (extremely positive). A score of 1 indicates that the sentiment is classified as neutral.

The positive and negative sentiment weights for various terms, which have been classified by humans, can be located within the EmotionLookupTable.txt document situated in the SentStrength_Data folder of the software's directory. The word strength list consists of 2,489 terms, of which 228 are of neutral polarity. It is important to note that all of these sentiment word terms have been checked through dictionaries by humans to avoid any incorrectly matching words (Thelwall et al. 2012: 166). It is with the help of this table that the program can provide human-level accuracy when analyzing the texts provided to it. This table can also be manually adjusted by editing the file, however, it has been left unchanged within the course of this study.

The majority of opinion mining algorithms aim to discern the sentiment polarity in text, categorizing it as positive, negative, or neutral. While this suffices for many various purposes, texts frequently contain a blend of positive and negative sentiments. In certain contexts, it is crucial to identify both simultaneously and detect the intensity of the expressed sentiment (Thelwall et al. 2010: 2544). In the context of song lyrics analysis, detecting both positive and negative sentiments is important for accurately understanding the emotional nuances conveyed by the artist in their lyrics, which, as a result, enhances our interpretation and appreciation of the music listened to.

SentiStrength incorporates a spelling correction algorithm that detects misspellings of the standard spellings of words that have been caused by repeated letters. This feature automatically removes excessively repeated letters from words if they occur more frequently than typically in English. Additionally, if a word is not found in the English dictionary, the algorithm deletes repeated letters to form a valid dictionary word (Thelwall et al. 2012: 166). For example, "heeeyyy" would be automatically interpreted as "hey", while "add" would not be immediately interpreted as "ad".

Among its many features, SentiStrength also includes various lists such as a booster word list. This list consists of words that intensify or diminish the emotional impact of subsequent words, whether positive or negative. Each booster word typically increases the emotional intensity of their following words by 1 or 2 points, with examples being words such as *very* or *extremely*. For instance, if the word *happy* has a positive sentiment score of +2, then *very happy* would have a positive score of +4. In contrast, a booster word like *some* reduces the positive sentiment of a word by increasing its negative sentiment by 1 point. Moreover, SentiStrength also includes a negating word list, which features words that reverse the emotional polarity of subsequent words, including any preceding booster words. For example, if *very happy* has a positive sentiment score of +4, then *not very happy* would produce a negative sentiment score of -4 (Thelwall 2010: 2551). Additionally, SentiStrength includes an emoticon list with assigned strengths (positive +2 or negative -2). Nevertheless, this feature proved unnecessary for the present study since none of the songs in the corpus of popular songs contain any emoticons.

2.3. Methodology

After compiling the corpus of popular song lyrics, the first course of action was to run all of the 197 songs through SentiStrength. As previously mentioned, all the songs were saved into separate folders according to the years that they were in the top spot, which made it easier to analyze several songs at once. Instead of having to conduct sentiment analysis one song at a time, this allowed the software to examine all of the song lyrics for each year in one go.

After the songs were assessed by the software, it generated result .txt files containing positive and negative sentiment scores for each line of the song. These new files were saved into the same folder as the files of the popular song lyrics. Each output file consisted of three columns: a line from the song, a positive score, and a negative score. It was important to open each song separately in Excel to calculate their average positive and negative sentiment score using the AVERAGE function. All of this had to be done manually, as there was no way to run this function through separate .txt files simultaneously. During this part of the process, it was also important to ensure that no mistakes were made, such as accidentally marking down the wrong number of lines, as that would result in an inaccurate calculation.

The next step involved aligning each calculated positive and negative score with its respective song in an Excel sheet containing the entire corpus of songs. This ensured that all scores were organized in one single location for efficient analysis of the sentiments present in the corpus. To determine the range of the sentiment scores in the corpus, the MIN and MAX values for each decade were calculated, followed by the subtraction of the two values. The dataset's range is analyzed to pinpoint extreme values in both positive and negative sentiment scores within the corpus, which as a result, provides a better understanding of the dataset's distribution. Afterwards, the AVERAGE function in Excel was used to calculate the mean scores of the positive and negative sentiments conveyed in song lyrics in both decades to compare their sentiment scores and see how much they differ from each other.

2.4. The results of the quantitative sentiment analysis

The analysis of the datasets revealed that during the 1990s, the maximum positive sentiment score was 2.38 and the minimum was 1.04, which resulted in a range of 1.34. For negative sentiment scores, the results showed a maximum score of 2.02 and a minimum of 1.00, resulting in a range of 1.02. The mean score for positive sentiment conveyed in the popular song lyrics from 1990 to 1999 was 1.44, while the mean score for negative sentiment score stood at 1.21. Looking over at the results of the 2010s, the maximum positive score was 2.41 and the minimum was 1.04, which means that the range value was 1.37. In the case of negative sentiment scores, the maximum score was 2.94 and the minimum was 1.00, resulting in a range of 1.94. Popular song lyrics from 2010 to 2019 showed an average positive sentiment score of 1.39 and an average negative sentiment score of 1.32. The main results are also summarized in Table 1 and the full list of popular songs alongside their sentiment scores can be found in Appendix 1 and Appendix 2.

Table 1. The average sentiment scores and ranges of sentiments from the 1990s and 2010s.

Decades	Average Positive Score (with Range)	Average Negative Score (with Range)
The 1990s	1.44 (1.04 – 2.38)	1.21 (1.00 – 2.02)
The 2010s	1.39 (1.04 – 2.41)	1.32 (1.00 – 2.94)

It is notable that in the 2010s, there was a significant increase in the maximum negative score of 2.94 compared to the 1990s score of 2.02, indicating that there was at least one song with a much higher negative scoring in that decade. The results also show that, on average, popular song lyrics from the 1990s tended to convey slightly higher levels of positive sentiment compared to the lyrics from the 2010s. In contrast, it is interesting to see that the song with the highest positive sentiment was in the decade with the lower mean score for positive sentiment. It is also worth noting that the minimum positive and negative scores were identical for both decades, with the minimum positivity score being only 0.04 higher than the negative result. Nevertheless, the results of the average negative and positive scores show that popular song lyrics have become less positive and more negative over time.

To delve deeper into understanding how the software understood and rated the sentiments of popular song lyrics, two songs were selected that had noteworthy results. The aim of this was to evaluate SentiStrength's ability to understand the sentiments conveyed in various popular songs and, thereby see the strengths and weaknesses of the software. The selected songs were "Gangsta's Paradise" by Coolio featuring L.V. and "I Swear" by All-4-One. These two songs were chosen as the scores given to them by SentiStrength seem to clash with what kind of sentiments are actually being expressed in the song. These songs were chosen to scrutinize how the software rated them, aiming to compare its sentiment scores with their interpretation of the sentiments conveyed in the song lyrics.

Starting off with "I Swear" by All-4-One, which had a mean score of 1.36 for the positive sentiment conveyed through its lyrics and a mean score of 1.67 for negative sentiment. Despite the song being a ballad in which the narrator pledges their eternal love to the significant other, suggesting that the positive sentiment should be higher, the mean score for negative sentiment is unexpectedly higher, prompting further analysis into the software's interpretation of this song. Upon closer inspection, it is revealed that the software rated words like *swear* and *hang* as words with negative connotations. It is also interesting to note that in the lyric "You'll only cry those happy tears", the software gave it a positive score of +2 and a negative score of -4 because of the word *cry* even though it is followed with *those happy tears*, which should indicate a positive sentiment due to the adjective *happy*. Because of the song constantly repeating the phrase "I swear", it is understandable after manual inspection why the software would rate the song as more negative, when it actually conveys positive sentiments.

The results of the analysis of "Gangsta's Paradise" by Coolio featuring L.V. contrasts from the results of "I Swear" by All-4-One. The song, which is about the difficulties and fears around street life during the 1990s, is scored as having a mean score of 1.82 for positive sentiment and only 1.46 for negative sentiment. When looking at the detailed results, it is revealed that this is mostly due to the chorus of the song repeating the phrases "Been spendin' most their lives livin' in the gangsta's paradise" and "Keep spendin' most our lives livin' in the gangsta's paradise" from which the word *paradise* is the biggest factor for boosting the sentiment of the entire song by giving all of these lines a positive score of +4. It seems that the software does not understand the ironic title of the song, which instead of an actual paradise, depicts the cruel conditions of street life during that time. This song demonstrates one of the weaknesses of SentiStrength – analyzing sarcasm and irony.

2.5. Discussion

Song lyrics act as a window into cultural studies due to them reflecting and expressing the values, beliefs, and emotions of a society. Music surrounds us daily, becoming an integral part of our lives, with many people listening to it on a regular basis throughout their everyday activities. As a result, people are bound to be influenced by the messages conveyed through song lyrics in one way or another. DeWall et al. (2011: 6) have noted that even just listening to the most popular songs on the radio can offer people greater insight into their generation's current psychological traits and how these traits may evolve over time.

While the study of song lyrics may not be considered a standalone academic field, it has still proven to be a valuable and useful source of information by many researchers, highlighting its importance for scholarly studies. For example, regarding the field of culture studies, Pettijohn II and Sacco Jr (2009) have studied the themes and trends of popular music during 1955 to 2003 in the United States and investigated how social, economic, and politically threatening conditions can influence song preferences through their lyrics. It was discovered that songs with longer sentences and a higher frequency of first, second, or third person pronouns were more popular. Additionally, during rough periods of time, listeners favored song lyrics that were more romantic, included more future references, and mentioned social processes such as friendship or having conversations. They also showed a high preference for songs with more sports references (Pettijohn and Sacco 2009: 304-305). It has to be noted that this study is only one of the countless examples of song lyrics being used as scholarly sources with the goal of understanding cultural changes and trends.

Reflecting on the findings of previous research involving the sentiment analysis of song lyrics discussed in Section 1.3 and the present thesis, it would be intriguing to examine how much the outcome of both of them align with each other. The research question of this study was “How do the sentiment scores of the lyrics of popular songs in the US from the 1990s differ from the ones from the 2010s?”. Based on previous research, it was hypothesised that the sentiments expressed in popular song lyrics would become more negative over the years. The sentiment analysis revealed a decrease in positive sentiment score and an increase in negative sentiment score from the 1990s to the 2010s. In more detail, the mean score of positive sentiment expressed during those years went from 1.44 to 1.39 and the mean score of negative sentiment went from 1.21 to 1.32. These findings support the study’s hypothesis that popular song lyrics have become more negative over the two decades. They are also consistent with the findings of previous analyses by researchers such as DeWall et al. (2011) and Napier and Shamir (2018), which also support this negative trend.

While there is no definitive reason for this increase in negativity, one possible explanation could be the rise in popularity of the hip-hop music genre during the 2010s. Werner (2019: 689) notes in his research that during the period from 2011 to 2016, rap music experienced a growth in profanity rates, resulting in the songs of that genre having more explicit lyrics. Brand et al. (2019: 10) have observed that songs with more negative lyrics tend to be more successful, possibly reflecting a general negativity bias among music listeners. However, this does not seem to be the case with the current study, as there are more songs in the corpus with higher positive sentiment scores compared to ones with higher negative scores.

To conduct sentiment analysis and explore changes in the sentiments expressed in popular song lyrics over the two decades, the study utilized SentiStrength. So far, this software has been underused as a tool for conducting sentiment analysis, especially in the field of studying song lyrics. Therefore, further exploration of the software's capabilities to automatically analyze the sentiments conveyed in songs is crucial in order to understand its strengths and weaknesses as a research tool. Consequently, evaluating SentiStrength's effectiveness for future research on song lyrics also became one of the main aims and merits of this study.

In order to understand some of the strengths and weaknesses of the software, it is important to look at some other examples of the songs with the most noteworthy sentiment scores from the corpus during both decades. The song with the highest positive score in the 1990s was "That's the Way Love Goes" by Janet Jackson with a score of 2.38. This score can be attributed to the song's more sensual and romantic lyrics, from which the constant repetition of the title of the song has the biggest impact to it, with each line scoring a positive sentiment score of +3 and a neutral negative score of -1. It is important to note that the software actually understood the positive sentiment expressed in the line “Come with me, don't you worry" by scoring it a +4, even though it has the negative word *worry* in it. This highlights that the software's ability to understand context goes beyond simple keyword recognition, further proving its usefulness for sentiment analysis.

The same can be seen in the results of "Lose You to Love Me" by Selena Gomez, which had the highest positive sentiment score of the 2010s with 2.41. The lyrics of the song discuss letting go of a past lover in order to rediscover and love oneself again. However, the repetition of the word *love* somewhat unduly inflates the positive sentiment score of the song. The song's high scoring may be mostly contributed to its chorus, namely the repeating of the lines:

"To love, love, yeah

To love, love, yeah

To love, yeah

I needed to hate you to love me, yeah"

SentiStrength scored both of the first two lines with +4, while the last two lines were scored +3. It could be argued that the repetition of the word *love* not only influences the software to rate it higher but also intensifies the emotional impact of the song on the listener, amplifying the feelings expressed in the song. It is worth noting that what makes song lyrics unique compared to other forms of text is the presence of repetitions. This is the main reason why all the repetitions were left in the song corpus of this study. One could contend that repetitions are part of the appeal for the listeners of popular songs, and removing them would fundamentally alter the understanding of the song and the emotions it may try to convey.

While SentiStrength being able to provide human-level accuracy with its automatic sentiment analysis is one of its strengths, it is also prone to making mistakes. As brought out in Section 1.1 of the literature review, sentiment analysis in general has weaknesses with identifying sarcasm or irony, as well as with linking the presence of strong opinions to particular keywords or phrases within sentences. Both of these limitations were also seen in some of the results of this study, with the example of SentiStrength's inability to understand sarcasm and irony within the context of song lyrics already being highlighted at the end of Section 2.4.

In the case of linking strong opinions to particular phrases within sentences, the results offer an example in the form of "We Found Love" by Rihanna featuring Calvin Harris. The song itself was given a positive sentiment score of 2.16 and a negative score of 2.55. The title of the song is part of the lyric "We found love in a hopeless place", which is constantly repeated throughout the song and SentiStrength scored the line as having a positive sentiment score of +3 but a negative sentiment score of -4. Given that the song is literally about finding love during rough times, it should mean that meaning of the phrase should be more positive and not negative.

Overall, the SentiStrength software was able to accurately rate the sentiments expressed in the popular lyrics, confirming the findings of previous studies that have also looked into song lyrics. The benefits of using the SentiStrength software include it being user-friendly to people interested in conducting sentiment analysis, its ability to process a large number of song lyrics quickly, and its easily understandable results. The weaknesses include the software's inability to fully understand all contexts and the actual meanings of some lyrics due to the usage of certain keywords, as well as the repetitiveness of certain negative keywords leading to inaccurate results. For example, both of these instances can be seen in how the song with the highest negative score of the 1990s, namely "Here Comes the Hotstepper" by Ini Kamoze, got its score of 2.02 mostly due to having the word *murderer* constantly repeated throughout the song.

Additional research is required to further look into the limitations of this thesis, such as explaining the reasons for popular song lyrics becoming more negative in the 2010s compared to the 1990s. It could also be interesting to look into how the social, economic, and politically threatening conditions of the 2010s influenced popular song preferences and see if those events had anything to do with popular song lyrics becoming more negative. A follow-up sentiment analysis could focus on different genres as well and see if these sentiment trends vary significantly between genres such as pop, hip-hop or rock. Lastly, it would be worth looking into how repetitive lyrics affect the sentiment scores of song lyrics by comparing the sentiment scores before and after manually removing repetitions.

CONCLUSION

Popular music plays a crucial role in today's society as it not only provides a soundtrack to our everyday lives but also mirrors our emotions and offers insights into our culture. Ter Bogt et al. (2011: 148-149) suggest that music helps young people gain information about the world around them and serve as a way for people to create their identities through the lyrics they listen to or the imagery of the artists they look up to. In recent years, there has been a notable increase in studies analyzing popular song lyrics. These studies have found a trend toward lyrics becoming more negative, more simple, and there being a decreased lexical richness.

This study aimed to examine whether this would remain the case when comparing the sentiments of popular songs from the 1990s and 2010s, for which this trend has only been investigated up to the year 2016. The purpose of this BA thesis was to conduct a quantitative corpus study using sentiment analysis in order to understand the sentiments conveyed in top-charting popular songs in the United States from the 1990s and 2010s. Another aim of this study was to assess how well the SentiStrength software could understand the sentiments present in these song lyrics. As SentiStrength had been previously underused in this field, this thesis aimed to expand the application of this tool in the context of popular song lyrics analysis, providing new insights into its strengths and weaknesses.

The research question of the study aimed at exploring the differences between the sentiments expressed in the popular songs of the 1990s compared to the ones from the 2010s. This was followed with the hypothesis based on the findings of previous studies that the song lyrics would become more negative. In order to find an answer to this research question, a corpus of popular songs had to be manually compiled. The corpus consisted of a total of 197 songs that had reached the number one position on the Billboard Hot 100 chart from 1990 to 1999 and from 2010 to 2019, prioritizing those songs that had stayed on that spot for more than three weeks.

To carry out the sentiment analysis, the SentiStrength software was used to quantitatively measure the positive and negative sentiments conveyed in the song lyrics of all 197 songs. After evaluating all of the songs with the help of SentiStrength, each of them had to be manually run through Excel and their mean score for positive and negative sentiment had to be calculated. The results were put into one Excel sheet, from which the extreme values in both positive and negative sentiment scores were found in order to determine the range of the datasets. This was followed by finding the mean scores of the positive and negative sentiments in both decades with the goal of comparing them and seeing how much they differ.

The findings of the study, which can be seen in Table 1, revealed that the popular song lyrics of the 1990s had a mean score of 1.21 for negative sentiment, while the 2010s had a score of 1.32. The 1990s also had a mean score of 1.44 for positive sentiment, whereas the 2010s had a score of 1.39. The analysis revealed a notable rise in the maximum negative score, increasing from 2.02 in the 1990s to 2.94 in the 2010s. Suprisingly, the 2010s had a higher maximum positive sentiment score compared to the 1990s. Overall, the results show that popular song lyrics became more negative and less positive during these two decades, which confirms the findings of previous studies that have also looked into the trends surrounding song lyrics. SentiStrength was proven to be a useful tool when analyzing song lyrics, being able to mostly give accurate feedback with the exception of a few songs that provided inaccurate results when taking into consideration the actual meaning of the song's lyrics.

In conclusion, this thesis further explores the capabilities of SentiStrength as a research tool when used for analyzing the sentiments expressed in popular song lyrics.

Seeing as this BA thesis confirms the findings of previous studies, it can be assumed that SentiStrength can be just as valuable as other tools used to study this field. The findings and limitations of this study provide room for future research, which can broaden our understanding of this topic. For example, further research could conduct sentiment analysis on various popular music from different genres and see how those sentiment trends differ over the years and from each other.

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APPENDICES

Appendix 1. Number one songs from the 1990s with positive and negative sentiment scores

Year	Song title	Artist	Positive Score	Negative Score
1990	"How Am I Supposed to Live Without You"	Michael Bolton	1.38	1.03
1990	"Opposites Attract"	Paula Abdul featuring The Wild Pair	1.54	1.16
1990	"Escapade"	Janet Jackson	1.39	1.22
1990	"Nothing Compares 2 U"	Sinéad O'Connor	1.27	1.20
1990	"Vogue"	Madonna	1.30	1.11
1990	"Step by Step"	New Kids on the Block	1.34	1.00
1990	"Vision of Love"	Mariah Carey	1.55	1.13
1990	"Love Takes Time"	Mariah Carey	1.29	1.60
1990	"Because I Love You (The Postman Song)"	Stevie B	1.47	1.27
1990	"Black Velvet"	Alannah Myles	1.62	1.15
1991	"Justify My Love"	Madonna	2.00	1.20
1991	"(Everything I Do) I Do It for You"	Bryan Adams	1.19	1.03
1991	"Black or White"	Michael Jackson	1.13	1.44
1991	"Emotions"	Mariah Carey	1.38	1.04
1991	"Rush Rush"	Paula Abdul	1.76	1.00
1991	"The First Time"	Surface	1.71	1.68
1991	"All the Man That I Need"	Whitney Houston	1.55	1.13
1991	"Coming Out of the Dark"	Gloria Estefan	1.29	1.07
1991	"Baby Baby"	Amy Grant	1.75	1.00
1991	"Cream"	Prince and the New Power Generation	1.24	1.06
1992	"End of the Road"	Boyz II Men	1.44	1.40
1992	"This Used to Be My Playground"	Madonna	1.29	1.16
1992	"Baby Got Back"	Sir Mix-a-Lot	1.37	1.38
1992	"Jump"	Kris Kross	1.13	1.14
1992	"Save the Best for Last"	Vanessa Williams	1.34	1.09
1992	"To Be with You"	Mr. Big	1.48	1.05
1992	"I'm Too Sexy"	Right Said Fred	2.07	1.12
1992	"I'll Be There"	Mariah Carey	1.51	1.00
1992	"How Do You Talk to an Angel"	The Heights	1.33	1.00
1992	"Don't Let the Sun Go Down on Me"	George Michael and Elton John	1.43	1.27
1993	"A Whole New World"	Peabo Bryson and Regina Belle	1.20	1.10
1993	"Informer"	Snow	1.17	1.30
1993	"Freak Me"	Silk	1.63	1.39
1993	"That's the Way Love Goes"	Janet Jackson	2.38	1.35
1993	"Weak"	SWV	1.53	1.45
1993	"Can't Help Falling in Love"	UB40	1.68	1.10
1993	"Dreamlover"	Mariah Carey	1.52	1.24
1993	"I'd Do Anything for Love (But I Won't Do That)"	Meat Loaf	1.51	1.08
1993	"Again"	Janet Jackson	1.49	1.21
1993	"I Will Always Love You"	Whitney Houston	2.28	1.00
1994	"All for Love"	Bryan Adams featuring Rod Stewart and Sting	1.54	1.12

1994	"The Power of Love"	Céline Dion	1.50	1.23
1994	"The Sign"	Ace of Base	1.11	1.09
1994	"Bump n' Grind"	R. Kelly	1.52	1.48
1994	"I Swear"	All-4-One	1.36	1.67
1994	"Stay (I Missed You)"	Lisa Loeb & Nine Stories	1.24	1.46
1994	"I'll Make Love to You"	Boyz II Men	1.57	1.00
1994	"On Bended Knee"	Boyz II Men	1.49	1.14
1994	"Here Comes the Hotstepper"	Ini Kamoze	1.30	2.02
1994	"Hero"	Mariah Carey	1.59	1.49
1995	"Creep"	TLC	1.27	1.17
1995	"Take a Bow"	Madonna	1.47	1.07
1995	"This Is How We Do It"	Montell Jordan	1.10	1.00
1995	"Have You Ever Really Loved a Woman?"	Bryan Adams	2.21	1.05
1995	"Waterfalls"	TLC	1.32	1.39
1995	"Kiss from a Rose"	Seal	1.51	1.35
1995	"You Are Not Alone"	Michael Jackson	1.04	1.10
1995	"Gangsta's Paradise"	Coolio featuring L.V.	1.82	1.46
1995	"Fantasy"	Mariah Carey	1.54	1.05
1995	"Exhale (Shoop Shoop)"	Whitney Houston	1.11	1.18
1996	"One Sweet Day"	Mariah Carey and Boyz II Men	1.55	1.08
1996	"Because You Loved Me"	Céline Dion	1.75	1.11
1996	"Always Be My Baby"	Mariah Carey	1.58	1.07
1996	"Tha Crossroads"	Bone Thugs-n-Harmony	1.32	1.36
1996	"How Do U Want It"	2Pac featuring K-Ci & JoJo	1.16	1.34
1996	"California Love"	2Pac featuring Dr. Dre and Roger Troutman	1.31	1.26
1996	"You're Makin' Me High"	Toni Braxton	1.30	1.17
1996	"Let It Flow"	Toni Braxton	1.28	1.26
1996	"No Diggity"	Blackstreet featuring Dr. Dre	1.36	1.20
1996	"Un-Break My Heart"	Toni Braxton	1.60	1.89
1997	"4 Seasons of Loneliness"	Boyz II Men	1.44	1.21
1997	"Wannabe"	Spice Girls	1.65	1.13
1997	"Can't Nobody Hold Me Down"	Puff Daddy featuring Mase	1.24	1.37
1997	"Hypnotize"	The Notorious B.I.G.	1.31	1.29
1997	"MMMBop"	Hanson	1.11	1.08
1997	"I'll Be Missing You"	Puff Daddy and Faith Evans featuring 112	1.20	1.19
1997	"Mo Money Mo Problems"	The Notorious B.I.G. featuring Puff Daddy and Mase	1.25	1.26
1997	"Honey"	Mariah Carey	1.68	1.08
1997	"Candle in the Wind 1997"	Elton John	1.31	1.21
1997	"Something About the Way You Look Tonight"	Elton John	1.13	1.00
1998	"The Boy Is Mine"	Brandy and Monica	1.14	1.24
1998	"I Don't Want to Miss a Thing"	Aerosmith	1.47	1.19
1998	"The First Night"	Monica	1.17	1.22
1998	"I'm Your Angel"	R. Kelly and Céline Dion	1.18	1.40
1998	"Gettin' Jiggy wit It"	Will Smith	1.19	1.17
1998	"All My Life"	K-Ci & JoJo	2.17	1.00
1998	"Doo Wop (That Thing)"	Lauryn Hill	1.29	1.33
1998	"Too Close"	Next	1.72	1.07
1998	"My Heart Will Go On"	Céline Dion	1.26	1.11
1998	"Nice & Slow"	Usher	1.58	1.25
1999	"Believe"	Cher	1.57	1.07

1999	"Smooth"	Santana featuring Rob Thomas	1.27	1.06
1999	"Angel of Mine"	Monica	1.34	1.00
1999	"Livin' la Vida Loca"	Ricky Martin	1.04	1.35
1999	"No Scrubs"	TLC	1.41	1.08
1999	"If You Had My Love"	Jennifer Lopez	1.89	1.29
1999	"Genie in a Bottle"	Christina Aguilera	1.40	1.03
1999	"Unpretty"	TLC	1.12	1.10
1999	"...Baby One More Time"	Britney Spears	1.40	1.47
1999	"Heartbreaker"	Mariah Carey featuring Jay-Z	1.70	1.25

Appendix 2. Number one songs from the 2010s with positive and negative sentiment scores

Year	Song title	Artist	Positive Score	Negative Score
2010	"TiK ToK"	Kesha	1.08	1.35
2010	"Rude Boy"	Rihanna	1.67	1.48
2010	"California Gurls"	Katy Perry featuring Snoop Dogg	1.32	1.12
2010	"Love the Way You Lie"	Eminem featuring Rihanna	1.62	1.84
2010	"Just the Way You Are"	Bruno Mars	1.73	1.11
2010	"OMG"	Usher featuring will.i.am	1.60	1.04
2010	"Imma Be"	The Black Eyed Peas	1.35	1.08
2010	"Nothin' on You"	B.o.B featuring Bruno Mars	1.53	1.34
2010	"Teenage Dream"	Katy Perry	1.13	1.05
2010	"Like a G6"	Far East Movement featuring The Cataracs and Dev	1.59	1.18
2011	"Rolling in the Deep"	Adele	1.16	1.55
2011	"Born This Way"	Lady Gaga	1.69	1.16
2011	"Party Rock Anthem"	LMFAO featuring Lauren Bennett and GoonRock	1.32	1.20
2011	"E.T."	Katy Perry featuring Kanye West	1.19	1.42
2011	"We Found Love"	Rihanna featuring Calvin Harris	2.16	2.55
2011	"Someone Like You"	Adele	1.67	1.61
2011	"Moves Like Jagger"	Maroon 5 featuring Christina Aguilera	1.50	1.09
2011	"Grenade"	Bruno Mars	1.30	1.42
2011	"Firework"	Katy Perry	1.25	1.19
2011	"Give Me Everything"	Pitbull featuring Ne-Yo, Afrojack and Nayer	1.45	1.09

2012	"Somebody That I Used to Know"	Gotye featuring Kimbra	1.40	1.24
2012	"Call Me Maybe"	Carly Rae Jepsen	1.22	1.31
2012	"We Are Young"	Fun featuring Janelle Monáe	1.13	1.11
2012	"One More Night"	Maroon 5	1.46	1.30
2012	"Diamonds"	Rihanna	1.90	1.03
2012	"Set Fire to the Rain"	Adele	1.04	1.44
2012	"Stronger (What Doesn't Kill You)"	Kelly Clarkson	1.12	1.47
2012	"We Are Never Ever Getting Back Together"	Taylor Swift	1.37	1.27
2012	"Sexy and I Know It"	LMFAO	1.37	1.12
2012	"Whistle"	Flo Rida	1.68	1.16
2013	"Locked Out of Heaven"	Bruno Mars	1.38	1.00
2013	"Thrift Shop"	Macklemore & Ryan Lewis featuring Wanz	1.34	1.27
2013	"Just Give Me a Reason"	Pink featuring Nate Ruess	1.63	1.12
2013	"Can't Hold Us"	Macklemore & Ryan Lewis featuring Ray Dalton	1.33	1.22
2013	"Blurred Lines"	Robin Thicke featuring T.I. and Pharrell	1.21	1.33
2013	"Royals"	Lorde	1.52	1.24
2013	"Roar"	Katy Perry	1.15	1.18
2013	"Wrecking Ball"	Miley Cyrus	1.31	1.45
2013	"When I Was Your Man"	Bruno Mars	1.28	1.21
2013	"The Monster"	Eminem featuring Rihanna	1.23	1.42
2014	"Timber"	Pitbull featuring Kesha	1.22	1.12
2014	"Dark Horse"	Katy Perry featuring Juicy J	1.39	1.17
2014	"Happy"	Pharrell Williams	2.06	1.16
2014	"All of Me"	John Legend	1.44	1.29
2014	"Fancy"	Iggy Azalea featuring Charli XCX	1.28	1.34
2014	"Rude"	Magic!	1.31	1.65
2014	"Shake It Off"	Taylor Swift	1.30	1.70
2014	"All About That Bass"	Meghan Trainor	1.29	1.08
2014	"Blank Space"	Taylor Swift	1.63	1.57
2015	"Uptown Funk"	Mark Ronson featuring Bruno Mars	1.12	1.09
2015	"See You Again"	Wiz Khalifa featuring Charlie Puth	1.26	1.02
2015	"Bad Blood"	Taylor Swift featuring Kendrick Lamar	1.72	1.61
2015	"Cheerleader"	Omi	1.38	1.10

2015	"Can't Feel My Face"	The Weeknd	1.94	1.25
2015	"What Do You Mean?"	Justin Bieber	1.28	1.16
2015	"The Hills"	The Weeknd	1.54	1.49
2015	"Hello"	Adele	1.07	1.26
2016	"Sorry"	Justin Bieber	1.14	1.67
2016	"Work"	Rihanna featuring Drake	1.18	1.22
2016	"Panda"	Desiigner	1.19	1.82
2016	"Love Yourself"	Justin Bieber	1.60	1.25
2016	"One Dance"	Drake featuring Wizkid and Kyla	1.08	1.09
2016	"Cheap Thrills"	Sia featuring Sean Paul	1.61	1.18
2016	"Closer"	The Chainsmokers featuring Halsey	1.19	1.13
2016	"Black Beatles"	Rae Sremmurd featuring Gucci Mane	1.36	1.54
2016	"Pillowtalk"	Zayn	1.82	2.12
2016	"Can't Stop the Feeling!"	Justin Timberlake	1.10	1.00
2017	"Shape of You"	Ed Sheeran	1.94	1.08
2017	"Look What You Made Me Do"	Taylor Swift	1.11	1.30
2017	"Bodak Yellow"	Cardi B	1.44	1.42
2017	"Rockstar"	Post Malone featuring 21 Savage	1.23	1.37
2017	"Perfect"	Ed Sheeran and Beyoncé	2.00	1.06
2017	"Bad and Boujee"	Migos featuring Lil Uzi Vert	1.23	1.79
2017	"Starboy"	The Weeknd featuring Daft Punk	1.30	1.25
2017	"HUMBLE."	Kendrick Lamar	1.16	1.70
2017	"That's What I Like"	Bruno Mars	1.39	1.06
2017	"I'm the One"	DJ Khaled featuring Justin Bieber, Quavo, Chance the Rapper and Lil Wayne	1.11	1.20
2018	"God's Plan"	Drake	1.24	1.29
2018	"Havana"	Camila Cabello featuring Young Thug	1.19	1.01
2018	"In My Feelings"	Drake	1.39	1.19
2018	"Girls Like You"	Maroon 5 featuring Cardi B	1.45	1.06
2018	"This Is America"	Childish Gambino	1.08	1.10
2018	"Nice for What"	Drake	1.18	1.30
2018	"Psycho"	Post Malone featuring Ty Dolla Sign	1.43	1.59
2018	"SAD!"	XXXTENTACION	1.12	2.94

2018	"SICKO MODE"	Travis Scott	1.23	1.24
2018	"Thank U, Next"	Ariana Grande	1.70	1.22
2019	"Old Town Road"	Lil Nas X featuring Billy Ray Cyrus	1.09	1.13
2019	"Truth Hurts"	Lizzo	1.45	1.55
2019	"Someone You Loved"	Lewis Capaldi	1.46	1.23
2019	"Circles"	Post Malone	1.20	1.37
2019	"7 Rings"	Ariana Grande	1.30	1.15
2019	"Without Me"	Halsey	1.20	1.24
2019	"Sunflower"	Post Malone and Swae Lee	1.32	1.42
2019	"Shallow"	Lady Gaga and Bradley Cooper	1.48	1.58
2019	"Lose You to Love Me"	Selena Gomez	2.41	1.41
2019	"All I Want for Christmas Is You"	Mariah Carey	1.31	1.07

RESÜMEE

TARTU ÜLIKOOL
ANGLISTIKA OSAKOND

Markus Toomsalu

Sentiment analysis of popular song lyrics in the US from the 1990s and 2010s. Ameerika Ühendriikide 1990. ja 2010. aastate levimuusika laulusõnade meelsusanalüüs

Bakalaureusetöö
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Annotatsioon:

Levimuusika on tähtis nähtus tänapäeva ühiskonnas, kajastades meie emotsioone ja kultuurilisi suundumusi. Kuigi tänapäeval keskenduvad muusikakuulajad sageli pigem laulu meloodiale ja rütmile, ei pöörata piisavalt tähelepanu sellele, milliseid sõnumeid need laulud üritavad edastada. Keeleteaduslikust vaatenurgast pakub levimuusika emotsionaalsete meelsuste analüüs väärtuslikke teadmisi ühiskondlikest väärtustest, kultuurilistest muutustest ja muusikaeelistustest. Käesoleva uuringu eesmärgiks on läbi viia kvantitatiivne korpusuuring, et veelgi laiendada meelsusanalüüsi kasutamise valdkonda laulusõnade uurimisel, vaadates 1990. ja 2010. aastatel Ameerika Ühendriigis levimuusika laulusõnades esinenud meelsusi. Uuringus kasutati SentiStrength tarkvara eesmärgiga esile tuua selle võimeid meelsusanalüüsi läbiviimiseks selles valdkonnas. Nende meelsuste analüüsimiseks koostati spetsiaalne korpus, mis koosnes lauludest, mis olid nendel aastakümnetel Billboard Hot 100 edetabelis esikohale jõudnud. Käesoleva uuringu uurimisküsimus seisnes selles, et kuidas erinesid mõlema kümnendi meelsuste tulemused.

Bakalaureusetöö on jaotatud kolmeks peatükiks: sissejuhatus, kirjanduse ülevaade ja empiiriline analüüs. Töö algab sissejuhatava osaga, milles määratletakse levimuusika tähendus, toob välja käesoleva uuringu läbiviimise põhjused ja annab ülevaate töö osadest. Kirjanduse ülevaade keskendub meelsusanalüüsi defineerimisele, mainides ka selle klassifikatsioone ja piiranguid, laulusõnade ja levimuusika tähtsusele, ja antakse ülevaade varasematest sarnastel teemadel tehtud töödest. Empiiriline osa keskendub laulukorpuse koostamisele, selgitab SentiStrength'i funktsionaalsust, ja esitab uuringu tulemused koos arutelu osaga. Terve töö lõpeb kokkuvõttega, mis toob esile uuringu tähtsamaid mõtteid.

Töös uuritud laulusõnade korpuse meelsusanalüüs näitas, et 1990. aastatel oli maksimaalne positiivne meeleolu skoor 2.38 ja miinimum 1.04, mis andis andmete vahemikuks 1.34. Negatiivse meeleolu skooride puhul näitasid tulemused maksimaalset skoori 2.02 ja miinimumi 1.00, mis andis vahemikuks 1.02. Aastatel 1990-1999 tuli levimuusikas esinenud positiivse meeleolu keskmiseks skooriks 1.44 ja negatiivse meeleolu keskmiseks skooriks 1.21. Vaadates 2010. aastate tulemusi, oli seal positiivse meeleolu maksimaalne skoor 2.94 ja miinimum 1.00, mille tulemuseks sai vahemik 1.94. Aastatel 2010-2019 oli positiivse meeleolu keskmiseks skooriks 1.39 ja negatiivse meeleolu keskmiseks skooriks 1.32. See tähendab seda, et laulusõnades esinev meeleolu oli läinud negatiivsemaks ja tõestab SentiStrength'i kasulikkust sellise teema uurimise puhul.

Märksõnad: meelsusanalüüs, laulusõnad, levimuusika, Ameerika Ühendriigid, SentiStrength, Billboardi edetabel, korpusuuring, laulud

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Tartus, 21.05.2024

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