A Transformer-Based Comparative Sentiment Analysis of McCartney and Lennon's Lyrics

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***Abstract*—This study used transformer-based sentiment analysis to quantitatively examine Paul McCartney and John Lennon's Beatles lyrics, seeking empirical support for the noted differences in their lyrical sentiment. Analyzing all Beatles lyrics attributed to each, we found McCartney's lyrics to be more positive, and Lennon's to be more negative, aligning with expectations. This supports traditional views of their contributions and demonstrates transformer models' ability to analyze musical lyrics' emotional content.**

I. Introduction

The Beatles, under the leadership of Paul McCartney and John Lennon, achieved a musical legacy that continues to captivate and influence [1]. Within their partnership, a notable contrast is apparent: McCartney is often recognized for his lyrical cheerfulness, considered by many to be the more commercial of the two, while Lennon is acknowledged for his introspective lyrics, his serious tone being praised by critics [2] [3] [4]. This paper seeks to quantitatively explore this contrast using transformer-based sentiment analysis tools, aiming to contribute empirical data relevant to this discussion. To do this, we must ask the following question: *To what extent do the lyrics written by Paul McCartney and John Lennon during their time with The Beatles quantitatively reflect the prevalent notions of McCartney's optimism and Lennon's pessimism?*

A. Motivation

Many people around the world would find the to answer this question interesting as The Beatles continue to be popular to this day [1] [5]. Access to empirical evidence supporting or challenging prevailing opinions offers a chance for discussions within communities that celebrate their music. This research also contributes to a framework for sentiment analysis in musicology and its relevance extends beyond fandom to touch on cultural analysis, showcasing how quantitative methods can validate or oppose ideas solidified by popular culture. This method is helpful in understanding The Beatles' lyrical legacy while also demonstrating how quantitative analyses can dissect cultural phenomena, deepening our understanding of musicology and cultural studies. By employing transformer-based sentiment analysis, this paper contributes to a growing body of work that leverages computational tools to offer insights into the complexities of artistic expression.

B. Relevance and Literature Review

Before the widespread availability of transformer-based models, researchers used a variety of methods to measure the sentiment of songs, using both lyrics and audio [6]. These methods allowed for many advances in this field, including the creation of music recommendation tools based on sentiment, such as SentiSpotMusic [7], and studies on popular music over time. Using linguistic analysis and deep learning methods [8], a paper observed shifts in popular music sentiment from 1951 to 2016, showing a decline in sentiment over the years towards negativity [9]. These studies lay a solid foundation and show a broad interest in exploring the emotions in music. Since the invention and increased availability of transformer-based models [10][1], evidence has supported that they outperform traditional methods of sentiment analysis for many types of text [12], including music [13]. They showed an "improved efficiency of contextual embeddings in sentiment analysis" [12], which could prove beneficial in the domain of music. Given the complexity of musical content, the ability to accurately discern sentiment through contextual cues is particularly advantageous. In addition, focused comparative analyses of individual songwriters within a band remain scarce. Previous works have provided foundational insights but often lack a quantitative comparison between McCartney and Lennon's contributions, choosing to focus on opinion-based, qualitative analyses [14] [15]. This gap presents an opportunity for this study to contribute novel insights to the field.

C. Aims and Objectives

The primary aim of this study is to apply sentiment analysis tools to the lyrics written by McCartney and Lennon, assessing whether empirical data supports the common perceptions of their sentiment tendencies. Objectives include:

- Acquiring and cleaning a comprehensive dataset of lyrics for the artists contribution to The Beatles' music.
- Performing sentiment analysis with a transformer model.
- Comparatively analyzing the sentiment of lyrics attributed to McCartney and Lennon.
- Discussing findings in the context of cultural perceptions.

The success of this study will be measured by its ability to accurately quantify and compare the sentiment in McCartney's and Lennon's lyrics, thereby providing empirical evidence that either confirms or challenges prevailing cultural narratives about their songwriting.

[1]The Google team behind "Attention is All You Need," introducing transformers, named it after a lyric from The Beatles' "All You Need is Love" [11]. Aptly, we now use transformers to analyze their lyrics.

II. Data Gathering and Methodology

This section details the methodology for data collection, preparation, and analysis used in this study, involving Python and various libraries for handling each step [16].

A. Data Gathering and Cleaning

The goal was to gather a complete set of McCartney and Lennon's Beatles lyrics, which included: fetching the Beatles discography from a lyrics database, filtering out duplicates and remixes, and distinguishing contributions within the Lennon-McCartney partnership.

Genius API was used to retrieve the lyrics for both artists [17]. Although this API provides the functionality to search and catalogue songs, it does not provide song lyrics directly, only links to them. Therefore, once the links to the relevant songs were stored, typical web-scarping techniques[2] (*requests* and *BeautifulSoup* libraries) were used to gather the lyrics [18]. Before scraping, regular expressions filtered out remixes and non-originals, and songs were attributed to either Lennon or McCartney. Songs were attributed to either artist by scraping a compiled list from the *Beatles Archive*, a trusted Beatles resource, to fill a "Composer" column in the dataset, with each row labeled as "Lennon" or "McCartney" [19]. Once lyrics were gathered, the dataset was stored as a loadable *Pandas dataframe* [20], with the columns: Song Name; Artist Name; Artist ID (corresponding to the Genius artist number); Release Date; Album Name; Lyrics; and Composer. Additional data, such as historical events from the period [21] and events from the two artists' personal lives [22] [23], were manually collected from online sources and literature, stored as *Python dictionaries*, and used during the visualisation process as described in Section II-B. The last step before sentiment analysis involved removing non-semantic vocalizations like "ooh" and "ah" from the lyrics, using a list created by analyzing word frequency to identify words without meaningful content.

B. Sentiment Analysis & Visualisation

After preparing the dataset, the aim was to use a transformer-based model for sentiment analysis of the lyrics, then compare this quantitative data through visualizations. The need to analyse emotionally complex lyrics led to the adoption of transformer-based models from the *Hugging Face* library [24], given the architecture's capacity for understanding context [12]. The *transformers* library provided a *pipeline* method, which streamlined the sentiment analysis process, offering a direct route to leveraging pre-trained models, as well as in-built functionality for text preprocessing [25]. This function takes a "pipeline" (the method to employ) as an argument, which in the case of this study was "zero-shot-classification", and a model with which to employ that method, in this case "roberta-large-mnli" [26]. The adoption of zero-shot classification, despite the existence of tools specifically designed for sentiment analysis, is justified by its flexibility in accommodating custom granularity; the classification spectrum adopted spans from "very negative" to "very positive," with "negative," "neutral," and "positive" in between. This zero-shot method has been employed in past research and results in a classification scenario which performs well and mirrors regular sentiment analysis [27]. The reason for selecting the "roberta-large-mnli" model lies in its capability for context-aware sentiment analysis and text type versatility, due to its training on diverse text sources [26], making it a suitable candidate for lyrical analyses.

This methodology provided a strong foundation for lyrical sentiment analysis, but it faced limitations. Specifically, the model's context window was smaller than most songs, and rather than giving a score from -1 (very negative) to 1 (very positive), it assigned a confidence score for each sentiment category. To address the context window limitation, a custom function, *split_lyrics*, was created to divide lyrics into smaller segments, which ensured that each section could be analyzed by the sentiment model without surpassing its constraints. For each lyric segment, the model calculated sentiment scores, which were aggregated to determine a song's overall sentiment. This process weighted the scores of each chunk based on a predefined sentiment-to-score mapping, converting emotional tones into a score range from -1 to 1. Upon completion of the sentiment analysis, the dataset was augmented with two new columns: "Category" and "Category Score". The former is the predominant sentiment of the song, derived from the averaged scores of its chunks and the later provides a numerical representation of the overall sentiment, offering a quantitative measure of the song's emotional valence.

To visualise the data, two libraries were used: *Matplotlib* [28] and *seaborn* [29]. The violin plot was selected for displaying sentiment score distributions, revealing score density at various points, and emphasising differences in the two artists' lyrics. Its design excels at showing clear shapes of distribution, which are intuitive enough for interpretation. Word clouds were created for each artist to highlight unique words in their Beatles lyrics - words common to both were excluded [30]. These clouds provide a qualitative view into each artist's distinctive word choices, showcasing their unique contributions to Beatles' songwriting. Although not quantitative, this approach reveals their individual styles and themes. Additionally, a moving average visual representation was introduced to analyse their sentiment over time, which includes overlays marking album releases and significant personal or historical events, offering insights into how external factors influenced their lyrical sentiment. This analysis provides a deeper understanding of their artistic development, highlighting the interplay between their personal experiences and their music's emotional tone.

III. Results, Discussion, & Conclusion

This analysis sought to quantitatively explore the emotional tendencies in Paul McCartney's and John Lennon's lyrics, aiming to substantiate or refute the popular beliefs about McCartney's optimism and Lennon's pessimism. The results in the following section reveal intriguing patterns that emerge from a comprehensive examination of their discographies.

[2]Scripted rate limiting ensured the *Genius* servers were not overloaded.

A. *Results & Discussion*

The first plot is the violin plot described in Section II-B:

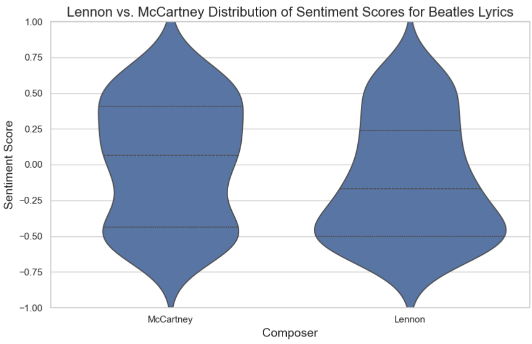

Fig. 1. *Sentiment Violin Plot: Lennon vs. McCartney*

Figure 1 shows that Lennon's lyrics do tend to be more negative than McCartney's overall, as the shape of Lennon's distribution is much wider in the negative region than McCartney's. This is supported by the second quartile line, which for Lennon is below neutrality and while McCartney's is above. McCartney's plot is more balanced, with the distribution seeming nearly symmetrical, while Lennon's is completely asymmetrical with a larger bulge at the negative end. The intuitive shape of these plots support the idea that Lennon is more negative than McCartney. To better understand these results, Figure 2 below provides some qualitative explainability:

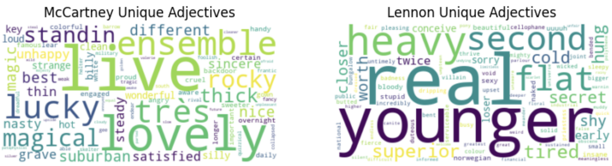

Fig. 2. *Word Cloud Plot: Unique Adjectives*

In the McCartney cloud, positive adjectives like "lucky," "magical," and "lovely" stand out, suggesting themes of positivity. Together with the French words such as "trés" (very) and "ensemble" (together), McCartney's vocabulary suggests a more whimsical and optimistic mood. Conversely, Lennon's cloud features adjectives like "heavy," "flat," and "tired," indicating more introspective or negative emotions. Words such as "real" and "younger," suggest themes that revolve around realism and reflection on youth. This figure, and Figure 2 provide a "top-down view" of the two artists, while Figure 3 adds a dimension to the comparison by considering how sentiment scores changed over time:

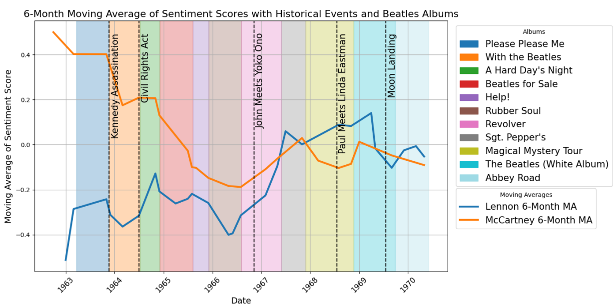

Fig. 3. *Sentiment Scores Over Time Plot: Lennon vs. McCartney*

The trend observed indicates an almost mirrored pattern, Lennon begins at his most negative and moves towards neutrality, while McCartney starts at his most positive and follows a similar path. Towards the end, both appear to settle just below neutral; as both artists matured, their lyrics likely became more complex and their emotional range broadened, leading to what appears as "neutrality." Although both artists seem to show almost opposite overall trends, they seem to "agree" on local trends. For example, in albums "With the Beatles," "Beatles for Sale," and "Rubber Soul", both artists dip towards negativity. The opposite is true for "Sgt. Pepper's," "The White Album," and "Revolver," where both increase their sentiment in similar ways. It's possible that the artists were attempting to keep a consistent sentiment within the same album, to ensure a harmonious emotional tone. Furthermore, the artists seem "in agreement" in sentiment after important events: both dip after the Kennedy Assassination, while both increase after the Civil Rights Act and after both meet their soon to be wives.

Together, the three figures corroborate each other and seem to support the cliché: Paul McCartney was the optimistic/commercial Beatles and John Lennon was the pessimistic/serious Beatles. These results appear convincing when presented side by side; this paper seems to have accomplished its aim by providing quantitative evidence in **supporting** a prevailing cultural narrative. However, despite these interesting observations, it's important to note that many of these correlations are largely speculative and not backed by further scientific evidence. Therefore, future work could significantly strengthen these findings by: enhancing the analysis with additional sentiment analysis tools for "second opinions" and employing statistical measures to validate the observed trends. Studying their solo careers and using more categories could provide deeper emotional insights. In addition, this framework's adaptability allows for its application to other artists or even other textual mediums.

B. *Conclusion*

This research quantitatively explores the sentiments in Paul McCartney and John Lennon's Beatles lyrics using a transformer-based analysis. It aimed to verify if McCartney's lyrics are more optimistic and Lennon's more pessimistic. Analyzing their entire Beatles discography, the study found McCartney's lyrics to indeed be more positive than Lennon's. This difference was supported both by sentiment scores and thematic analysis, with a temporal examination revealing how their sentiments evolved.

Despite its limitations, such as the complexity of mapping emotions to lyrics and speculative bridging, the study offers quantitative insights into musicology, a field often focused on qualitative analysis. It confirms the narratives about McCartney and Lennon's contributions, showcasing computational tools' potential in understanding artistic expression. This approach provides a new perspective on their music, encouraging further exploration into other artists and mediums, highlighting the growing intersection between technology and humanities.

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