Twitter Sentiment Analysis: Sentiments in the Global BLM Movement Post-George Floyd"

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Abstract

Twitter sentiments following the tragic death of George Floyd, exploring the global Black Lives Matter (BLM) movement. Utilizing sentiment analysis, we scrutinize an extensive dataset of tweets to reveal intricate discussions on police brutality, racial justice, and BLM protests. Leveraging Twitter data, our study captures contemporaneous reactions, emotions, and viewpoints, offering a thorough comprehension of the socio-political panorama. The outcomes contribute to discussions on digital-age social activism, illuminating the influence of social media on public perceptions and the cultivation of dialogues regarding crucial societal matters.

Keywords: Twitter, Sentiment Analysis, Black Lives Matter, George Floyd, Social Activism.

1. Introduction

Social media has changed how people talk about important issues worldwide, giving everyone a place to share their views and feelings on major events. One significant event that sparked global conversations was the tragic passing of George Floyd in May 2020, reigniting the Black Lives Matter (BLM) movement on an international scale. During this resurgence, Twitter became a key platform for people to express their thoughts, and emotions, and engage in discussions about police brutality, racial justice, and the BLM protests. This study sets out to explore the feelings expressed on Twitter after uncovering the many-sided stories that make up today's discussions about racial inequality and social justice.

Broad Problem: In the realm of social media, a crucial question arises—how does online discourse, especially on platforms like Twitter, shape discussions on critical societal issues such as police brutality and racial justice? This concern explores the intricate dynamics of digital conversations, examining how platforms like Twitter impact public opinion and contribute to the broader narrative of social justice movements.

Specific Problem: In this vast digital conversation, a crucial question arises: how do the sentiments shared on Twitter mirror and impact the bigger talks about police brutality, racial justice, and the Black Lives Matter movement? The specific problem we're tackling in this study involves diving into the complex layers of sentiment found in Twitter discussions to understand the patterns, emphases, and differences. Our goal is to reveal the hidden dynamics shaping the narrative around the BLM movement, providing useful insights for the ongoing conversation on activism in the digital age.

1.1 Purpose Statement

The purpose of this study is to analyze the sentiments expressed on Twitter in the aftermath of George Floyd's death, concentrating on understanding the complex discussions related to police brutality, racial justice, and the worldwide Black Lives Matter movement. Utilizing sentiment analysis on Twitter data, the research seeks to provide insights into the role of digital platforms in influencing and mirroring conversations about significant social issues.

1.2 Literature Review

The scholarly discourse on social media and activism has accentuated the transformative role of digital platforms in mobilizing public opinion and fostering social change (Castells, 2015; Bennett & Segeberg, 2013). Twitter has been recognized as a crucial space where marginalized voices find amplification and grassroots movements gain momentum (Castells, 2015). It serves as an arena for disseminating information and shaping the narrative of social movements (Bennett & Segeberg, 2013).

Moreover, research on sentiment analysis within the context of social media sheds light on the intricate dynamics of emotional expression in the online sphere (Tumasjan et al., 2010). Twitter data has been effectively utilized for sentiment analysis, providing valuable insights into public sentiment during political events (Tumasjan et al., 2010). However, scholars also acknowledge challenges, including the potential for online echo chambers and the manipulation of sentiments through the spread of misinformation (Tumasjan et al., 2010). These challenges underscore the necessity for a nuanced understanding of the interplay between social media, sentiment, and activism.

Despite the growing body of literature on social media and activism, limited research has specifically focused on unraveling the sentiments expressed on Twitter following critical events, such as instances of police brutality. Understanding how sentiments unfold on Twitter in response to such events is pivotal for gaining insights into the dynamics of contemporary social movements and understanding the role of digital discourse in shaping societal narratives.

In conclusion, the literature review highlights the significant role of social media, particularly Twitter, in shaping and influencing discussions on critical societal issues like police brutality and racial justice. The reviewed studies collectively underscore the transformative impact of digital platforms on public discourse, providing individuals from diverse backgrounds a space to voice their opinions and contribute to broader conversations. As evidenced by the research, Twitter has become a central hub for real-time reactions and discussions, amplifying the narratives surrounding social justice movements, including the global Black Lives Matter (BLM) movement sparked by the tragic death of George Floyd. The findings emphasize the need for continued exploration of the complexities within online conversations, acknowledging the potential of social media to both reflect and shape societal attitudes. Moving forward, the research at hand seeks to contribute to this evolving dialogue by delving into the sentiments expressed on Twitter following George Floyd's demise, adding nuance to our understanding of the intersection between digital discourse and contemporary social activism.

1.3 Conceptual Framework

Our study revolves around a clear conceptual framework:

- *Digital Discourse Impact:* Investigates online discussions on platforms like Twitter.
- *Sentiment as Indicator:* Employs sentiment analysis to gauge emotions and opinions expressed in tweets.
- *Themes in Online Activism*: Explores Twitter conversations on social issues and the BLM movement, contributing to digital activism.

1.4 Research Questions

To fulfill the objectives and purpose of this project, we have formulated the following research questions:

1. How do the most common words on Twitter, identified through frequency analysis, exhibit temporal changes and variations?

2. How did recognizing positive and negative terms enhance the comprehension of the evolving sentiments expressed?

3. What were the prevalent positive words in the expressions related to societal issues, and how did these words contribute to shaping the discourse during the specified period?

4. To what extent did individual words contribute to shaping different sentiments expressed on Twitter?

5. How did the identified sentiments change throughout the analysis, particularly in response to key events or developments related to the Black Lives Matter movement and police brutality?

6. How frequently was the term 'George Floyd' mentioned in the analyzed Twitter data?

2. Methodology: Data Collection

2.1 Data Overview

The dataset for this research was collected through quantitative analysis of Twitter data spanning from June 2020 to August 2020. The data collection process involved web scraping, resulting in six distinct datasets, each corresponding to a specific week within the mentioned timeframe. The Twitter data was divided into three months (June, July, and August), with each month containing two data files.

2.2 Data Structure

The Twitter datasets, collected from June 2020 to August 2020, consist of six individual datasets, each containing information related to tweets about George Floyd's death, protests, and related topics. The data cleaning process and the creation of a standardized structure were applied consistently across all datasets. The key attributes of each dataset are summarized as follows:

1. Date and Time:
Variable: X1. Date.Time
Type: Character (chr)
Description: Represents the date and time when the tweet was posted.

2. Tweet Content:
Variable: X2. Tweet
Type: Character (chr)
Description: Contains the actual content of the tweet, expressing sentiments and opinions.

3. Hashtags:
Variable: X3. Hashtags
Type: Character (chr)
Description: Includes hashtags associated with the tweet, reflecting trending topics.

4. Tweet Type:
Variable: X4. Type
Type: Character (chr)
Description: Indicates the type of tweet, such as original tweets or replies.

5. Author Information:
Variables: X6. Author, X7.Author.s.real.name, X8..Author.s.location, X10..Author.s.URL, X11.Author.s.description
Types: Character (chr)
Description: Provides details about the tweet's author, including username, real name, location, URL, and profile description.

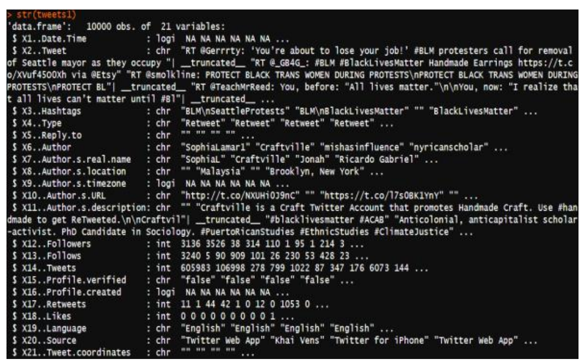
6. Author Statistics:
Variables: X12.Followers, X13.Follows, X14.Tweets
Types: Integer (int)
Description: Quantifies the author's influence through metrics such as followers, following, and total tweets.

7. Engagement Metrics:
Variables: X17.Retweets, X18.Likes
Types: Integer (int)
Description: Measures the tweet's popularity through retweets and likes.

8. Language and Source:
Variables: X19.Language, X20.Source
Types: Character (chr)
Description: Specifies the language of the tweet and the source platform or device used for tweeting.

9. Additional Information:
Variables: X5.Reply.to, X9. Author’s. Time zone, X15.Profile. verified, X16.Profile. created, X21.Tweet. coordinates
Types: Character (chr) or Logical (logical)
Description: Provides additional details such as reply to information, author's time zone, profile verification status, profile creation date, and tweet coordinates.

These datasets collectively offer a comprehensive view of Twitter activity during the specified period, allowing for detailed analysis of public sentiments, engagement patterns, and the impact of social media discourse.



```
> str(tweets1)
'data.frame':   10000 obs. of  21 variables:
 $ X1..Date.Time          : logi  NA NA NA NA NA NA ...
 $ X2..Tweet              : chr  "RT @Gerrrty: 'You're about to lose your job!' #BLM protesters call for removal of Seattle mayor as they occupy "| __truncated__ "RT @_GB4G_: #BLM #BlackLivesMatter Handmade Earrings https://t.co/XVuf45OOXh via @Etsy" "RT @smolkline: PROTECT BLACK TRANS WOMEN DURING PROTESTS\nPROTECT BLACK TRANS WOMEN DURING PROTESTS\nPROTECT BL"| __truncated__ "RT @TeachMrReed: You, before: "All lives matter."\n\nYou, now: "I realize that all lives can't matter until #Bl"| __truncated__ ...
 $ X3..Hashtags           : chr  "BLM\nSeattleProtests" "BLM\nBlackLivesMatter" "" "BlackLivesMatter" ...
 $ X4..Type               : chr  "Retweet" "Retweet" "Retweet" "Retweet" ...
 $ X5..Reply.to           : chr  "" "" "" "" ...
 $ X6..Author             : chr  "SophiaLamar1" "Craftville" "mishasinfluence" "nyricanscholar" ...
 $ X7..Author.s.real.name : chr  "SophiaL" "Craftville" "Jonah" "Ricardo Gabriel" ...
 $ X8..Author.s.location  : chr  "" "Malaysia" "" "Brooklyn, New York" ...
 $ X9..Author.s.timezone  : logi  NA NA NA NA NA NA ...
 $ X10..Author.s.URL      : chr  "http://t.co/NXUHiOJ9nC" "" "https://t.co/l7sOBK1YnY" "" ...
 $ X11..Author.s.description: chr  "" "Craftville is a Craft Twitter Account that promotes Handmade Craft. Use #handmade to get ReTweeted.\n\nCraftvil"| __truncated__ "#blacklivesmatter #ACAB" "Anticolonial, anticapitalist scholar-activist. PhD Candidate in Sociology. #PuertoRicanStudies #EthnicStudies #ClimateJustice" ...
 $ X12..Followers         : int  3136 3526 38 314 110 1 95 1 214 3 ...
 $ X13..Follows           : int  3240 5 90 909 101 26 230 53 428 23 ...
 $ X14..Tweets            : int  605983 106998 278 799 1022 87 347 176 6073 144 ...
 $ X15..Profile.verified  : chr  "false" "false" "false" "false" ...
 $ X16..Profile.created   : logi  NA NA NA NA NA NA ...
 $ X17..Retweets          : int  11 1 44 42 1 0 12 0 1053 0 ...
 $ X18..Likes             : int  0 0 0 0 0 0 0 0 0 1 ...
 $ X19..Language          : chr  "English" "English" "English" "English" ...
 $ X20..Source            : chr  "Twitter Web App" "Khai Vens" "Twitter for iPhone" "Twitter Web App" ...
 $ X21..Tweet.coordinates : chr  "" "" "" "" ...
```

Figure 1. Data Structure of the Tweets Dataset

2.3 Data Pre-processing and Cleaning

To ensure the focus on English-language tweets, a data-cleaning process was implemented. A series of custom functions were employed to filter tweets based on language, extracting relevant information, and structuring the datasets uniformly. The cleaning process involved retaining only the essential variables for analysis, specifically the 'tweet' content and a newly created 'tweet number' variable to track the order of tweets within each dataset.

```
library(readr)

tweets1 <- read.csv("week2.csv", header = TRUE)
tweets2 <- read.csv("week3.csv", header = TRUE)
tweets3 <- read.csv("week5.csv", header = TRUE)
tweets4 <- read.csv("week6.csv", header = TRUE)
tweets5 <- read.csv("week11.csv", header = TRUE)
tweets6 <- read.csv("week12.csv", header = TRUE)
```

Figure 2. Reading Tweets Dataset

The resulting datasets, namely tweets1 to tweets6, were structured consistently, facilitating a standardized approach to subsequent analyses. This meticulous data cleaning methodology ensures the integrity and relevance of the Twitter data, laying the foundation for comprehensive and accurate insights into the sentiments and discourses surrounding the Black Lives Matter movement post-George Floyd's tragedy.

The raw Twitter datasets obtained for this study underwent a rigorous data preprocessing phase to ensure the extraction of pertinent information while maintaining data quality and consistency. The primary objective was to create a standardized dataset containing only English-language tweets, laying the groundwork for subsequent analyses.

Data Cleaning Using Customized Functions: To achieve a uniform and language-specific dataset, a custom data cleaning function was implemented. The function was applied to six individual datasets (tweets1 to tweets6), resulting in a list of cleaned datasets, denoted as result_list. The key steps of the data-cleaning process are outlined below:

Subset English Tweets: Tweets were filtered based on the language attribute (X19..Language == "English"), ensuring that only English-language tweets were retained for further analysis.

Variable Creation: A new variable, tweet, was introduced to store the textual content of each tweet. An additional variable, tweet number, was added to assign a unique identifier to each tweet, facilitating subsequent tracking and analysis.

Data Standardization: The resulting datasets were standardized to include only the essential variables (tweet and tweet number), promoting clarity and consistency across datasets

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Documentation and Exploration: Original and modified column names were meticulously documented for transparency and reproducibility. The structure of each cleaned dataset, including data types and initial rows, was examined and printed using the str() function.

Handling Empty Datasets: In cases where no English tweets were found in a dataset, a clear notification was printed, and an empty data frame was returned.

Resulting Cleaned Datasets: The final output of the data preprocessing phase is a set of six cleaned datasets, each containing English-language tweets with corresponding identifiers. These cleaned datasets, stored in the result list, form the foundation for subsequent analyses, providing a coherent and language-consistent dataset essential for extracting meaningful insights from the Twitter conversations under investigation. The meticulous data-cleaning process ensures the reliability and interpretability of subsequent analyses, aligning the study with its objectives and enhancing the overall quality of the research findings.

2.4 Initial Data Visualization

To derive meaningful insights from the Twitter datasets, an initial data visualization approach was employed, focusing on the frequency distribution of words within the English-language tweets. This exploratory analysis aimed to uncover patterns, trends, and prevalent themes present in Twitter conversations over three months.

Counting the Frequency of Each Word: The first step involved counting the frequency of each word across the entire dataset. This process enabled the identification of frequently used terms, shedding light on the overarching topics and discussions within the Twitter-sphere. The frequency count provides a quantitative representation of the significance of words, guiding our understanding of the prevalent narratives during the study period.

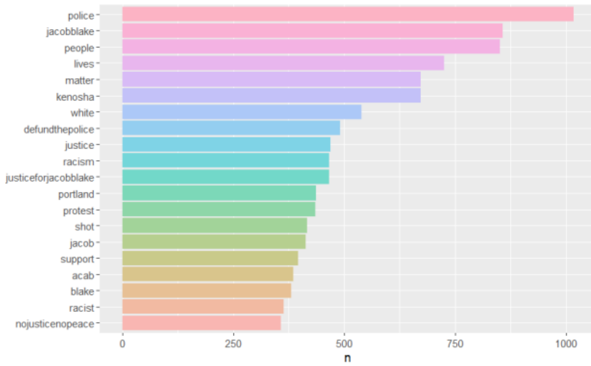

Figure 3. positive word count frequency

Removing Non-English Tokens: To ensure the accuracy and relevance of the analysis, non-English tokens were systematically removed from the dataset. This step was crucial in focusing the analysis exclusively on English-language content, eliminating noise, and enhancing the precision.

Temporal Analysis of Word Frequency: A compelling aspect of the analysis involved examining whether the most common words exhibited significant variations over the three months. This temporal analysis aimed to discern whether certain topics gained or lost prominence during specific intervals.

Identifying Positive and Negative Words: Beyond the broad exploration of word frequency, the study delved deeper into sentiment analysis by identifying positive and negative words. This nuanced approach allowed for a more granular understanding of the sentiments expressed in the tweets. By categorizing words based on their emotional tone, we aimed to uncover subtle shifts in sentiment and discern any emerging sentiments over time.

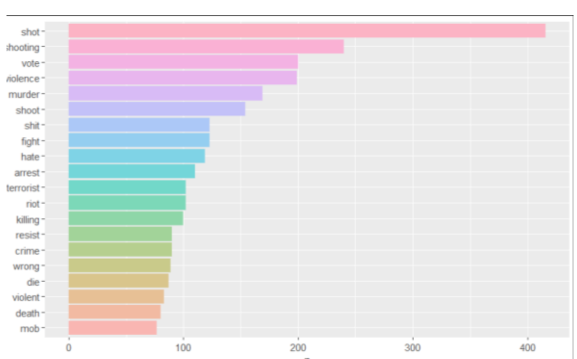

Figure 4. Identifying the most common negative word count frequency

Implications for Subsequent Analyses: The insights gained from this initial data visualization phase set the stage for more in-depth analyses. The identification of prevalent words, temporal trends, and sentiment nuances provides a foundation for subsequent investigations into the underlying dynamics of Twitter conversations. As we progress in our analysis, these preliminary findings will inform the development of targeted research questions and guide the selection of appropriate methodologies for a comprehensive understanding of the dataset.

2.5 Developing and Assessing Analytical Models

In the pursuit of comprehending the dynamic landscape of public discourse on Twitter regarding the Black Lives Matter movement over three months, a comprehensive analytical framework was developed and rigorously assessed. Employing sophisticated methods such as word frequency analysis, sentiment analysis, temporal analysis, and word association networks, our study aimed to distill meaningful patterns and unveil underlying sentiments within the vast Twitter dataset. Our methodology is structured around five specific research questions (RQs):

1. How do the most common words on Twitter, identified through frequency analysis, exhibit temporal changes and variations?

2. How did recognizing positive and negative terms enhance the comprehension of the evolving sentiments expressed?

3. What were the prevalent positive words in the expressions related to societal issues, and how did these words contribute to shaping the discourse during the specified period?

4. To what extent did individual words contribute to shaping different sentiments expressed on Twitter?

5. How did the identified sentiments change throughout the analysis, particularly in response to key events or developments related to the Black Lives Matter movement and police brutality?

6. How frequently was the term 'George Floyd' mentioned in the analyzed Twitter data?

To address our RQ1 we applied the word frequency model allowed for the identification of prevailing themes, while sentiment analysis afforded a nuanced exploration of evolving emotional tones. Word association networks, unveiling relationships between terms, provided a unique perspective on the interconnectedness of discourse. The assessment of this analytical model involves a qualitative examination of the generated plots. Each plot represents a distinct dataset, offering a comparative view of the most common words across different time points. Through visual inspection, we can discern the stability or variability of key terms within the Black Lives Matter conversation. The absence of drastic shifts in the top 20 words suggests a degree of consistency in the discourse. However, subtle changes may indicate evolving emphases or emerging topics of discussion.

In RQ2 the analysis aimed to enhance the understanding of evolving sentiments by identifying positive and negative terms within the Black Lives Matter discourse. Utilizing word clouds generated for each of the six Twitter datasets, the model integrated sentiment information through the 'Bing' lexicon, which classifies words into positive or negative categories. The word clouds were configured to present a maximum of 50 words, employing distinct color shades ('gray20' representing negative and 'gray80' representing positive) to distinguish between sentiments. This approach facilitated the identification of key terms associated with each sentiment category, contributing to uncovering the intricate emotional aspects embedded in Twitter discussions related to Black Lives Matter.

For the RQ3, the model assessment involved employing the 'NRC’ sentiment lexicon to identify and visualize the most common positive words within the Black Lives Matter discourse across the six datasets obtained from Twitter. The generated bar plots illustrated the frequency distribution of these positive terms, highlighting the evolving patterns over the three months. Notably, the initial sentiments expressed included themes of love, unity, and justice. As time progressed, there was a discernible shift in the most common positive words, with an emphasis on calls for donations and a subsequent focus on advocating for justice through the electoral process. The model effectively captured these temporal variations in sentiment, providing valuable insights into the changing emotional landscape of the Black Lives Matter conversations on Twitter. The use of the 'NRC' lexicon contributed to a nuanced understanding of positive sentiments, revealing the dynamic nature of the discourse and its evolving priorities.

In RQ4 we implemented sentiment analysis aimed to quantify the contribution of each word to distinct sentiments within the Black Lives Matter discourse across the six Twitter datasets. Leveraging the 'Bing' sentiment lexicon, which classifies words as positive or negative, the analysis identified and visualized the top 30 words contributing to each sentiment category. The resulting facetted bar plots effectively showcased the magnitude of each word's impact on sentiments, revealing the distinctive patterns associated with positive and negative expressions. By considering the contribution of words to sentiment categories, the model provided a nuanced perspective on the key linguistic elements shaping the emotional tone of the Twitter conversations surrounding Black Lives Matter. The visualization allowed for a comprehensive understanding of how specific terms influenced sentiments, contributing to a more insightful exploration of the evolving nature of public discourse on this critical social issue.

The research question pertaining to sentiment analysis (RQ5) involved the development of a model aimed at comprehensively examining the shifting sentiments within the Black Lives Matter discourse across six Twitter datasets. Utilizing the 'Loughran' sentiment lexicon, which classifies words into distinct financial sentiment categories like positive, negative, uncertainty, and litigiousness, the analysis entailed the identification and visualization of the top 10 words contributing to each sentiment category. The model provided a means to evaluate the evolution of sentiments, yielding valuable insights into the dynamic nature of public discourse surrounding Black Lives Matter. Additionally, it highlighted pivotal terms that played a crucial role in influencing changes in sentiment. This methodology significantly contributed to an enhanced understanding of how language choices contributed to the evolving emotional nuances in discussions related to this pivotal social issue.

Lastly, In RQ6 the analysis focused on quantifying the frequency of mentions of the term 'George Floyd' across the six Twitter datasets, aiming to comprehend how discussions surrounding this topic evolved. The model employed a customized function to identify and select tweets containing the specified term, followed by calculating the length of the resulting dataset for each period. The resulting 'George Floyd' frequency data was then visualized using a line plot, where the x-axis represents the six different datasets, and the y-axis indicates the respective frequency of 'George Floyd' mentions. This analysis contributes valuable insights into the dynamics of public discourse concerning the 'George Floyd' topic on Twitter during the specified period.

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3. Findings

The findings of the analysis shed light on the dynamic nature of sentiments within the Black Lives Matter discourse on Twitter over three months. By employing various sentiment lexicons, including 'bing' and 'nrc,' the study revealed the prevalence of both positive and negative sentiments in the tweets related to this social movement.

In our RQ1 the findings from the word frequency analysis reveal a consistent set of predominant terms across the six datasets, providing a temporal comparison over the three months. Notably, words such as "police," "jacobblake," "lives," and "people" emerged as the most frequently used, with substantial counts, indicating their sustained prominence throughout the studied timeframe. The word counts of around 1000 for some key terms and approximately 780 and 730 for others underscore their prevalence and significance in the Black Lives Matter discourse on Twitter. We can also see words like fun, hope, and talk are the least common positive words.

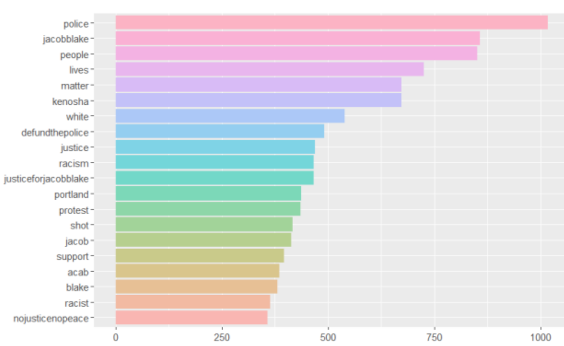

Figure 5. Most common positive word frequency

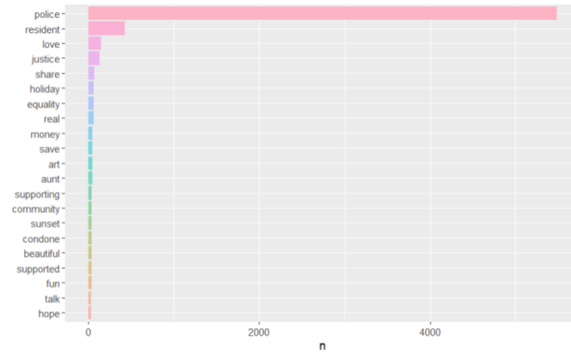

Figure 5. ;Least Common positive word frequency

In RQ2 the visualization using word clouds presents a compelling portrayal of prevalent positive and negative words within the discourse of Black Lives Matter across the six datasets. By utilizing sentiment information from the 'bing' lexicon, words are sorted into either a negative or positive category, facilitating a clear representation of sentiments. The word clouds, limited to exhibiting a maximum of 50 words with distinct shades of gray (indicating negativity and positivity), serve as a visually impactful tool for understanding the evolving sentiments expressed on Twitter. Positive terms such as "support," "love," "trump," "happiness," and "peace" are discernible in the positive cloud, while negative terms like "racism," "racist," and "kill" are evident in the negative cloud. This visual analysis provides a nuanced perspective on the prevalent emotional tones embedded in the Black Lives Matter conversation.

Figure 6. Word cloud with positive and negative words

Figure 7. Word cloud with positive and negative

In RQ3 Initially, Twitter users predominantly emphasized themes of love, unity, and justice in their tweets, as revealed by the sentiment analysis. However, the narrative evolved over time, with a noticeable shift towards advocating for donations as a means of supporting the Black Lives Matter cause. Subsequently, there was a discernible trend of urging followers to engage in voting, suggesting a strategic approach to pursue justice through civic participation. The evolving sentiments reflected a dynamic conversation on Twitter, illustrating a diverse range of strategies and calls to action employed by individuals. The overarching theme conveyed a collective desire for governmental or legal entities to take meaningful action in response to the issues raised within the Black Lives Matter movement.

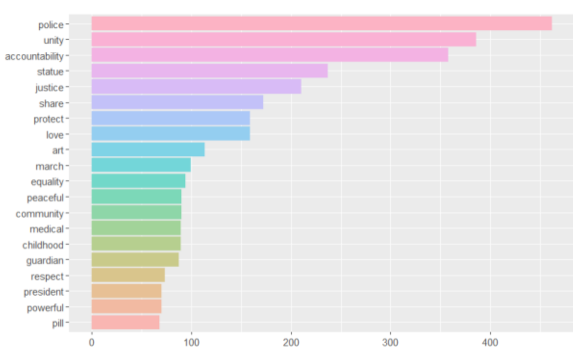

Figure 8. Positive words found in tweets

For RQ4, The analysis of word contributions to sentiments to classify words as either positive or negative. The resulting facetted bar plots, visualizing the top 30 words contributing to each sentiment category, provided a detailed overview of the linguistic elements influencing the emotional tone of the Twitter conversations. Notably, in the negative sentiment category, words such as "racist," "racism," and "protest" emerged as the top contributors, underscoring the prevalence of discussions around racial injustice and protests. Conversely, in the positive sentiment category, terms like "support," "Trump," and "lost" were prominent, indicating a diverse range of sentiments associated with support, political figures, and outcomes. This nuanced analysis allowed for a comprehensive understanding of the specific terms shaping sentiments, contributing valuable insights into the evolving nature of public discourse on the critical social issue of Black Lives Matter.

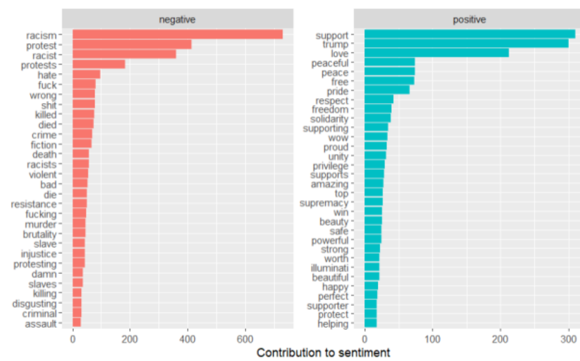

Figure 9. Contributing each word to sentiments

In RQ5, The visualizations, encompassing six facetted bar plots, illuminated distinct patterns in sentiment changes over the three-month period. First, there was a noticeable surge in litigious sentiments, suggesting an escalating demand for legal actions, particularly through petitions, as individuals sought justice. Second, a temporal shift in negative sentiments was observed, with a decrease from June to July followed by a resurgence in response to the incident involving Jacob Blake in Wisconsin. Notably, the focal point of negativity centered around expressions of 'violence.' Third, similarities between sentiments in June and August were discerned, reflecting consistent reactions to pivotal events, namely George Floyd and Jacob Blake. Lastly, a decrease in uncertainty over the three months indicated a growing sense of calmness, possibly influenced by the collective efforts towards legal change. This nuanced analysis enhances our understanding of the dynamic nature of sentiments within the Black Lives Matter discourse, capturing the multifaceted emotional responses and their temporal evolution.

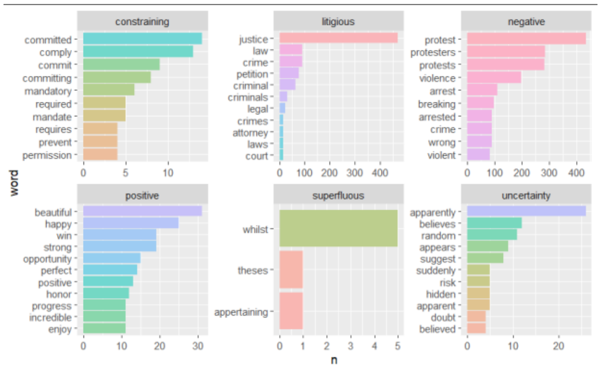

Figure 10. sentimental changes

In the last RQ6, The line graph presents six data points, each denoting the instances of 'georgefloyd' mentions across the six Twitter datasets spanning a three-month period. The graph features a blue dashed line and corresponding blue points, indicating a declining trend. This suggests a reduction in the frequency of tweets referencing 'georgefloyd' over time. The decrease in mentions may imply a waning focus or diminished intensity of discussions on this particular topic within the broader Black Lives Matter discourse. Possible contributing factors to this trend include shifts in the news cycle, the emergence of new events, or changes in public attention. This observation highlights the dynamic and fluid nature of online conversations, where topics can experience fluctuations in prominence over time.

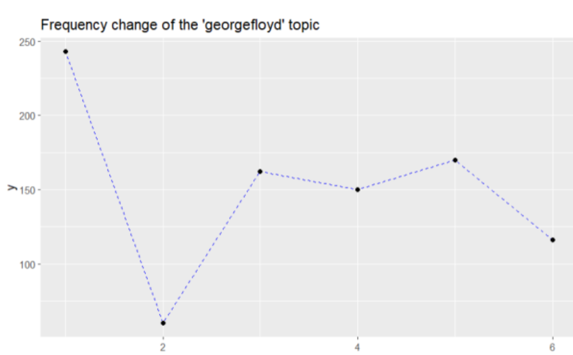

Figure 11. Key frequency change in sentiments

4. Discussions and Recommendations

The analysis conducted on the Black Lives Matter discourse on Twitter yielded valuable insights into the dynamic nature of public sentiment and conversation surrounding this crucial social issue. The examination of word frequencies, sentiment changes, and key terms' contributions to sentiments across six datasets over three months provided a comprehensive understanding of the evolving discourse. The identification of persistent terms, such as 'police,' 'jacobblake,' 'lives,' and 'people,' revealed a degree of stability in the most common words used over time. This stability may indicate consistent themes within the discourse or essential topics that retain prominence. However, the subtle changes in the top 20 words across the datasets suggest nuanced shifts in emphasis or emerging discussions.

The sentiment analysis, incorporating both the 'bing' and 'loughran' lexicons, added depth to our exploration. The word clouds visually represented the most common negative and positive words, offering an accessible means to comprehend the evolving sentiments. The model assessing word contributions to sentiments further enriched our understanding, revealing key terms influencing emotional tones.

The temporal analysis of sentiment changes highlighted noteworthy trends. The initial emphasis on themes of love, unity, and justice transitioned to calls for donations and an appeal to voting for justice. This dynamic progression signifies the multifaceted nature of the discourse, reflecting a strategic shift in approaches to supporting the Black Lives Matter cause.

Some Recommendations: Incorporation of User-Generated Content: Integrating user-generated content, such as replies and comments, into the analysis can offer a more holistic understanding of sentiment dynamics. This can provide insights into how conversations evolve through interactions and engagements.

Contextual Analysis: Further exploration into the contextual factors influencing sentiment changes is recommended. Understanding the external events or news cycles that coincide with shifts in sentiment can provide a more nuanced interpretation of the observed trends.

Community Engagement: Actively engaging with the online community through surveys, polls, or direct interactions can help researchers gain qualitative insights into the motivations behind sentiment shifts. This engagement can enhance the interpretive depth of the analysis.

5. Limitations

Despite the valuable insights gained from the analysis of the Black Lives Matter discourse on Twitter, it is essential to acknowledge certain limitations that may impact the interpretation and generalizability of the findings. Firstly, the study relies on data obtained from Twitter, which represents a specific online platform with its user demographics, culture, and communication norms.This limits the generalizability of the findings to other social media platforms or offline discussions within the broader community. Additionally, the analysis is contingent on the accuracy and completeness of the data collected, and the exclusion of certain contextual elements may introduce bias. The use of sentiment lexicons, while providing a quantitative framework for analysis, inherently simplifies the complexity of human emotions and may not capture the full spectrum of sentiment expressed in the tweets. Moreover, the study does not delve into the nuances of individual user characteristics, potentially overlooking variations in perspectives, motivations, or regional differences. public conversations surrounding social issues like Black Lives Matter.

6. Future Research

Future research endeavors in the realm of online discourse surrounding social movements, such as the Black Lives Matter movement on Twitter, can build upon the insights gained from this study. One avenue for exploration involves a more nuanced analysis of user characteristics and demographics to better understand how different groups engage with and contribute to the discourse. Investigating the impact of influential events and news cycles on sentiment dynamics over time could provide a deeper understanding of the evolving nature of online conversations. Additionally, exploring the role of multimedia content, such as images and videos, in shaping sentiments could contribute to a more comprehensive analysis. Comparative studies across various social media platforms and their unique environments may offer valuable insights into the transferability and platform-specific nuances of discourse. Future research endeavors should also consider integrating advanced natural language processing techniques to capture subtle shifts in language use and sentiment expression. Such approaches could further enrich our understanding of the complexities inherent in online discussions related to social justice movements and contribute to the development of more sophisticated analytical models.

7. References

- The scholarly discourse on social media and activism has accentuated the transformative role of digital platforms in mobilizing public opinion and fostering social change (Castells, 2015; Bennett & **Segeberg**, 2013).

- Twitter **has** been recognized as a crucial space where marginalized voices find amplification and grassroots movements gain momentum (Castells, 2015).

- It serves as an arena for disseminating information and shaping the narrative **of social** movements (Bennett & **Segeberg**, 2013**).**

- Twitter data has been effectively utilized for sentiment analysis, providing valuable insights into public sentiment during political events (Tumasjan et al., 2010)

- scholars also acknowledge challenges, including the potential for online echo chambers and the manipulation of sentiments through the spread of misinformation (Tumasjan et al., 2010)

- **https://www.pewresearch.org/internet/2018/07/11/an-analysis-of-blacklivesmatter-and-other-twitter-hashtags-related-to-political-or-social-issues/**

- **https://thinkingneuron.com/sentiment-analysis-of-tweets-using-bert/**