Term Paper

Sentiment Analysis with Twitter Data during the COVID-19 Pandemic

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Contents

1 Motivation & Related Work

The COVID-19 pandemic has not only posed health challenges but has also triggered shifts in societal attitudes and sentiments. Social media platforms, especially Twitter, have become important channels for individuals to express their thoughts and emotions in real-time. This study aims to shed light on the changing sentiments of Twitter users throughout the pandemic, employing changepoint analysis techniques to understand trends over time.
The goal of this paper is to provide a comprehensive view of Twitter users' sentiment during the COVID-19 pandemic. We will analyze the changes in sentiment of tweets during different phases of the pandemic. Also, we will investigate tweets that have been frequently retweeted to gauge the popularity and social impact of specific sentiments within Twitter users. In addition to the sentiment analysis, we will explore the language used in tweets by analysing the occurrences of specific positive and negative words throughout the pandemic.

This study is motivated by using "non-standard" data and analyze digital behavioral data as in recent research, such as "COVID-19, lockdowns and well-being: Evidence from Google Trends," by Brodeur et al. (2021) which examines sentiments using Google Trends data. Their study reveals a substantial increase in search intensity for boredom, loneliness, worry and sadness during the pandemic and lockdown period. Moreover, the immediate effects of the lockdown included increased boredom and impairment, reduced panic, and little short-run impact on stress, sadness, suicide or worry. These results highlight the potential negative effects of the COVID-19 pandemic and associated lockdowns on mental health and well-being, emphasizing the importance of addressing these issues in public health and policy responses.

Although Google Trends provides information on how people search for information, our focus on Twitter enables us to capture the immediate and emotional aspects observed in individual tweets. Our objective is to provide insights into how sentiments develop on online platforms during global health crises by comparing our findings with relevant studies.
Twitter's particular advantages in capturing real-time, personalized expressions of sentiment are the motivation for the decision to analyze Twitter data for sentiment during the COVID-19 pandemic rather than Google Trends data. The following factors, which emphasize the possible advantages of using Twitter data for our research, served as a basis for our choice.

First of all, people can communicate more precisely and individually on Twitter than they can in the aggregated form of Google Trends data. The short and fast format of tweets allows for a more in-depth examination of personal feeling and a better understanding of how people express and react to current events.
Second, Twitter data may be used to provide a thorough analysis of sentiment changes over time. Because the platform is real-time, we may see attitude changes in response to specific pandemic-related events, government statements, or societal developments. This provides a contextual and dynamic view of how sentiment has evolved throughout the different phases of the pandemic. This is especially important for understanding how sentiments evolve under rapidly changing situations (like lockdowns), providing an overview of the general emotional reaction as events develop.
Thirdly, retweet counts could be used to analyze the social relevance and popularity of specific opinions and sentiments on Twitter. This gives the sentiment analysis a social network viewpoint and provides information about how sentiments are shared and have an overall influence among Twitter users.
In essence, the features of Twitter provide a more detailed, timely, and socially informed understanding for sentiments, improving our sentiment analysis during the COVID-19 pandemic.

In summary, our findings not only expand sentiment analysis methodologies during crises, but also give practical insights into how individuals express and change their feelings online during challenging occurrences like during the COVID-19 pandemic. We want to identify trends in Twitter data that will help us answer the central question: Is it possible to use Twitter data to demonstrate the influence of the COVID-19 pandemic and its restrictions on peoples' mental well-being and emotional states?

The structure of this paper is outlined as follows: I start by describing the data source and methodology employed. Subsequently, the analysis section is divided into three parts: examining the sentiment of tweets over time, exploring the occurrence of specific words in tweets and investigating the sentiment of tweets with a high number of retweets. This aims to address the following questions: How does the sentiment of tweets change over different time periods and are there specific periods (e.g. lockdowns) with notable shifts in sentiment? Does the frequency of tweets that contain words with a particular positive or negative connotation change over time, such as during stay-at-home orders? What kind of tweets are being retweeted the most and how does the number of retweets correlate with the sentiment of tweets? Finally, the paper concludes with a summary of key findings and a discussion on the limitations of the analysis undertaken.

2 Data

The dataset employed in this study originates from the "TweetsCOV19" repository, provided by GESIS (German Research Institute for Empirical Social Sciences) and is openly available on their website[1]. Specifically, it is a subset of TweetsKB, which is a publicly accessible RDF corpus containing a collection of more than 2 billion semantically-annotated tweets that are collected since February 2013. The subset was extracted from TweetsKB using a seed list including 268 keywords related to COVID-19, such as "virus", "test" and "face mask" (Dimitrov et al., 2024). The tweets in TweetsCOV19 contain at least one keyword from the set of seed terms and are written in English. In addition, there is an exclusion of retweets to focus solely on original content. This approach enables a thorough investigation of the societal discourse about COVID-19 on Twitter (Dimitrov et al., 2020).

The collection includes tweets related to the COVID-19 pandemic that are enriched with semantic annotations. The main objective is to capture the online discourse concerning various facets of the pandemic and its societal implications. The dataset comprises a substantial volume with the temporal scope of the dataset spanning from October 2019 to August 2022. This provides a broad view of the evolving discourse. However, for our further analysis, we will limit on the period October 2019 to December 2020 as we are mostly interested during the time where the first stay at home orders were imposed (around April 2020). This period totals in 19,969,565 tweets contributed by 7,349,920 distinct users.

The dataset includes the following key information:

- **Tweet ID**: A unique identifier assigned to each tweet within the dataset.
- **Username**: Encrypted representation of the usernames associated with each tweet, ensuring user privacy while enabling analytical insights.
- **Time & Date**: Timestamp indicating the precise moment of each tweet's publication.
- **Entities**: For each entity identified within a tweet, the dataset aggregates the original text, the annotated entity, and the corresponding score obtained from the FEL (Fast Entity Linker) library. This comprehensive annotation offers valuable contextual information for subsequent analysis.

[1] `https://data.gesis.org/tweetscov19/#dataset`

- **Number of retweets**: The count of times each tweet has been retweeted, providing insights into the tweet's reach and impact.
- **Mentions**: An indicator of whether a tweet contains mentions of other users, contributing to the understanding of social interactions within the Twitter discourse.
- **Hashtags**: An indication of whether a tweet contains hashtags, offering insights into prevalent themes and topics within the discourse.
- **URLs**: An indicator of whether a tweet contains URLs, providing context to external resources shared within the tweets.
- **Sentiment**: Sentiment score for positive (ranging from 1 to 5) and negative (ranging from -1 to -5) sentiments

More specifically, to gauge sentiment within the dataset, SentiStrength was employed. It is a tool specifically designed for estimating the strength of positive and negative sentiments in short texts. Also, it can even be used for informal language that is prevalent on social media platforms like Twitter. SentiStrength generates two scores for each tweet: one indicating the strength of negative sentiment (-1 to -5, with -1 denoting not negative and -5 representing extremely negative), and another for positive sentiment (1 to 5, with 1 signifying not positive and 5 indicating extremely positive). The use of two scores allow for a parallel processing of positive and negative sentiments, accounting for multiple emotions that can be conveyed in tweets.

3 Method

For our further research, we apply a changepoint analysis to find significant shifts in the data. We want to answer questions like: How does the sentiment of tweets change over different time periods? Are there specific periods (e.g. lockdowns) with notable shifts in sentiment? Which particular positive or negative words were tweeted more frequently?

In the context of time series analysis, a changepoint is a particular point in a data sequence where the data's underlying statistical features significantly change or shift. This shift might show up as a rapid rise or fall in the data series' mean, variance, trend, or other features.
In order to discover significant transitions or events in the data, changepoint detection is important in a number of domains and also for our analysis at hand during the outbreak COVID-19. By locating these transitional points within a dataset, changepoint analysis enables researchers to identify precisely the dates and times of changes. Analysts can divide the data into several homogeneous parts by looking for changepoints, which makes it possible to analyze and explain the underlying processes with more accuracy. All in all, changepoint identification is essential for comprehending trends, patterns, and anomalies in time series data (Killick et al., 2016).
In order to implement the changepoint analysis, the R package 'changepoint' is used. The R package was developed for changepoint analysis, especially the detection of several changepoints within a time series or sequence of data. The package offers users a choice of different changepoint search techniques. However, in the following we will focus on the "binary segmentation" changepoint algorithm most widely used multiple changepoint search method and originates from the work of Edwards and Cavalli-Sforza (1965), Scott and Knott (1974) and Sen and Srivastava (1975).
The most prevalent method for locating multiple changepoints is to minimize

$$\sum_{i=1}^{m+1} \left[C\left(y_{(\tau_{i-1}+1):\tau_i} \right) \right] + \beta f(m) \tag{1}$$

where C is a cost function for a segment, such as negative log-likelihood and $\beta f(m)$ is a penalty to prevent overfitting.
As mentioned above, we will apply the binary segmentation algorithm to search for changepoints. In summary, binary segmentation involves splitting the data into two parts at the position of a changepoint. Initially, a single changepoint test statistic is applied to the entire dataset. Following the initial segmentation, the same changepoint technique is then applied to the two resulting subsets. If changepoints are identified in either subset, fur-

ther divisions occur. This process iterates until no additional changepoints are detected in any portion of the data. This iterative approach approximates the minimization of (1) with $f(m) = m$, given that changepoint locations are influenced by previously identified changepoints. Moreover, when finding changepoints, binary segmentation finds a compromise between speed and accuracy. While it is computationally fast, the changepoints that it finds might not be as accurate as those obtained using precise techniques. Nevertheless, binary segmentation is still a useful and effective method for finding multiple changepoints in time series data because of its ability of finding a balance between computing speed and accuracy, making it a frequently conducted algorithm.

For the analysis, the changepoint package is implemented by using this general code in R:

```r
library(changepoint)

# Find changepoints in mean and variance
changepoints <- cpt.meanvar(
    data$column,
    method="BinSeg"
)

# Return the changepoint locations
changepoints

# Plot the trend and changepoints along with the data
plot(changepoints)

# Return the estimated mean and variance
changepoints@param.est
```

Further information regarding the code and the subsequent analysis is accessible on GitHub[2].

[2]https://github.com/thaotran2000/CSS---Sentiment-Analysis

4 Analysis

In the following sections, we analyze the tweets, first focusing on their general sentiment evolution over time, and then on their content, analyzing entities in particular to determine the frequency of certain positive and negative words (like depression), and assessing the sentiment of the most popular tweets and how they differ from the overall sentiment of the tweets. We systematically assess the prevalence of sentiments in the dataset from October 2019 to December 2020. Following this, a changepoint analysis is conducted to identify any significant shifts in sentiment over this time frame. Using this technique, we may identify trends in the sentiment dynamics seen in the Twitter data across the given time frame.

First, we analyze the total number of tweets that were gathered over the designated period, concentrating on COVID-19-related tweets. There is a major increase in Twitter activity starting in March 2020 that reaches its peak (more than 120,000 tweets per day) until the end of the month and then starts to fall. Around the same time, orders to stay at home were implemented at this time throughout the majority of the world. After that, there is a decrease down to around 50,000 tweets per day which lasts until the end of 2020. A small maximum is seen in October 2020 with about 60,000 tweets.

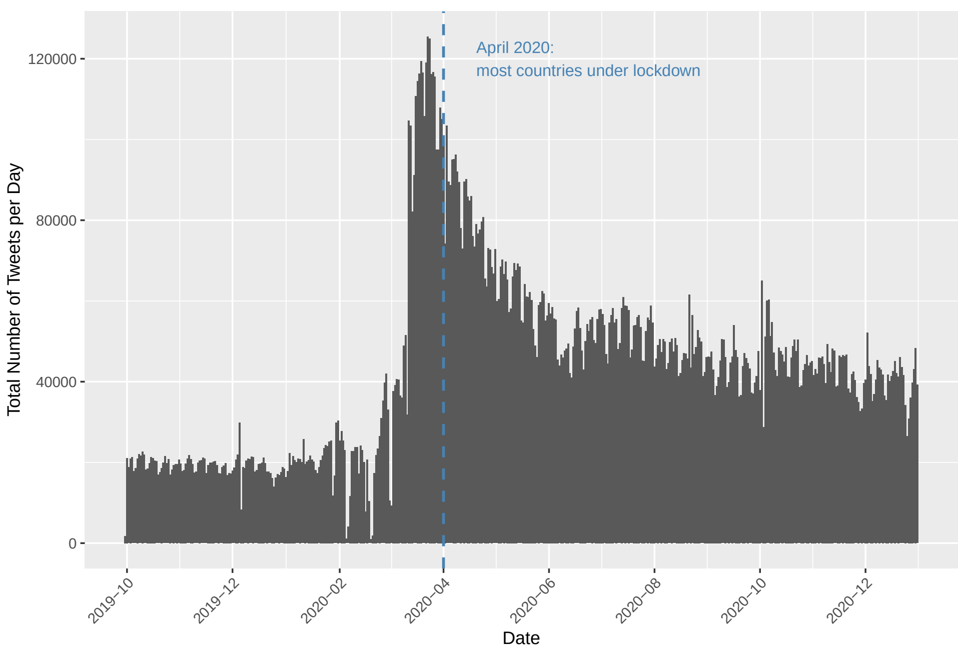

Figure 1: Total number of tweets related to COVID-19 from October 2019 to December 2020

4.1 Sentiment

In this section we analyse the each the positive and negative sentiment of tweets over time. For that, the mean sentiment of each day is presented in figure 2.

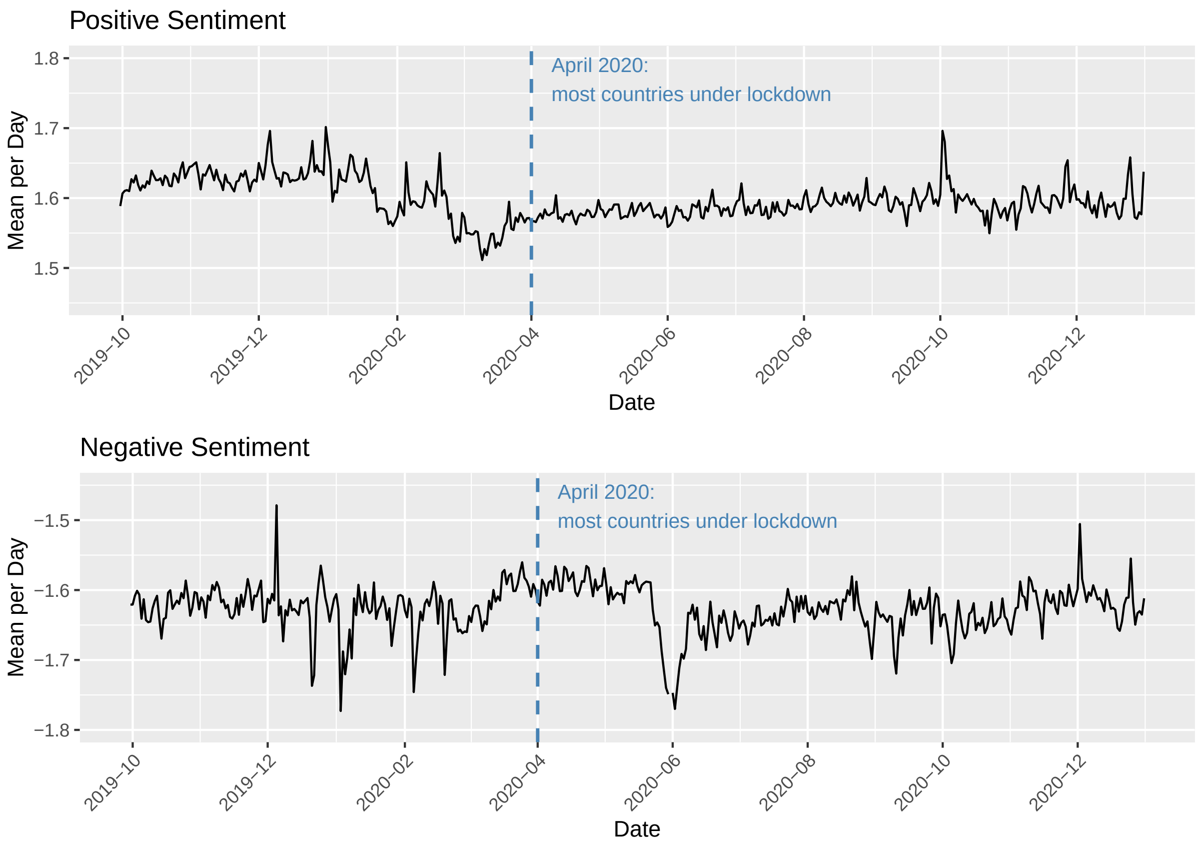

Figure 2: Positive and negative sentiment of tweets related to COVID-19 from October 2019 to December 2020. Average of each day.

Figure 2 illustrates the average positive sentiment (top) and average negative sentiment (bottom) for each day spanning October 2019 to December 2020. The positive sentiment ranges between 1.7 (most positive) and 1.51 (least positive). Notably, the positive score peaks in December 2020 and then declines until March 2020, when it reaches its lowest point of 1.5, which also happens to be the month that several countries implement broad lockdowns. here is a slight positive sentiment recovery, but it remains below the pre-lockdown levels. An isolated peak is evident in October 2020, with a value of 1.7. However, the mean positive sentiment decreases thereafter.
In contrast, the mean negative sentiment score exhibits a higher variance compared to positive sentiment. The highest value is -1.48 (least negative) and the lowest value is -1.8 (most negative). It displays a notable peak in early December 2019, reaching its highest

value (-1.48). Following this peak, negative sentiment experiences subsequent valleys, hovering around -1.74. Interestingly, the mean negative sentiment increases during the period of lockdown restrictions and maintains this elevated level. Only until June 2020, there is a major decrease to the value of -1.77. However, the average sentiment increases again afterward in a fluctuating way.

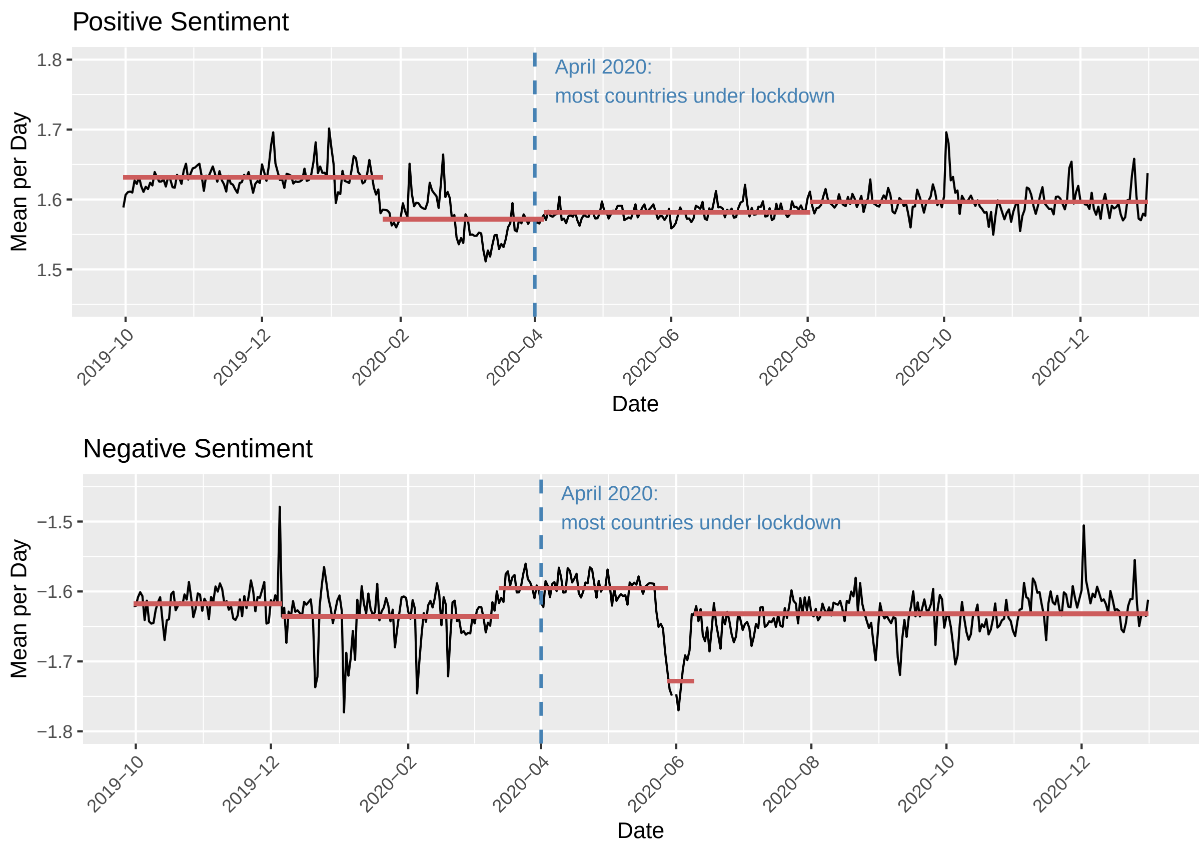

Figure 3: Changepoint analysis: Positive and negative sentiment of tweets related to COVID-19 from October 2019 to December 2020. Average of each day. With horizontal lines for the underlying (fitted) mean.

Conducting a changepoint analysis to identify trends and shifts in the data validates our earlier observations. The trend in mean positive sentiment reveals a decrease leading up to and during the period of lockdowns, persisting at a lower level thereafter. In contrast, the trend in mean negative sentiment displays a slight decline in the months preceding lockdowns, followed by an increase around the lockdown period (from the end of March to April). However, a substantial valley occurs in June 2020, after which sentiment gradually increases but remains at a subdued level.

In conclusion, the sentiment trends indicate a decline in positive sentiment before and during lockdowns, suggesting a diminished sense of optimism or positivity. Fluctuations in negative sentiment, with an increase around lockdowns and a subsequent major decrease in June 2020, may reflect the complex emotional responses of individuals during these critical periods.

4.2 Entities (words)

This section examines the usage of words (or their stems) that have a particular positive or negative meaning. Examples of these terms are "depress," which may also include the words like depression or depressive, as well as "love" and "hate.". Thereafter, a trend analysis is applied.

Tweets containing the stem "depress"

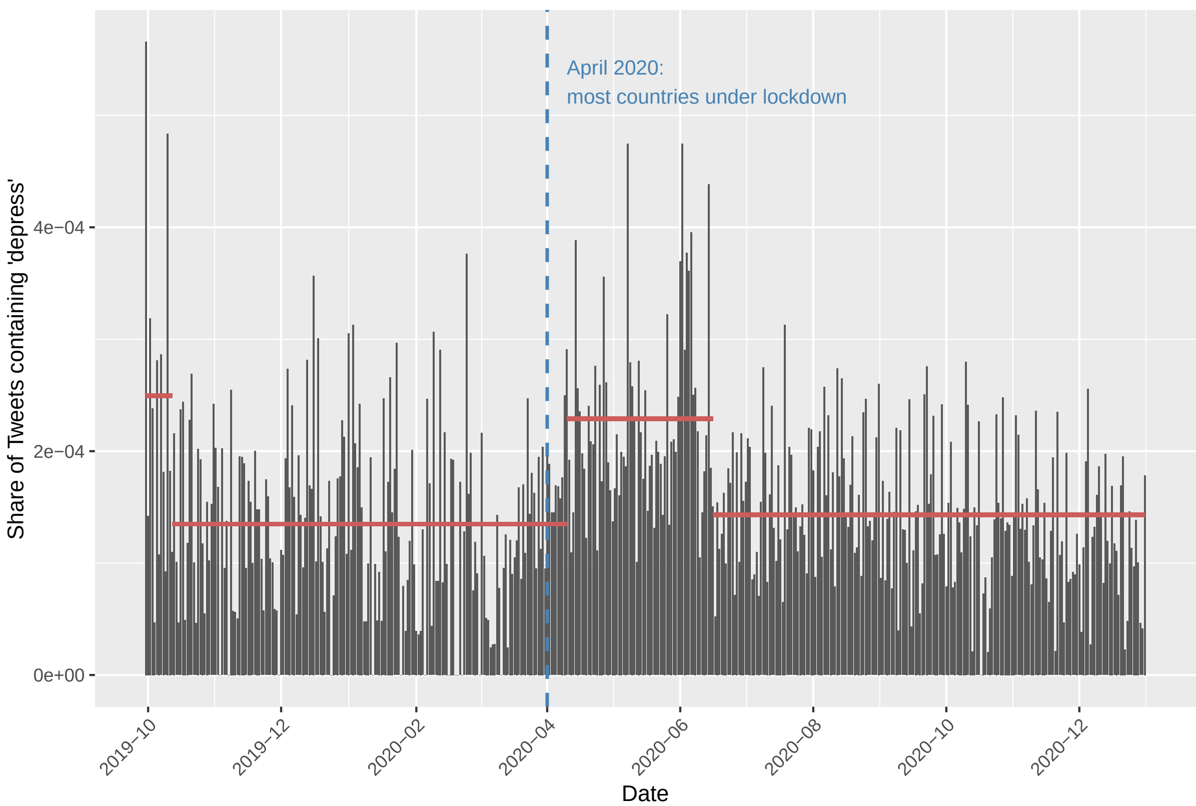

Figure 4: Changepoint analysis: Share of tweets related to COVID-19 containing the stem "depress" from October 2019 to December 2020. With horizontal lines for the underlying (fitted) mean.

Figure 4 illustrates the proportion of tweets containing the stem "depress" relative to all tweets related to COVID-19. Given a significant increase in the overall number of tweets around March, as seen in Figure 1, analyzing the proportion of tweets instead of the total number is more insightful. Starting October 2019, there is a peak (0.025%) in the percentage of tweets using the words with the stem "depress" which might be related to World Mental Health Day which falls on October 10th. Subsequently, a lower average trend (0.013%) persists until the end of March. Following this period, there is a sudden increase in tweets, reaching 0.023%, aligning with the global implementation of lockdowns. This heightened level lasts until mid-June 2020, followed by a decline to the initial level. The information indicates a notable rise in tweets that use the word stem "depress" during the lockdown, pointing to a possible correlation between pandemic-related restrictions and an increase in depressed sentiments on Twitter. The decrease in depressing tweets after the lockdown raises the possibility that the easing of restrictions have had a positive impact again.

Tweets containing "love"

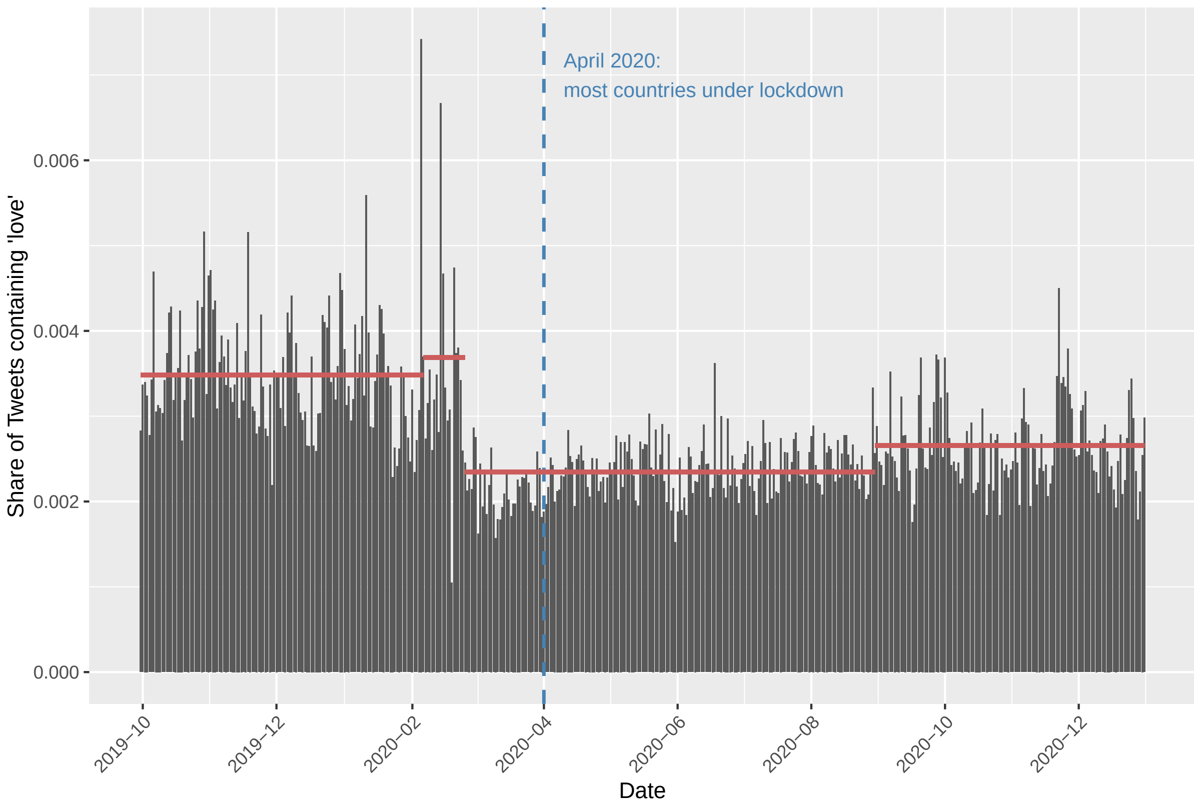

Figure 5: Changepoint analysis: Share of tweets related to COVID-19 containing "love" from October 2019 to December 2020. With horizontal lines for the underlying (fitted) mean.

The percentage of tweets featuring the term ”love” in relation to COVID-19 is shown in Figure 5, with an initial average of 0.35% which lasts until February 2020. Then, a slight uptick is observed, likely linked to Valentine’s Day on February 14th. Subsequently, a substantial decline in the trend occurs, reaching 0.23% around a month before the majority of countries implemented lockdowns, persisting until September. Following this period, there is a minor increase, but the overall level remains relatively low. All in all, the observed trends suggest that the implementation of lockdown measures have led to a significant decrease in tweets featuring the term ”love.”. This could point to a change in the way people express themselves online when there are only restricted social interactions.

Tweets containing ”hate”

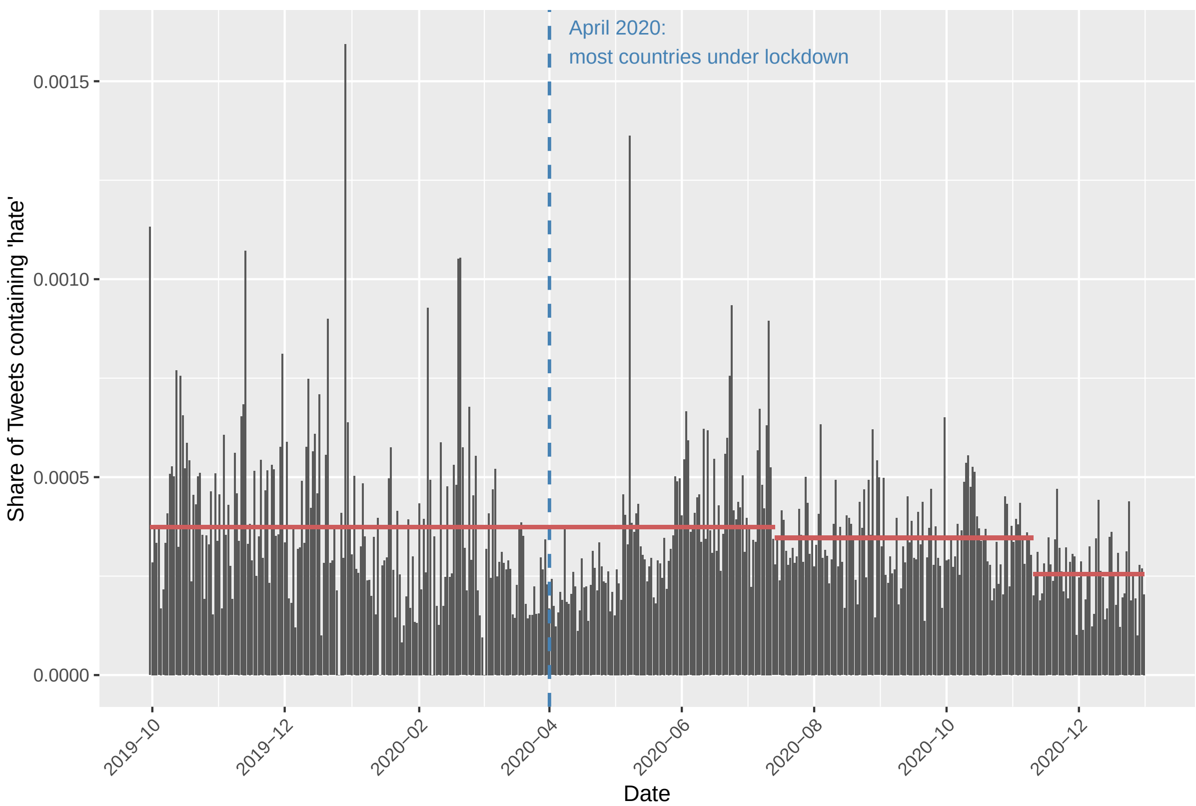

Figure 6: Changepoint analysis: Share of tweets related to COVID-19 containing ”hate” from October 2019 to December 2020. With horizontal lines for the underlying (fitted) mean.

Figure 6 shows the percentage of tweets that contain the word ”hate,” and it reveals minimal shifts compared to previous graphs. Up until mid-July, the initial trend is steady at 0.037%. After that, there is a little fall to 0.035% which is followed in early November by a more noticeable decline to 0.026%. Consequently, it is evident that during the period when the majority of shutdown restrictions were enforced worldwide, there were no significant shifts in the percentage of tweets containing hate. This could imply that, unlike other emotional expressions, sentiments of hate remained consistent during the global implementation of lockdown restrictions.

4.3 Number of retweets

In this section, we examine popular tweets, i.e. a subset from all tweets that have been retweeted 200 times or more. They make up for around 3% of the most poplar tweets. The mean number of retweets is 40 while the the tweet with the most retweets has 308,686. As before, we apply a changepoint analysis to find shifts and trends in the positive and negative sentiment from October 2019 to December 2020.

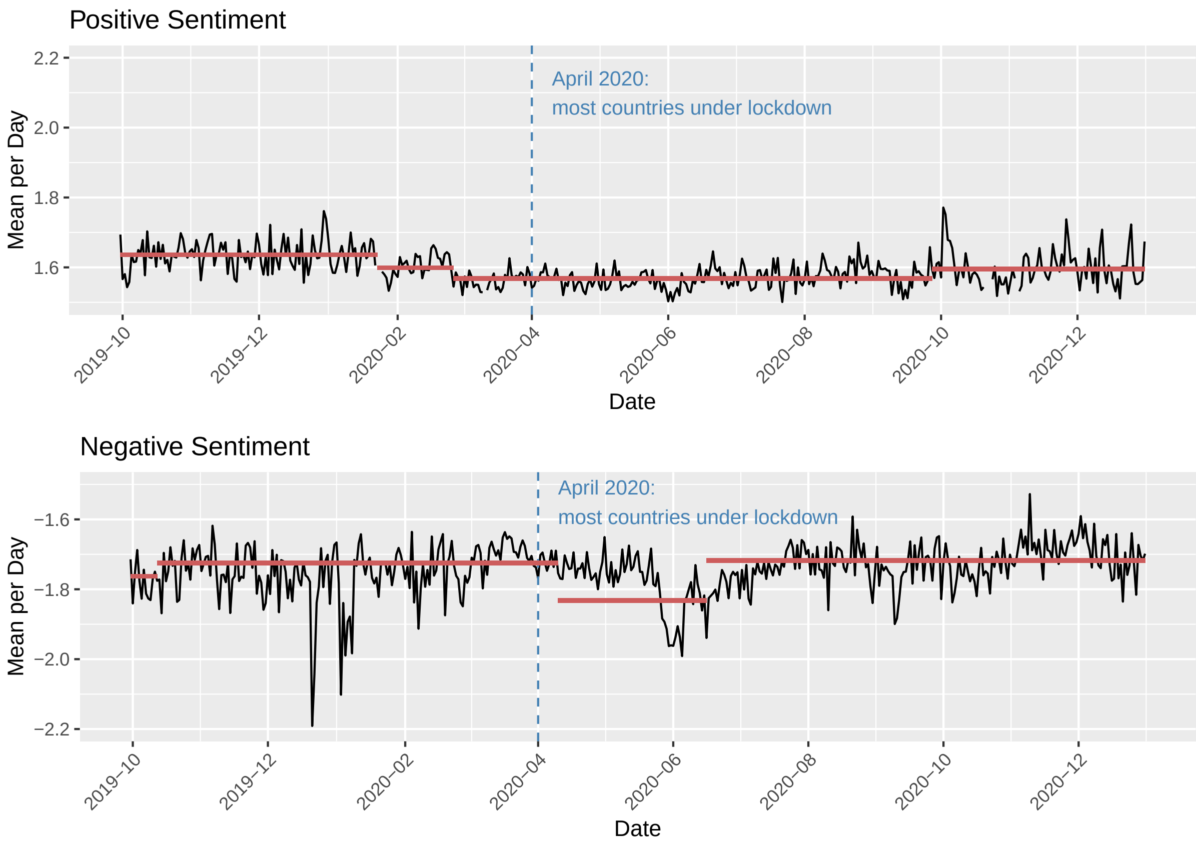

Figure 7: Changepoint analysis: Popular tweets related to COVID-19 with at least 200 retweets from October 2019 to December 2020. With horizontal lines for the underlying (fitted) mean.

Overall, figure 7 shows that the variance is higher in both the positive and negative sentiment score of frequently retweeted tweets compared to the total number of tweets. The variance ranges in the positive sentiment from 1.46 to 1.77. It even ranges more for the negative sentiment score from -1.53 to -2.19. This indicates that especially tweets that have strong positive/negative sentiment are rather retweeted and more popular than neutral tweets.

If we analyze the trend of the positive sentiment, we can see that it is gradually shifting downwards from 1.63 to the lowest point of 1.57 exactly shortly before most countries were under lockdown. Afterward in September, the mean positive trend is increasing a bit. Therefore, we can conclude that during the time of the lockdowns, the sentiments of tweets became less positive. This is matching the outcomes obtained from the analysis of all tweets (see figure 3).

Likewise, the negative sentiment exhibits a consistent trend over time. The mean negative sentiment decreases around the time when most countries implement lockdown measures (from -1.72 to -1.83). Although this decline occurs slightly later than the decrease in positive sentiment, it may still be attributed to the effects of lockdown restrictions. By mid-June, the mean negative sentiment rebounds to its previous level. This suggests that the lockdowns may have affected people in a negative way, as reflected in the sentiment of their tweets. However, these findings contrast with the analysis of all tweets, where the negative sentiment score increases during lockdown but experiences a significant decrease towards the end of May and beginning of June (see figure 3).

Overall, the analysis reveals that tweets with over 200 retweets tend to exhibit a notably stronger negative sentiment (compared to all tweets), as reflected by their average sentiment scores being skewed towards lower values. The result suggests that tweets that have received more retweets, or higher levels of interaction, are more likely to express negative emotions. This may indicate that Twitter users are more likely to engage with content that evokes strong emotional reactions, especially negative ones. Additionally, it may indicate that negative or controversial topics are more likely to go viral on the platform.

5 Conclusion

In this study, we conducted a comprehensive sentiment analysis utilizing Twitter data to explore the emotional trends and shifts during the COVID-19 pandemic. Employing a changepoint analysis, we examined the sentiment dynamics over time and additionally focused on specific words such as "depress" (as a word stem), "love" and "hate".

Our findings revealed noteworthy patterns in sentiment trends. Notably, we observed a decrease in positive sentiment during the implementation of lockdown measures, indicating a shift towards less optimistic expressions among Twitter users. Conversely, the mean negative sentiment exhibited an initial increase, followed by a significant decrease, suggesting that more negative expressions were not in the beginning but rather in the later phase of the pandemic.

Additional insight of the discussion on Twitter was obtained through the examination of certain terms. The stem "depress" became much more frequent just after lockdowns were implemented, suggesting that conversations about mental health issues were more prevalent during that period. On the other hand, the term "love" was used less frequently during lockdowns, which may indicate changes in sentiments towards a less positive one during a period of restrictions. Notably, occurrences of the word "hate" were mostly constant, which shows that this particular word and its negative connotations were merely affected by the situation.

Furthermore, a closer look tweets with higher levels of engagement (measured by retweets) showed a greater variance in sentiment scores — both positive and negative — highlighting the engagement with emotionally charged content on the platform. Notably, we observed a decline in the mean positive sentiment score and a decline in the mean negative sentiment score around the time where stay-at-home orders were enforced. These observations suggest that there were general shifts towards more negative sentiments at these times and that exactly these negative connoted tweets were popular among Twitter users.

Nevertheless, it is important to be aware of the limitations of Twitter data, especially in terms of user demographics and location and general representativeness. Twitter users are not a representative sample of the broad population, and their demographics may skew towards certain groups, such as younger individuals or those with specific interests. Moreover, Twitter users may not fully reflect the sentiments and experiences of the broader population, due to the fact that not everyone uses Twitter (e.g. due to access difficulties) to or shares their thoughts online.

Despite these limitations, our results support earlier research on the influence of COVID-19 on people's emotional states. Especially, if we compare our results to the study of (Brodeur et al., 2021) as mentioned in the beginning, we can see similarities as our results reveal potential negative effects of the COVID-19 pandemic and associated lockdowns on mental health and well-being due to increased negative or less positive sentiments and increased usage of negative connoted words and likewise decrease in positive connoted words.

In conclusion, our study provides an understanding of the Twitter online discourse around the pandemic. Yet, it is important to keep in mind the constraints that come with utilizing Twitter as a non-standard data source. Despite the previously mentioned difficulties, our research increases our knowledge of the pandemic's impact on the sentiment of tweets and its impact on people's emotional states. It also stresses the importance of carefully interpreting results in considering Twitter's specific user base and demographics.

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