Exploring Sentiment Analysis on Xenophobic Tweets from 2017 to 2022: A Case Study of South Africa

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Abstract

This study delves into the sentiment dynamics within the realm of xenophobia-related tweets over the period of 2017 to 2022, concentrating on the area of South Africa. Against the backdrop of significant socio-political events, this research seeks to uncover patterns and shifts in sentiment expressed by users during this transformative timeframe. The methodology involves comprehensive data collection from twitter, emphasizing xenophobia-related content relevant to South Africa within the specified temporal scope. The temporal dimension of the analysis aims to correlate sentiment trends with major events, while the geographical aspect dissects sentiment variations across diverse regions within South Africa. The anticipated results of this study hold the potential to unravel sentiment trends over time, offering insights into public reactions during pivotal moments related to xenophobia. Moreover, regional sentiment disparities may shed light on localized dynamics that contribute to sentiment variations. The implications of these findings extend to informing policy decisions, societal awareness initiatives, and academic research in the sphere of social sentiment on xenophobia.(Alexandra Balahur, 2013)(Medhat et al., 2014)

***Keywords*:** xenophobia, sentiment analysis, sentiment dynamics, south Africa, socio-political events, data collection, regional sentiment patterns, public reactions

1. Introduction

2. Problem Definition

Xenophobia is the fear or hatred of people who are perceived as being different, especially those from other countries or cultures. It is a prevalent societal concern in South Africa and understanding the sentiments surrounding xenophobia is essential for informing policy and programming aimed at addressing this issue.

This study explores sentiment trends in tweets related to xenophobia from 2017 to 2022. This period encompasses a time of significant socio-political change in South Africa, marked by pivotal events that have sparked discussions, protests, and controversies about xenophobia. By focusing on sentiment dynamics, this study seeks to provide insights into the evolving public perceptions, catalysts and reactions surrounding xenophobia.

The study acknowledges the complexity of sentiment analysis. Sentiments expressed through text can be subtle and subjective, influenced by cultural nuances, linguistic diversity, and the evolving nature of language. The intent of this study is not to simply quantify sentiments, but to interpret the emotions, attitudes, and perceptions that shape the discourse around xenophobia. This aligns with the broader objective of comprehending public sentiment, identifying patterns, and recognizing potential influencing factors. The study aims to illuminate trends that may reveal themselves over distinct periods and across different geographical locations in South Africa.

Ultimately, this knowledge can contribute to informed and strategic decision-making, awareness campaigns, and dialogue aimed at addressing xenophobia and fostering social cohesion in South Africa in order to avoid repeating mistakes in solving this issue.

3. Method

The South African Xenophobia Tweet Dataset from Kaggle was used in this study. This dataset contains five years of historical tweets discussing xenophobia and xenophobic attacks in South Africa. The tweets were extracted using the Twitter API from January 2017 to July 2022, and a total of 15,912 tweets were collected. The tweets were manually annotated as positive, negative, or neutral, and the districts (urban or rural) and number of attacks were also manually annotated.

The dataset contains the following fields:

- DateCreated: The date when the tweet was posted.
- TimeCreated: The time when the tweet was posted.
- CleanedTweet: A processed post that represents users' opinions.
- Sentiment: A view of or attitude toward a situation or event; an opinion (positive, negative, or neutral).
- Likes: The number of users who liked the tweet.
- No of replies: The number of replies to the tweet.
- Language: The language in which the tweet was written.
- Retweet: The number of times the tweet was retweeted.
- User Location: The location of the user who posted the tweet.
- Tweet Origin: The place where the tweet was posted.
- Coordinates: The geographic coordinates of the tweet, represented by latitude and longitude.
- District: The locality of the tweet (urban or rural).
- Province: The administrative division of the country in which the tweet was posted.

- No of Attacks: The number of places affected by xenophobic attacks at the time the tweet was posted.

For the purpose of this project, the sentiment of each tweet was calculated using a sentiment analysis algorithm. There were some discrepancies in the dataset, so the following columns were dropped: Sentiment, Likes, No_of_replies, Language, User Location, Coordinates, District, Province, and No of attack.

3.1 Data Preprocessing

In order to prepare the data for analysis, several steps were undertaken.

Firstly, essential libraries for data manipulation, text processing, and visualization were imported.

The dataset on xenophobia was then read from a CSV file, and specific columns such as Sentiment, Likes, No_of_replies, Language, User Location, Coordinates, District, Province, and No of attacks were eliminated as they held discrepancies.

To facilitate analysis, the TimeCreated and DateCreated columns were converted into datetime format.

Any rows containing NaN values, which represent missing or invalid data, were removed.

Additionally, a dictionary of shorthand texts was compiled from a website to facilitate text cleaning, eliminating slang and jargon that might hinder comprehension of the text and slang expressions were substituted with their corresponding formal equivalents.

Subsequently, lemmatization was applied to the sanitized text, thereby reducing words to their fundamental base forms.

To further refine the dataset, an elimination of stopwords was conducted to remove words that contribute minimally to the overall meaning of the text.

3.2 Sentiment Analysis

The assessment of the sentiment of tweets were found, classifying them into: 'Positive', 'Negative', or 'Neutral’.

3.3 Temporal Analysis

Temporal analysis was undertaken by extracting distinct dates from the dataset, facilitating an in-depth understanding of its chronological span. The 'TimeCreated' and 'DateCreated' columns were adeptly converted into a unified datetime format and specific years were isolated from the 'DateTimeCreated' column, which is a joint of both columns, and judiciously utilized to form a distinct 'Year' column.

3.4 Sentiment Variation Over Time

Conversion of sentiment labels into corresponding numerical values was performed and grouped into both year and its corresponding sentiment category, enabling the derivation of the prevailing sentiment trend within each temporal context. A line chart was drawn, serving as a visual conduit to illustrate the evolving sentiment trends embedded within xenophobia-related tweets over distinct time periods.

3.5 Sentiment Variation Across Regions

This was extended to regional contexts, achieved through a grouping of the dataset based on 'Tweet Origin' (region) and sentiment classifications. Within these defined groupings, the prevalent sentiment orientation was effectively computed. A perceptive scatter plot was drawn to convey the nuanced variations in sentiment across diverse regions.

3.6 Identifying Notable Sentiment Changes

Sentiment distribution was undertaken by computing it on a daily basis, subsequently juxtaposed against sentiment distribution. In order to identify days characterized by significant shifts in sentiment distribution, a discerning threshold was established, and a graph was constructed, effectively charting the temporal evolution of sentiment distribution while prominently highlighting days marked by notable deviations.

3.7 User Engagement Analysis

Data segmentation was done to establish discerning thresholds for both high and low sentiment ranges. Subsequently, engagement metrics, encompassing average sentiment, retweet count, and the proportion of positive messages, was astutely calculated for the identified high and low sentiment intervals. A bar chart was then crafted to effectively elucidate the contrasting patterns of user engagement witnessed during periods of heightened and subdued sentiment.

4. Results

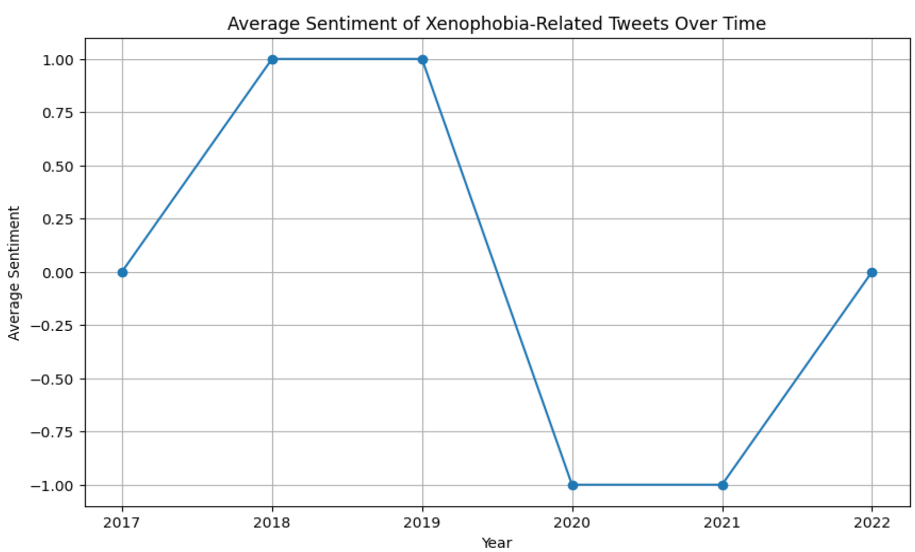
4.1 Sentiment Trends

A table and a line chart were developed to see the distribution sentiment trends over the years from 2017 to 2022.

The table and line chart created provided a comprehensive overview of sentiment analysis outcomes for various tweets pertaining to the topic of xenophobia across different years. The numerical values within each sentiment category per year indicate the frequency or count of tweets exhibiting that particular sentiment.

Sentiment Year	Negative	Neutral	Positive
2017	186	255	200
2018	278	244	336
2019	929	672	975
2020	1418	804	1314
2021	880	648	863
2022	2013	2204	1689

1: Distribution of Sentiment on Xenophobia between the years 2017-2022



2: Average Sentiment of Xenophobia-Related Tweets over Time

These presents a picture of sentiment trends in relation to xenophobia-related tweets for each year. Here's what implies for each year:

2017: In the observed year, the sentiment distribution appears to be skewed towards neutral and positive expressions, with a notable scarcity of negative sentiments. This finding may initially seem incongruent with the broader socio-political context of that time period, particularly with regard to the xenophobic incidents South Africa faced. In the year under examination, 2017, South Africa encountered a series of xenophobic attacks, particularly during the initial and closing months of the year. The apparent divergence between the documented sentiment analysis outcomes and the historical occurrences prompts a deeper inquiry into potential underlying factors. One plausible explanation lies in the realm of user behavior dynamics. The muted representation of negative sentiments in the dataset might be attributed to a reduced level of user activity on Twitter during that year, as compared to the subsequent years.(Lee-Anne Bruce, n.d.)

2018: During the assessed period, a discernible shift in sentiment distribution becomes apparent, characterized by a more equilibrium between positive and negative expressions, while neutral sentiments maintain a substantial presence. This observed trend resonates with the contextual events of the year, aligning with reported incidents.(Loren B Landau, n.d.)

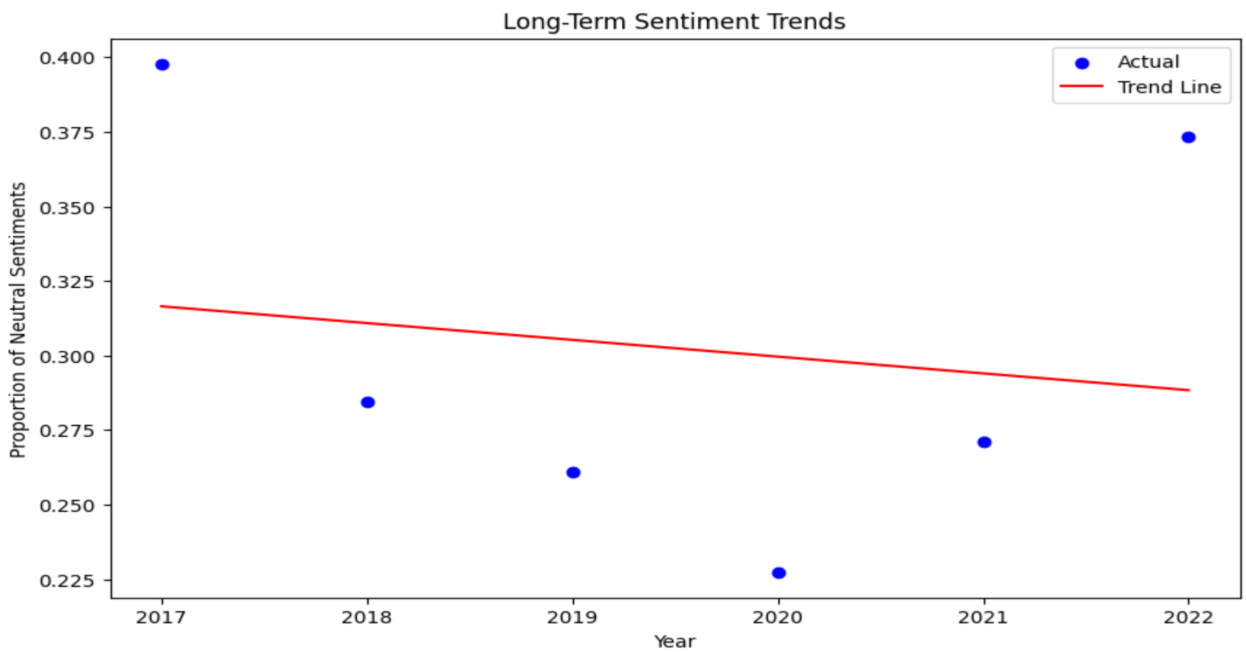
2019: Throughout this particular year, a discernible shift is observed within the sentiment distribution landscape. Negative sentiments experience a notable upsurge, subsequently establishing themselves as the prevailing sentiment category. Simultaneously, positive sentiments exhibit a robust presence, and neutral sentiments continue to maintain a noteworthy share. This intricate sentiment dynamic potentially unveils an intensified emotional discourse encompassing the theme of xenophobia. Intriguingly, this sentiment pattern aligns with reported incidents during this temporal period. Within this specific year, the occurrence of a mass shooting, ostensibly driven by xenophobic sentiments, marked a somber event. Furthermore, the year witnessed a mobilization of Nigerians advocating against xenophobia, substantiating the heightened emotional undercurrents prevalent within society.(Watch, 202 C.E.)

2020: Negative sentiments continue to be prominent, surpassing both neutral and positive sentiments. This might be reflective of the global socio-political events of that year.

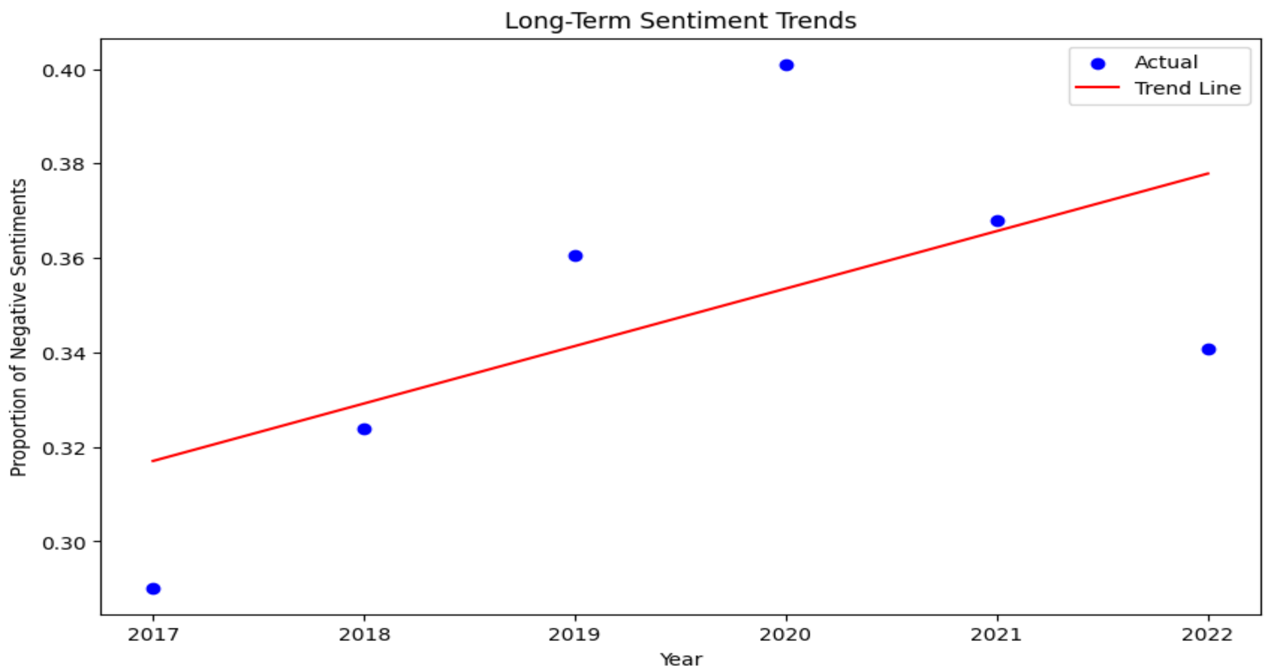
2021: The sentiment distribution becomes more balanced once again, with negative and positive sentiments being closer in count. Neutral sentiments remain substantial. During this year, the attacks made on Durban, South Africa were a prevalent topic in tweets as seen when a WordCloud was developed.

2022: Interestingly, negative sentiments decrease significantly compared to the previous years, while neutral and positive sentiments become more prevalent. This might suggest a shift in the discourse or public sentiment around the topic as a number of rallies were held to advocate against xenophobia.

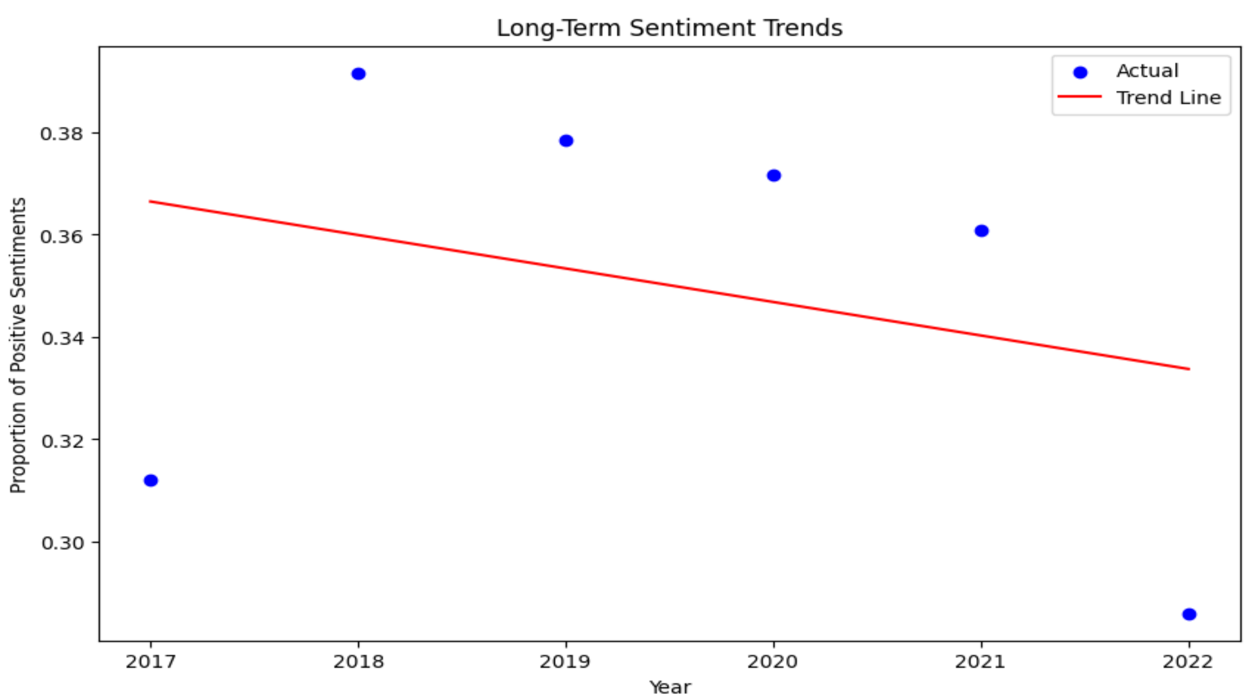
4.2 Long-Term Trends



3: Long-Term Sentiment Trends for Neutral Sentiments



4: Long-Term Sentiment Trends for Negative Sentiments

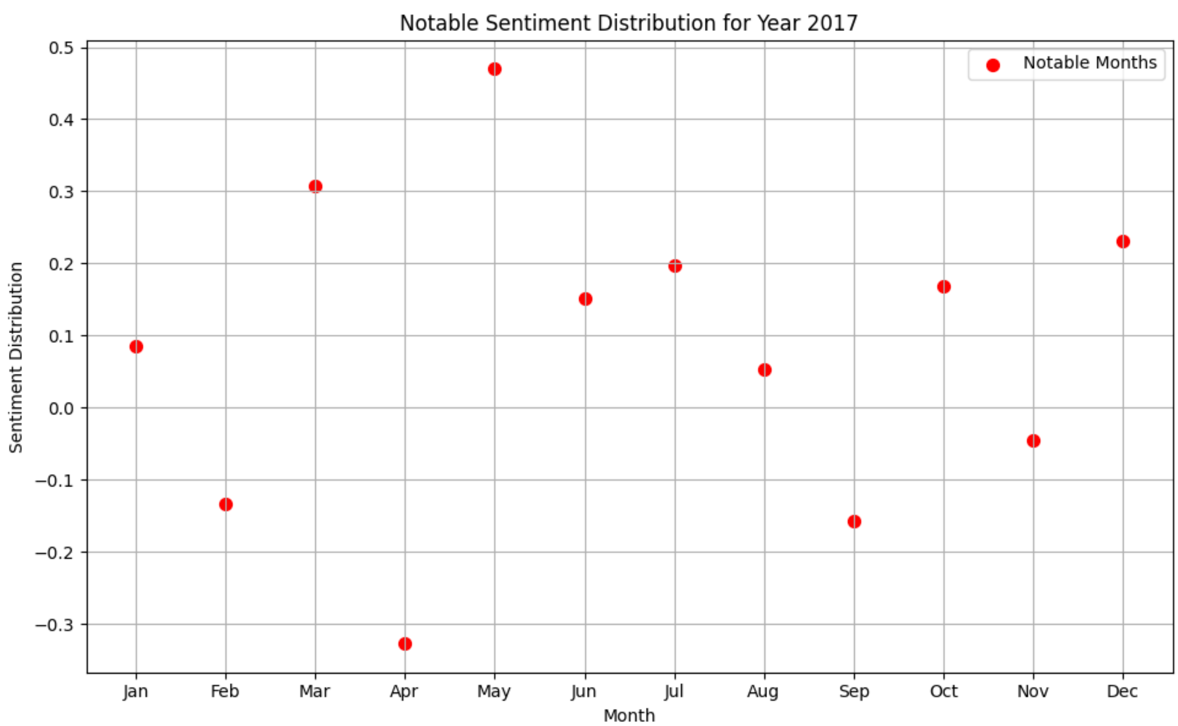


5: Long-Term Sentiment Trends for Positive Sentiments

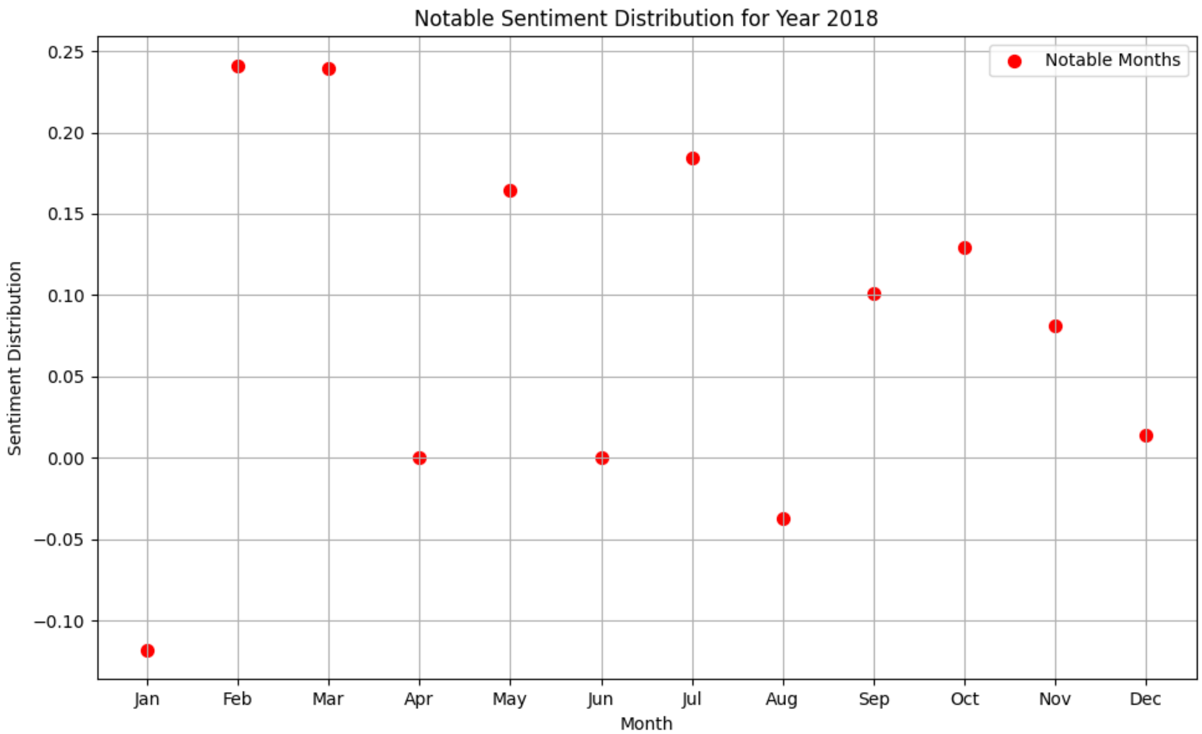
The analysis of sentiment trends over time in relation to xenophobia in South Africa reveals a clear pattern: negativity is on the rise. This suggests that the efforts in place to address this problem might not be effective. The graph of predicted tweets for each category on a linear regression model show that negative sentiments are increasing, while positive sentiments are decreasing. The decline in neutral sentiments, though slower compared to positive sentiments, indicates a growing divide between positive and negative opinions.

This analysis highlights the need for a reevaluation of current approaches to combat xenophobia. The upward trend in negative sentiments emphasizes the urgency of more effective strategies. Addressing the issue requires practical policies and interventions that are well-grounded in evidence and aimed at curbing the escalating negativity associated with xenophobia.

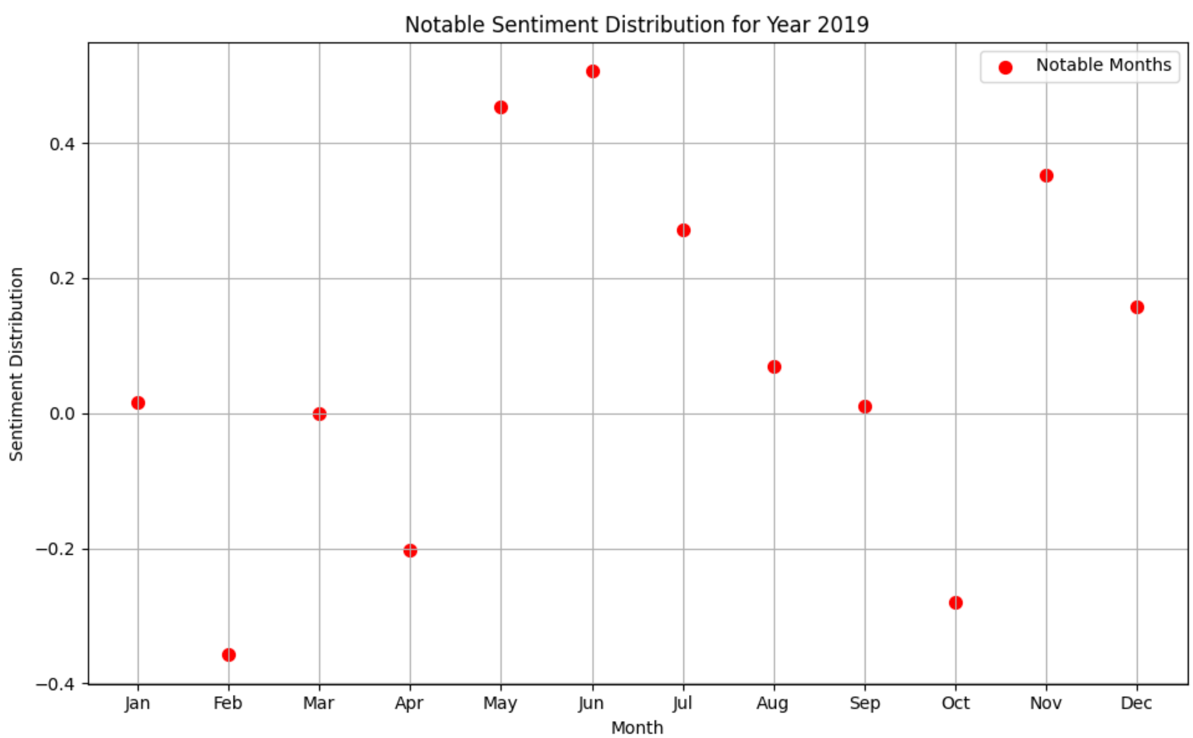
4.3 Notable Months in Sentiment Distribution



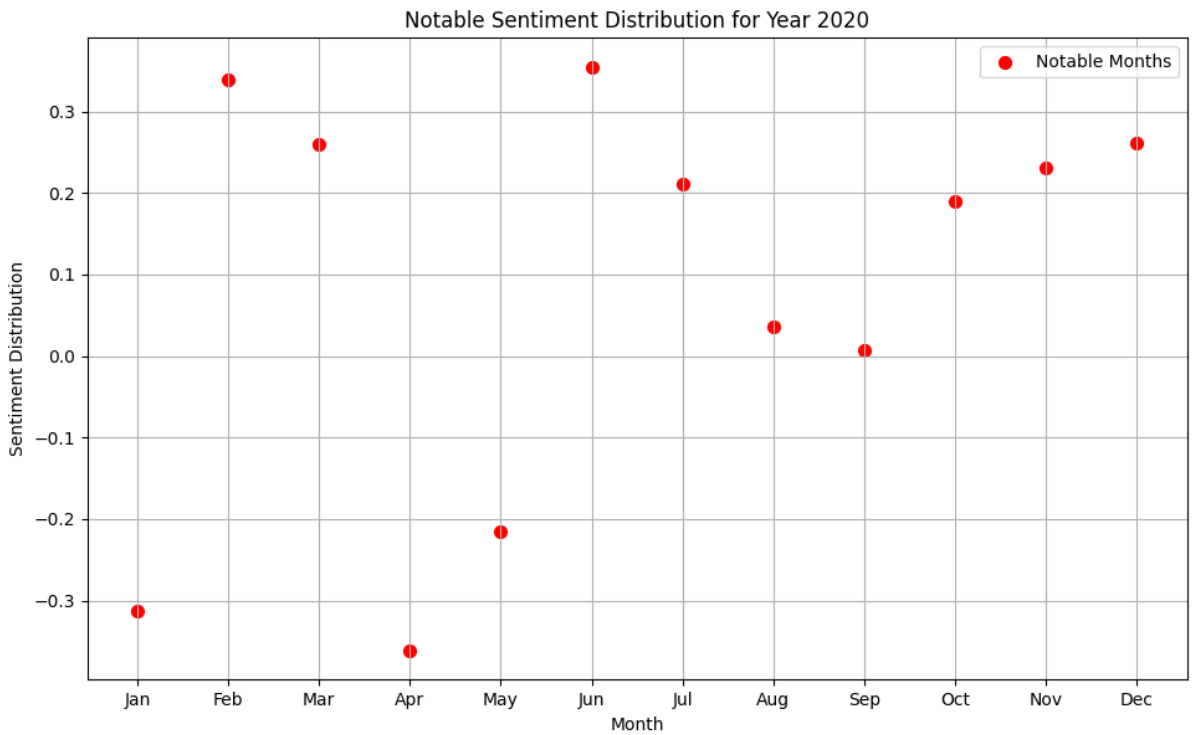
6*: Notable Sentiment Distribution for Year 2017*



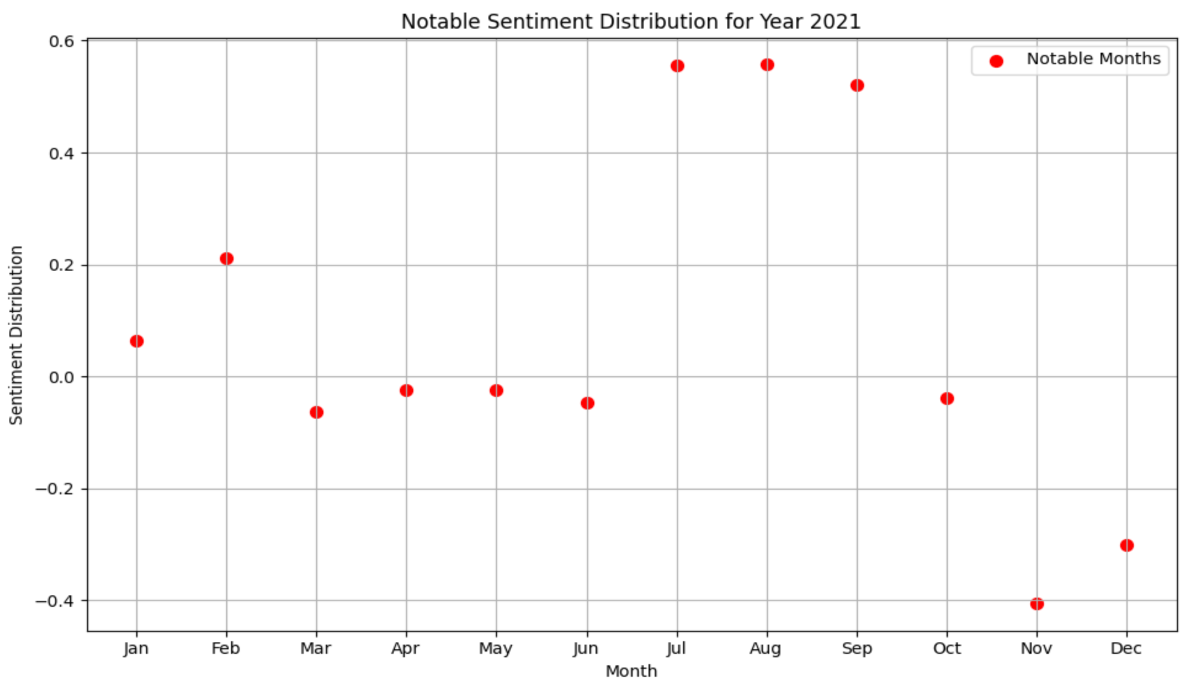
7: Notable Sentiment Distribution for Year 2018



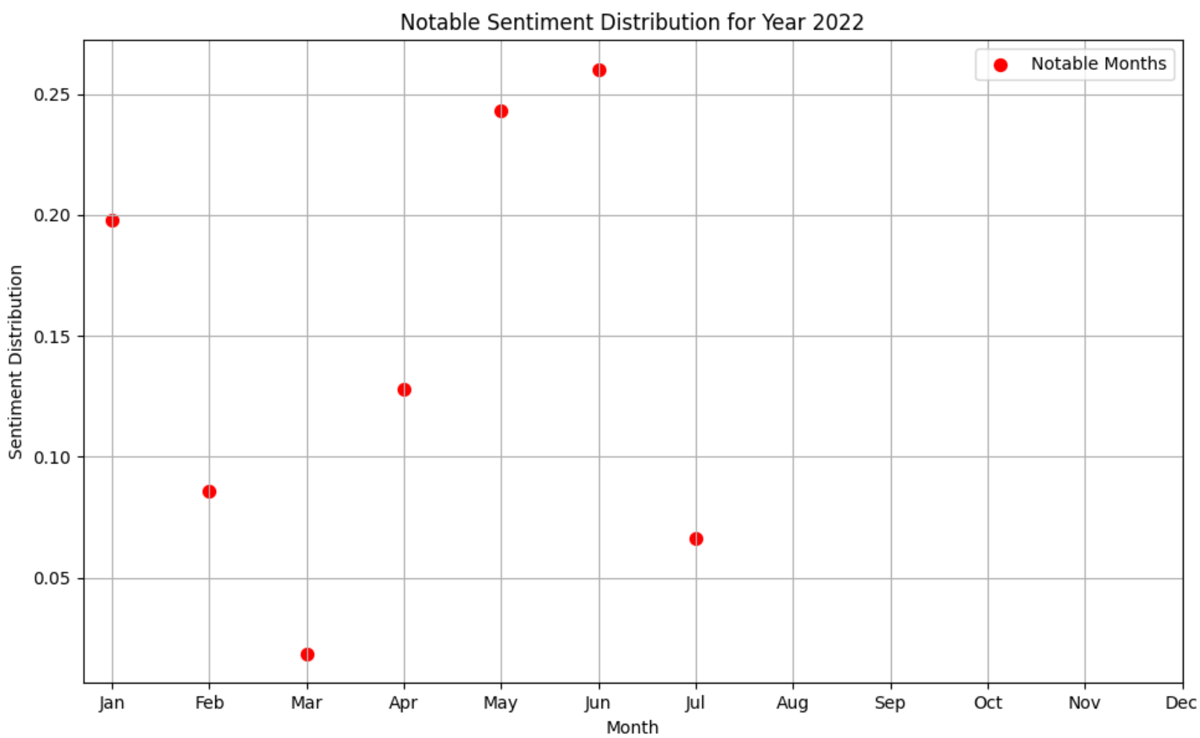
8: Notable Sentiment Distribution for Year 2019



9: Notable Sentiment Distribution for Year 2020



10: Notable Sentiment Distribution for Year 2021



11: Notable Sentiment Distribution for Year 2022

Above are graphs depicting notable moments where sentiment reaches extreme ends for each year from 2017 to 2022. This essentially provides a visual representation of the most emotionally charged or polarized periods within each year regarding the topic of xenophobia. By identifying and graphing these extreme sentiment months, the graph aims to highlight the spikes in emotional intensity, indicating moments of heightened positivity or negativity within each year.

For instance, spikes in positive sentiment might signify instances when positive discourse, counteractions, or resolutions took place, potentially showcasing progress in addressing xenophobia-related issues. Conversely, peaks in negative sentiment could indicate periods of increased tension, incidents, or discourse exacerbating xenophobia, demanding further attention and intervention.

The graph illustrates a consistent trend where each month is marked as significant in relation to the issue of xenophobia. This pattern implies that the country is facing internal challenges in managing and curbing xenophobic activities within its population.

2017: Throughout this year, there are noticeable fluctuations in the sentiment surrounding xenophobia, with a majority of the sentiment tending to be positive with the year ending on such note. Throughout the months, the ratio of dominant positive to negative sentiment is at 8:4.

2018: In a similar pattern to the previous year, the sentiment regarding xenophobia also experiences significant shifts this year. However, it's worth noting that the sentiment starts off negatively at the beginning of the year and gradually transitions to almost neutral by the end. Throughout the months, the ratio of dominant positive to negative sentiment is at 8:2.

2019: This year continues to adhere to the established pattern seen in previous years, maintaining a consistent ratio of dominant positive to negative sentiment throughout the months, with a ratio of 7:3.

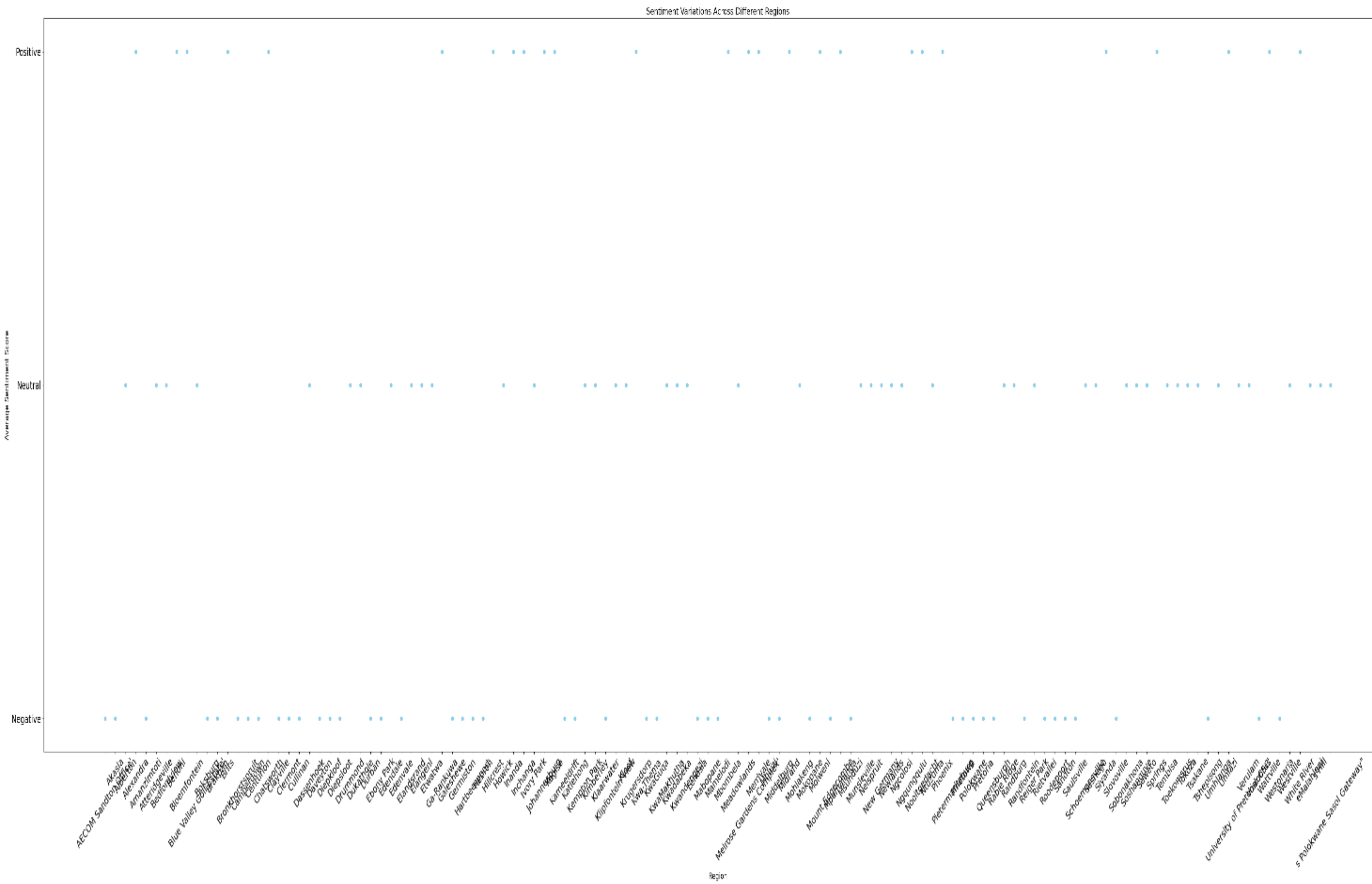
2020: This year continues to adhere to the established pattern seen in previous years, maintaining a consistent ratio of dominant positive to negative sentiment throughout the months, with a ratio of 9:3.

2021: This year stands in stark contrast to the patterns observed in previous years, as it experiences noteworthy shifts in sentiment moving in the opposite direction. The year begins with an almost neutral sentiment on the topic, which then transitions to a predominantly negative sentiment over time. Across the months, the ratio of dominant positive to negative sentiment shifts to 5:7.

2022: During the initial 7 months of the year, positive sentiment was consistently evident in discussions about xenophobia. This suggests that the topic was generally perceived positively during this period. Unfortunately, data for the remaining 5 months is unavailable due to the lack of collected tweets. Throughout the recorded months, the ratio of dominant positive to negative sentiment maintains a strong skew of 7:0.

By presenting this information over the years, the graph allows for the identification of temporal patterns in sentiment extremes, potentially leading to insights into recurring events, societal responses, and shifts in public perception. This visualization offers a valuable tool for pinpointing critical junctures and assessing the effectiveness of initiatives, policy changes, or public discourse aimed at curbing xenophobia over the years.

4.4 Variations Across Different Regions



12: Sentiment Variations Across Different Regions

From the above it is visible that there is a fair distribution of neutral, positive, and negative tweets among different regions in the country.

The above sentiment analysis graph across different geographic locations with regard to sentiment on xenophobia provides a visual representation of sentiment variations across different regions. This graph could imply:

Regional Disparities: Positive sentiment in one region may contrast with negative sentiment in another, reflecting varying levels of xenophobia awareness or experiences.

Hotspots: Spikes in negative sentiment within specific regions might indicate areas where xenophobia is particularly prevalent or has gained attention due to incidents or events.

Positive Efforts: Conversely, surges in positive sentiment could signify regions where efforts to combat xenophobia are making progress, demonstrating the effectiveness of initiatives or community responses.

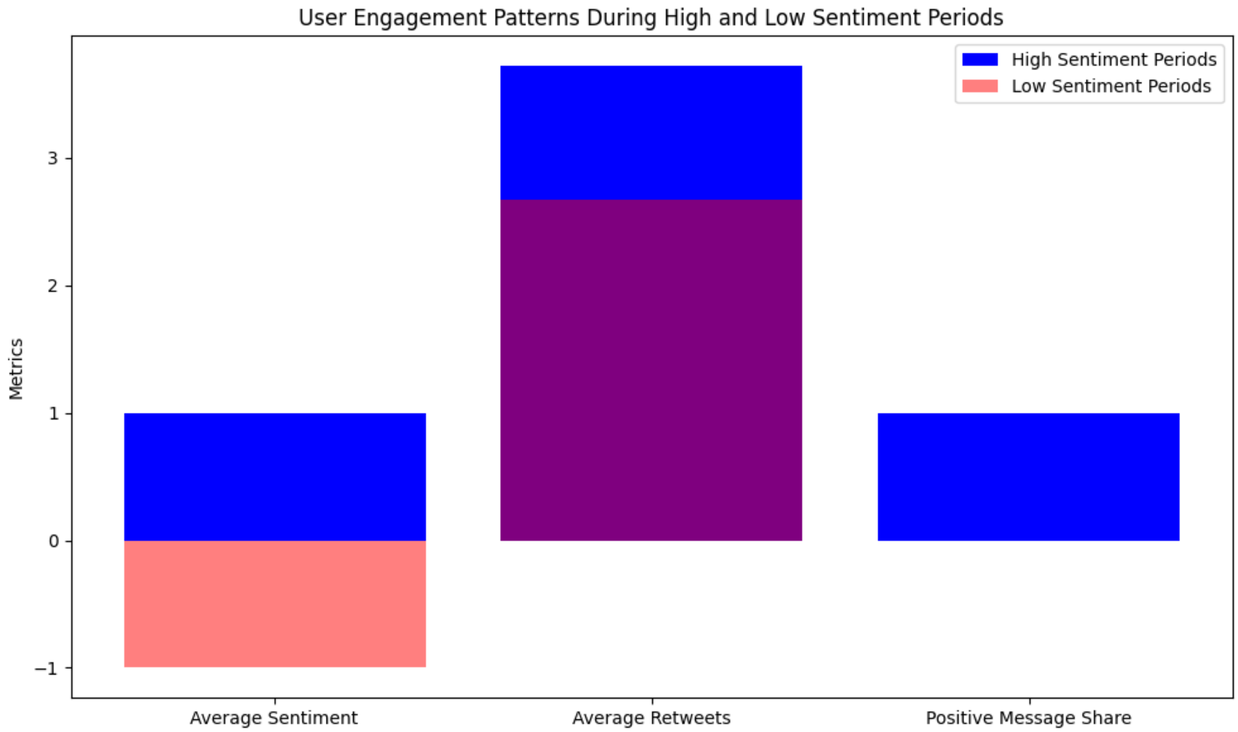
Awareness and Discourse: The graph can provide insights into how discussions on xenophobia are distributed geographically, potentially uncovering areas where awareness and conversation are more pronounced.

Policy Evaluation: For policymakers and organizations, this visualization can aid in evaluating the impact of interventions and policies across different locations.

Data-Driven Strategies: Organizations addressing xenophobia can use regional sentiment trends to tailor interventions, campaigns, and outreach efforts to specific geographic contexts.

In essence, the graph showcases the sentiment landscape surrounding xenophobia in a spatial context, helping to identify areas of concern, progress, and nuanced perceptions across diverse geographic regions.

4.5 User Engagement Patterns



13: User Engagement Patterns During High and Low Sentiment Periods

Average Sentiment: The above graph is developed to analyze the average sentiment of the tweets during high and low sentiment periods. This metric provides insights into how users' sentiments are aligned with the sentiment of the tweets. High sentiment periods might see users expressing similar sentiments to the tweets, while low sentiment periods might show a disconnect between users' sentiments and the tweets' sentiments.

Average Retweets: It also shows the average number of retweets during high and low sentiment periods. This metric indicates the level of engagement and the reach of the tweets. High retweet counts during high sentiment periods suggest strong user engagement and sharing of content related to xenophobic tweets.

Positive Message Share: It also provides the proportion of positive messages (tweets with positive sentiment) out of all messages during high and low sentiment periods. This metric helps assess the nature of engagement—whether users are predominantly sharing positive messages during high sentiment periods and if this positivity influences retweet behavior.

The bar chart visualizes these engagement metrics, making it easier to compare user engagement patterns during high and low sentiment periods. The blue bars represent high sentiment periods, while the red bars represent low sentiment periods. This visual comparison enables you to observe any trends or disparities in engagement behaviors during different sentiment periods.

The graph shows that users are more likely to engage with content during high sentiment periods than during low sentiment periods. This is likely because users are more likely to be positive and open to new information when they are feeling good.

The specific metrics of average sentiment, average retweets, and positive message share are all ways to measure the engagement in xenophobic tweets. Average sentiment measures the overall positivity or negativity of the content that users are sharing. Average retweets measure how often users are sharing content with others. Positive message share measures the percentage of content that is positive in nature.

The graph shows that all three metrics are higher during high sentiment periods than during low sentiment periods. Overall, the graph shows that user engagement on xenophobia is higher during high sentiment periods than during low sentiment periods.

5. Discussion

5.1 Conclusions

Based on the comprehensive analysis and visualizations presented, several conclusions can be drawn:

Sentiment Trends

2017: The sentiment distribution is skewed towards neutral and positive expressions, with limited negative sentiments. This divergence between sentiment analysis outcomes and historical occurrences prompts further investigation into potential user behavior dynamics during this year.

2018: Sentiment distribution shows more equilibrium between positive and negative expressions, with maintained presence of neutral sentiments.

2019: A notable increase in negative sentiments aligns with significant events and incidents related to xenophobia during the year.

2020: The prominence of negative sentiments might reflect the global socio-political events impacting the sentiment landscape.

2021: The distribution becomes more balanced, with substantial neutral sentiments, potentially indicating a moderation in discourse.

2022: A decrease in negative sentiments coupled with increased neutral and positive sentiments suggests a potential shift in public discourse due to advocacy efforts.

Long-Term Trends

Over time, negative sentiments related to xenophobia are increasing, while positive sentiments are decreasing. This suggests that current efforts to address the issue might not be effectively mitigating negative sentiment trends.

Notable Months in Sentiment Distribution

Extreme sentiment months highlight emotionally charged periods within each year. Positive spikes indicate positive actions, while negative peaks suggest heightened tension, necessitating further attention and intervention.

Variations Across Different Regions

Sentiment distribution across regions is fairly balanced between neutral, positive, and negative tweets, providing insights into regional disparities, hotspots, and policy evaluation.

User Engagement Patterns

User engagement is higher during high sentiment periods, indicating a positive correlation between user sentiment and engagement behaviors.

In conclusion, the sentiment analysis and visualizations collectively indicate that the sentiment around xenophobia in South Africa is multifaceted, evolving over the years with varying dynamics across regions. The increasing negativity suggests the need for more effective strategies to combat xenophobia. While progress has been made through advocacy efforts, addressing the underlying causes of negative sentiment remains a critical endeavor. Understanding sentiment dynamics, regional variations, and user engagement patterns can guide evidence-based interventions and policy decisions to effectively address the issue of xenophobia.

6. Project Code

The code to this project can be found here, GitHub. The project was completed using Python within the Google Colab environment.

7. Related Literature & References

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