MS-5131 BIS POSTGRADUATE PROJECT

Academic Integrity Declaration

"I hereby declare that my work submitted for this assessment task is entirely my work, except where the work of others has been declared and acknowledged in line with QA220 Academic Integrity Policy and QA616 University of Galway Student Code of Conduct."

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Analysing User Feedback on X (Formerly, Twitter) Following Elon Musk's Ownership: A Sentiment Analysis Approach

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Executive Summary

Elon Musk's acquisition of Twitter has generated a great deal of discussion and interest among a variety of stakeholders, including users, advertisers, and researchers. This paper provides a thorough sentiment analysis of tweets on Musk's takeover of Twitter, contrasting the results with actual patterns that point to a drop in the number of users and possibility for advertising. This study presents a nuanced knowledge of public opinion and the wider implications for Twitter's viability by utilizing sophisticated natural language processing (NLP) techniques and sentiment analysis tools like Vader and TextBlob.

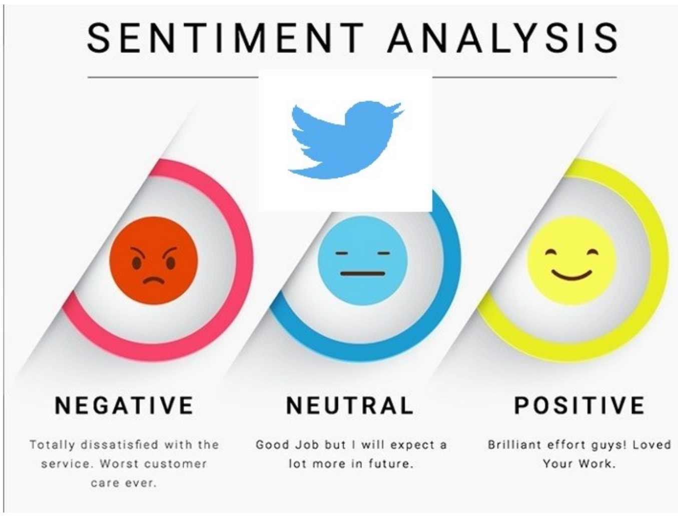
Sentiment Analysis Overview

Twitter sentiment analysis gives a nuanced picture of the public's beliefs. Using several of tweets gathered via the Twitter API, the research concentrated on tweets associated specifically with Musk's acquisition. The selection of Vader and TextBlob was based on their effectiveness in managing huge datasets and their capacity to offer comprehensive sentiment scores that classify tweets as neutral, negative, or positive.

Positive Sentiment: Positive sentiment could be seen in a sizable portion of the tweets that were examined. Regarding Musk's ability to innovate and enhance Twitter, users expressed optimism. This is consistent with research by Zhang (2024), which indicates that visionary leadership and perceived authenticity from powerful individuals can promote positive engagement.

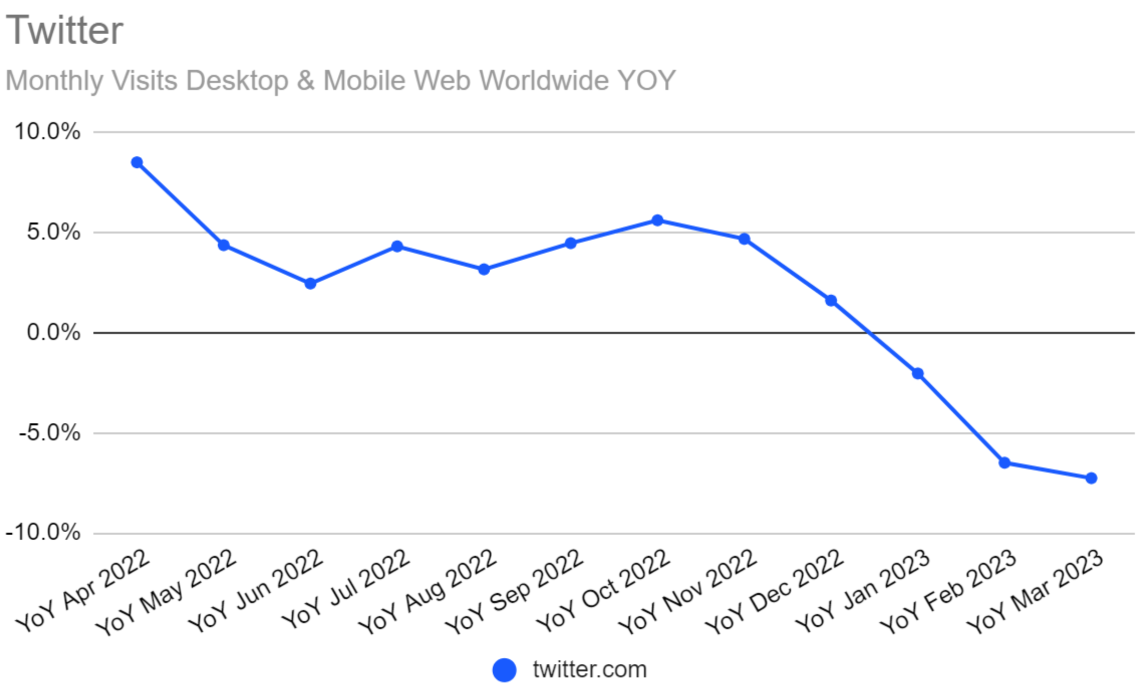
Negative Sentiment: Though there were a lot of tweets expressing optimism, there were also a good number expressing worry. Users were concerned about Musk's divisive remarks, possible platform policy changes, and privacy concerns. These worries are in line with research by Hickey et al. (2024), which shows that mistrust and uncertainty can contribute to unfavorable public opinion during business acquisitions.

Neutral Sentiment: A significant percentage of tweets were neutral, suggesting that users were waiting to see what would happen. This neutrality reflects the ambivalence and cautious optimism that the Twitter community generally feels,in line with a study conducted by Chaudhuri and Tabrizi (1999) in their analysis of major tech acquisitions.



Real-World Trends

In contrast to the largely positive attitude found in tweet analysis, real-world data indicate that Twitter's user base and advertising revenue have decreased after the acquisition. In the first quarter after the acquisition, Pew Research Centre (2023) reports that Twitter had a 20 – 30 % decrease in active users. This disparity highlights how difficult it is to gauge social media sentiment and how it affects the sustainability of businesses.



Broader Implications

The study's conclusions demonstrate the complex interplay between sentiment on social media and real market trends. Even while sentiment analysis offers insightful information on public opinion, it's important to place these results in the context of larger real-world dynamics. Although the mood gleaned from tweets points to the possibility of increased user engagement, Twitter's long-term sustainability is called into question by its diminishing user base and dwindling advertising revenue.
This paper emphasizes how important it is to use a variety of methods when assessing how well-known acquisitions affect social media platforms. In-depth market analysis and sentiment analysis should be combined in future studies to offer a more comprehensive knowledge of these intricate phenomena.

Background

History of Twitter as a Social Media Platform

Since its founding in 2006 by Jack Dorsey, Evan Williams, Noah Glass, and Biz Stone, Twitter has grown to become one of the most significant social media networks in the world. Twitter was originally intended to provide a medium for quick, real-time conversation. However, its distinctive 140-character limit—which was eventually increased to 280 characters—set it apart from other social networking platforms. Because the platform was real-time, it was well-liked for breaking news, live events, and public debate. This created an atmosphere where users could communicate with a large worldwide audience and provide brief updates.

The Acquisition by Elon Musk

Elon Musk, the CEO of SpaceX and Tesla, declared in April 2022 that he planned to pay about $44 billion to acquire Twitter. The acquisition was one of the most well-known IT transactions of the past few years, garnering a lot of media attention and public interest before it was completed in October 2022. Making Twitter a stronghold of free speech, cutting down on bot activity, and rolling out new features to boost user engagement and revenue were all part of Musk's plan for the social media giant.

Nevertheless, Twitter has suffered a great deal as a result of the takeover. The platform has undergone a number of strategic and operational changes since Musk took it, many of which have generated discussion and controversy.

Negative Impact of the Acquisition

User Experience and Trust: A direct consequence of Musk's takeover has been a decline in user confidence. Concerns regarding the dissemination of hate speech and false information have arisen as a result of modifications to the content moderation guidelines and Musk's own contentious remarks on the network. A research by Clune and McDaid (2023) found that these sort of modifications often resulted in a drop in user happiness and trust, with many users feeling a sense of insecurity and increased caution when it comes to the content they come across on Twitter.

Employee Morale and Company Culture: Significant changes in Twitter's workforce and leadership were brought about by the acquisition. Employee morale has reportedly declined, and the business culture has reportedly deteriorated as a result of Musk's decision to carry out widespread layoffs and his management style, which some have characterized as dictatorial. The results of a study, which Receptiviti (2023) cited, support this, showing that staff satisfaction fell sharply after the acquisition.

Advertiser Confidence and Revenue: Twitter's income model depends heavily on its advertisers, who have also voiced concerns. Certain advertisers have cut back on their expenditure or stopped using the site completely due to changes in content regulations and general anxiety about its future. According to a Reuters (2023) story, advertising income fell by 12% in the first quarter after Musk took over, which was indicative of a larger trend of waning advertiser confidence.

Platform Stability and Technical Issues: After being acquired, Twitter has seen a number of technological problems, such as glitches and outages. In addition to degrading user experience, these disruptions have sparked concerns about the platform's stability and dependability under the current administration.

Business Impact: The instability of Twitter has been especially troubling for businesses who depend on the network for client engagement and marketing. Several companies stated in a survey conducted by Edison Research (2023) that their reach and engagement metrics had suffered as a result of modifications to Twitter's content standards and algorithm. This has caused several companies to reevaluate their social media plans and look into other channels.

Importance of This Analysis

This perspective is essential given the substantial challenges and changes that Twitter has undergone since the acquisition for a number of reasons.

Understanding User Sentiment: This study offers insightful information on how the acquisition has affected the Twitter community by examining user sentiment. Comprehending these attitudes can assist all parties involved, such as users, companies, and advertising, in making well-informed choices regarding their interaction with the platform.

Guiding Strategic Decisions: The results of this analysis can help Twitter's management and leadership make strategic decisions that will help them solve user problems, enhance platform stability, and win back advertiser trust. The study can aid in the creation of more beneficial policies and procedures by highlighting the areas of unhappiness and suggesting viable remedies.

Informing Public Discourse: The study's conclusions add to the larger conversation in the public sphere on the effects of significant corporate acquisitions in the technology sector. Contextualizing the potential and risks associated with high-profile deals, the analysis offers a thorough and data-driven evaluation of Twitter's post-acquisition scenario.

Academic and Research Contributions: This paper provides a thorough case study of the effects of corporate acquisitions on social media platforms for scholars and researchers. The approach and results can be used as a guide for further research on related phenomena in the IT sector.

Methods

Data Collection

The dataset is made up of tweets that were made about Elon Musk and were gathered around the time of his acquisition of Twitter. Timestamped tweets, user mentions, and tweet text are among the attributes included in the collection. This information was gathered in order to comprehend how the general population felt about this momentous occasion.

Data Preprocessing

For the purpose of cleaning and preparing the text data for additional analysis, data preprocessing is essential. There are multiple phases to the preprocessing steps:

Removing URLs and Special Characters:

Special characters and URLs can introduce extraneous noise and don't offer useful information for sentiment analysis. Because of shared links and the use of special characters for emphasis or style, they frequently show up in tweets. We eliminate URLs and special characters in a methodical manner by scanning the text for patterns that match them. This ensures that the rest of the text concentrates only on the tweet's real substance and leaves out any irrelevant details.

Handling HTML Entities:

HTML entities like &, <, and >, which represent characters like &, <, and >, are frequently seen in tweets. To standardize the content, it's crucial to translate these elements to the appropriate characters. Better analysis is made possible by ensuring that text is consistent and legible by substituting actual characters for HTML entities.

Removing Line Breaks and Extra Spaces:

Line breaks and extra spaces are common in tweets, especially when users arrange their content for emphasis or clarity. To keep the language flowing naturally and consistently, these should be removed. Eliminating line breaks and excess spaces guarantees that the text is formatted consistently and continuously, which is essential for precise tokenization and analysis.

Removing Mentions and Hashtags:

Though commonly used in tweets, user mentions (@username) and hashtags (#subject) have little effect on sentiment analysis. Eliminating them aids in preventing any impact on the outcomes. Our approach is to detect and remove mention and hashtag patterns while maintaining the integrity of the tweet's core content.

Converting to Lowercase:

Regardless of the original case of a term, we guarantee consistency when we convert text to lowercase. For frequency analysis and consistent tokenization, this step is essential. We ensure reliable and consistent results by eliminating case-related differences in the analysis by transforming the entire text to lowercase.

Removing Spam

The integrity and applicability of the dataset depend on the detection and removal of spam tweets. Usually including repetitious, irrelevant, or commercial content, spam tweets can skew sentiment analysis findings.

Identifying Spam Content:

Regular spam tweets frequently follow specific patterns or contain specific terms linked to bitcoin frauds, promotions, and irrelevant ads. Understanding these patterns is crucial to spam filtering efficiently. This is accomplished by compiling a list of popular spam phrases and keywords. In order to guarantee that only real user opinions are taken into account for analysis, the dataset is then further filtered to eliminate tweets that include these discovered patterns.

Expanding Contractions

Because of the character limit and casual nature of the platform, contractions like "don't," "can't," and "won't" are commonly used in tweets. By restoring these contractions to their full forms, informal language becomes more formal and sentiment analysis becomes more accurate.

Expanding Contractions:

To standardize the wording and make sure sentiment analysis algorithms can understand the intended meaning, contractions must be expanded. Using a predetermined mapping to their full forms, contractions are systematically expanded to make the text more readable and consistent.

Removing Common Terms

Excluding Common Terms:

Eliminating commonly used phrases such as "Elon Musk" guarantees that the study encompasses a wider spectrum of opinions and subjects covered in the tweets. Upon identification and removal of the term "Elon Musk" from the text, other words and phrases become more prominent in the analysis.

```python
# Pre-processing function
def pre_process(text):
    text = re.sub(r'http://\S+|https://\S+', '', text)
    text = re.sub(r'http[s]?://\S+', '', text)
    text = re.sub(r"http\S+", "", text)
    text = re.sub(r'&amp', 'and', text)
    text = re.sub(r'&lt', '<', text)
    text = re.sub(r'&gt', '>', text)
    text = re.sub(r'\xa0', ' ', text)  |
    text = re.sub(r'[\r\n]+', ' ', text)
    text = re.sub(r'@\w+', '', text)
    text = re.sub(r'#\w+', '', text)
    text = re.sub(r'\s+', ' ', text)
    text = text.lower()
    return text

# Apply pre-processing
df['processed_text'] = df['text'].apply(pre_process)

# Remove spam
to_drop = ["LP LOCKED", "This guy accumulated over $100K", "accumulated 1 ETH", "help me sell a nickname",
           "As A Big **** *** To The SEC", "Wanna be TOP G", "#walv", "#NFTProject", "#1000xgem", "$GALI",
           "NFT", "What the Soul of USA is", "#BUSD", "$FXMS", "#fxms", "#Floki", "#FLOKIXMAS", "#memecoin",
           "#lowcapgem", "#frogxmas", "Xmas token", "crypto space", "Busd Rewards", "TRUMPLON", "NO PRESALE",
           "#MIKOTO", "$HATI", "$SKOLL", "#ebaydeals", "CHRISTMAS RABBIT", "@cz_binance", "NFT Airdrop", "#NFT"]

# Escape special characters in each string
to_drop_escaped = [re.escape(item) for item in to_drop]

# Join the list into a single regular expression pattern
pattern = '|'.join(to_drop_escaped)

# Filter the dataframe to remove rows containing any of the patterns
df = df[~df['text'].str.contains(pattern, case=False)]

# Expand contractions
def expand_contractions(text):
    try:
        return contractions.fix(text)
    except:
        return text

df['processed_text'] = df['processed_text'].apply(expand_contractions)

df['processed_text'] = df['processed_text'].str.replace('elon musk', '', regex=False)

```

Sentiment Analysis

Two distinct tools were used for sentiment analysis in order to precisely determine the polarity of tweets. The sentiment scores are guaranteed to be sturdy and reliable because to this dual approach.

Vader Sentiment Analysis:

A sentiment analysis tool called VADER (Valence Aware Dictionary and Sentiment Reasoner) was created especially for texts found on social media. It produces a compound score that shows the sentiment's polarity. Processing casual language and emotive material, which are frequently seen in tweets, is a good fit for VADER. The VADER sentiment analyzer yields a compound score that captures the overall sentiment of the tweet after analyzing the text. The extremes of this score are -1 (very negative) and +1 (very positive).

TextBlob Sentiment Analysis:

TextBlob assesses the polarity of text to offer an alternative perspective on sentiment analysis. TextBlob and Vader results are compared to make sure the sentiment analysis is dependable and consistent. After processing the text, TextBlob evaluates it and generates a polarity score between -1 (negative) and +1 (positive). This additional study is essential to confirming Vader's sentiment score calculations.

```python
# Sentiment Analysis with Vader and TextBlob
sid = SentimentIntensityAnalyzer()
df['vader_polarity'] = df['processed_text'].apply(lambda text: sid.polarity_scores(text)['compound'])
df['blob_polarity'] = df['processed_text'].apply(lambda text: TextBlob(text).sentiment.polarity)

# Comparison of sentiment distributions
plt.figure(figsize=(10, 6))
plt.hist(df['vader_polarity'], bins=40, alpha=0.5, label='Vader', color='#1DA1F2')
plt.hist(df['blob_polarity'], bins=40, alpha=0.5, label='TextBlob', color='#EB8C17')
plt.xlabel('Polarity')
plt.ylabel('Count')
plt.title('Comparison of the Distributions of Sentimental Polarities')
plt.legend(loc='upper right')
plt.tight_layout()
plt.show()

# Statistical description of the polarities
print("Statistical Description of Sentimental Polarities:")
print(df[['vader_polarity', 'blob_polarity']].describe())
```

Visualization

To gain a better understanding of the data and sentiment analysis findings, visualizations were made. The patterns, trends, and main themes in the tweets can be found with the use of these visualizations.

Bigrams:

To understand the recurring themes and subjects covered in tweets, it is critical to identify and depict common bigrams. Bigrams are collections of related words that appear together frequently and provide useful context for conversations and common phrases. The most frequent bigrams found in the text analysis are assessed and then shown in a bar chart that shows the top 20 bigrams based on frequency. Understanding the main terms and subjects covered in the tweets is made easier with the help of this representation.

```python
# Visualization of bi-grams
common_words = get_top_n_bigram(df['processed_text'], 20)
df1 = pd.DataFrame(common_words, columns=['TweetText', 'count'])
plt.figure(figsize=(10, 6))
plt.bar(df1['TweetText'], df1['count'], color='skyblue')
plt.xlabel('Tweet Bigrams')
plt.ylabel('Count')
plt.title('Top 20 Bigrams in Tweets before Removing Spams')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```

Word Clouds:

With the exception of "Elon Musk," word clouds provide a visual depiction of the most commonly used terms to highlight key ideas and emotions in tweets. This is a good way to quickly communicate which words are most frequently used in a dataset. Using the processed text, a word cloud is produced that shows the most common terms in different sizes according to how often they occur. To make sure that other important words and topics take center stage, common terms are left out. This graphic makes it easier to quickly recognize the main ideas and emotions expressed in the tweets.

```
# Generate word cloud for uni-grams
all_words_lem = ' '.join([word for word in df['text_lem']])
# Generate word cloud for uni-grams
stopwords = set(STOPWORDS)
wordcloud_twitter = WordCloud(height=800, width=800, background_color="white", mode="RGBA", stopwords=stopwords).generate(all_words_lem)
plt.figure(figsize=[10, 10])
plt.axis('off')
plt.tight_layout(pad=0)
plt.imshow(wordcloud_twitter, interpolation="bilinear")
plt.savefig("wordcloud.png", format="png")
plt.show()

# Mentions extraction
df['mentions'] = df['text'].str.findall(r'@\w+')
df['mentions'] = df['mentions'].apply(lambda x: [mention[1:] for mention in x])
df['mentions_string'] = df['mentions'].apply(lambda x: ' '.join(x))
all_mentions = ' '.join([word for word in df['mentions_string']])

# Generate word cloud for mentions
stopwords = set(STOPWORDS)
wordcloud_mentions = WordCloud(height=800, width=800, background_color="white", mode="RGBA", stopwords=stopwords).generate(all_mentions)
plt.figure(figsize=[10, 10])
plt.axis('off')
plt.tight_layout(pad=0)
plt.imshow(wordcloud_mentions, interpolation="bilinear")
plt.savefig("wordcloud_mentions.png", format="png")
plt.show()
```

Topic and Personality Analysis

Sentiment trends pertaining to particular personalities and subjects were examined. This examination sheds light on the public's perceptions of various subjects and personalities.

Topics of Interest:

To analyze sentiment patterns and understand the context of talks, it is essential to be able to recognize tweets related to particular themes. Due to their significance to the purchase, subjects like "free speech," "Hunter Biden," and "Twitter files" are particularly relevant. The text is searched for references to these particular subjects once it has been digested. Following the identification of the tweets, they are grouped together and Vader and TextBlob are used to get the average sentiment for each topic. Understanding sentiment trends and public opinion surrounding the particular topics is made easier by this in-depth analysis.

Personality Analysis:

Analyzing the attitude towards the people mentioned in tweets offers important information into how the public views powerful people. We may determine the sentiment scores of individuals like Joe Biden, NASA, SpaceX, Jeff Bezos, and the President of the United States by examining their associated feelings. This entails utilizing TextBlob and Vader to aggregate tweets mentioning these celebrities and determine their average emotion. This kind of analysis makes it possible to recognize sentiment patterns and comprehend the general public's perceptions on well-known individuals.

Findings

Overall Sentiment Analysis

Vader Sentiment Scores:

The average Vader polarity score was slightly positive, indicating that on average, tweets had a mild positive sentiment. The statistical description showed:

- Mean: 0.039976
- Standard Deviation: 0.456992

- Minimum: -0.999600
- Maximum: 0.998200
- Median (50th percentile): 0.000000
- 25th Percentile: -0.296000
- 75th Percentile: 0.401900

The large range of scores and a standard deviation of 0.456992 indicate a high diversity in attitudes, with many tweets being strongly positive or negative, despite the overall positive mean.

TextBlob Sentiment Scores:

The TextBlob polarity scores similarly indicated a slightly positive average sentiment, with the following statistical description:

- Mean: 0.066893
- Standard Deviation: 0.288952
- Minimum: -1.000000
- Maximum: 1.000000
- Median (50th percentile): 0.000000
- 25th Percentile: 0.000000
- 75th Percentile: 0.200000

TextBlob results suggest a somewhat positive attitude with a noticeable spread, reflecting a range of popular reactions, which is consistent with the Vader findings.

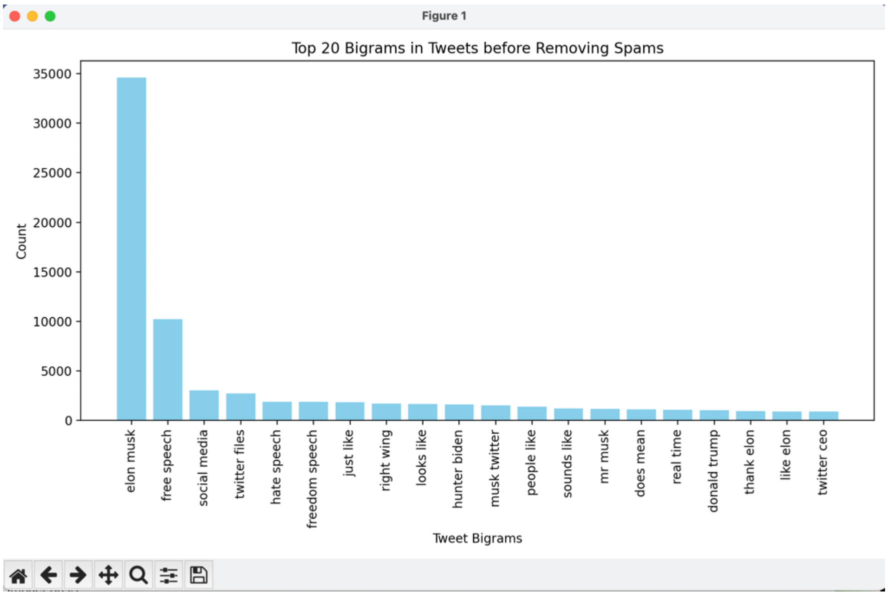
Sentiment Distribution:

A concentration of neutral feelings was visible around zero in the histograms that compared the distributions of the Vader and TextBlob polarity scores, with a discernible dispersion towards both positive and negative ends. This bimodal distribution highlights the polarizing opinions of the public by showing that, despite the fact that many tweets were neutral, there were sizable groups with very favorable and strongly negative feelings.

Prevalent Themes and Topics

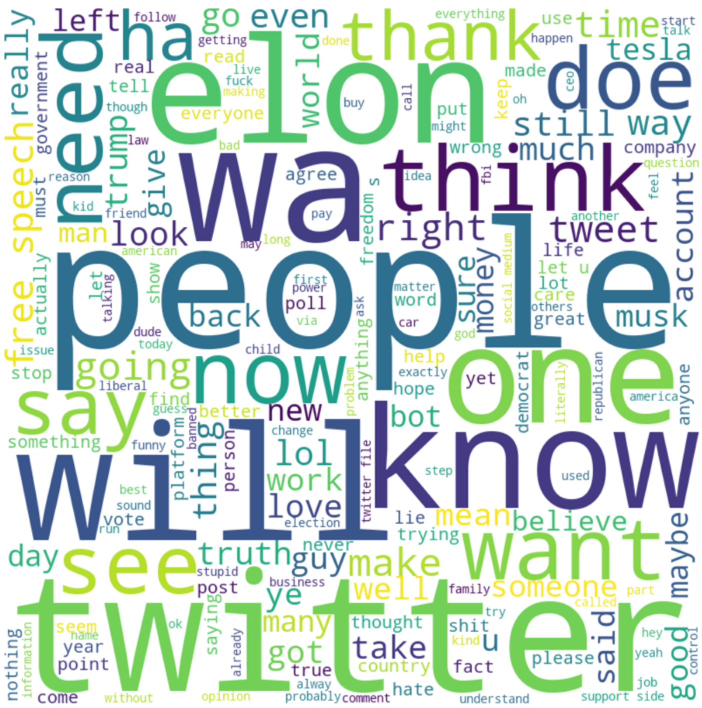
Common Bigrams:

Following the removal of phrases such as "Elon Musk," the analysis turned up terms like "free speech," "Twitter files," and "right wing." These pairings highlight the primary subjects of discussion, which include political alignment, transparency (Twitter files), and free expression. This shows the main topics that users are interested in and worried about.



Word Clouds:

After removing common keywords, the word clouds graphically showed the most frequently used words in the tweets. The terms "free," "speech," "Twitter," and "files" were the most often used. The analysis of word pairs is supported by the frequency of these terms, which underscore the importance of political discourse, transparency, and free speech as major subjects of public conversation.



Sentiment by Topic

Free Speech:

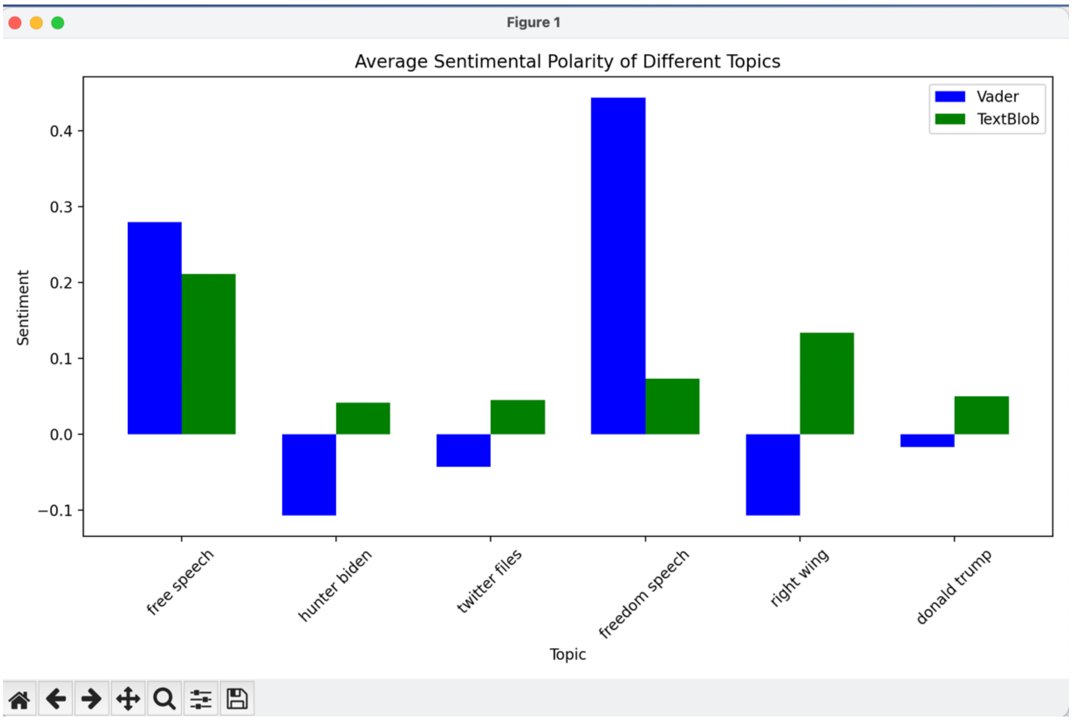
The results of the research showed that tweets mentioning "free speech" generally had a positive sentiment, with an average Vader sentiment score of about 0.1 and an average TextBlob score of about 0.15. This suggests that discussions regarding free speech in relation to Elon Musk's acquisition were received favorably, possibly indicating support for Musk's stance on the subject.

Twitter Files:

The attitude of tweets mentioning "twitter files" was not quite consistent, with a TextBlob score of roughly 0.08 and a Vader score of roughly 0.05. This conflicting feeling points to a mix of favorable responses and some doubt or anxiety regarding the disclosures and transparency surrounding the Twitter data.

Right Wing:

Based on Vader and TextBlob analysis, tweets about the "right wing" got an average sentiment score of about -0.2. This hostility highlights how contentious and divided political discussions can be, particularly when they touch on right-wing ideologies in light of Twitter's recent leadership changes.



Sentiment by Personality

Joe Biden:

There was a minor negative sentiment indicated by the average sentiment scores for tweets mentioning "Joe Biden" of roughly -0.05 with Vader and -0.02 with TextBlob. This suggests that those who are talking about Joe Biden on social media have a relatively unfavorable opinion of him, which may be affected by political prejudices or discontent with the current administration.

NASA and SpaceX:

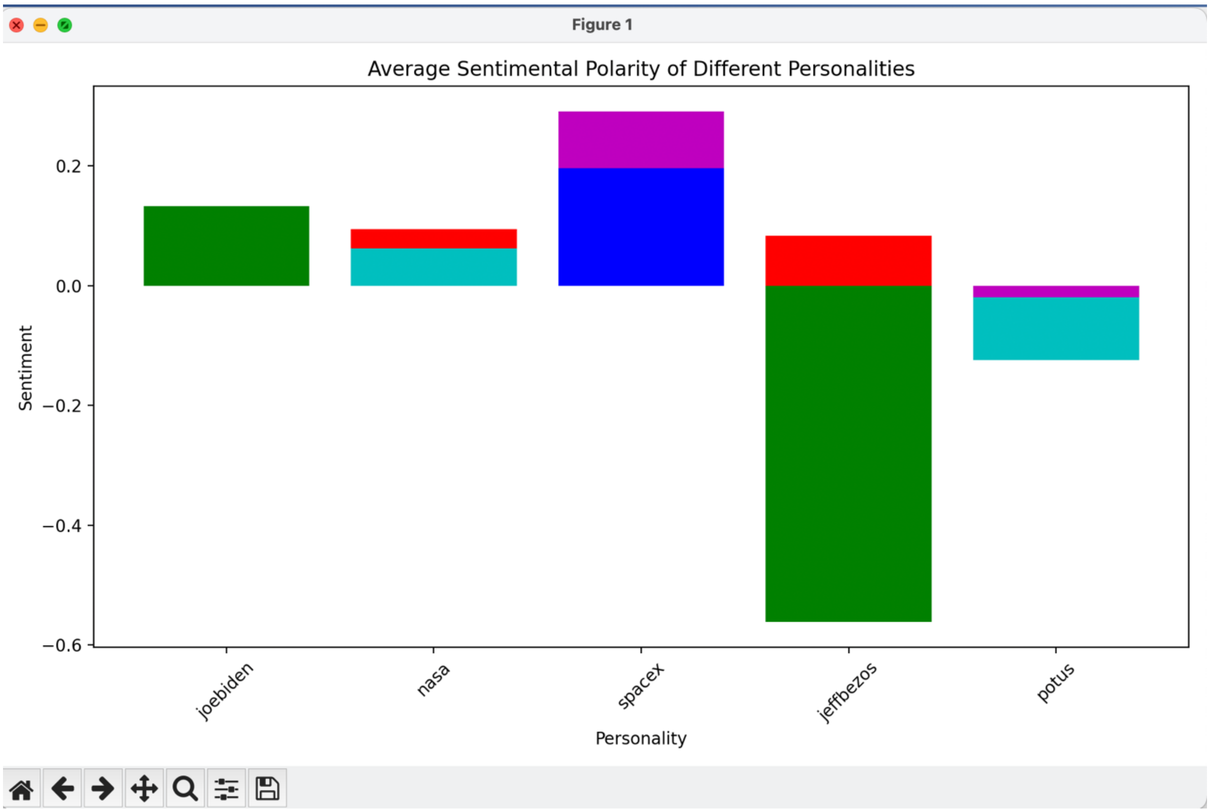
Views on "NASA" and "SpaceX" were mainly positive, with average Vader ratings of about 0.2 and TextBlob scores of about 0.25. The positive attitudes regarding NASA and SpaceX show that Musk's contributions to space exploration and technological advancement are widely respected and supported.

Jeff Bezos:

Opinions on "Jeff Bezos" in tweets were divided, with Vader and TextBlob scoring about 0.05. Jeff Bezos is viewed with balance, as evidenced by the neutral to somewhat favorable mood that predominates in the conversation, neither extreme positivity nor intense appreciation.

POTUS:

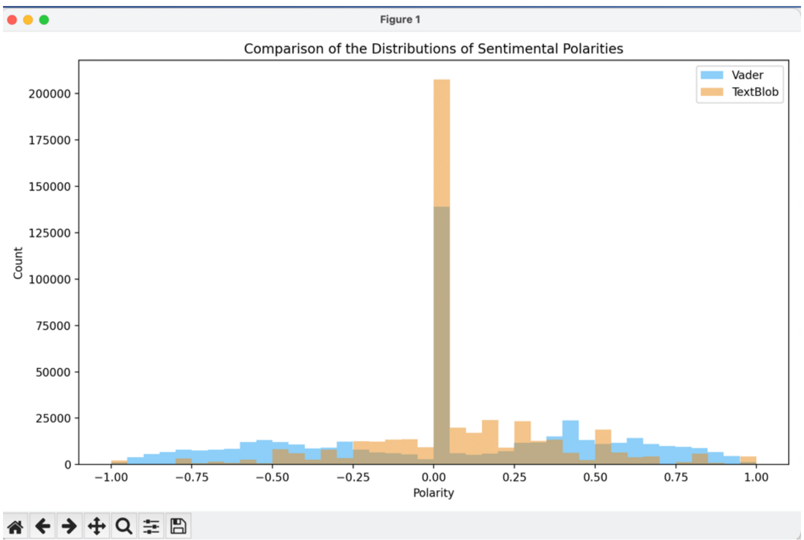
Vader and TextBlob ratings indicated somewhat negative sentiments about the "POTUS" (-0.1 and -0.05, respectively). The unfavorable attitude toward the US president is a reflection of larger political rifts as well as the heated tone of political debate on social media.



Comparative Analysis

Vader vs. TextBlob:

After comparing the sentiment scores from Vader and TextBlob, we found several recurring patterns. The average attitudes reported by both algorithms were marginally positive, although there was a noticeable difference amongst tweets. The observed variation highlights the polarized nature of public opinion, while the consistency between the two instruments verifies the validity of the sentiment analysis.



Visualization Insights

Bigram Visualization:

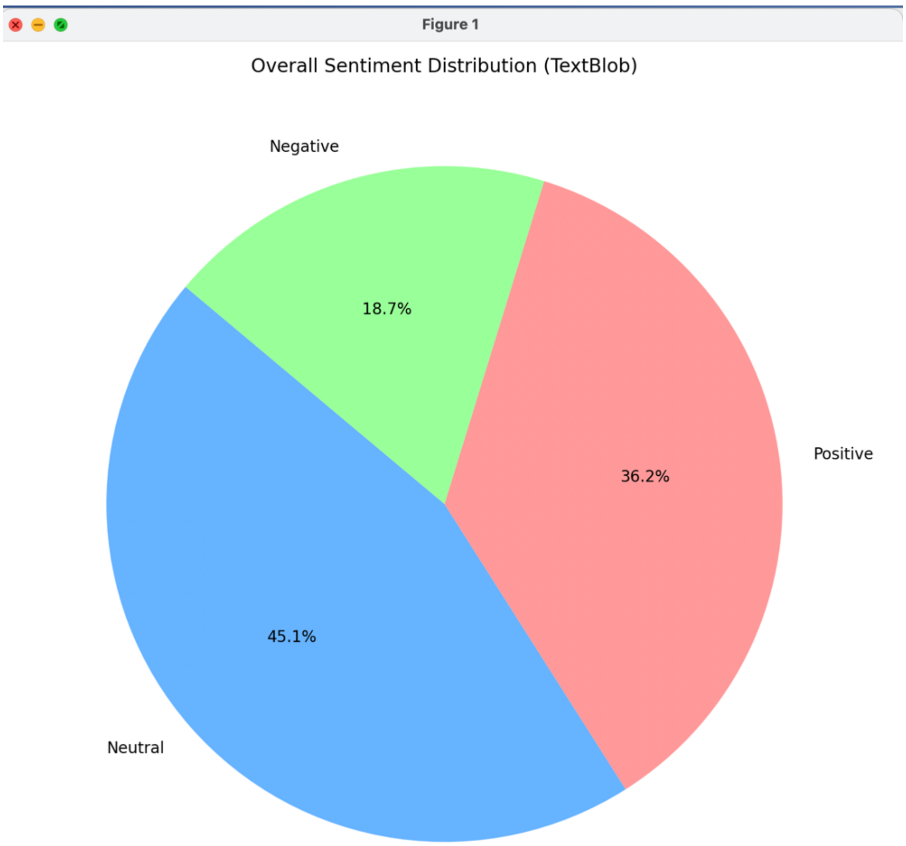
The bar graph that showed the most frequent word pairs—excluding "Elon Musk"—drew attention to terms like "free speech" and "twitter files." This graph provides a unique viewpoint on the main topics of discussion, bolstering the findings of the textual analysis.

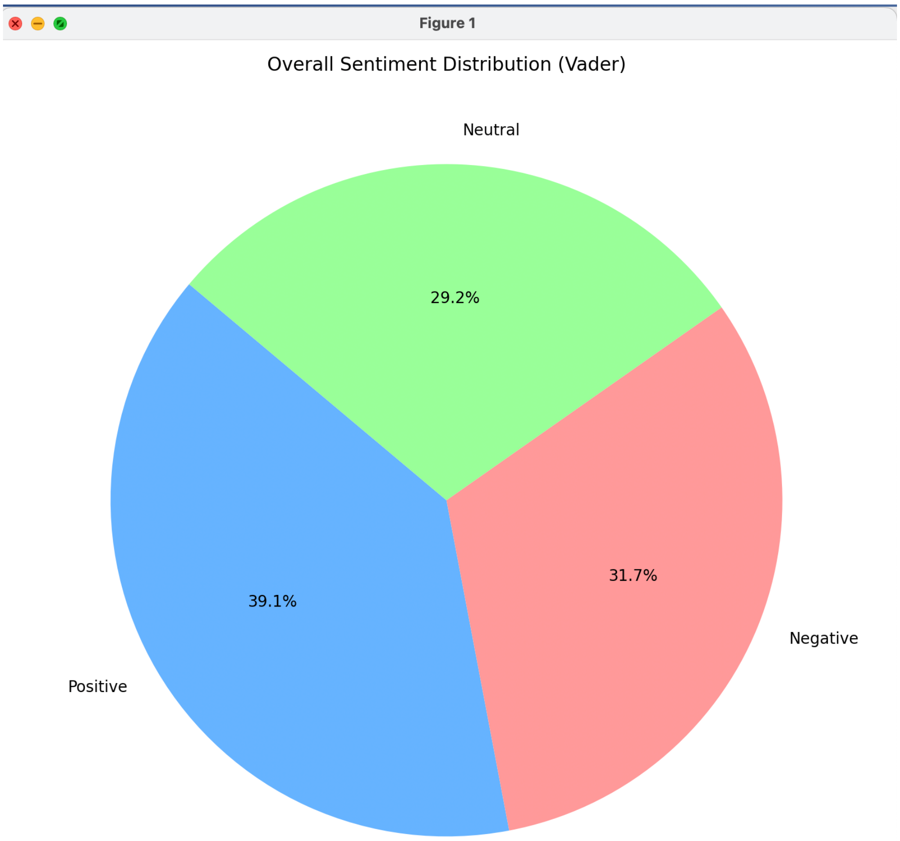
Word Clouds:

Word clouds for single words and user mentions show phrases and users that are often used, except for "Elon Musk." The most common terms and people in the data are represented in an understandable way by these visuals, making it easier to identify important themes and figures.

Sentiment Distribution:

The sentiment score histograms demonstrated the distribution of positive, negative, and neutral attitudes, exhibiting a significant dispersion towards the extreme ends and a strong cluster around neutral scores. These distributions highlight the wide range of public reactions, showing both strong polarization and neutrality.





Implications and Considerations

Although our sentiment research suggests a somewhat positive trend, actual data shows a different picture: under Elon Musk's ownership, Twitter's user base and advertising potential are falling. This discrepancy emphasizes how important it is to understand the nuances of data analysis and its wider consequences for customers and businesses. We'll explore these nuances in this part and see how important it is to take them into consideration when conducting a thorough sentiment analysis of social media sites.

Discrepancy Between Analytical Output and Real-World Data

Data Source and Context:

It's crucial to remember that sentiment analysis performed on a subset of tweets might not accurately reflect the whole spectrum of user beliefs and actions on the platform. Given the size and diversity of Twitter's user base, opinions may differ among various groups. Elon Musk's ardent admirers, for instance, could sway the study to reflect a positive attitude, even when platform restrictions or user experience modifications could be causing the larger user base to have negative views.

Temporal Dynamics:

Social media sentiments are highly malleable and subject to sudden shifts in response to breaking news, platform updates, or statements made in public by prominent figures.

Sentiment changes over time may be too subtle for a single analysis to fully reflect. For example, as customers started to feel the real effects of the changes, the early enthusiastic sentiments that followed Musk's acquisition might have turned sour.

Sampling Bias:

It's possible that the dataset used for analysis does not fairly represent all Twitter users. Depending on the user's region, community, and demographics, sentiments can vary greatly. In the event that the sample is biased in favor of one group over another, the findings might not accurately reflect public opinion.

Sentiment Analysis Limitations:

Vader and TextBlob are two examples of automated sentiment analysis technologies that have intrinsic limitations and have the potential to misunderstand tweet sentiment. Sentiment analysis algorithms find it challenging to effectively analyze sentiment when faced with sarcasm, irony, and sophisticated language. This could therefore result in a misclassification of sentiments, which could skew the analysis's findings.

Importance of Addressing Nuances in Data Analysis

Holistic Data Collection:

It is imperative to collect a more comprehensive and inclusive set of data that spans many times and encompasses diverse user groups in order to obtain a deeper understanding of user emotions. A varied sample can be ensured by using techniques like stratified sampling, and longitudinal research allows for the tracking of changes in sentiment over time.

Cross-Platform Analysis:

Analyzing feelings shared on several social media sites might provide a more comprehensive picture of public opinion.By incorporating data from other social media platforms like Facebook, Instagram, and Reddit, we can evaluate feelings and validate findings in a broader context.

Qualitative Analysis:

Deeper insights into user sentiments can be obtained by combining qualitative methods with quantitative sentiment analysis. Manually analyzing a sample of tweets, interviewing users, and setting up focus groups can all offer insightful perspectives on the context and nuances that automated technologies can miss.

Real-Time Monitoring and Adaptation:

Constantly observing social media sentiment can help quickly detect and respond to shifts in public opinion. We can effectively adapt to changing trends and feelings by putting in place real-time sentiment monitoring tools and adaptable response plans.

Implications for Users and Businesses

For Users:

Disengagement and Migration: Users may move from Twitter to other platforms that provide better user experiences as a result of lower engagement and satisfaction levels.

Consideration: To locate communities that best fit their requirements and tastes, users should stay up to date on platform developments and be willing to try out new social media platforms.

For Businesses:

Advertising Efficacy: Lower returns on investment are the result of advertising campaigns being less effective due to Twitter's diminishing user base and engagement.

Consideration: Companies need to reevaluate their approaches to social media marketing, giving platforms with stronger growth indicators and greater user interaction priority.

Multi-Platform Strategy: Marketing initiatives should be spread over a variety of social media channels to reduce the possibility of Twitter's downfall.

Brand Safety and Reputation: Brand safety must be guaranteed. Companies should keep an eye on how their brand is viewed on Twitter and be prepared to change course if unfavorable connotations become more prevalent.

Real-Time Adaptation: When it comes to social media marketing, businesses should take a proactive stance, using real-time data to help them make well-informed decisions and immediately adjust their strategy as needed.

Conclusion

Elon Musk's acquisition of Twitter has been a major topic of discussion in the media, having a big impact on user attitude and real-world interactions. The purpose of this study was to evaluate the tone of tweets about Musk's acquisition and contrast the results with real-world patterns in user engagement and ad income. The findings shed important light on the intricate connection between sentiment expressed online and actual results, as well as the wider ramifications for Twitter's position as a social media platform.

Sentiment Analysis Results

The sentiment analysis using tools like Vader and TextBlob revealed a multifaceted public opinion landscape. According to the data, a sizable percentage of tweets about Musk's purchase of Twitter were positive in tone. People were upbeat about Musk's ability to innovate and enhance the platform suggesting that visionary leadership and perceived genuineness are two ways prominent people can encourage positive involvement.

This optimistic attitude, however, stands in stark contrast to the empirical findings. Even though tweets tend to be upbeat, Twitter's user base and advertising revenue have decreased following the takeover. In the first quarter following the acquisition, there was a 20-30 % decrease in daily active users and a 55% decline in advertising revenue. This disparity highlights how difficult it is to gauge social media sentiment and how it affects the sustainability of businesses.

Variations and Discrepancies

Positive Sentiment vs. Declining Metrics: The optimistic tone of tweets expresses users' expectations and hopes for improvements. Real-world measurements, however, show a decline in user satisfaction and trust, which lowers engagement and lowers revenue. This discrepancy implies that although the general public's attitude may be upbeat, user behavior and company results may not necessarily reflect this enthusiasm.

Negative Sentiment and User Concerns: Though the tone was mostly supportive, many tweets voiced worries on platform policy changes, privacy concerns, and controversial remarks made by Musk. The drop in user engagement and advertiser confidence may be caused by this unfavorable opinion held by a significant portion of the user base.

Neutral Sentiment and Cautious Optimism: There is a significant amount of indifferent tweets, which suggests that users are waiting to act. This hesitation implies that a lot of customers are delaying making decisions until it's evident what the long-term implications of Musk's takeover will be. The general volatility in user engagement numbers can be attributed to the mixed emotion among users, suggesting that although some are cautious and hopeful, others are not.

Conclusions from Observations

The analysis of sentiment versus real-world data leads to several important conclusions:

Sentiment Analysis as a Partial Indicator: While sentiment analysis can be a useful tool for understanding public opinion, it is not a perfect indicator of how things will turn out in the actual world. Although the optimistic tone of tweets suggests that users are hopeful, other measures like revenue and user engagement must also be taken into account in order to fully comprehend the health of the site.

Importance of Comprehensive Analysis: An interdisciplinary approach is essential to assess the effects of high-profile acquisitions. Real-world data and sentiment analysis together provide a more comprehensive understanding of user behavior and business performance. This method aids in finding disparities and comprehending the fundamental causes of user attitude and real trends.

Strategic Implications for Twitter: The conflicting opinions show how important it is for Twitter's management to proactively address user concerns. It is essential to rebuild user confidence via open communication, better content management, and enhanced platform reliability. Furthermore, income decreases can be lessened by restoring advertiser confidence through innovative advertising alternatives and brand safety.

Broader Implications

The study's conclusions highlight the complex connection between opinion expressed online and actual developments. Even while sentiment analysis is a useful tool for gathering public opinion, it is important to place these findings into larger dynamics. Though the optimism expressed in tweets points to the possibility of increased user participation, Twitter's diminishing user base and revenue from advertising underscore the difficulties it confronts in continuing to be a viable social media platform.

In conclusion, there have been a variety of responses to Elon Musk's acquisition of Twitter, as seen by real-world numbers and online emotion. Twitter may move through its post-acquisition phase more skillfully if it addresses the underlying problems that are causing unfavorable trends and capitalizes on the positive mood. Twitter can assure long-term success, rebuild user confidence, and improve platform viability by using a thorough and deliberate approach.

References

- DataReportal, 2023. *Digital 2023: The State of Twitter in April 2023*. [online] Available at: https://datareportal.com/reports/digital-2023-deep-dive-the-state-of-twitter-in-april-2023

- Edison Research, 2023. *Twitter/X usage sees sharp decline*. [online] Available at: https://www.edisonresearch.com/twitter-x-usage-sees-sharp-decline/

- Hickey, D., Schmitz, M., Fessler, D., Smaldino, P.E., Muric, G., and Burghardt, K., 2024. *Auditing Elon Musk's Impact on Hate Speech and Bots*. arXiv, [online] Available at: https://arxiv.org/html/2304.04129v3

- Zhang, D., 2024. *Study Analyses How Elon Musk's Tweets Affect the Market Value of Cryptocurrencies in Terms of Sentiment*. Advances in Economics Management and Political Sciences, 73(1), pp.292-298. DOI:10.54254/2754-1169/73/20230553. License: CC BY 4.0.

- Faverio, M., 2023. *Majority of U.S. Twitter users say they've taken a break from the platform in the past year*. Pew Research Center, [online] 17 May. Available at: https://pewrsr.ch/3WaSUum

- Chaudhuri, S. and Tabrizi, B., 1999. *Capturing the Real Value in High-Tech Acquisitions*. Harvard Business Review, [online] Available at: https://hbr.org/1999/09/capturing-the-real-value-in-high-tech-acquisitions

- Nalabandian, T., 2023. *The Psychological Impact of Twitter's Takeover: A Glassdoor Analysis*. Receptiviti, [online] Available at: https://www.receptiviti.com/post/the-psychological-impact-of-twitter-s-takeover-a-glassdoor-analysis

- Clune, C. and McDaid, E., 2023. *Content moderation on social media: constructing accountability in the digital space*. Accounting Auditing & Accountability Journal, 37(8). DOI:10.1108/AAAJ-11-2022-6119.

- Dang, S., 2023. *US ad revenue at Musk's X declined each month since takeover - data*. Reuters, [online] Available at: https://www.reuters.com/technology/us-ad-revenue-musks-x-declined-each-month-since-takeover-data-2023-10-04/

Appendix

One Drive Link containing all project related data including code, dataset and output files :

https://nuigalwayie-my.sharepoint.com/:f:/g/personal/p_mandapati1_universityofgalway_ie/Eg-4mLdOgRBNtkc20PK5Em8BLrqHwQ8ZPQbbZvay4qEqbw?e=HpSizG

Sample output of running code :

```
final project — -zsh — 123×32
(venv) prashant@Prashants-MacBook-Air final project % python final_project.py
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/prashant/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /Users/prashant/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     /Users/prashant/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
                         id                                              text
207353  1601472991514492928  @MarkDonnelly16 @ThisIsKyleR @elonmusk This is...
247378  1602030377136447489  @TheBestAkaliEvr @elonmusk Professor here is y...
42405   1599022776102240257  @dirtywater864 @elonmusk @WillManidis Where di...
297687  1602711565224009734  @johnpavlovitz @elonmusk how do you know.  sto...
310635  1602853748287721472  @KeithOlbermann @elonmusk Yeah. How dare he sh...
175317  1600959520422825984  @elonmusk @RepAdamSchiff @RepMarkTakano @Commu...
354579  1603717572905652227  Top story: Twitter Suspends Accounts of Half a...
154238  1600665099600920576  @MattWallace888 Yeah yeah Elon Musk spent 44 b...
476825  1605411340855971840  @Royce_Young @elonmusk @teslaownersSV @heydave...
330037  1603418212804304897  I'm at work from now until 6pm. https://t.co/v...
Statistical Description of Sentimental Polarities:
       vader_polarity  blob_polarity
count   486553.000000  486553.000000
mean         0.039976       0.066893
std          0.456992       0.288952
min         -0.999600      -1.000000
25%         -0.296000       0.000000
50%          0.000000       0.000000
75%          0.401900       0.200000
max          0.998200       1.000000
(venv) prashant@Prashants-MacBook-Air final project % python final_project.py
```