Tweeting Emotions: Unveiling The Sentiment Shifts In ChatGPT Discourse

Anonymous authors
Paper under double-blind review

Abstract

Social media data can be a valuable source of information during new technological advances. User-generated messages from social media provide a window into people's minds during such times, allowing us insights into their moods and opinions. In the field of artificial intelligence, understanding the sentiment dynamics within conversational models like ChatGPT is crucial for enhancing user experience and guiding model development. Furthermore, LLMs impact day-to-day life activities across various domains such as education, workplace productivity, healthcare, entertainment, etc. This study delves deep into the sentiment analysis of Twitter discourse surrounding a popular large language model known as ChatGPT. By analyzing over a million tweets from November 2022 to May 2023 and Reddit comments, we investigated Twitter and Reddit data and verified the topics within the dataset related to ChatGPT discourse. Followed by analyzing public perceptions and attitudes towards ChatGPT utilizing data analysis and showing sentiment shifts using various methodologies, such as Vader, TextBlob, and the BERT model, and comparing the sentiment distributions across all models. Finally, we fine-tuned our BERT model to find the optimal parameter for training. Our findings show that the dataset contains ChatGPT-related content. Data analysis provides insight into our Twitter data, by showing the top ten most frequent tweets, relationships between likes and retweets, and the number of tweets per week. Finally, analyzing the sentiments of the data shows that Twitter people have more negative sentiment towards ChatGPT than positive sentiment. On the other hand, sentiment analysis on our Reddit dataset shows more positive than negative sentiment on ChatGPT. Overall, our study provides insight into the public sentiments towards ChatGPT and the sentiment shifts over time, which offers valuable insights into user perceptions and interactions with AI and paves the way for determining the impact of ChatGPT.

1 Introduction

Twitter is a social media platform where many users tweet out their opinions on trending topics across the world. Due to the recent growth in the popularity of the Large Language Model, primarily ChatGPT, there has been a large amount of discourse on Twitter surrounding the state of AI and LLMs. Understanding how users feel towards new technologies is important as this can be an opportunity to disprove misconceptions and further enhance the product through understanding the general users' feelings towards it. This is why, in our study, we will be analyzing the sentiment of tweets that pertain to ChatGPT to understand better how users of the technology feel about it. Our study focuses on using Data analysis to provide insight into our data. Also, natural language processing methods, such as topic modeling using LDA (Latent Dirichlet Allocation), were used to find relevant topics concerning ChatGPT terms within the dataset. Additionally, a pre-trained language model (BERT) on domain-specific data was trained to predict sentiments for unlabeled data. Also, rule-based and lexicon-based models (Vader and TextBlob) were used to find a sentiment distribution towards the ChatGPT-related discourse within Twitter social media. Comparing the results of two rule-based and transformer-based models, we provide insights into the sentiment shifts of ChatGPT tweets from December 2022 to May 2023.

2 Related Works

Due to the introduction of different LLMs, numerous studies have been published into investigating the impact of ChatGPT on Twitter. Additional related works that analyze sentiment evolution rather than pure sentiment response also exist; a salient study that accomplishes this is the cross-language data science analysis research paper by Kruspe et al. The study focuses on sentiment analysis of Twitter messages across various European countries during the initial months of the COVID-19 pandemic (Kruspe et al.,2020). It analyzes user-generated content to gain insights into people's emotions and opinions on a large scale using a neural network and multilingual sentence embedding. They categorize sentiment labels by country of origin and correlate them with significant events, such as lockdown announcements. The findings reveal a consistent pattern: lockdown announcements coincide with a temporary decline in mood across most surveyed countries, followed by a relatively swift recovery. This is where our initial idea background for this paper came into being. Additionally, our study focuses particularly on ChatGPT discourse over a certain period of time. Another related work that's similar to our analysis of ChatGPT sentiment is the Computation and Language cross-language research paper (Leiter et al.,2023). Leiter's work presents an analysis of over 300,000 tweets and 150 scientific papers to explore the public perception and discussion surrounding ChatGPT. Their findings indicate that ChatGPT is generally well-regarded, with positive sentiment prevailing on social media platforms, although there has been a slight decline in its perception since its introduction. According to the paper, there has been an increase in (negative) surprise, particularly in languages other than English. The study provides a comprehensive overview of ChatGPT's perception 2.5 months post-release, aiming to contribute to ongoing public discourse and guide its future development. The data collected for the analysis is also made accessible for further research, which is helpful to the larger NLP community. On the other hand, in our study, we merge two different datasets from December 2022 to May 2023 and analyze over a million tweets worth of data. We discuss our data analysis, provide insights into the dataset, illustrate the diverse opinions and topic distributions of our dataset, and finally train a model to predict the sentiment associated with the dataset. A study was also conducted (Su et al.,2023) by using a dataset of 500,000 tweets and tools such as Wolfram Mathematica to gain insight into public perception of ChatGPT and Transfer Learning tweets (section A.10. However, our study shows various data analyses that provide a deep understanding of the Twitter dataset, as well as depicting the type of sentiments associated with the tweets, for example, providing positive and negative word clouds within the dataset. There are many studies showcasing the analysis of public opinion through sentiment analysis models. This is clearly a critical topic of research as understanding public opinion can help further the technology shift and provide insight into how public opinion may change with new updates and releases of features.

3 Methodology

The methodology and procedure, from data acquisition to analysis techniques to training a model, are explained in great detail. We first gathered multiple datasets on tweets related to ChatGPT, removed languages other than English from the multilingual dataset, and merged those datasets together. Then, we use the newly created dataset and performed data pre-processing methods to remove the hashtags, links, new line characters, remove multiple space characters, substitute characters like & with 'and,' and lastly, convert all the text to lowercase letters. After merging the dataset, we kept two versions of the datasets; one performed sentiment analysis using the VADER Model and TextBlob, where both use rule-based and lexicon-based sentiment analysis, and the other for data analysis and topic modeling. The first version of the dataset contains only the necessary tweets to perform unsupervised sentiment analysis using the VADER model and TextBlob. The second dataset contains all the other necessary columns, such as the count of likes, retweets, locations, and much more. Furthermore, we analyzed the newly created dataset, identified the top 10 most frequent tweets, and plotted graphs illustrating the relationship between likes and retweets and the number of tweets per week. We also analyzed bigram, trigram, and unigram counts, mention words and hashtag word clouds. Additionally, we performed topic modeling on the dataset, demonstrating the topics or themes of the acquired dataset. This will provide insight into the related topics or themes of our data. We used two other labeled and non-labeled datasets. The BERT model was trained with the labeled dataset, and after training the model, the non-labeled datasets were predicted by the model. The non-labeled datasets are then classified into positive, negative, and neutral sentiments. In later sections, we show the sentiment distributional analysis of the predicted tweets. Additionally, after using the BERT model to predict the non-labeled tweets and Reddit comments on ChatGPT, sentiment analysis was conducted, comparing the results between Vader, TextBlob, and Bert to ensure the validity of our analysis. Finally, we provide details on finetuning the BERT model. In conclusion, we used the above tools to show sentiment shifts in ChatGPT discourse.

3.1 Dataset

There are a total of 4 collective datasets. Two datasets contained tweets which were collected using the hashtag, #ChatGPT, #GPT. In one dataset, we collected tweets from November 2022 till the end of April 2023; the other is dated from April to May. Upon merging the two datasets, the maximum date retrieved was `2022-11-30`, and the minimum date obtained was `2023-05-12`. The 2 sets contained approximately 1,000,000 tweets and their corresponding date, tweets, usernames, user-created, user-verified, user-followers, retweets, likes, locations, and descriptions. We also collected a labeled dataset based on Twitter data on terms like ChatGPT, and additionally collected unlabeled Reddit data on ChatGPT.

3.2 Data cleaning

Two datasets containing tweets collected from Kaggle had multilingual texts, so we removed the non-English texts from the datasets, removed null values, and cleaned the dataset utilizing regex expression. After obtaining a new dataset containing **362,566** tweets, it is noted that the dataset deviates from the original tweets, which consisted of a million data. Appendix A section A.1 refers to the code cleaning process. The pre_process function removes the link, substitutes it with characters, removes new line characters, removes leading strings from and # characters, removes multiple space characters, and, lastly, converts to lowercase all the characters in the tweet. We also removed data that didn't belong into the category of English alphabets, numeric values, single spaces, and periods ("."), in other words, we removed all special characters. The labeled dataset was pre-processed already. However, the unlabeled dataset contained non-ChatGPT terms and comments unrelated to AI, so the dataset was filtered using ChatGPT terms.

3.3 Data Analysis

In the Twitter dataset, various data analyses and comparisons between data labels were performed to find insightful statistics showing the sentiment shifts in the first six months of ChatGPT-related conversation on Twitter. After pre-processing the data, we first looked at the top 10 most frequent tweets in our dataset, which helped us understand the popular tweets within the dataset. Additionally, LDA **(Latent Dirichlet Allocation)** was used for topic modeling, identifying the latent topics within a corpus of text. Following that, topic modeling helped identify the topics and themes present within the dataset. Utilizing this topic analysis, we recognized the topics presented within the dataset without going through it manually. Furthermore, analyzing the likes and retweet relationships, helped determine the level of interest and potential retweets of the content within the dataset. Moreover, exploring the number of tweets per week from December 2022 to May 2023 aided in visualizing the number of tweets tweeted per week, depicting a timeline of tweets related to ChatGPT. We also performed text analysis on the dataset, such as Bi-gram and Tri-gram counts, along with word clouds of unigrams, mentions, and hashtags. All of these data analytics contributed context for the datasets, as well as insights on relevant topics, patterns, and trends throughout time. The goal is to provide a full overview of sentiment shifts and trends over the first six months of the ChatGPT timeline, as well as significant insights into the evolution of discussions and interests surrounding ChatGPT.

3.4 Topic Modeling

Topic modeling assisted in identifying the topic names within the tweets. First, topics were extracted using LDA **(Latent Dirichlet Allocation)**, a topic modeling technique for unsupervised data classification, which helped discover the topics within the dataset. After taking the first 10K data from the dataset, stop words were removed from the dataset. Also, a set of user-defined stop words were removed from the dataset. "Word Net Lemmatizer" was used to lemmatize the tweets, and then a dictionary was created with words and their frequencies. Afterward, a document-term matrix was created from the dictionary. Lastly, we used an LDA model to perform topic modeling.

3.5 Sentiment Analysis: Vader and TextBlob

Sentiment analysis was performed on the dataset using Vader and TextBlob, where both are lexicon and rule-based models. The columns of the datasets were dropped, keeping only pre-processed tweets. Then, Vader was imported using the NLTK sentiment library, and Sentiment Intensity Analyzer was applied to the processed tweets to determine the Vader Polarity of each tweet. Following that, TextBlob was imported from their respective library and a mapping function was applied to assign a sentiment polarity score to the Twitter dataset. Furthermore, a comparison of sentiment analysis between these two sentiment models was conducted, showing the distribution of sentiment polarity scores of Vader and TextBlob of the tweets from December 2022 to May 2023 (section A.9).

3.6 Sentiment Analysis: Bert LLM

A Twitter-labeled dataset on ChatGPT topics was used to train the BERT model. The following dataset contained string labels, which were then converted from string to numeric value. For instance, The dataset contained three labels: good, bad, or neutral. The labels were then converted by mapping each tweet's label from "good" to "1", "bad" to "2", and "neutral" to "0". Additionally, the training dataset was prepared by copying 15000 rows from each sentiment and merging the dataset later to perform training on the BERT model. For example, we took 15000 negative, 15000 positive, and 15000 neutral labels from the labels column and merged all the data points into a new pandas data frame. Furthermore, A Reddit unlabeled dataset was pre-processed, and columns were reduced to ID and Comments only. The trained model later predicts this dataset. After preparing the training dataset, Huggingface libraries were used to import the Bert Tokenizer and Bert For Sequence Classification. Then, tweets and labels from the training dataset were converted into a Python list from the Pandas data frame. Following this, the training data was split into a training dataset of 80% and a testing dataset of 20% of the actual dataset. Later, a user-defined dataset class was used to convert the existing training and validation dataset to a compatible format with PyTorch. This allowed us to integrate PyTorch's data-loading utilities to train the model. Then, we used Training Arguments and Trainers to train our model. After training the model, we used our testing datasets, which were crafted from Reddit comments, and the Twitter dataset to perform sentiment analysis and predicted the sentiments of these two unlabeled datasets(section A.10 and section A.12). A confusion matrix (section A.11) is shown to aid in assessing the classification model performance by visually representing predicted versus actual classifications for the datasets. It assists in evaluating BERT's effectiveness in categorizing text into the sentiment categories: negative, neutral, and positive. This offers insight into model accuracy, error tendencies, and its handling of class imbalances. The compute metric used is the accuracy score, which was used to determine the model's accuracy.

Accuracy Formula
$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100\%$

The BERT model was fine-tuned utilizing a hyperparameter search with 10 trials to find the maximized accuracy of the trained model. After searching for the hyperparameter, the optimized parameters were determined: **Learning Rate: 3.7988668524141836e-05**, **Num_train_epochs = 3**, **Seed = 3**, **per_device_train_batch_size = 16**. Following that, the trainer arguments were updated to the most optimal parameters and then the model was trained. Furthermore, Lexicon and Rule-based models were compared with Transformer-based models to demonstrate sentiment distribution in the above-mentioned datasets. The differences between the models highlight the distinctions between these models and offer valuable insights into the sentiment shifts across ChatGPT discourse.

4 Results

4.1 Data Analysis: Top 10 most frequent tweets

The following (section A.2) in Appendix A provides the top 10 most frequent tweets in our dataset. The first tweet is provided in the table below.

Enhance your business with cutting-edge AI technology. Our ChatGPT for beginners course offers the perfect introduction for companies embracing the digital world. Sign up now! **BusinessInnovation AI**

4.2 Data Analysis: Likes Vs Retweets

Likes vs retweets were analyzed and examined, and a graph was plotted with 1000 likes and 200 retweets (section A.5). Each data point represents a tweet post. The graph depicts that as the number of likes increases, the number of retweets also tends to increase. We used the Pearson correlation coefficient to investigate the strength and direction of the linear relationship between likes and retweets. It was found that the Pearson correlation coefficient between likes and retweets is 0.59514746580502, which is not relatively high, but we can infer that there is a significant positive correlation between the number of likes and retweets. This shows that the audience received the information well. One possibility is that people are likelier to retweet a tweet on ChatGPT discourse that they have already liked. Lastly, retweeted tweets on ChatGPT conversation are more likely to be seen by a larger audience and, therefore, receive more likes.

4.3 Data Analysis: Number of Tweets Per Week

After examining the relationships between likes and retweets, the distribution of tweets is shown per week within the time period from the dataset (section A.6). By analyzing the number of tweets per week, we identified that people were actively tweeting about ChatGPT-related terms. Note that, in the graph, there was an increase in tweets around the second week of March, when Chat GPT 4 was released. People have been talking more about ChatGPT 4 than ChatGPT 3 in previous weeks.

4.4 Bi-gram and Tri-gram Counts

The top 20 bigram and trigram counts within our dataset are shown in (section A.7), showcasing their relevance toward trends and topics found within the time frame of the tweets from our Twitter data. These bigrams and trigrams suggest that the tweets in this dataset are about artificial intelligence, particularly large language models like ChatGPT. The analysis helped in understanding the dataset's significance and capturing the popular trends and topics. For instance, From the graphs (section A.7), we can infer that bigrams like "Chat Gpt" and trigrams like "Natural Language Processing" suggest that ChatGPT, a specific LLM, is a major topic of discussion.

4.5 Word Clouds

The top unigrams, mentions, and hashtags in our dataset were represented as word clouds (section A.8). In Figures 8 and 9, We identified positive and negative word clouds of our dataset regarding ChatGPT-related tweets. To gain a more nuanced understanding of sentiment towards ChatGPT, we also identified and analyzed the mention words, hashtag words associated with the dataset. This helps with a deeper understanding of public perception towards ChatGPT.

4.6 Topic Modeling

Topic modeling has helped identify topic names within the content. A word cloud was created to show all the top topic words present in the dataset. (section A.3) refers to the word cloud for topic words. The word cloud shows the topic by word clustering, whereas topic 7 is related to ChatGPT, AI, and Generative AI words. After performing a Topic-by-document analysis, it was found that topic 7 had the highest distribution within the dataset. After analyzing the dataset utilizing, topic-by-document distribution, it is evident that ChatGPT is the most dominant topic within the dataset. (Section A.4) refers to the topic by document distribution graph.

4.7 Sentiment Analysis: Vader, and Blob

After performing sentiment labeling using Vader, and TextBlob, we plotted the predicted labels in a graph(section A.9) by showing a distribution of sentimental polarities between Vader and TextBlob, to see the accuracy between both models within the Twitter dataset.

4.8 Sentiment Analysis: BERT

After training the BERT model on the labeled dataset, we created a confusion matrix (section A.11 Figure 14), that shows the number of correct predictions compared with the incorrect predictions of the Bert model. In Figure 14, the diagonal cells represent the correctly classified sentiments, and the non-diagonal cells refer to the misclassified sentiments. The BERT model trained had an accuracy of 90% on our validation dataset; with the trained model, we showed Bert's sentiment distribution on our Twitter dataset (section A.10). The trained model was also used to predict labels for the Reddit unlabeled dataset on ChatGPT to show the sentiment distribution of the Reddit community (section A.12), and conclude the sentiment shifts of ChatGPT discourse. Finally, we plotted the sentiment distribution of all the models and showed a sentiment analysis over time of Tweets based on ChatGPT from Dec 2022 to May 2023 to depict the sentiment shifts overall.

5 Discussions

To study the public attitudes towards ChatGPT, we applied various data analysis techniques and a sentiment analysis model to extract related topics, meaningful insights, and sentiment of tweets. The extracted topic keywords provided insights into our dataset, proving the theme related to ChatGPT discourse (section A.3). Furthermore, the topic by document distribution (section A.4) shows many Twitter users discussing ChatGPT-related content. Furthermore, there is a positive linear relationship between the number of likes and retweets from users with regard to ChatGPT (section A.5). Twitter people are expressing their opinions on ChatGPT and its impacts. The number of tweets per week (section A.6) shows that people are tweeting on ChatGPT, chatbots, or Generative AI model-related terms on a regular basis. The unigrams were examined using positive and negative unigram word clouds. **'learn,' 'question,' 'answer,' 'chatbot,' 'thank,' 'best,' and 'future'** are some related positive keywords towards ChatGPT that Twitter people used. Refer to (section A.8, Figure 8 & 9) for positive word clouds on ChatGPT discourse. Some negative sentiments towards ChatGPT discourse are **'gpt4', 'response,' 'bad,' 'tried'** etc. some of the examples from the negative word cloud. From the hashtags and mentions cloud (section A.8 Figure 10 & 11), it is evident that OpenAI's ChatGPT is a well-known topic among big celebrities such as Elon Musk, news channels such as the New York Times and Forbes, large tech companies Google, Youtube, etc. are expressing their opinions on ChatGPT and there is a social media buzz around it. Additionally, in the sentiment distributions from the BERT model, we found that ChatGPT has negative and positive impacts, while some people are expressing neutral opinions. Using our dataset on the time frame from **December 2022 to May 2023**, we found that **40.8%** Twitter people showed more negative sentiment towards ChatGPT, **29.9%** positive sentiments, and the rest **29.3%** are neutral on the perception of ChatGPT (section A.10). On the other hand, the Reddit community showed a more positive sentiment towards ChatGPT. Almost **42%** of the people showed positive sentiment, followed by **31.8%** negative sentiment, and **26.2%** showed neutrality towards ChatGPT (section A.12). The following graph **figure 1** was plotted to see the sentiment shifts over time from **December 2022 to May 2023**. According to the predictions, negative sentiments towards ChatGPT appear

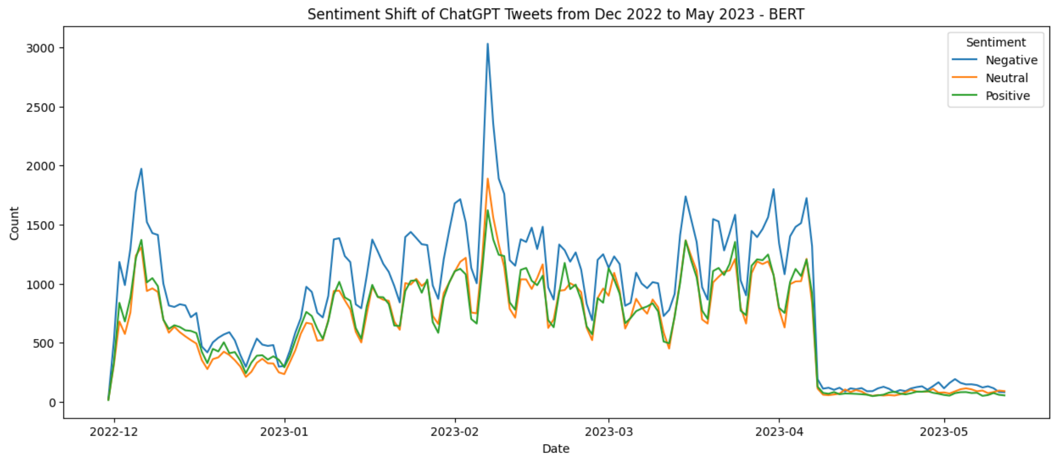


Figure 1: Sentiment shifts Over Time: Dec 2022 to May 2023

to be the dominant sentiment throughout the period within the Twitter Dataset, and positive sentiment is more dominant within the Reddit dataset. Furthermore, people's opinions on ChatGPT seem to shift and vary over time. Additionally, Vader's sentiment prediction (section A.14) for positive is 53.3%, 16.4% negative, and 30.3% neutral. Also, TextBlob's sentiment distribution (section A.15) is similar to Vader's sentiment distribution: positive is 52.3%, 33.5% neutral, and 14.2% negative. Finally, For comparison analysis of the predicted sentiments using Vader, TextBlob, and BERT model, the sentiment shifts are shown in (section A.13).

6 Conclusion

Our study delved deeper into public perceptions of ChatGPT, providing insightful observations on the diverse statements and discussions within the Twitter and Reddit Communities. While Twitter users exhibited a mixed sentiment with a notable amount of negative sentiment, whereas the Reddit community showed a more positive view towards it. Celebrity endorsements and media coverage contributed to its widespread recognition. However, despite the variations over time, negative sentiments persist as a dominant view, as depicted in the model comparison analysis utilizing Vader, TextBlob, and BERT. This study really highlights the different perceptions surrounding Large Language models like ChatGPT and illustrates the sentiment shifts in ChatGPT discourse from December 2022 to May 2023.

7 Limitations

7.1 Limited Data

The paper studies sentiment shifts in ChatGPT discourse within the first 6 months, due to the changes in Twitter data access policy. The data ranges from December 2022 to May 2023. This might not be a representative sample of global public opinion due to data sparsity. Also, there is one more discrepancy here, which is that data from April to May isn't enough in the English language. The study does not consider multi-lingual. However, this could be a future work. Furthermore, The labeled data for training the model might be biased toward negative sentiment despite balancing the dataset by taking an equal amount of labeled data from each sentiment label. It could be due to the negligence of the human annotators. Overall, Due to Sparse data, this may not fully capture the latest trends and discussions. In conclusion, The study only captures a certain period in the history of ChatGPT discourse.

A Appendix

A.1 Text Pre-processing

```
def pre_process(text):
    # Removes link
    text = re.sub('http://\S+|https://\S+', '', text)
    text = re.sub('http[s]?://\S+', '', text)
    text = re.sub(r"http\S+", "", text)

    #substitues &amp, &lt, &gt with 'and', '<', '>'
    text = re.sub('&amp', 'and', text)
    text = re.sub('&lt', '<', text)
    text = re.sub('&gt', '>', text)

    # Remove special characters
    text = re.sub(r'[^a-zA-Z0-9\s]', '', text)

    # Removes new line character
    text = re.sub('[\r\n]+', ' ', text)


    text = re.sub(r'@\w+', '', text)
    text = re.sub(r'#\w+', '', text)
     #Keeps the character trailing @
    text = re.sub(r'@\w+', lambda x: re.sub(r'[^a-zA-Z0-9\s]', '',
                                        x.group(0)), text)
    #Keeps the character trailing
    text = re.sub(r'#\w+', lambda x: re.sub(r'[^a-zA-Z0-9\s]', '',
                        x.group(0)), text)
    # Remove multiple space characters
    text = re.sub('\s+',' ', text)

    # Convert to lowercase
    text = text.lower()
    return text
```

A.2 Top 10 Most Frequent Tweets

Table 1: Top 10 Most Frequent Tweets

Content
Enhance your business with cutting-edge AI technology. Our ChatGPT for beginners course offers the perfect introduction for companies embracing the digital world. Sign up now! *BusinessInnovation AI*
Discover the power of ChatGPT with our beginner-friendly course. Empower your business with AI-driven solutions for better communication and productivity. Enroll now! *AI DigitalTransformation*
AI World Congress 2023, June 78, London. Book now! `AI ArtificialIntelligence BigData MachineLearning EdgeComputing QuantumComputing Metaverse OpenAI Robotics Robots IoT AIoT InternetOfThings 5G AR Web3 ChatGPT`
EdTech World Forum 2023, London, May 17-18. Book now! `EdTech eLearning Education OnlineEducation EdTechPlatform DigitalEducation HigherEducation EducationalTechnology ChatGPT EdTechStartups OnlineLearning Edutech Coursera Udemy Google`
What is ChatGPT and why are people saying it could give Google a run for its money? `ChatGPT Chatbot`
Unlock the power of artificial intelligence for your business. 121 ChatGPT prompts for internet marketers. `OpenAI JasperAI AI ArtificialIntelligence ChatGPT3 WFH WorkFromHome MakeMoneyOnline SideHustle SideHustles ChatGPTPrompts`
Read post: "ChatGPT for beginners course" published on Yuhanito. ChatGPT Mastery: unlock the true potential of ChatGPT. Learn how to ask the right questions and get the best answers. `ChatGPT LearnChatGPT`
Looking for a reliable AI copywriter for your blog? Check out these top picks. CopyAI, WriteSonic, Katteb, WriterZen, Outranking. These AI tools can help you create high-quality content with ease. Give them a try! `BloggingTips AIWriting`
Learn about the latest developments in AI governance and having effective policies to ensure the responsible and ethical use of AI technology. `AIGovernance AIEthics ChatGPT AI ML`
Another day, another scam. Crooks are taking advantage of the massive hype around ChatGPT. They're setting up fake sites to spread malware that steals money and passwords. `ChatGPT Cybercrime NewMalware`

A.3 WordCloud: Topic Modeling

Figure 2: Topic Modeling Word Cloud

A.4 Graph: Topic Distribution

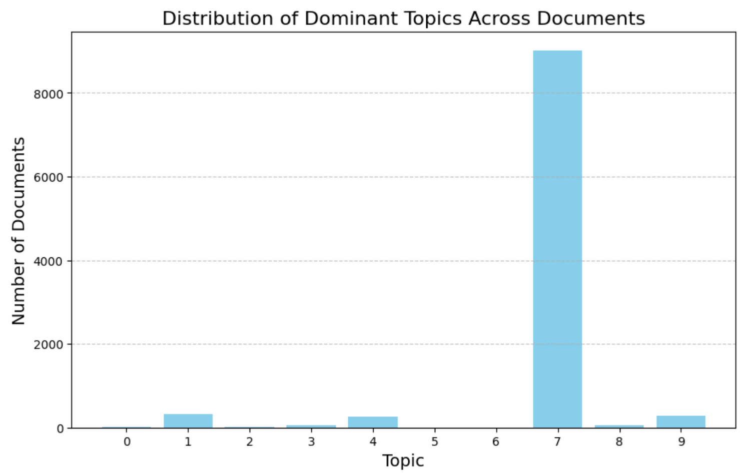


Figure 3: Distribution of Dominant Topics Across Documents

A.5 Graph: Likes Vs Retweets

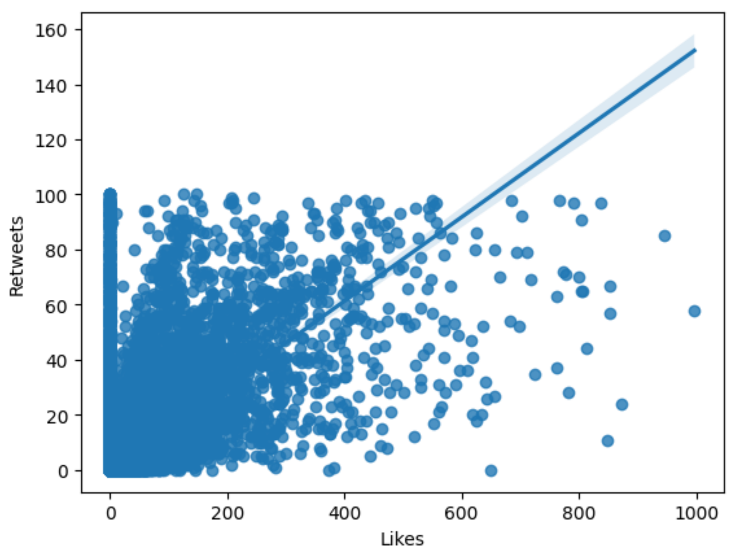


Figure 4: Relationship: Likes Vs Tweets Regression Plot

A.6 Graph: Number of Tweets Per week

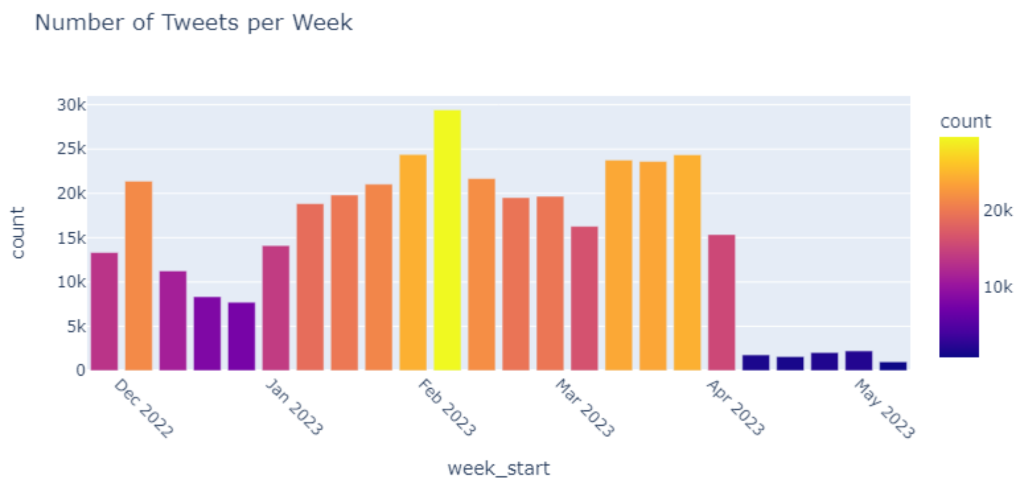
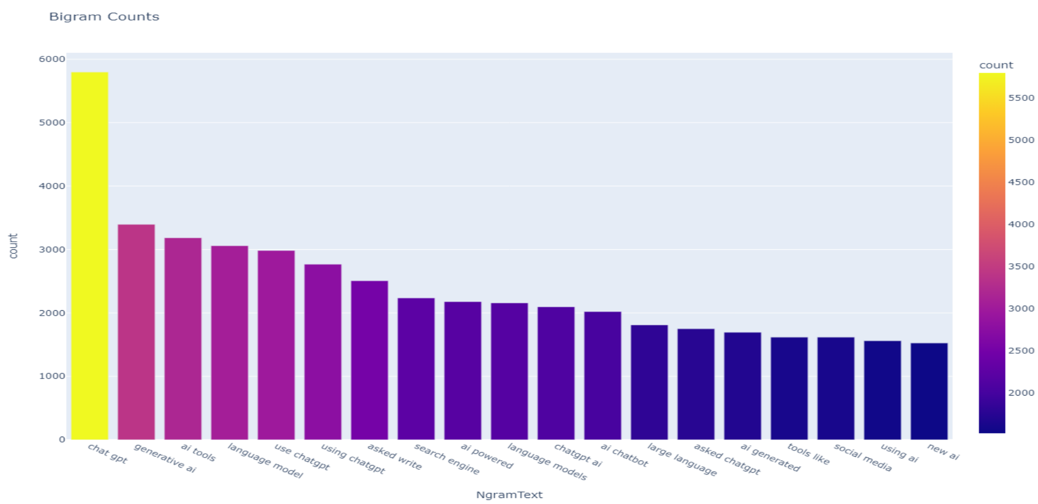


Figure 5: Number of Tweets Per week

A.7 Graph: Bi-gram and Tri-gram Counts



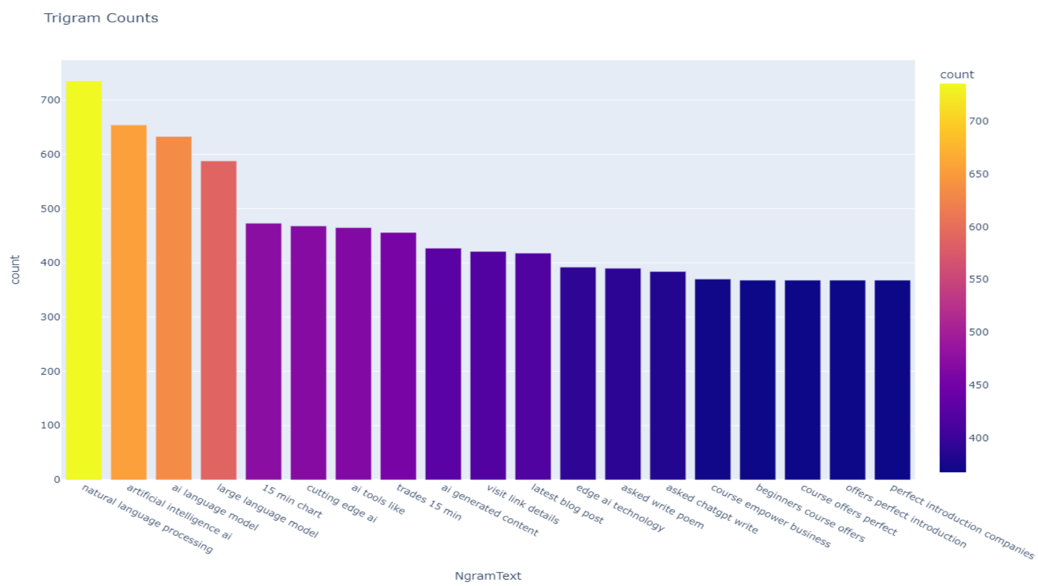


Figure 6: Unigram Cloud

A.8 Graph: Word Clouds

Figure 7: Unigram Word Cloud: Positive, Negative, Neutral

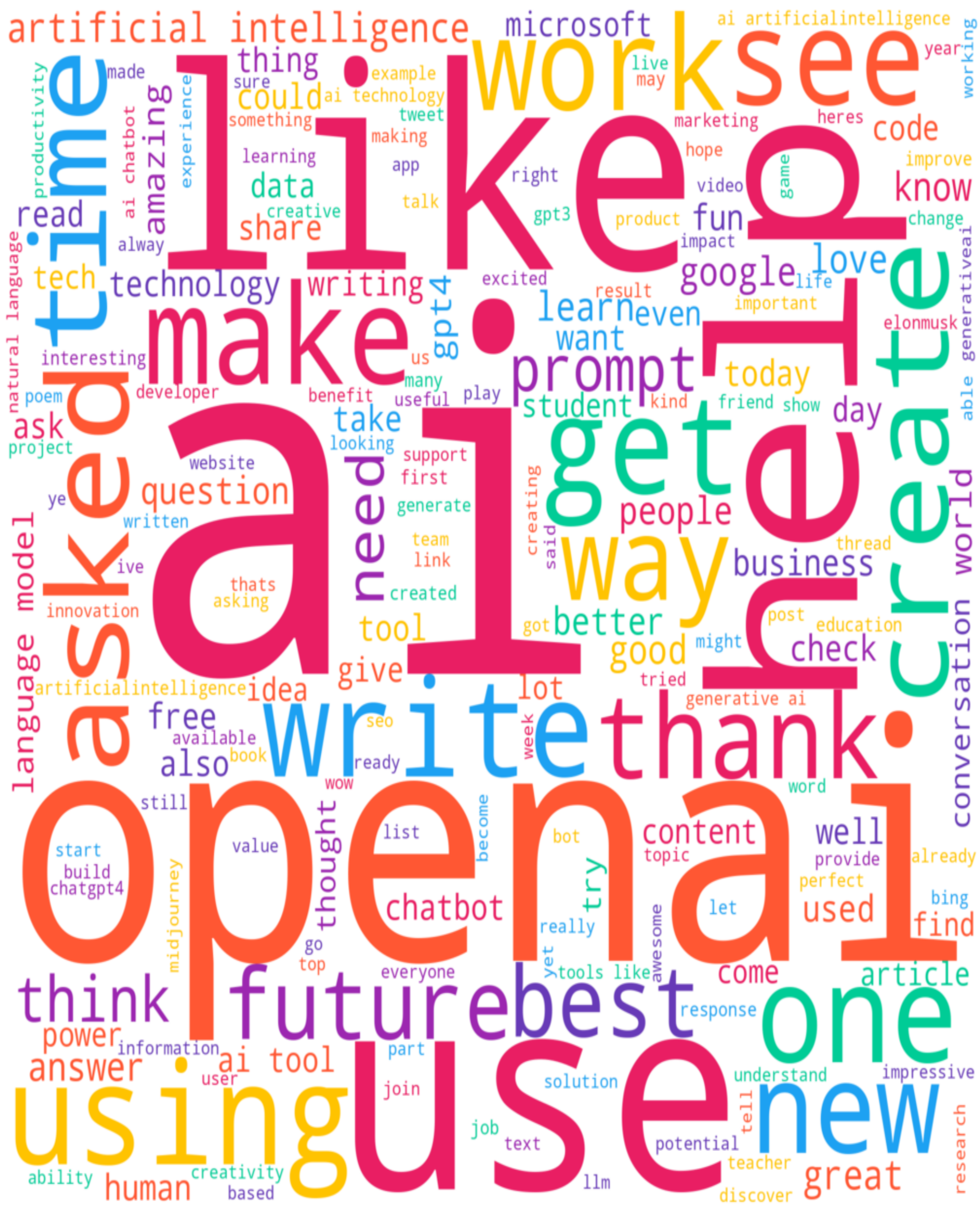


Figure 8: Unigram Positive Word Cloud

Figure 9: Unigram Negative Word Cloud

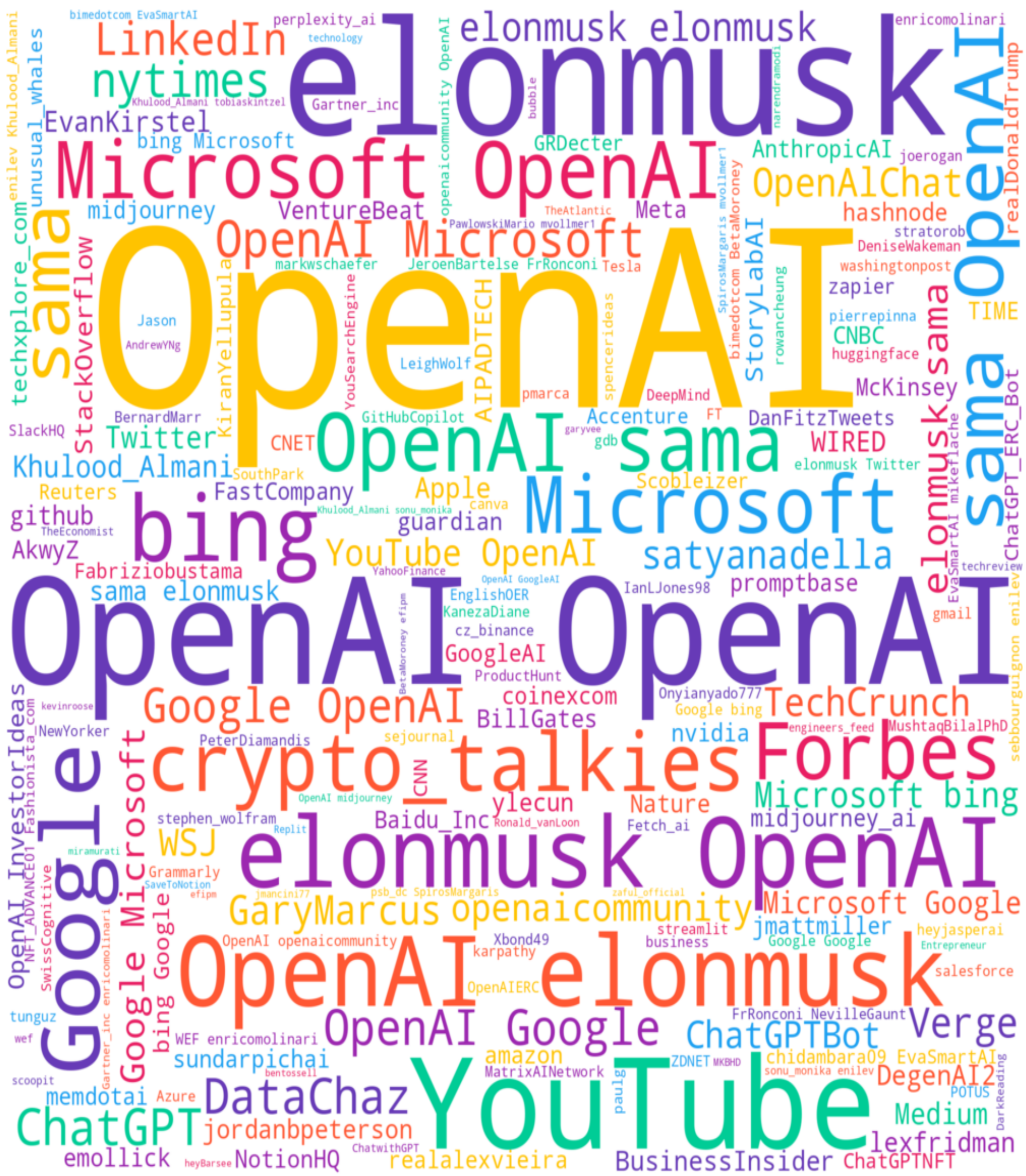


Figure 10: Mention Cloud

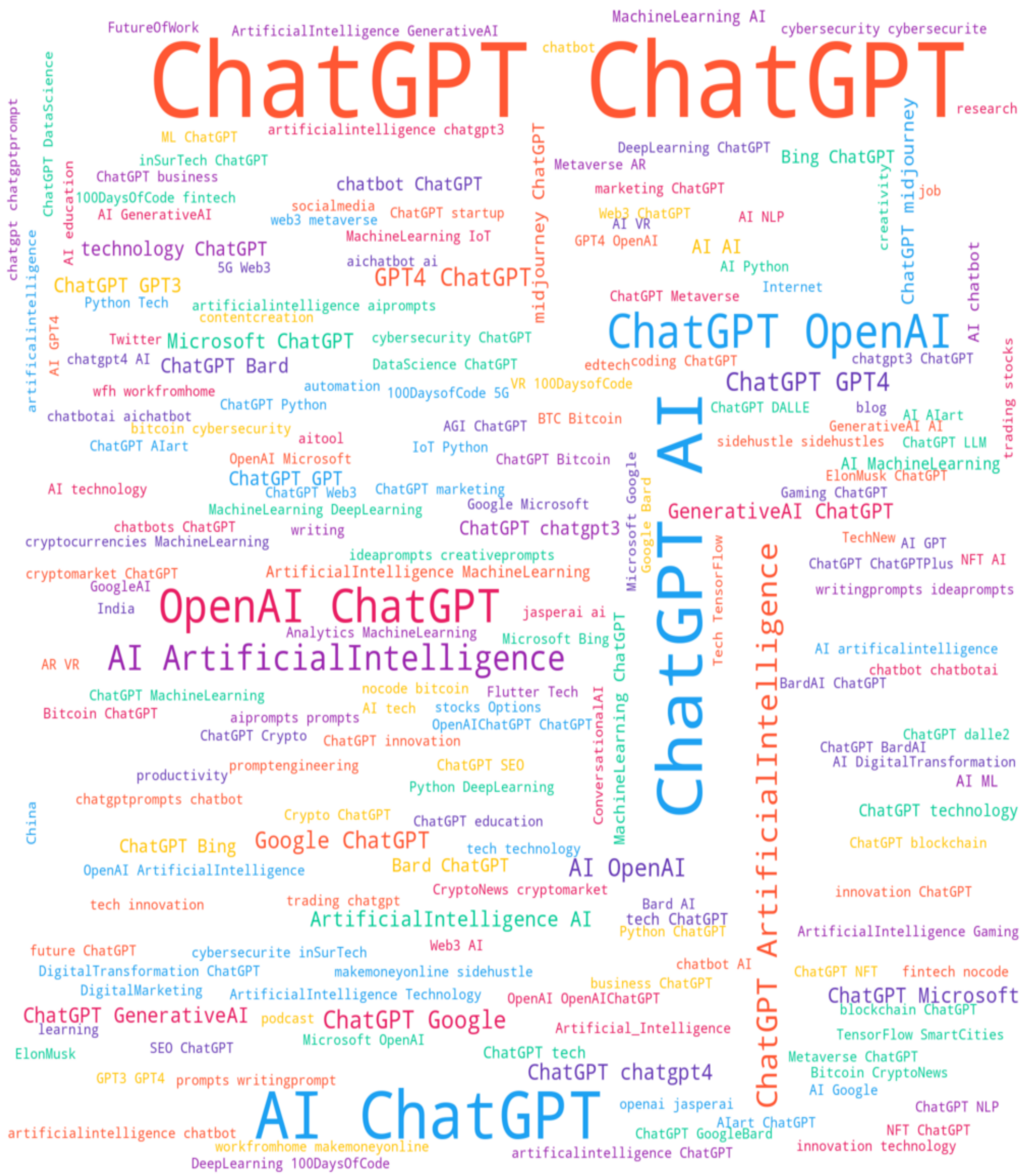


Figure 11: Hashtag Cloud

A.9 Graph: Sentiment Distributions Comparisons and Analysis of Vader and TextBlob

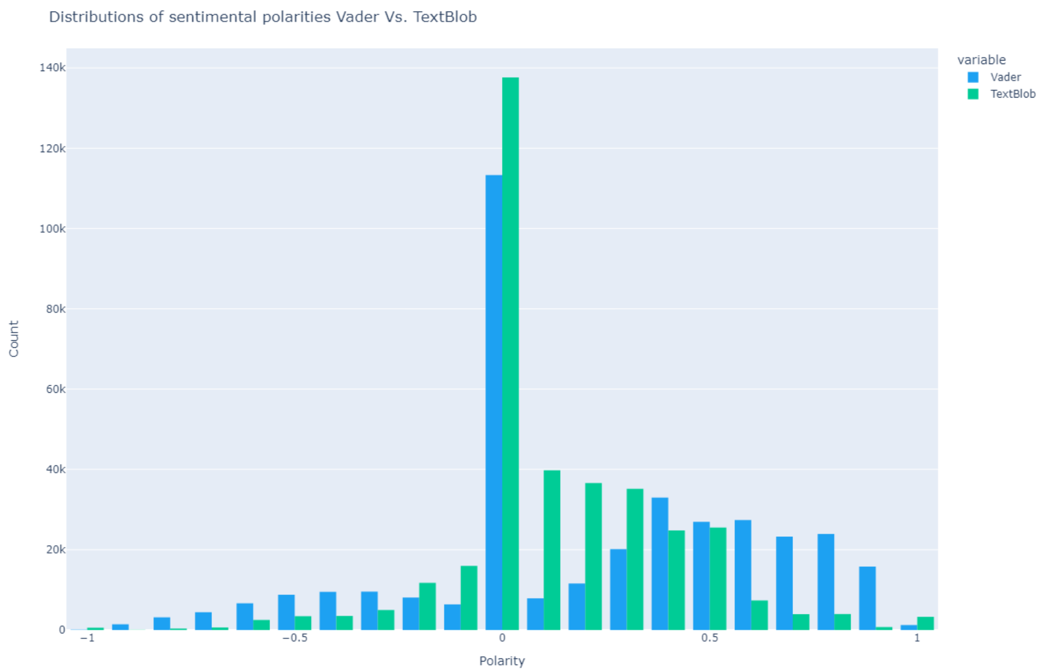


Figure 12: Distributions of sentimental polarities Vader Vs. TextBlob

A.10 Graph: Bert Sentiment Distributions

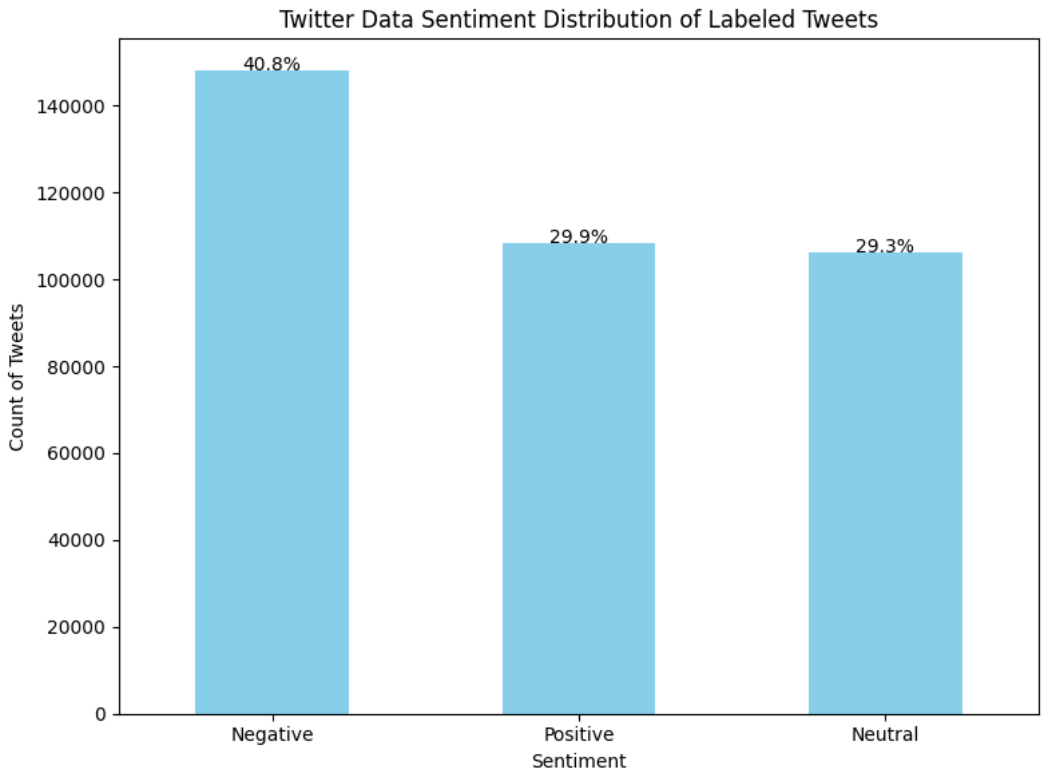


Figure 13: Sentiment Distribution of Labeled Tweets Using BERT

A.11 Graph: Confusion Matrix

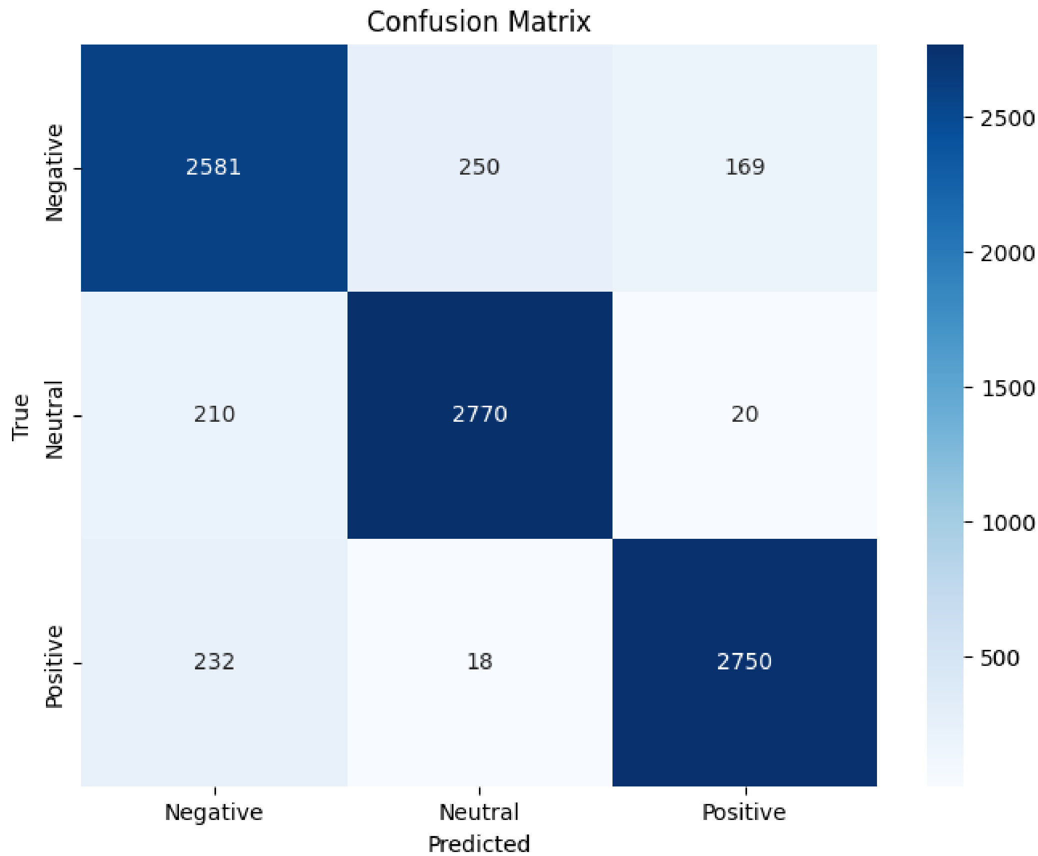


Figure 14: Confusion Matrix

A.12 Graph: Reddit Sentiment Distributions

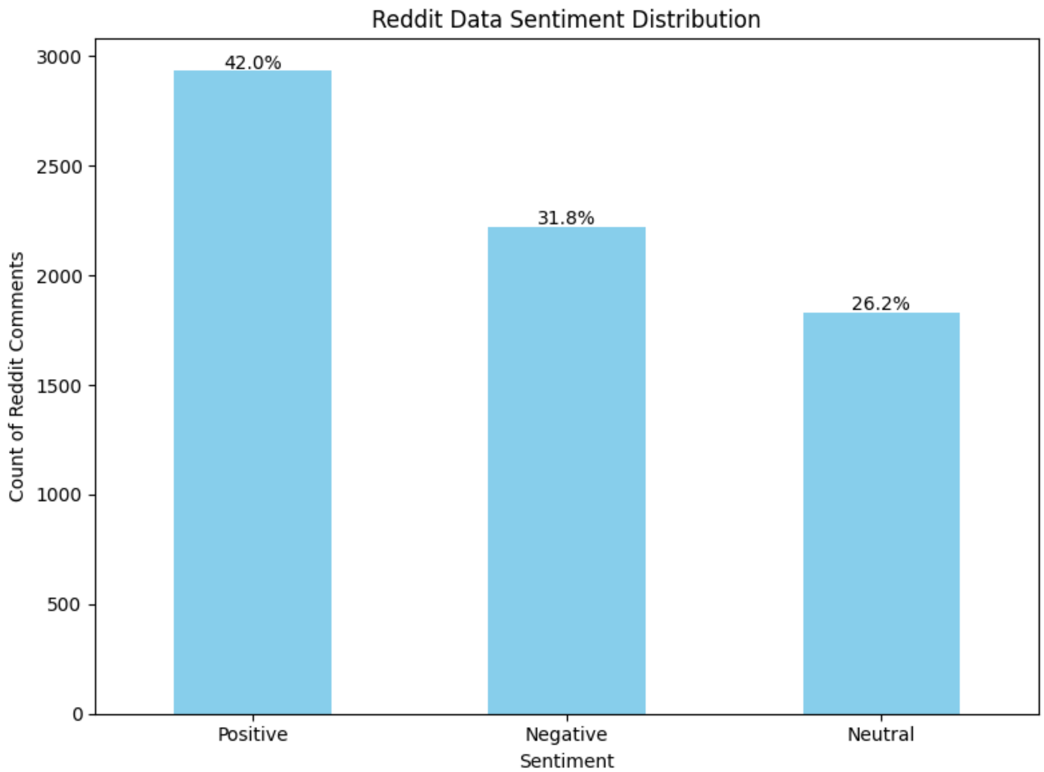


Figure 15: Sentiment Distribution of Labeled Tweets Using BERT

A.13 Graph: Sentiment Distribution of Labeled Tweets Using Vader, TextBlob, and BERT

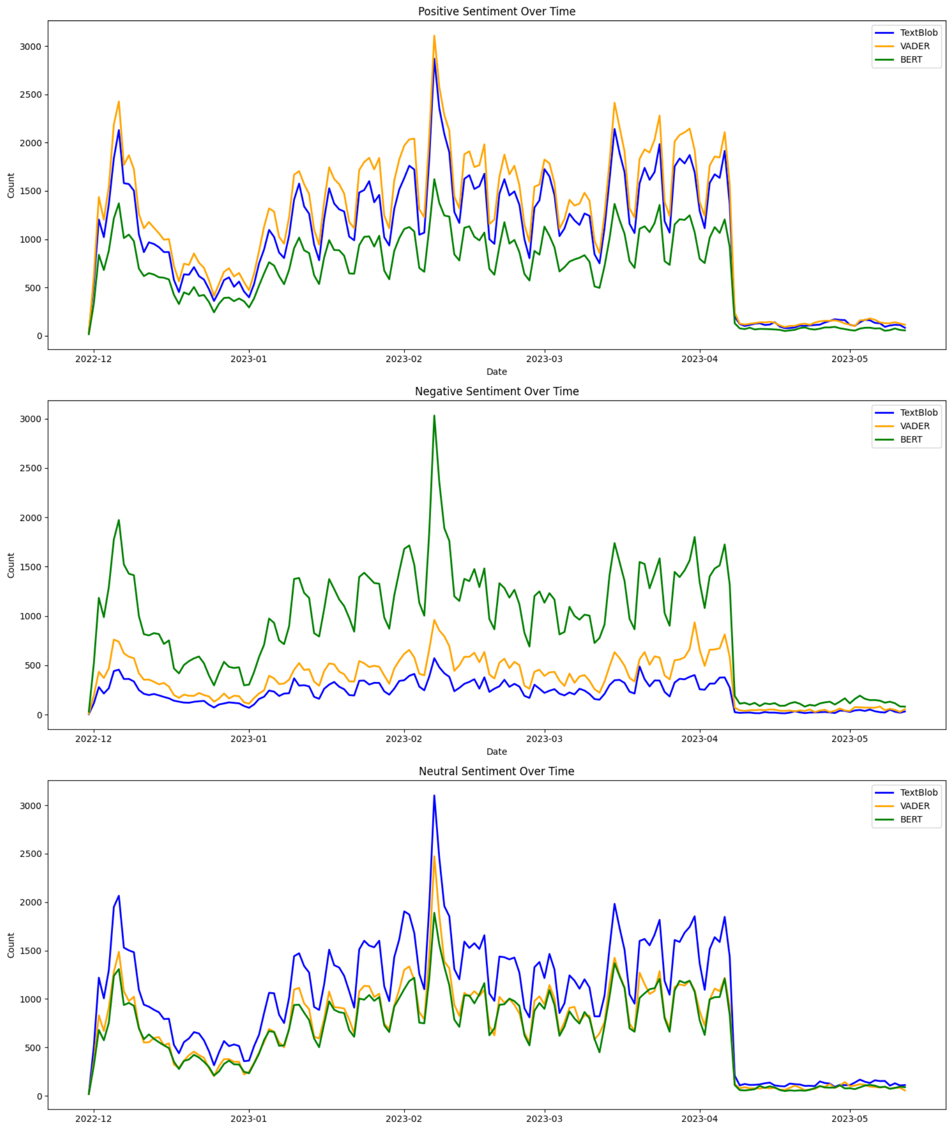


Figure 16: Sentiment Distribution of Labeled Tweets Using Vader, TextBlob, and BERT

A.14 Graph: Sentiment Distribution of Labeled Tweets Using Vader

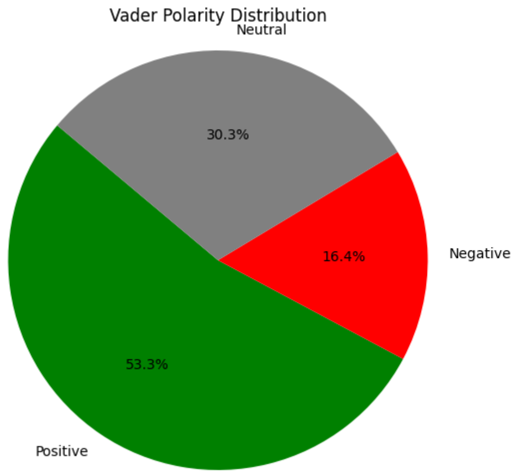


Figure 17: Sentiment Distribution of Labeled Tweets Using Vader

A.15 Graph: Sentiment Distribution of Labeled Tweets Using TextBlob

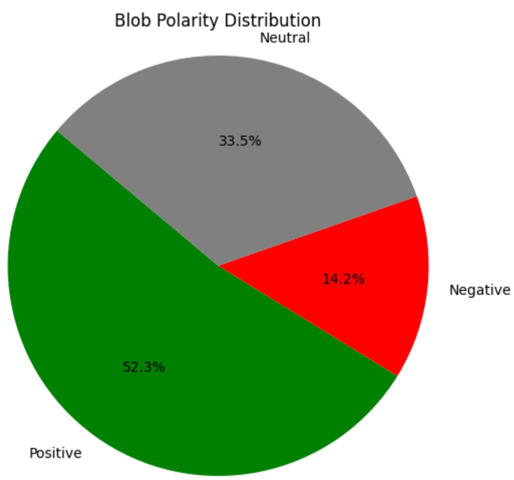


Figure 18: Sentiment Distribution of Labeled Tweets Using TextBlob

References

[1] Kruspe, A., Haberle, M., Kuhn, I., & Zhu, X. X. (2020). *Cross-language sentiment analysis of European Twitter messages during the COVID-19 pandemic.* In *Proceedings of the 1st Workshop on NLP for COVID-19 at ACL 2020.* https://aclanthology.org/2020.nlpcovid19-acl.14/

[2] Leiter, C., Zhang, R., Chen, Y., Belouadi, J., Larionov, D., Fresen, V., & Eger, S. (2023). *ChatGPT: A Meta-Analysis after 2.5 Months.* arXiv:2302.13795 https://arxiv.org/abs/2302.13795

[3] Su, Y., & Kabala, Z. J. (2023). *Public Perception of ChatGPT and Transfer Learning for Tweets Sentiment Analysis Using Wolfram Mathematica. Electronics*, *12*(12), 180. https://www.mdpi.com/2306-5729/8/12/180

[4] Kaggle. (n.d.). *CHATGPT Dataset Nov 2022-Jan 2023*. Retrieved April 26, 2023, from https://www.kaggle.com/datasets/manishabhatt22/tweets-onchatgpt-chatgpt

[5] Kaggle. (n.d.). *CHATGPT Dataset On Reddit*. Retrieved April 26, 2023, from https://www.kaggle.com/datasets/armitaraz/chatgpt-reddit

[6] Kaggle. (n.d.). *CHATGPT Dataset Jan 2023-Mar 2023*. Retrieved April 26, 2023, from https://www.kaggle.com/datasets/khalidryder777/500k-chatgpt-tweets-jan-mar-2023

[7] Kaggle. (n.d.). *CHATGPT Dataset Apr 2023-May 2023*. Retrieved April 26, 2023, from https://www.kaggle.com/datasets/edomingo/chatgpt-1000-daily-tweets

[8] HuggingFace. (n.d.). *Our Bert Model On HuggingFace*. Retrieved April 26, 2023, from https://huggingface.co/anonymous/bert-finetuned-chatGPT-discourse