**SENTIMENT ANALYSIS OF RUSSIAN INVASION OF UKRAINE WITH TWITTER DATA**

**Hüsne Seyda Eroğlu**

**CSSM502 Fall 2022**

**Final Project**

Abstract

This paper aims to analyze public sentiment towards the Russian-Ukrainian conflict of 2022 using sentiment analysis of social media data. In February 2022, Russia initiated an unjustified and unsupportable invasion of Ukraine, causing destruction of peace in Europe and drawing attention from the international community. (Al Jazeera, 2022) The ongoing conflict has caused enormous damage, with thousands of individuals being forced to flee, many more being internally displaced, and entire cities being destroyed. Additionally, hospitals, infrastructural facilities, and historic sites have been damaged or destroyed, and war crimes have been committed. Due to the widespread discussion of the conflict on social media, sentiment analysis presents a valuable opportunity to understand public opinion on the matter. Despite the fact that there are numerous sentiment analysis projects regarding the conflict, this study aims to explore whether public sentiment has changed on a country basis over time.

## INTRODUCTION

Conflict is defined as a state of discord or disagreement between individuals, groups, communities, or countries caused by perceived differences in needs, interests, or concerns. This state of disharmony can manifest in a variety of ways, including physical, emotional, political, or social forms, and is frequently filtered through the lens of one's values, culture, beliefs, experiences, and gender.The outbreak of major military conflict between Russia and Ukraine in 2022 led to the disruption of peace in the region. The event, being the first of its kind in decades, caused a significant stir and drew attention from the international community. The public opinion was also heavily divided on social media, as people took sides on the matter. Therefore, conducting sentiment analysis with data from Twitter be extremely useful when researching the topic of Russia's invasion of Ukraine in 2022. Twitter is a widely used social media platform and a significant amount of discussion about have taken place on the platform. Analyzing tweets has provided valuable insights into the attitudes and opinions of the general public, as well as identify key influencers and trends in the conversation. Additionally, sentiment analysis can be used to quantify the overall sentiment responding to the event. This can be especially useful for determining how public opinion may change over time.

## SENTIMENT ANALYSIS METHODS

Sentiment analysis is the process of determining the emotional tone or attitude expressed in a piece of text. The two primary ways to perform sentiment analysis are supervised and unsupervised. Supervised sentiment analysis involves training a model using labeled data to classify text into positive, negative, or neutral categories. The success of this method depends on the availability and quality of labeled data. (Li and Liu, 2018) In contrast, unsupervised sentiment analysis does not use labeled data and instead employs methods such as clustering, topic modeling, and lexicon-based techniques to uncover patterns and trends in the text. This approach is less reliant on labeled data but may not be as precise as supervised methods. (Jiang et al., 2017) Python offers a variety of libraries and packages to perform this task, such as NLTK (Bird et al., 2009), TextBlob (Loria, 2018), and VADER (Hutto & Gilbert, 2014). TextBlob, for instance, combines machine learning models and lexicon-based methods. VADER, on the other hand, is designed specifically for social media text and informal language.

In recent times, deep learning techniques have also been employed for sentiment analysis using RNNs and LSTM networks (Zhang et al., 2018), achieving state-of-the-art results. TensorFlow (Abadi et al.,

2016) and PyTorch (Paszke et al., 2019) have pre-trained models such as BERT (Devlin et al., 2019) and GPT-2 (Brown et al., 2020) that can be fine-tuned for sentiment analysis. Additionally, there are several Python packages available for specific tasks related to sentiment analysis such as sentiment analysis for specific languages or platforms. The choice of method and package will depend on the task and dataset at hand.

## RELATED WORK

The paper "Investigating Public Sentiments on the Russian Invasion of Ukraine: A Twitter Sentiment Analysis" is a recent study published by authors Manuel B. Garcia and Armi Cunanan. The study focuses on the use of sentiment analysis to investigate the public sentiments from the international community on the Russian invasion of Ukraine. This study is one of the few studies that have explored the use of twitter data in this context. The authors used twitter data to perform their analysis and found that the majority of sentiments were negative, and sadness was the most salient emotion. The study is unique in that it is one of the few studies that have explored twitter data in the context of the Russo-Ukrainian War. The authors also found an indication that the public sentiment leans against the aggressor country through the belief that "no one wins in a war". Additionally, they highlighted the potential of social media, particularly Twitter, as a source of public opinion and a vehicle for mass communication in the political and social context of war. They also suggested that future research should continue to examine the platform as a channel for public participation in peacemaking. Furthermore, the study contributes to the existing literature on social media mining by using sentiment analysis in the context of war, and it provides valuable insights into the public opinion on the Russian invasion of Ukraine. The authors also discussed the implications of their findings and how it could be used to improve the understanding of public sentiment in similar situations.

In their study called "A sentiment analysis of the Ukraine-Russia conflict tweets using Recurrent Neural Networks", López Ramírez & Méndez Vargas analyzed tweets related to the Ukraine-Russia war from around the world. They began by cleaning the data and conducting exploratory data analysis for better understanding of the tweets. They then used the pre-trained sentiment analyzer VADER to classify the sentiment of the tweets and used these tweets as the training and test datasets for a machine learning model based on Recurrent Neural Networks (RNN). The RNN model performed well with an accuracy of 93% on the validation set and 90% on the test set. The study found that the majority of the tweets related to the conflict were negative. The authors also noted that the RNNs are known for their performance in natural language processing tasks. The study also highlighted that even during difficult times, some people tried to spread positivity through their tweets.

Al Maruf et al. used an ensemble approach and found that it was the most effective method for emotion detection in their paper called "Emotion Detection from Textual Format using Machine Learning Techniques". They faced challenges in determining optimal accuracy but achieved it by integrating various data preparation methods. They found that XGBclassifier algorithm had 90% accuracy in identifying mood in text. The study also examined individuals' perceptions of the Ukraine-Russia conflict, revealing that nearly half of Twitter users held unfavorable views (43%). The study also highlighted the potential for future developments such as the use of multiple or large datasets and deep learning techniques. The authors hope this study will contribute to fields of emotion recognition, racism detection, and sentiment analysis.

## DATA PREPARATION

Data preparation is a crucial step in any data analysis project, as it ensures that the data is clean, complete, and in a format that can be easily analyzed. As a fundamental step in the sentiment analysis process, a set of hashtags and keywords were carefully selected to collect data relevant to the topic of interest. The hashtags #ukraineconflict, #ukrainerussiawar, and #UkraineWar were chosen as they are commonly used in discussions related to the ongoing Russia-Ukraine conflict. Additionally, the keywords 'Russia-Ukraine Conflict' and 'Russia-Ukraine War' were included in the search criteria to ensure that all relevant tweets were captured. To minimize bias, care was taken to avoid the use of hashtags or keywords that could skew the results, such as #stopPutin, #stopwar, or #PrayForUkraine.

The next step was to collect a representative sample of tweets that were posted in English language between February 24, 2022, and December 31, 2022. The Python-based snscrape (SNS) module (Desai, 2022) was utilized for this purpose. snscrape is a scraping tool that enables the extraction of data from social media platforms without the use of Twitter API, allows developers to interact with the Twitter platform and access its features such as tweets, user profiles, and followers. (Twitter Developer, n.d.). SNS can be used to gather information such as users, user profiles, hashtags, searches, threads, and list posts. The software was made available on July 8, 2020 and has been increasingly used in research and data mining because of its efficiency and reliability. In this project, a large dataset of tweets was collected using web scraping techniques, resulting in a total of 270,000 tweets.

The next step in preparing the data was to create a data frame, a two-dimensional labeled data structure with columns of potentially different types, from the collected tweets. This allowed for easy manipulation and analysis of the data, as well as the ability to drop any irrelevant or missing information. The columns include Date, ID, URL, username, location, hashtags, tweet, and num_of_likes, num_of_retweet. Figure 1 provides an overview for the dataframe created from collected tweets. ID, URL, num_of_likes, and num_of_retweet columns were not included.

*Figure 1. Dataframe overview*

| | Unnamed: 0.1 | Date | username | location | hashtags | tweet |
|---|---|---|---|---|---|---|
| **0** | 0 | 2022-12-30 23:51:05+00:00 | b001_steve | Somewhere in Virginia | ['Russians', 'RussianMobilization', 'DeadMeat'... | Tick-Tock #Russians,\nSoon you will be sent,\n... |
| **1** | 1 | 2022-12-30 23:50:14+00:00 | yorukhunnn | Kyiv,Ukraine | ['Ukraine', 'UkraineWar', 'Russia'] | Defense Minister Oleksii Reznikov warned Russi... |
| **2** | 2 | 2022-12-30 23:47:00+00:00 | techjunkiejh | NaN | ['Russia', 'Ukraine', 'UkraineWar', 'MoviesTvTj'] | CNN reporter says she'll never forget iconic m... |
| **3** | 3 | 2022-12-30 23:44:21+00:00 | OneVenusThrow | Manna-hata | ['Moscow', 'NewYear', 'Russian', 'Ukraine', 'C... | In #Moscow, the #NewYear is the country's main... |
| **4** | 4 | 2022-12-30 23:39:38+00:00 | Mickey17176 | United States | ['Putin', 'Russia', 'UkraineFrontLines', 'Ukra... | #Putin Can't Fix This Disaster: Is #Russia Run... |
| **5** | 5 | 2022-12-30 23:37:10+00:00 | OneVenusThrow | Manna-hata | ['Chechens', 'Russia', 'Bosnia', 'Balkan', 'Eu... | A group of ethnic #Chechens fleeing #Russia ar... |

Previous research has demonstrated that a small percentage (0.85%) of tweets are geotagged, which limits the search queries that can be used. (Sloan & Morgan, 2015) In this case, it is more practical to extract location information using snscrape, as many users include location information in their user profiles, even if they do not geotag their tweets. The location column in the dataset that was created includes the location information that users enter in their bios, not the geotags in the tweets. However, it should be noted that there may be cases where users do not provide complete or accurate location information in their profiles. The next step was to drop rows with no location information in the location column. This was done in order to ensure that the dataset only included tweets that could be accurately and meaningfully analyzed in terms of sentiment. This resulted in a dataset of 180,000 tweets.

In addition to dropping rows with missing location information, the dataset was further cleaned by dropping any rows where a username was already present in the username column. The reason for this was to minimize the contribution of a single user to the overall sentiment analysis, as multiple tweets from the same user can skew the results. This step helped to ensure that the sentiment analysis was based on a diverse set of tweets, rather than a small number of highly active users.

Overall, the data preparation process for this project involved several key steps to ensure that the data was clean, complete, and in a format that could be easily analyzed. The focus was on ensuring that the dataset only included tweets that could be accurately and meaningfully analyzed in terms of sentiment, and that the results were not skewed by a small number of highly active users. The final dataset of approximately 30k tweets was ready to use for further analysis, and it was expected to yield more reliable results. And,

DATA PREPROCESSING

Data preprocessing is an essential step in any data analysis project, as it helps to ensure that the data is clean, relevant, and in a format that can be easily analyzed. In this project, several preprocessing steps The first step was to convert all text to lowercase, which helps to ensure consistency in the dataset and minimize errors that may occur due to case sensitivity. This step also helps to improve the efficiency of the analysis by reducing the complexity of the data. The second step was removing hashtags from the text of the tweets, as a separate column had already been created to include the hashtags, and they were not needed for the sentiment analysis. Next, the dataset was further cleaned by removing punctuation, URLs, special characters, and stop words from the text. This helps to ensure that the dataset is free from irrelevant information and noise that could skew the results of the sentiment analysis. Additionally, Figure 2 illustrates the word counts of the tweets in the dataset, showing the most frequent 20 words that appear in the tweets. This helps to identify any common themes or patterns in the data that may be relevant for the sentiment analysis. It also allows for a quick visual representation of the data, making it easy to identify any outliers or unusual words. Overall, the data preprocessing steps taken in this project helped to ensure that the dataset was clean and relevant for the sentiment analysis, and the word counts in Figure 2 provide valuable insight into the content of the tweets.

*Figure 2. Word Counts*

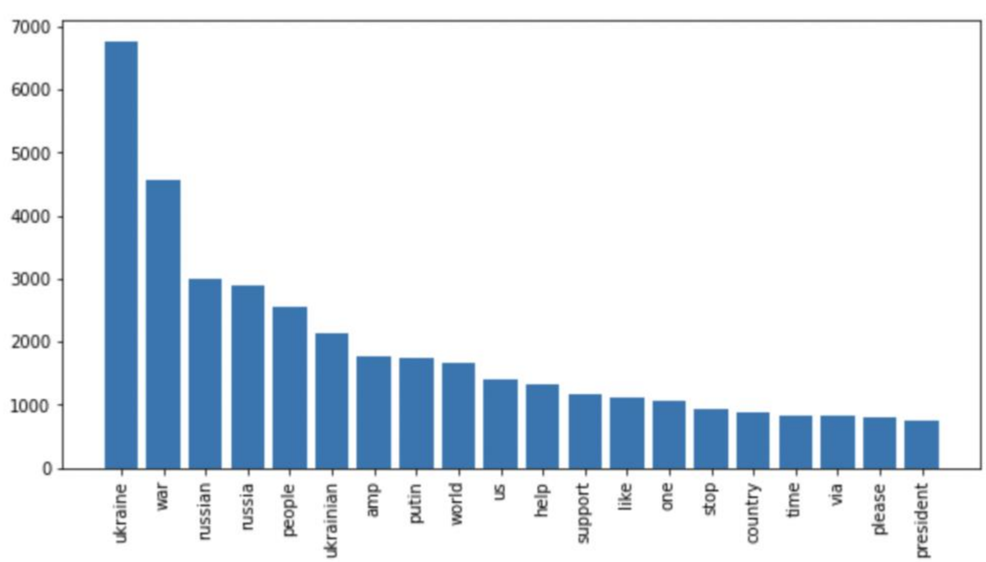
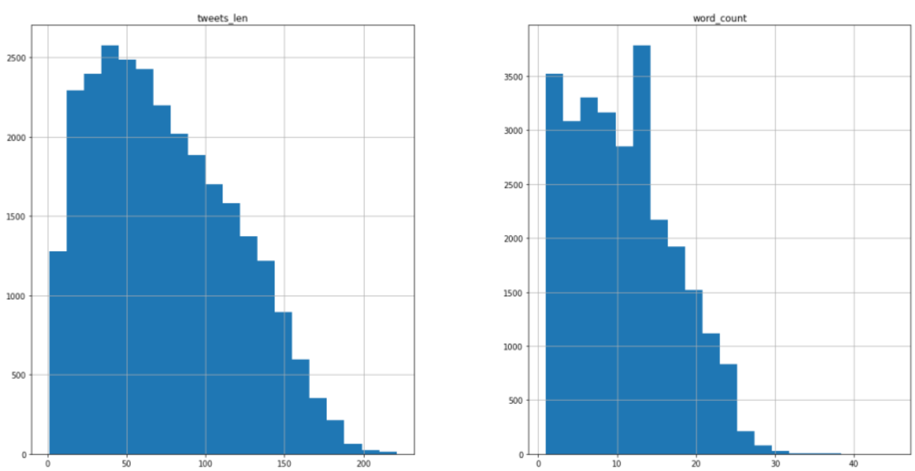


*Figure 3. Trigram Counts in the tweets*

| | Trigrams | Counts |
|---|---|---|
| **0** | (russia, ukraine, war) | 79 |
| **1** | (russian, invasion, ukraine) | 51 |
| **2** | (armed, forces, ukraine) | 36 |
| **3** | (ukraine, russia, war) | 34 |
| **4** | (president, volodymyr, zelensky) | 30 |
| **5** | (world, war, iii) | 29 |
| **6** | (president, vladimir, putin) | 28 |
| **7** | (ukrainian, president, volodymyr) | 27 |
| **8** | (intl, community, towards) | 27 |
| **9** | (community, towards, suffering) | 27 |

Figure 3 above provides the most common rigrams found in the tweets, which gives a sense of the specific phrases and word combinations that are frequently used when discussing this topic. The trigrams can be a small indication that the dataset might not have off-topic tweets. World War 3 is also among the trigrams, and this shows the conflict was seen as the 3rd World War. Below, figure 4 shows tweet lengths and word counts, tweets do not vary greatly in length and word counts.

*Figure 4. Tweet lengths and word counts*




In addition to the insights provided by the trigrams in Figure 3 and Figure 4 which shows the tweet length and word counts, further preprocessing steps were taken to improve the analysis of the dataset. Lemmatization was applied to the cleaned column of text. Lemmatization is a technique of natural language processing that reduces words to their root form, it groups together different forms of a word, such as "running" and "ran" to their base form "run". This process helps to improve the analysis by reducing the dimensionality of the data and making the analysis more efficient. It also helps to group together different forms of a word, which can be useful for analysis.

ANALYSIS

In my sentiment analysis project, I aimed to classify the sentiment of tweets in my dataset, which was unlabeled. Developing a machine learning model for this task would have been a complex and time-consuming process, so I chose to use automatic sentiment classification with pre-existing text classification packages in Python. I used Textblob and VADER to classify the tweets in my dataset as positive, negative, or neutral. In addition to using text classification packages, I also attempted to label my data with BERT text classifier.

The use of a threshold value in sentiment analysis allows for more nuanced classification of text, rather than simply using a binary classification system. The choice of threshold value can have a significant impact on the results of sentiment analysis, and a value of 0.2 is often considered to be a reasonable threshold for sentiment analysis tasks. That's why, I have chosen 0.2 as the threshold. As said before, different text classification methods were used to classify tweets, however, the result were not consistent across all methods. Textblob classified 77.6% of the tweets as negative, 20.1% as positive, and only 2.3% as neutral. On the other hand, VADER classified 66.7% of the tweets as negative and 33.3% as positive as it can be seen from the Figure 5.

*Figure 5.*

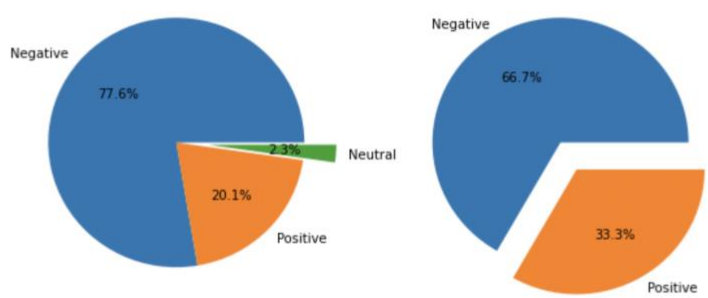
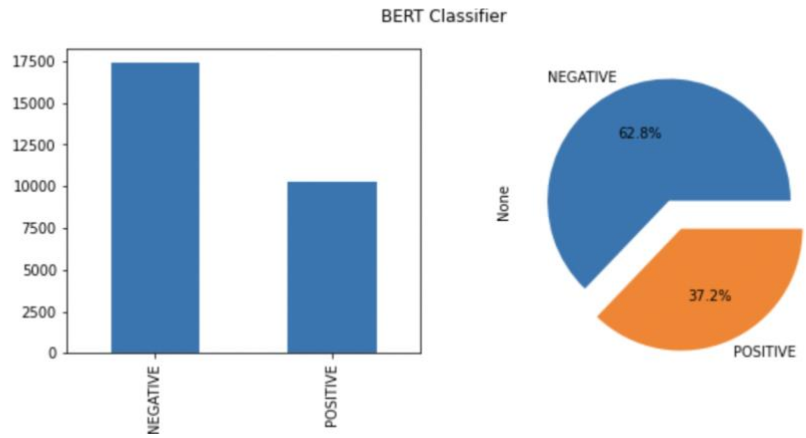



Figure 6 shows that BERT labeled 62.8% of the tweets as positive and 37.2% as negative. The reasons for these different classifications might be due to the underlying algorithms and pre-trained models used in each method. Textblob uses a pre-trained Naive Bayes classifier, VADER uses a combination of lexicon-based and grammatical heuristics, and BERT is a pre-trained transformer-based model. Each method has its own strengths and weaknesses and may perform differently on different datasets or tasks. Furthermore, the use of different threshold value might have an impact on the results of the classification.

*Figure 6.*

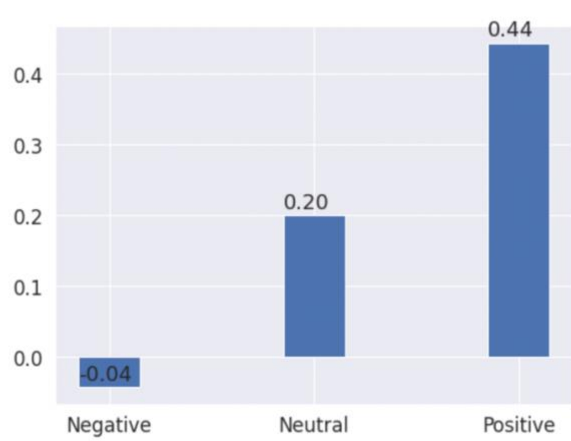



Additionally, the nature of the tweets and the specific language used within them could also play a role in the different classifications. For example, tweets containing sarcasm or irony may be difficult for some methods to classify correctly. The data pre-processing steps, and the quality of the data also can have an impact on the results.

BERT-based classifiers would be the most reasonable choice for my sentiment analysis task. BERT is a pre-trained transformer-based model that has achieved state-of-the-art results in a wide range of natural language processing tasks, including sentiment analysis. The pre-trained BERT model has been trained on a large corpus of text data, which allows it to understand the context of the text and make more accurate predictions. Furthermore, BERT-based classifiers have been shown to have high performance and accuracy on sentiment analysis tasks, and it's a widely used method in the field.

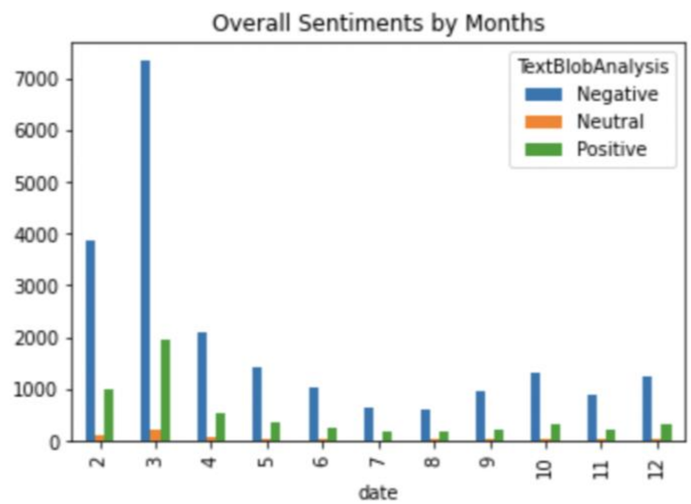
Many researchers and practitioners have used BERT-based models to classify the sentiment of text, and it has been demonstrated that it is able to outperform other methods. However, BERT uses binary classification, and this could be a limitation in our case since the classification of neutral tweets is important for the task. Thus, I have chosen to continue the analysis with the data labeled with Textblob. The mean polarity scores of tweets are shown in Figure 7. The average polarity score for neutral tweets is 0.20, while the average polarity score for positive tweets is 0.44, and the average polarity score for negative tweets is 0.04.

*Figure 7.*



The figure below illustrates the changes in sentiment scores on a monthly basis. As it can be observed, negative sentiments are more prevalent than positive sentiments in each month. This suggests that there was no change in public opinion over the months.

*Figure 8*

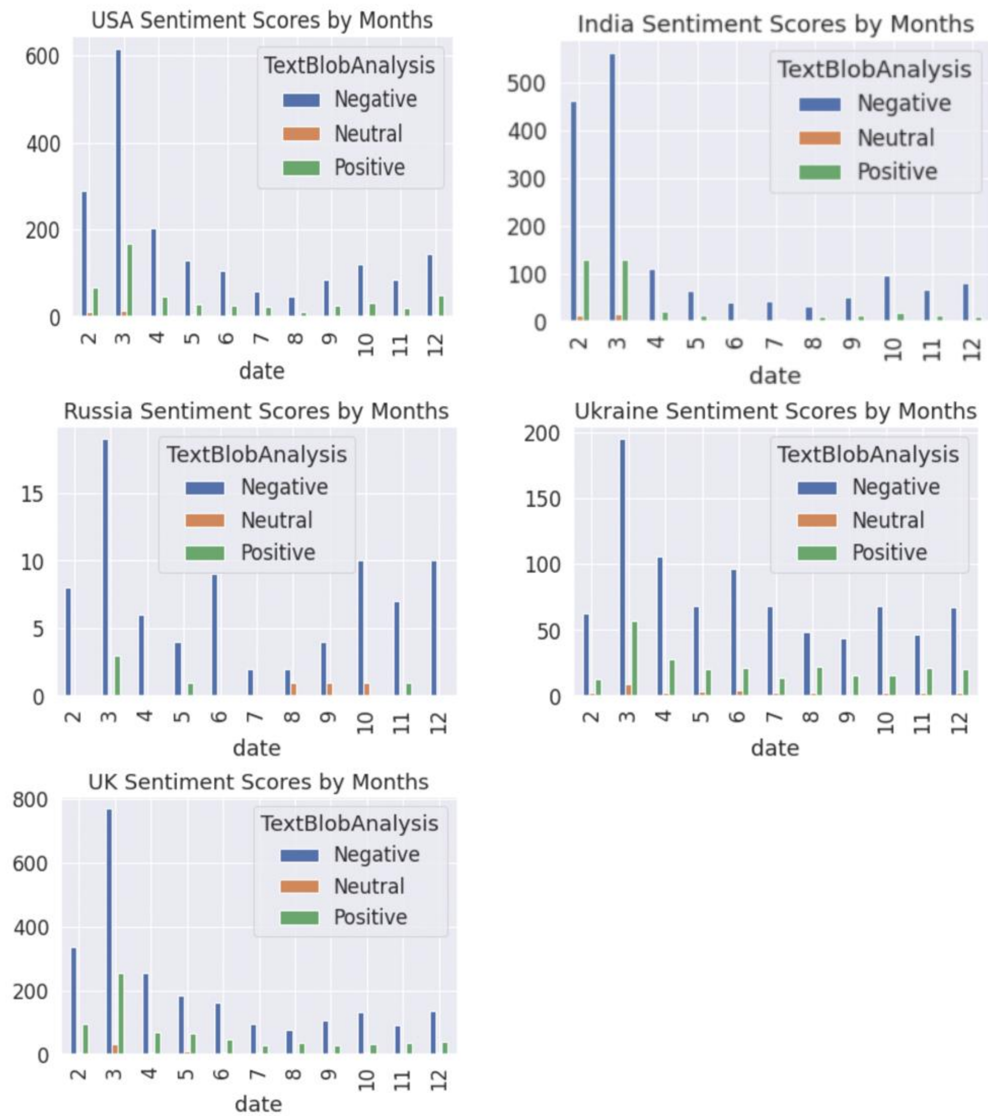



Initially, I aimed to identify which countries had more mentions in the location column, as I was planning to conduct a country-based analysis. The results revealed that the highest number of tweets about the subject were from India, the United States, the United Kingdom and Ukraine. Based on these findings, I have selected the countries to be included in the analysis, by adding Russia to these top 4 countries. The figure below, Figure 7, illustrates the fluctuations in sentiment scores on a monthly basis. As it can be observed, negative sentiments are more prevalent than positive sentiments in each month. This suggests that there is no clear change in public opinion over time.

COUNTRY- BASED SENTIMENT SCORES

The figure presented below provides a clear representation of the sentiment analysis results for the five countries that were studied. As it can be observed, throughout the entire period of analysis, there was no significant variation in the ratio of sentiment scores when comparing the different countries. A consistent pattern can be seen, where negative sentiment consistently dominates over positive and neutral sentiment in India, the United Kingdom, the United States, Ukraine, and Russia. This suggests that the negative sentiment is a prevalent sentiment among the population of these countries, regardless of the time frame or specific context of the analysis.

*Figure 9*




CONCLUSION

In conclusion, this sentiment analysis project aimed to provide insights into the public opinion about a specific conflict through the analysis of social media data. However, the results of the study did not bring any new information to the table and were consistent with previous research which had already shown that the general opinion of the right regarding the conflict in question was negative. One of the main challenges faced during this project was the difficulty in developing a domain-specific classifier. In natural language processing, a classifier is a model that is trained to identify the sentiment of a text. A domain-specific classifier is a model that is trained on data that is specific to a certain topic or domain, in this case, the conflict in question. However, due to the lack of labeled data in the domain, it was not possible to develop a classifier that was specifically trained for this project. As a result, a non-domain-specific classifier was used to label an unlabelled tweet dataset within the context of the war. Another limitation of the study was that it was based on location-based analysis, which means that the data used in the analysis came from specific geographic locations. However, this approach has its own limitations, as it may not be representative of the entire population of the country or the world. Additionally, only a small portion (10%) of the total dataset was used, which may have had a significant impact on the overall results. In light of these limitations, it can be argued that this project was somewhat of a dead-end and did not bring any new information to the table.

Citations:


Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D. G., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., … Zheng, X. (2016, May 31). *TensorFlow: A system for large-scale machine learning*. arXiv.org. Retrieved January 16, 2023, from https://arxiv.org/abs/1605.08695

Al Maruf, A., Ziyad, Z. M., Haque, M. M., & Khanam, F. (2022). *Thesai.org*. The Science and Information Organization. Retrieved January 16, 2023, from https://thesai.org/Downloads/Volume13No12/Paper_101-Emotion_Detection_from_Text_and_Sentiment_Analysis_of_Ukraine_Russia_War.pdf

Al Jazeera. (2022). *2022 review: Visualising how the russia-ukraine war unfolded*. Infographic News | Al Jazeera. Retrieved January 15, 2023, from https://www.aljazeera.com/news/2022/12/28/2022-review-visualising-how-the-russia-ukraine-war-unfolded

Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with python*. O'Reilly Online Learning. Retrieved January 16, 2023, from https://www.oreilly.com/library/view/natural-language-processing/9780596803346/

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., … Amodei, D. (2020, July 22). *Language models are few-shot learners*. arXiv.org. Retrieved January 16, 2023, from https://arxiv.org/abs/2005.14165

Desai, R. (2022). *How to scrape millions of tweets using snscrape*. Medium. Retrieved January 15, 2023, from https://medium.com/dataseries/how-to-scrape-millions-of-tweets-using-snscrape-195ee3594721

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (n.d.). *Bert: Pre-training of deep bidirectional Transformers for language understanding*. ACL Anthology. Retrieved January 16, 2023, from https://aclanthology.org/N19-1423/

Garcia, M. B., & Cunanan, A. (2022, July). *Public sentiment and emotion analyses of Twitter data on the 2022* ...ResearchGate.net. Retrieved January 16, 2023, from https://www.researchgate.net/publication/361218371_Public_Sentiment_and_Emotion_Analyses_of_Twitter_Data_on_the_2022_Russian_Invasion_of_Ukraine/citations

Hutto, C., & Gilbert, E. (2014). *Vader: A parsimonious rule-based model for sentiment analysis of social media text*. Proceedings of the International AAAI Conference on Web and Social Media. Retrieved January 16, 2023, from https://ojs.aaai.org/index.php/ICWSM/article/view/14550

López Ramírez, I. G., & Méndez Vargas, J. A. (2022, June). *A sentiment analysis of the Ukraine-russia conflict tweets using Recurrent Neural Networks*. ResearchGate.net. Retrieved January 16, 2023, from https://www.researchgate.net/publication/361275253_A_sentiment_analysis_of_the_Ukraine-Russia_conflict_tweets_using_Recurrent_Neural_Networks

Loria, S. (2018). TextBlob: Simplified Text Processing. Journal of Open Source Software, 3(28), 774.

Paszke, A., Gross, S., Chintala, S., Chanan, G., Yang, E., DeVito, Z., Lin, Z., Desmaison, A., Antiga, L., and Lerer, A. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library. Retrieved January 16, 2023, from https://papers.nips.cc/paper/2019/file/bdbca288fee7f92f2bfa9f7012727740-Paper.pdf

Twitter Developer. (n.d.). Twitter API. Retrieved from https://developer.twitter.com/

Sloan, L., & Morgan, J. (2015). Who Tweets with Their Location? Understanding the Relationship between Demographic Characteristics and the Use of Geoservices and Geotagging on Twitter. PloS one, 10(11), e0142209. https://doi.org/10.1371/journal.pone.0142209

Zhang, Y., Li, X., & Liu, Y. (2018). Deep learning for sentiment analysis: A survey. ACM Computing Surveys (CSUR), 51(6), 1-38.