Exploring Crisis-Driven Social Media Patterns: A Twitter Dataset of Usage During the Russo-Ukrainian War

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Abstract

On February 24, 2022, Russia's invasion of Ukraine, now known as the Russo-Ukrainian War, sparked extensive discussions on Online Social Networks (OSN). To capture this dynamic environment, including analyzing the discussed topics and detecting potential malicious activities, we initiated an ongoing data collection effort using the Twitter API. As of the writing of this paper, our dataset comprises 119.6 million tweets from 10.4 million users. Given the dataset's diverse linguistic composition and the absence of labeled data, we approached it as a zero-shot learning problem, employing various techniques that required no prior supervised training on the dataset.

Our research covers several areas, including sentiment analysis to gauge the public response to the distressing events of the war, topic analysis to compare narratives between social media and traditional media, and an examination of message toxicity levels, which has led to increased Twitter suspensions. Additionally, we explore the potential exploitation of social media for acquiring military-related information by belligerents, presenting a pipeline for classifying such communications.

The findings of this study provide fresh insights into the role of social media during conflicts, with broad implications for policy, security, and information dissemination.

Introduction

Twitter is one of the most popular and widely used online social networks, serving as a primary platform for communication and information dissemination in the digital world. Over the years, Twitter has been extensively employed to analyze political crises and significant events (Siapera, Hunt, and Lynn 2015; Chibuwe 2020; Chiluwa and Ifukor 2015; Antonakaki, Fragopoulou, and Ioannidis 2021; Burns and Eltham 2009; Shevtsov et al. 2023; Mendoza, Poblete, and Castillo 2010; Öztürk and Ayvaz 2018; Shevtsov et al. 2022).

In light of this, our data collection initiative commenced on February 24, 2022, coinciding with Russia's invasion of Ukraine, commonly referred to as the Russo-Ukrainian War. The primary objective of this effort is to leverage Twitter data to analyze the prevailing trends and discussions within this online discourse. We aim to monitor user behavior, identify and assess potential instances of malicious activity, conduct sentiment analysis on the text, examine the presence of hate speech or propaganda within Online Social Networks (OSNs), and gain insights into the broader implications of these interactions.

Our particular focus on the Russo-Ukrainian War stems from its status as an escalation of an ongoing conflict originating with Russia's annexation of Crimea. This conflict carries significant implications for European security and marks a historic turning point. By selecting this topic, we have amassed a substantial dataset related to a major international conflict, involving nations with widespread access to social media. Through social media platforms, individuals have been expressing their emotions, sharing their perspectives, and providing commentary on the War, the involved parties, and the unfolding events.

Sentiment analysis has been employed to extract public sentiments and comprehend how individuals respond to distressing events such as armed conflicts. While the mainstream media traditionally narrates significant events, the advent of social media enables the recording and examination of the general public's viewpoints. We employ topic modeling to identify current themes and contrast them with narratives presented in traditional media, thereby evaluating the divergence between social media and mainstream reporting.

Throughout our data collection, we observed a rising number of user suspensions by Twitter. This piqued our interest, leading us to investigate the reasons behind these suspensions. To achieve this, we analyze the toxicity levels in the messages posted by suspended users.

Furthermore, since the onset of the conflict, there have been suggestions from media and journalists that belligerents may utilize social media platforms like Twitter to acquire military-related information from local residents, military personnel, and open-source analysts (Infosec Resources 2013). To explore this hypothesis, we developed a methodology incorporating machine learning techniques to classify communications with a military connection and aggregate comprehensive details on a large scale.

Previous research has employed Natural Language Processing (NLP) techniques, sentiment analysis, topic modeling, and toxicity analysis to examine sentiment in datasets related to crises like the Syrian refugee crisis, encompassing both Turkish and English tweets. For instance, (Öztürk and Ayvaz 2018) reveals a balanced distribution of positive sentiment towards refugees. Additionally, other studies have investigated the dissemination of fake news and terrorism (Carchiolo et al. 2018). However, a comprehensive analysis combining all these methods has been lacking. Hence, we undertake a thorough analysis of our extensive multilingual dataset, employing state-of-the-art methods and machine learning models. We also conduct a specialized study to extract military-related information from Twitter.

Related Work

Several studies examining social network analysis and machine learning for sentiment analysis have been explored, as indicated by (Giachanou and Crestani 2016). This survey provides a comprehensive view of the subject by looking into and briefly explaining the algorithms that have been suggested for sentiment analysis on Twitter. The investigations are clustered in accordance with the technique they follow. Furthermore, we examine the areas associated with sentiment analysis on Twitter, such as Twitter opinion retrieval, tracking sentiments over time, irony recognition, emotion detection, and tweet sentiment quantification, matters that have recently gained growing attention. Moreover, for multilingual corpus (Dashtipour et al. 2016), state-of-the-art techniques are utilized. In the context of multilingual corpora, state-of-the-art techniques have been utilized. For instance, a pivotal study that aligns closely with our work is "Sentiment Analysis Using XLM-R Transformer and Zero-shot Transfer Learning on Resource-poor Indian Language" (Kumar and Albuquerque 2021). This paper demonstrates the effectiveness and cross-lingual capabilities of XLM-R for sentiment analysis in resource-poor languages, a methodology we have also adopted in our research. Inspired by the work of Barbieri et al. in their paper "XLM-T: Multilingual Language Models in Twitter for Sentiment Analysis and Beyond" (Barbieri, Anke, and Camacho-Collados 2021), we decided to further fine-tune the XLM-Roberta model using XNLI and MNLI to improve the performance of sentiment labeling. The authors' methodology of fine-tuning the XLM-R model on sentiment analysis provided a valuable reference point for our research. By building upon their work and incorporating additional fine-tuning strategies, we aim to enhance the effectiveness of sentiment analysis in our study.

Fundamental research exploring toxicity on Twitter during significant events (Qayyum et al. 2018), South Asian elections (Fan et al. 2021), and the UK Brexit (Fan et al. 2021) has utilized deep-learning techniques (BERT), which are akin to the methodologies employed in our study.

Studies exploring the use of large-scale data and social networks for military intelligence are still emerging. A couple of notable studies, such as (Kok, Mestric, and Street 2019) and (Wang et al. 2018), have presented techniques for extracting military-related entities from text data, shedding light on the practical applications in this domain.

Significant research has been conducted in the realm of topic modeling on social media. Various methods have been explored to filter noise from tweets and enhance accuracy. For instance, early-stage considerations included the Dirichlet technique (Yang et al. 2014; Wallach 2006). Beyond these, (Vayansky and Kumar 2020) has delved into alternative techniques beyond traditional Latent Dirichlet Allocation. Additionally, (Curiskis et al. 2020) is investigating clustering techniques coupled with neural embedding feature representations, a methodology aligned with our approach in this study.

It's important to acknowledge the existence of other research papers and datasets that have explored Twitter discourse during the Russo-Ukrainian War. One such dataset, "Tweets in Time of Conflict: A Public Dataset Tracking the Twitter Discourse on the War between Ukraine and Russia" (Chen and Ferrara 2023), is anticipated to overlap with our dataset in terms of shared tweets. Our work is intended to complement existing research by providing a comprehensive, reproducible, and in-depth analysis.

#Ukraine, #Ukraina, #ukraina, #Украина, #Украине, #PrayForUkraine, #UkraineRussie, #StandWithUkraine, #StandWithUkraineNOW, #RussiaUkraineConflict, #RussiaUkraineCrisis, #RussiaInvadedUkraine, #WWIII, #worldwar3, #Война, #BlockPutinWallets, #UkraineRussiaWar, #Putin, #Russia, #Россия, #StopPutin, #StopRussianAggression, #StopRussia, #Ukraine_Russia, #Russian_Ukrainian, #SWIFT, #NATO, #FuckPutin, #solidarityWithUkraine, #PutinWarCriminal, #PutinHitler, #BoycottRussia, #with_russia, #FUCK_NATO, #ЯпротивВойны, #StopNazism #myfriendPutin #UnitedAgainstUkraine #StopWar #ВпередРоссия, #ЯМыРоссия, #ВеликаяРоссия, #Путинмойпрезидент, #россиявперед, #россиявперёд, #ПутинНашПрезидент, #ЗаПутина, #Путинмойпрезидент, #ПутинВведиВойска, #СЛАВАРОССИИ, #СЛАВАВДВ

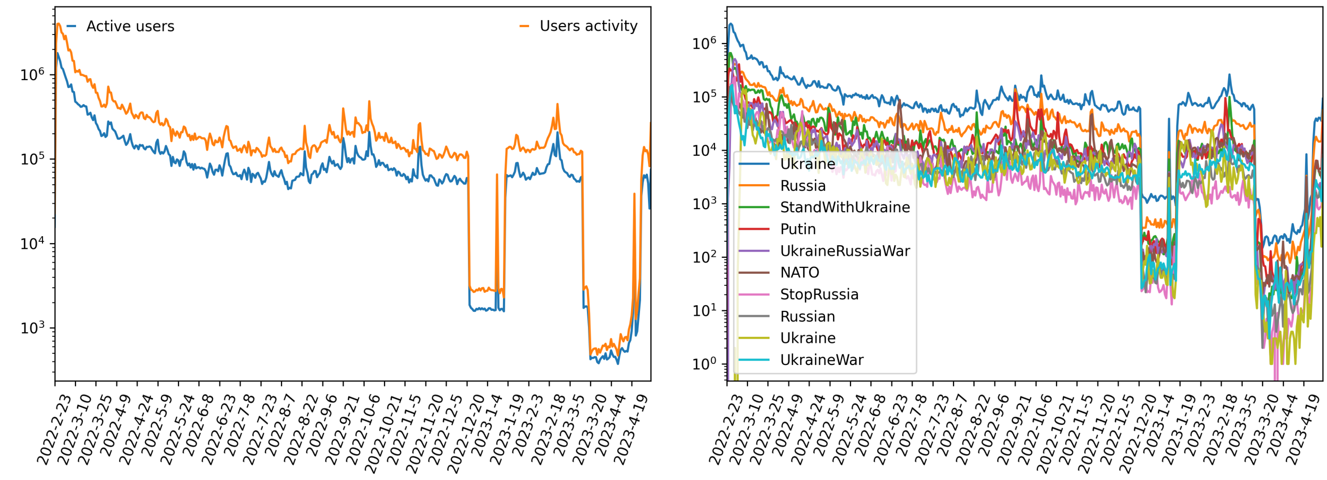
Table 1: Set of hashtags used in our data collection query written in Russian, Ukrainian, and English.

Data

To facilitate our research, we commenced the data collection process approximately 22 months ago, guided by the identification of correlated popular hashtags (see Table 1). To date, we have amassed a substantial historical dataset encompassing over 119 million tweets. However, given the extended duration and technical complexities involved, it is important to note that the dataset may exhibit certain inconsistencies and instances of missing dates.

As illustrated in Figures 1a and 1b, specific time periods, notably from December 22, 2022, to January 17, 2023, and from March 15, 2023, to April 25, 2023, experienced lower traffic. Unfortunately, our data collection script encountered technical challenges during these intervals, resulting in the inability to retrieve data. In response, we leveraged the Twitter full archive search API to reconstruct publicly available data for these periods. While we encountered limitations such as user post suspensions or deletions, we managed to partially reconstruct the missing data and gather a substantial volume of information for these time frames.

In parallel with data collection, we employed the Twitter compliance API to identify that a total of 289,837 user accounts had been suspended by Twitter itself, while an ad-



(a)

(b)

Figure 1: Daily volume of (a) registered users activity and (b) 10 most popular hashtags.

ditional 32,973 user profiles were deactivated. The gathered information is stored in MongoDB in the form of JSON objects, as this database system offers efficient storage, filtering, and querying capabilities for such data types.

We provide access to the dataset through two distinct sharing platforms. For the research community with Twitter API access, we will furnish a daily list of tweet IDs and the results of our analysis via a GitHub repository[1]. Researchers can utilize this list to retrieve complete tweet objects and any supplementary information through the Twitter API. Furthermore, in light of recent announcements pertaining to Twitter API subscription plans, we make the entire text corpus from our collected dataset available via Zenodo's file-sharing service[2]. To ensure user privacy, we anonymize user names and IDs within the shared texts. Additionally, we offer an online platform featuring in-depth analysis and comprehensive statistics derived from the dataset.

Data Anonymization

Ethical considerations and user privacy are central to social media data analysis. Our research, although broad in scope, requires stringent data anonymization procedures to ensure compliance with individual user privacy. To this end, we used a robust anonymization policy for the 119 million tweets stored in our dataset.

Anonymization Process

The cornerstone of our anonymization process includes the use of the blake2b cryptographic hash function. Preferred for speed and security, blake2b is an ideal tool for converting Twitter user IDs to an anonymous status. By hashing each user ID, we effectively create a unique immutable and non-reversible token that has no relationship to the original ID.

[1]https://github.com/alexdrk14/RussoUkrainianWar_Dataset

[2]https://zenodo.org/records/8431047

Tracking Anonymized IDs

An important feature of our anonymization pipeline is to be able to track the individual users even on anonymous state. Using a Redis database to easily track tweets and associate them with their respective anonymous user IDs, this database maintains a mapping between original user IDs and their anonymous counterparts.

Methodology

The size and linguistic diversity of an unlabeled dataset presented significant challenges, particularly in achieving accurate fine-tuning of models. To address these limitations, we adopted techniques that do not necessitate specialized training to attain satisfactory accuracy.

This study seeks to determine the level of support enjoyed by both countries and their leaders among Twitter users, utilizing sentiment analysis. Additionally, we assess the prevalence of toxic messages in an effort to elucidate the increasing number of suspensions. We also investigate the hypothesis surrounding the potential use of contemporary social media as a source of military intelligence during a conflict. To advance these approaches, it is imperative to refine our source data to reduce clutter and extraneous information. In the subsequent sections, we detail each step of our research. Furthermore, it is noteworthy that all inference and training throughout this study were conducted on a machine equipped with 64 threads and an Nvidia RTX 3080 TI, complemented by 128GB of DDR4 RAM.

Preprocessing

Prior to analyzing the collected dataset, it is essential to perform text preprocessing. Tweets are typically composed of informal text, misspelled words, emoticons, hashtags, and various elements that introduce noise and hinder the application of analytical algorithms. Text preprocessing involves filtering and removing the following elements:

- Any URLs (e.g., www.xyz.com) are removed for all types of analysis.
- Unnecessary spacing characters (e.g., spaces, tabs, and newlines) are stripped.
- Hashtags (e.g., #topic) and usernames (e.g., @user) are removed for sentiment analysis and toxicity analysis.
- Emoticons are removed, except in the case of sentiment analysis.

The specific preprocessing steps may vary depending on the type of analysis being conducted. For instance, sentiment analysis algorithms may benefit from retaining emoticons for improved results.

Sentiment Analysis

Our analysis of the collected dataset begins with sentiment analysis, providing insight into the general emotions expressed by the users towards the selected entities. To ensure the utmost accuracy in sentiment analysis, we conducted a comparative study of existing approaches. Presently, two primary methodologies are commonly applied: rule-based (also known as lexicon-based) (Hardeniya and Borikar 2016; Taboada et al. 2011) and AI-based models (Chakriswaran et al. 2019; Sufi and Khalil 2022).

Rule-based models offer an attractive advantage in terms of ease of comprehension and implementation. However, they require an extensive lexicon and a stringent set of linguistic rules, which can take months to develop and validate (Zhang et al. 2020),(Zhang et al. 2021).

Conversely, AI-based approaches can provide more accurate results without the need for manual rule creation by a team of language experts. These approaches can be categorized into two types of implementations. First, simpler machine learning models like the Naive Bayes model (Wang and Li 2013) make use of attributes that are straightforward for humans to understand. While these models offer a rapid training process and satisfactory sentiment analysis results, their simplicity limits their ability to learn and combine multiple languages into a single model. These limitations, coupled with the requirement for pre-labeled datasets, render these types of sentiment analysis impractical for multilingual datasets.

More advanced AI approaches for sentiment analysis rely on sophisticated Neural Network models (Severyn and Moschitti 2015; Ouyang et al. 2015; Dos Santos and Gatti 2014; Medrouk and Pappa 2017; Islam, Islam, and Amin 2020). These models, owing to the complexity of their weights and structure, excel in capturing linguistic nuances across multiple languages. In our study, we opted for the XLM-RoBERTa multilingual transformer model (Conneau et al. 2019) due to its proficiency in handling large volumes of diverse languages and its exceptional performance in sentiment analysis tasks (Kumar and Albuquerque 2021; Barbieri, Anke, and Camacho-Collados 2021).

XLM-RoBERTa has been pre-trained using a vast amount of data. This includes 100 languages extracted from approximately 2.5TB of filtered CommonCrawl data, which serves as pre-training material for the model. RoBERTa is a transformers model that has been pre-trained on a sizable corpus in an unsupervised manner. This implies that an automatic method has been used to generate inputs and labels from those texts and that it was pre-trained on the raw texts only, with no human labeling of any kind (which explains why it may use a lot of material that is readily available to the public). It has been pre-trained with the masked language modeling (MLM) purpose, to be more precise. The model takes a text as input and randomly masks 15% of the words, processes the full sentence through the model, and then predicts the hidden words. This contrasts with conventional recurrent neural networks (RNNs), which typically perceive the words sequentially, and with auto-regressive models like GPT, which internally conceal the upcoming tokens. The model can acquire a two-way representation of the sentence thanks to this.

To address the challenges posed by our diverse dataset, we fine-tuned our implementation of XLM-RoBERTa as Facebook team suggests (Lample and Conneau 2019), on the MultiNLI dataset(Williams, Nangia, and Bowman 2018), a crowd-sourced collection of 433k English sentence pairs annotated with textual entailment information, and XNLI(Conneau et al. 2018), a subset of a few thousand examples from MNLI which has been translated into 14 different languages. Multilingual NLI models are capable of classifying NLI texts without receiving NLI training data in the specific language (cross-lingual transfer). This allows the model to perform NLI on the 100 other languages that XLM-RoBERTa was trained on.

Moreover, the model is further fine-tuned on the task of NLI using a combination of the MNLI train set and the XNLI validation and test sets. In the final stage of training, the model is exposed to one additional epoch solely on XNLI data, where the translations for the premise and hypothesis are shuffled. This means that for each example, the premise and hypothesis come from the same original English example, but are in different languages. We used the Transformers' Trainer and Dataset library, from HuggingFace, for loading the model and datasets and training. The parameters that were adjusted on the Trainer are: Number of train epochs=3, Per device train batch size=128, Per device eval batch size=128, Warmup steps=10% of the total size of the train set. We decided on the number of epochs after training on the Russian and Ukrainian subset of the dataset with 10 epochs and noticed that after the 3rd epoch, as seen in the Table: 2.

The fine-tuning process enhances the accuracy of the model's predictions for our zero-shot classification task on this dataset. We use the 'positive', 'neutral', and 'negative' as sentiment labels towards the entities of *Ukraine*, *Russia*, *Zelensky*, and *Putin*. Preferring the use of labels directly linked to key topics of the event allows us to increase the accuracy of the classification and the interpretability of the results.

Topic Modelling

To unveil latent patterns and relationships among words in the shared tweets, we employ the topic modeling method. This approach allows us to uncover the predominant ideas or concepts within the text data without the need for pre-

Epoch	RUS		UKR	
	Loss	Accuracy	Loss	Accuracy
1	0.6832	0.7378	1.0129	0.6357
2	0.5448	0.7763	0.9628	0.6470
3	0.4795	0.7614	0.9407	0.6643
4	0.4243	0.7635	0.9205	0.6546
5	0.3745	0.7627	0.9001	0.6594
6	0.3313	0.7631	0.8791	0.6502
7	0.2929	0.7618	0.8593	0.6627
8	0.2608	0.7566	0.8404	0.6514
9	0.2369	0.7606	0.8242	0.6558
10	0.2183	0.7590	0.8118	0.6514

Table 2: Performance of XLM-Roberta during the training on XNLI Russian and Ukrainian subset.

defined categories or manual labeling. By automatically detecting topics, topic modeling provides a means to organize, summarize, and explore vast amounts of textual data.

The tweets in our dataset are characterized by their unstructured and concise nature, and the daily volume of tweets, combined with spam tweets that employ popular hashtags related to the Russo-Ukrainian War for promoting products (such as cryptocurrencies and NFTs), introduces noise into our topic modeling. To mitigate this noise, we have chosen to focus our topic analysis on specific key days when the average sentiment reached its peak for each label (as illustrated in Figure 2a,2b,3a and 3b), during which most users tweeted about pivotal events of the War.

Conventional topic modeling techniques like latent Dirichlet allocation and latent semantic analysis require knowledge of the exact languages used in the corpus for every tweet. However, our dataset comprises tweets in more than 70 languages, making it challenging to determine the language of each tweet.

To address this challenge, we employed the BERTopic(Grootendorst 2022) pipeline, which can extract topics using embeddings derived from multilingual models (SBERT(Reimers and Gurevych 2019)). The pipeline of BERTopic consists of the following steps:

- *Embeddings*: We initiated the process by converting our documents into vector representations using language models.
- *Dimension Reduction*: We reduced the dimensionality of the vector representations to facilitate the clustering algorithms in finding clusters effectively (utilizing UMAP(McInnes, Healy, and Melville 2018), PCA).
- *Clustering*: We applied a clustering algorithm to cluster the reduced vectors and identify semantically similar ones (employing HDBSCAN(McInnes, Healy, and Astels 2017), k-Means, BIRCH).
- *Bag of Words*: We tokenized each topic into a bag-of-words representation, enabling us to process the data without affecting the input embeddings (employing CountVectorizer).
- *Topic Representation*: We calculated words that are related to each topic using a class-based TF-IDF procedure known as c-TF-IDF.

The hyperparameters utilized for the topic modeling included the number of topics (set to 'auto'), N-Gram range (1,2), and minimum topic size (300).

Toxicity Analysis

Toxic comment classification is an emerging research field with several studies addressing diverse tasks towards the detection of unwanted messages on communication platforms. Although sentiment analysis is an accurate approach for observing crowd behavior, it is incapable of discovering other types of information in the text, such as toxicity, which can usually reveal hidden information. The number of suspended accounts from the start of the War is increasing, so it is important for us to detect whether toxicity was the reason for suspension. We used toxic comment classification Detoxify(Hanu, Laura and Unitary team 2020), a state-of-art model, pre-trained in social media datasets and it can classify multilingual corpus. After researching the field of toxicity classification methods, we decide that for our multilingual corpus, this model would provide the best accuracy and performance without custom training.

Military Intelligence

Besides the described analysis in previous sections, we are also interested in testing novel methods of military intelligence combined with social media information and location identification. This methodology is able to identify and provide military-based content based on the text shared on social media such as Twitter. Based on some recent investigations, during the Russo-Ukrainian conflict social media has a vast amount of military content with a high percentage of fake information (BBC 2023; Pierri et al. 2023). Gathering military information through social media poses a challenge since it's still an unexplored field in NLP and there is not much-related work to refer to at present. Additionally, at present, there is no big-scale open military domain corpus, making it challenging to identify military-named entities with data. To extract open-source military information from tweets, we need to train a Named-entity recognition (NER) model to recognize military-type entities. For this purpose, we use as a base spaCy's NER model and fine-tune and train it (Train split = 70%, Validation split = 30%) with the only open-source military dataset(Defence Science and Technology Laboratory UK 2017) by the Defence Science and Technology Laboratory of the UK and our. The Entity Schema of the NER model is in the Table 4. As is shown in Table 3 we achieved our best performance on epoch 42.

The training parameters for the NER model are:

1. Warmup steps = 250
2. Total epochs = 71
3. Initial rate = 5e-5

We create a pipeline that is able to filter our dataset and extract Military entities, with the following steps:

1. XLM-RoBERTa model for zero-shot classification using the label "military" with a threshold > 0.7 (range 0-1)
2. Use our NER model to extract entities

Epoch	Step	Accuracy
14	200	0.66
28	400	0.73
42	600	0.74
57	800	0.73
71	1000	0.73

Table 3: Performance of Spacy's NER training on (Defence Science and Technology Laboratory UK 2017)

CommsIdentifier, DocumentReference, Frequency, Location, MilitaryPlatform, Money, Nationality, Organization, Person, Quantity, Temporal, Url, Vehicle, Weapon

Table 4: Entity Schema of the NER model

3. Filter location entities per tweet for Ukrainian locations.

Using the extracted tweets and entities we can perform data analysis and statistics for military events and information daily for any Ukrainian location.

Experimental Results

In this chapter, we provide the result of the developed analysis. The results are separated similarly as in the methodology section, by each category of analysis: sentiment, topic, toxicity, and military intelligence.

Sentiment Analysis

We initiated our analysis by conducting sentiment analysis on the collected dataset, focusing on two primary sets of entities: country presidents (Zelensky vs. Putin) and countries (Ukraine vs. Russia).

Concerning sentiment analysis of countries, as illustrated in Figures 2a and 2b, the general sentiment trend tends to exhibit higher positive sentiment towards Ukraine (with higher values indicating greater support from Twitter users). Notably, negative sentiments are also more pronounced when referring to the Ukraine entity. These patterns could be attributed to the negativity of the discussion topic, given that tweets containing the term "Ukraine" often describe various aspects of the war incidents. Such discussions are naturally inclined to evoke negative sentiments.

Furthermore, we examined the sentiment vectors of country presidents, as presented in Figures 3a and 3b. Our analysis indicates that President Zelensky received a notably higher positive sentiment. This observation can be attributed to the substantial support expressed by Twitter users towards Ukraine and President Zelensky during the Russo-Ukrainian War.

In both cases, there are discernible spikes in sentiment, which will be elucidated in the following section.

Topic Analysis

As previously mentioned, we conducted topic analysis on days with notable sentiment peaks, and we present examples of these days, including the top 20 topics by size, in correlation with significant events reported by mainstream media.

One example is a surge in positive sentiment towards Ukraine on May 14, 2022. On this day, mainstream media reported that Ukraine had won Eurovision 2022 (Eurovision.tv 2022), contributing to the overall increase in positive sentiment. Additionally, the Ukrainian military continued its counteroffensive in the northeastern region of Kharkiv (Reuters 2022). Our topic analysis ranked these significant events as the top discussion topics (1st and 3rd) as shown in Table 5.

Another noteworthy instance from our dataset is a significant increase in negative sentiment on July 14, 2022, as evident in Figure 2b. On this date, Ukrainian officials reported that at least 23 people died due to a Russian strike in Vinnytsia, central Ukraine, according to mainstream media reports (BBC News 2022). The results of our topic modeling, which ranked this tragic incident as the 3rd topic (Table 5), align with the observed sentiment trends and mainstream media coverage. Moreover, this topic was associated with user discussions calling for the recognition of Russia as a terrorist state.

Furthermore, we examined user discussions on May 8th when President Zelensky experienced a positive sentiment peak. According to mainstream media reports, President Zelensky had invited musicians Bono and the Edge for a show in Kyiv, coinciding with his address for the Day of Remembrance and Reconciliation (Rolling Stone 2022).

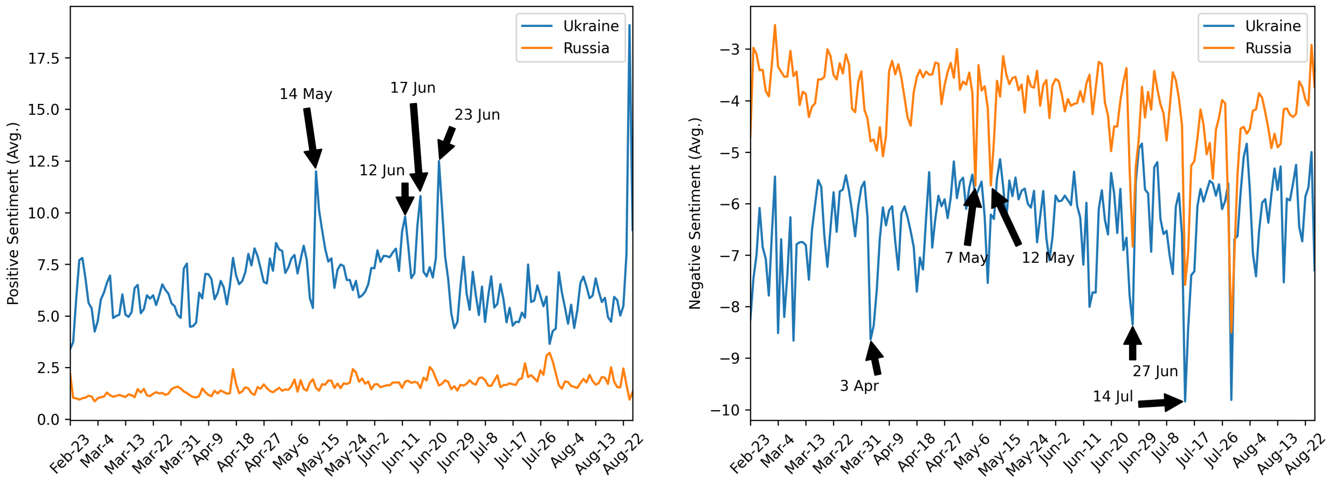
As indicated in Table 5, the top-ranked topic on May 8th was indeed the invitation of Bono and the Edge, aligning with mainstream media coverage.

Upon closely scrutinizing our extracted topics in correlation with mainstream media reports, we observed that each day, we identified 20 topics, including those that were reported by mainstream media. This finding suggests that Twitter users tend to follow the narrative presented by mainstream media. The remaining topics, not covered by mainstream media, often included references to Twitter accounts mentioning the War (e.g., @mavkaslavka), indicating that a significant number of users incorporated events reported by other Twitter users into their conversations.

In addition, we identified topics related to cryptocurrencies and NFTs, which were posted by spam accounts attempting to exploit popular hashtags. However, further investigation is needed to confirm these accounts' status as spam.

Toxicity Analysis

With the use of Detoxify (Hanu, Laura and Unitary team 2020) toxic classification model we analyze 1,883,507 tweets originating from suspended accounts. We examine this part of the dataset in order to identify whether the toxicity of messages plays an important role in the suspension decision. Unfortunately, our analysis shows that the percentage of toxic comments among the suspended users is very low (2.1%), so we conclude that toxicity is not the main factor of suspension by Twitter in our dataset.



(a) Positive

(b) Negative

Figure 2: Positive and negative sentiment towards each country.

Topic	8 of May	14 of May	14 of July
1	bono	ukraine	ukraine
	kyiv	putin	fighting
	ukrainian	eurovision	forget
	rt	russie	european
	edge	stereotypes	ukrainians fighting
2	conference zoom	rt	recognize russia
	resists azovstal	rt mavkaslavka	recognize
	commanders regiment	mavkaslavka	world recognize
	plant press	kerziouk today	call world
	killed city	deepl	russia terrorist
3	btc humanitarian	city	fuck
	59 3gc13	battle	vinnytsya
	3gc13	kharkiv axis	including dead
	59	threat city	area casualties
	b1 25 63	kharkiv	dialing

Table 5: Most popular topics for dates with high user activity.

sending messages to #UAF soldiers on the front in the #Severodonetsk-#Lisichansk boiler on the radio: Short translation: #Zelensky betrayed you like #Azov There will be no help. Further resistance will lead to death. The only chance to live is to run or surrender-Save your lives #Russia
In the last couple of weeks, #Russia concentrated a large number of armored units (tanks, TOS-1A, etc), VDV force remnants (from Kiev op mostly), and mercenaries to cut off #Bakhmut - #Severodonetsk highway. They were unsuccessful, but it made UA ops in the area more difficult.
The 8th Regiment of the SSO of #Ukraine pulls out a dead soldier during a clash with the Russian Armed Forces in the industrial zone of #Severodonetsk.
A Russian mortar position was located and destroyed by the Ukrainian 20rd Separate Special Regiment of the Ukrainian SOF near Severodonetsk, Luhansk Oblast.#Russia #Ukraine

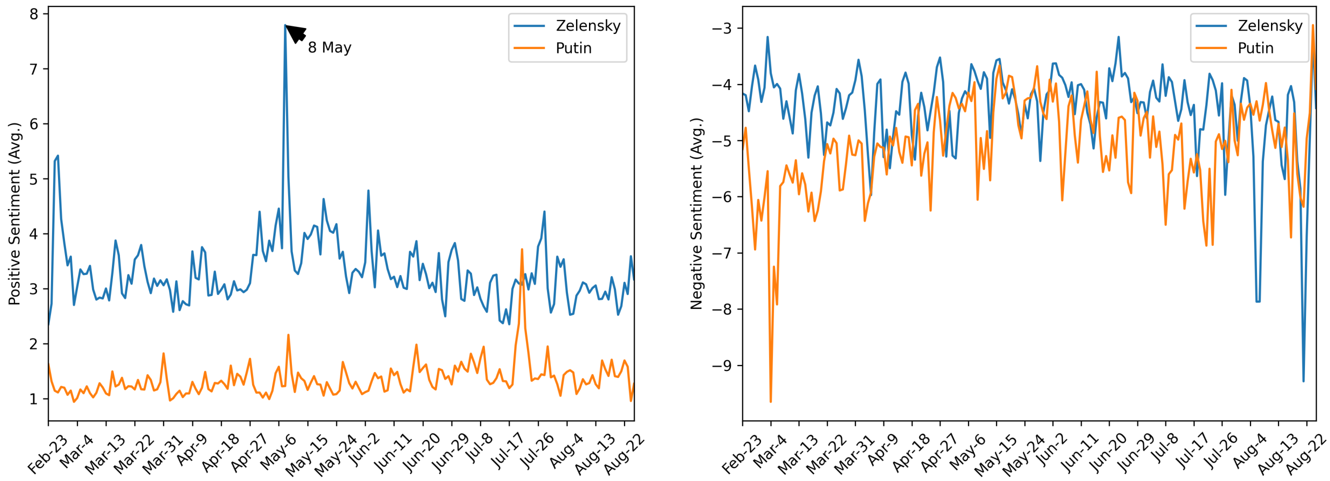
Table 6: Examples of tweets with military information

Military Intelligence

Our analysis, as presented in Figure 4, reveals that the collected dataset contains a significant volume of military intelligence content. This distribution of identified content closely mirrors the volume of user activity among registered users, as depicted in Figure 4. Through manual inspection, we were able to confirm that the identified content indeed contains military-related information directly correlated with the conflict. Table: 6 provides a selection of random examples of these identified tweets containing military content. Upon further investigation, we discovered tweets reporting on troop movements and sightings, often accompanied by photos and videos. Leveraging the extracted entities, such as locations and weapons, an automated notification system could be established based on volume and entity filtering (e.g., Location = Kyiv) to monitor military events and movements.

Conclusion

In the current study, we utilize Twitter API to obtain a dataset of 119M tweets originating from 10.4M users within a period of 184 days and perform extensive analysis on a multilingual dataset, using state-of-the-art methods and machine learning models. The results show that a conflict such as the Russo-Ukraninan War creates a surge of activity on



(a) Positive

(b) Negative

Figure 3: Positive and negative sentiment towards each President.

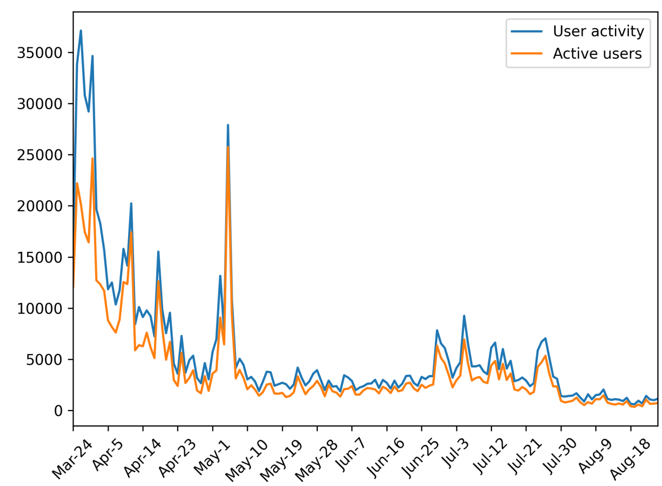


Figure 4: The Daily military volume and activity of registered users.

social media with a generally negative attitude. Although the negative sentiment is high on both sides, the positive sentiment is higher towards Ukraine and Zelensky, leading to the deduction that the negativity is in disagreement with the War rather than Ukraine and Zelensky themselves. Furthermore, it is evident that toxicity is not the sole cause of suspensions on Twitter, and further research needs to be done to discover the other factors involved. The topics extracted are in line with the narrative of mainstream media. Additionally, there are several spam accounts that are active and posting in large volumes, often referring to cryptocurrencies, NFTs, and other such products that have no connection to the War. Studies of military intelligence on social media suggest that it will progress in the future, necessitating the implementation of intelligent technology for monitoring battles, making command decisions, and interfacing with computers. Military-named entity recognition is a key part of military data extraction and provides the basis for the intelligent handling of military information from social media, which will be included in our future plans. Furthermore, we make the collected dataset available to researchers in two formats: tweet IDs for those with API access and anonymized tweets via the Zenodo data sharing platform, ensuring the protection of user privacy.

Ethical Discussion

1. **Privacy and Anonymization**
   Ethics and user privacy are crucial when analyzing social media data, especially when dealing with delicate subjects like the Russo-Ukrainian War. For the dataset of 119 million tweets, the study used a strong anonymization policy to guarantee adherence to user privacy.
2. **Limitations and Bias Awareness**
   An essential ethical aspect is acknowledging the dataset's limits and potential biases. Certain limitations are implied by the data collection process's reliance on the Twitter API. Rate constraints, linguistic variances in the content, or geographical location may have prevented some tweets from being viewed, which could have resulted in an inadequate portrayal of viewpoints regarding the Russo-Ukrainian War. This acknowledgement shows that the methodology's inherent limitations are understood, including the possibility of problems with sentiment analysis, topic analysis, and military information extraction in terms of accuracy, robustness, and generalizability.
   By being open and honest about the study's limits, acknowledging these restrictions shows a dedication to ethical research. This openness is essential to preserving the integrity of research since it makes it evident what the

study covers and where it may fall short, enabling a more complex analysis of the results.

3. **Compliance with The FAIR Data Principles**
   - Data Anonymization: In order to exclude personally identifiable information, we anonymized the dataset that was gathered.
   - Datasheet and Data Availability: We did construct a specific datasheet for the dataset; We intend to make the dataset available in text form via Zenodo and GitHub in the format of tweet IDs. Enabling these platforms to host the dataset improves its discoverability and use.

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