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

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Abstract. On 24 February 2022, Russia's invasion of Ukraine, now known as the Russo-Ukrainian War, sparked extensive discussions on Online Social Networks (OSN). We initiate a data collection using the Twitter API to capture this dynamic environment. Next, we perform an analysis of the topics discussed and a detection of potential malicious activities. Our dataset consists of 127.2 million tweets originating from 10.9 million users. Given the dataset's diverse linguistic composition and the absence of labeled data, we approach it as a zero-shot learning problem, employing various techniques that require no prior supervised training on the dataset.

Our research covers several areas, including sentiment analysis capturing the public's response to the distressing events of the war, topic analysis comparing narratives between social networks and traditional media, and examination of the correlation between message toxicity levels and Twitter suspensions. Furthermore, we explore the potential exploitation of social networks to acquire military-related information by belligerents, presenting a pipeline to classify 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. Finally, due to the recent Twitter API changes, we share anonymized data for any further research purposes.

Keywords: Russo-Ukrainian War, sentiment analysis, Twitter, military intelligence, dataset

1 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 [9,1,37,27,38].

In this study, we focus on the Twitter public discussion related to the 2022 Russo-Ukrainian conflict as an escalation of an ongoing conflict originating with Russia's annexation of Crimea. This conflict has significant implications for European security and marks a historic turning point. By selecting this topic, we have accumulated a substantial dataset related to a major international conflict involving nations with widespread access to social networks. 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. In light of this, our data collection was initiated on February 23, 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 the 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. Throughout our data collection, we observe a rising number of Twitter user suspensions. This piqued our interest, leading us to investigate the reasons behind these suspensions. To achieve this, we analyze the levels of toxicity in the messages posted by suspended users.

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 residents, military personnel, and open-source analysts [22]. To explore this hypothesis, we develop a methodology that incorporates 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, which include Turkish and English tweets. For example, [27] reveals a balanced distribution of positive sentiment towards refugees. Additionally, other studies have investigated the dissemination of fake news and terrorism [6]. However, there is a lack of a comprehensive analysis combining all of these methods. Hence, we undertake a thorough analysis of our extensive multilingual dataset, employing state-of-the-art methods and AI models. We also conduct a specialized study to extract military-related information from Twitter. Finally, we employ topic modeling to identify current themes and contrast them with narratives presented in traditional media, thus evaluating the divergence between social media and mainstream reporting.

2 Related Work

Several studies have examined social network analysis and machine learning for sentiment analysis, as indicated by [17]. This survey provides a comprehensive view of the subject by looking at 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, issues that have recently gained growing attention.

In the context of multilingual corpora, state-of-the-art techniques have been utilized [13]. For example, a pivotal study closely aligned with the work we have adopted is the 'Sentiment Analysis Using the XLM-R Transformer and Zero Shot Transfer Learning in the resource-poor Indian language' [24]. This paper demonstrates the effectiveness and cross-lingual capabilities of XLM-R for sentiment analysis in resource-poor languages.

Fundamental research studies exploring Twitter toxicity during significant events [29], South Asian elections [16], and the Brexit of the UK [16] have used deep learning techniques (BERT), which are similar to the methodologies used in our study.

Studies exploring the usage of large-scale data and social networks for military intelligence are still emerging. A couple of notable works, such as [23] and [44], 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 networks. Various methods have been explored to filter noise from tweets and enhance accuracy. For example, early-stage considerations included the Dirichlet technique [46,43]. Beyond these, [42] has delved into alternative techniques beyond traditional Latent Dirichlet Allocation. Furthermore, [12] have investigated clustering techniques coupled with neural embedding feature representations, a methodology also aligned with our approach.

It is important to acknowledge the existence of other research papers and datasets that have explored Twitter discourse during the Russo-Ukrainian war [8,20,39,5]. Existing data sets are very limited in terms of monitoring periods combined with the limited information available according to the content of shared posts. Data sharing via Twitter_id is limited due to recent Twitter API access limitations. Our work intends to complement existing research by providing a comprehensive, reproducible, and in-depth analysis combined with a high volume of anonymized users' text posts.

3 Data

For this research, we acquire a Twitter dataset about public user discussions concerning the 2022 Russo-Ukrainian War. To accomplish this objective, our initial approach involves gathering popular hashtags from three distinct language groups: English, Russian, and Ukrainian (see Table 1). The selection of specific hashtags was guided by their relevance to the topic, as evidenced by their usage in relevant posts. It is pertinent to acknowledge that these hashtags represent

Table 1: Set of hashtags used in our data collection query written in Russian, Ukrainian, and English provided with translation for non-English hashtags.

#Ukraine, #Ukraina, #ukraina, #Украина(Ukraine), #Украине(Ukraine), #PrayForUkraine, #UkraineRussie, #StandWithUkraine, #StandWithUkraineNOW, #RussiaUkraineConflict, #RussiaUkraineCrisis, #RussiaInvadedUkraine, #WWIII, #worldwar3, #Война(War), #BlockPutinWallets, #UkraineRussiaWar, #Putin, #Russia, #Россия(Russia), #StopPutin, #StopRussianAggression, #StopRussia, #Ukraine_Russia, #Russian_Ukrainian, #SWIFT, #NATO, #FuckPutin, #solidarityWithUkraine, #PutinWarCriminal, #PutinHitler, #BoycottRussia, #with_russia, #FUCK_NATO, #ЯпротивВойны(I'm against war), #StopNazism #myfriendPutin #UnitedAgainstUkraine #StopWar #ВпередРоссия(Go Russia), #ЯМыРоссия(I/we Russia), #ВеликаяРоссия(Great Russia), #Путинмойпрезидент(Putin is my president), #россиявперед(Go Russia), #россиявперёд(Go Russia), #ПутинНашПрезидент(Putin is our president), #ЗаПутина(For Putin), #ПутинВведиВойска(Putin send the troops), #СЛАВАРОССИИ(Glory to Russia), #СЛАВАВДВ(Glory to Russian Airborne Forces)

the most prevalent ones, as indicated by Twitter statistics, potentially reflecting biases in public opinion.

Using the identified hashtags, we retrieve our dataset using the Twitter Research API spanning from February 23, 2022, to June 23, 2023. The collected dataset consists of 127,275,386 tweets authored by 10,990,275 users. However, it is imperative to acknowledge that, due to the extended duration and technical intricacies involved, the dataset may exhibit certain inconsistencies and instances of missing dates.

As illustrated in Figures 1 and 2, specific time periods, notably from December 22, 2022, to January 17, 2023, and from March 15, 2023, to April 25, 2023, experience lower traffic. Unfortunately, our data collection script encounters technical challenges during these intervals, resulting in an inability to retrieve data. In response, we used 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 partially reconstruct the missing data and gather a substantial volume of information for these time frames.

In parallel with the data collection, we use the Twitter compliance API to identify that a total of 289,837 user accounts had been suspended by Twitter itself, while an additional 32,973 user profiles were deactivated. The gathered information is stored in MongoDB as 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 access to Twitter API, we will provide a daily list of tweet IDs and the results of our analysis through a GitHub repository [3]. Researchers can use this list to retrieve the complete tweet objects and any

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

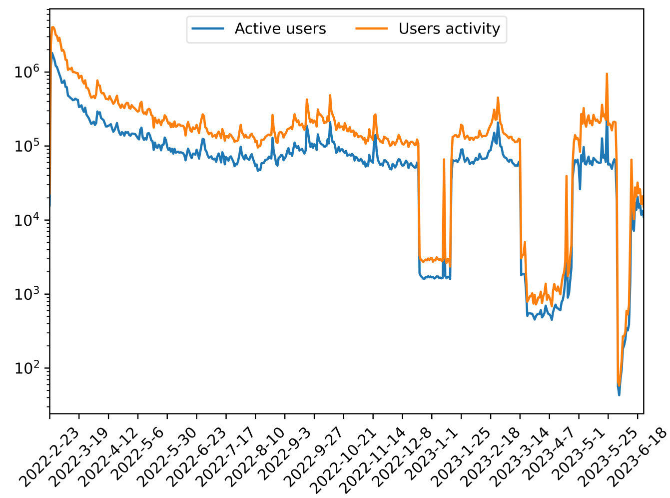

Fig. 1: Daily volume of registered users activity.

additional information through the Twitter API. Furthermore, in light of recent announcements regarding the Twitter API subscription plans, we anonymize the entire text corpus and make it available via Zenodo's file sharing service[4]. The provided data are anonymized via blake2b cryptographic hash function [33] over the tweet and user IDs. Additionally, user mentions are replaced with the anonymized user_id in order to hide the user identity while keeping the link between tweets where the same user is mentioned or which post the user has shared.

4 Methodology

The size and linguistic diversity of an unlabeled dataset presents significant challenges, particularly in achieving accurate fine-tuning of AI models. To address these limitations, we adopt techniques that do not necessitate specialized training to attain satisfactory accuracy. All inferences and training during this study are carried out on a machine equipped with a 64-thread CPU and a Nvidia RTX 3080 TI, complemented by 128GB of DDR4 RAM.

4.1 Preprocessing

Before analyzing the collected dataset, it is essential to perform text pre-processing. Tweets are typically composed of informal text, misspelled words, emoticons, hashtags, and various elements that introduce noise and hinder the application

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

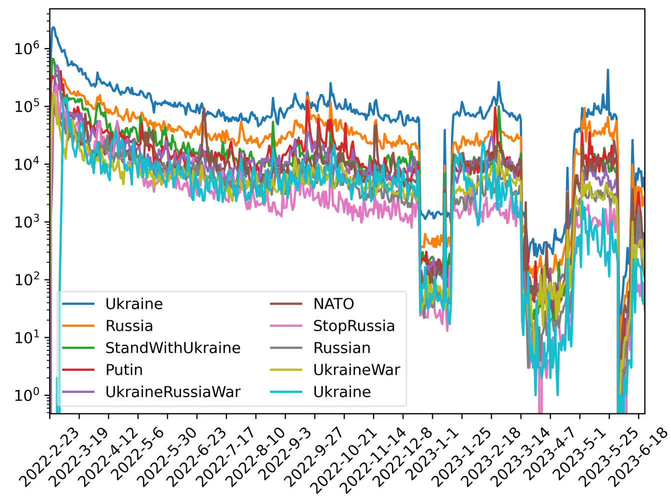

Fig. 2: Daily volume of 10 most popular hashtags.

of analytical algorithms. Text prepossessing varies depending on the analysis type and includes the removal of URLs, unnecessary spacing characters (e.g. spaces, tabs, and newlines), hashtags and usernames (in case of sentiment and toxicity analysis) and emoticons (except for the case of sentiment analysis).

4.2 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. We conduct a comparative study of existing approaches to ensure the highest accuracy in sentiment analysis. Currently, two primary methodologies are commonly applied: model-based (also known as lexicon-based) rules [21,41] and AI-based models [7,40].

Rule-based models offer attractive advantages 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 [47].

In contrast, AI-based approaches can provide more accurate results without the need of manual rule creation by a team of language experts. These approaches can be categorized into two types of implementation. First, simpler machine learning models like the Naive Bayes model making use of attributes straightforward for humans to understand. Although 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 labeled datasets, render these types of sentiment analysis impractical for multilingual datasets.

More advanced AI approaches for sentiment analysis are based on sophisticated neural network models [34,15]. 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 multilingual transformer model XLM-RoBERTa [10] due to its proficiency in handling large volumes of diverse languages and its exceptional performance in sentiment analysis tasks [24,2].

More specifically, the selected XLM-RoBERTa model is an extension of the original RoBERTa implementation which takes advantage of the original implementation and applies it to the Cross-lingual language model (XLM) objective. In such a scenario, the data are processed without additional translation, and only the original language model mask is applied. The selected implementation 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.

To address the challenges posed by our diverse dataset, we fine-tune our implementation of XLM-RoBERTa as Facebook team suggests [25], on the MultiNLI dataset[45], a crowdsourced collection of 433k English sentence pairs annotated with textual entailment information, and XNLI[11], a subset of a few thousand examples from MNLI that 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).

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 in different languages. We use the Transformers Trainer and Dataset library, from HuggingFace, in order to load the model, the datasets, and the training. The parameters adjusted on the Trainer include the following: number of train epochs = 3, batch size = 128, and warm-up steps = 10% of the total size of the train set. After training on the Russian and Ukrainian subsets of the dataset for 10 epochs, we observed that the accuracy converged and reached a plateau after just 3 epochs. This convergence is clearly illustrated in Table 2, which depicts the accuracy values across the training epochs. Based on this observation, we determine that 3 epochs would be sufficient for training on the full dataset, as additional epochs beyond this point were unlikely to yield significant improvements in model performance.

We use positive, neutral, and negative labels as sentiment labels towards the entities of *Ukraine*, *Russia*, *Zelenskyy*, 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.

4.3 Topic Modelling

To unveil latent patterns and relationships among words in the shared tweets, we employ a topic modeling method. This allows us to uncover the predominant

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

Metric	Epoch									
	1	2	3	4	5	6	7	8	9	10
RUS Loss	0.6832	0.5448	0.4795	0.4243	0.3745	0.3313	0.2929	0.2608	0.2369	0.2183
RUS Acc (%)	73.78	77.63	76.14	76.35	76.27	76.31	76.18	75.66	76.06	75.90
UKR Loss	1.0129	0.9628	0.9407	0.9205	0.9001	0.8791	0.8593	0.8404	0.8242	0.8118
UKR Acc (%)	63.57	64.70	66.43	65.46	65.94	65.02	66.27	65.14	65.58	65.14

ideas or concepts within the text data without the need of predefined categories or manual labeling. By automatically detecting topics, topic modeling provides a means to organize, summarize, and explore vast amounts of textual data.

Conventional topic modeling techniques, like latent Dirichlet allocation and latent semantic analysis, require the 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[18] pipeline, which can extract topics using embeddings derived from multilingual models (SBERT[30]). The pipeline of BERTopic consists of the following steps:

- *Embeddings*: We initiate the process by converting our documents into vector representations using language models.
- *Dimension Reduction*: We reduce the dimensionality of the vector representations to facilitate the clustering algorithms in finding clusters effectively (utilizing UMAP, PCA).
- *Clustering*: We apply a clustering algorithm to cluster the reduced vectors and identify semantically similar ones (employing HDBSCAN[26], k-Means, BIRCH).
- *Bag of Words*: We tokenize each topic into a bag-of-words representation, enabling us to process the data without affecting the input embeddings (employing CountVectorizer).
- *Topic Representation*: We calculate words related to each topic using a class-based TF-IDF procedure known as c-TF-IDF.

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

4.4 Toxicity Analysis

Toxic comment classification is an emerging research field, with several studies addressing diverse tasks to detect unwanted messages on communication platforms. Although sentiment analysis is an accurate approach to observe 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 since the beginning of the war is increasing, so we need to detect whether toxicity was the reason for the suspension. We use toxic comment classification Detoxify[19], a state-of-the-art model, pre-trained in social media datasets to classify multilingual corpus. After research in 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.

4.5 Military Intelligence

In addition to the analysis described in previous sections, we test novel methodologies of military intelligence combined with social media information and location identification. This methodology can identify and provide military-based content based on text shared on social media such as Twitter. Based on some recent investigations, during the Russo-Ukrainian conflict, we find that a large amount of military content is contained in social networks, with a high percentage of fake information [3,28]. Gathering military information through social media poses a challenge, as it is still an unexplored field in NLP and currently there is not much related work to refer to. Additionally, there is still no large-scale open military domain corpus, making the identification of military-named entities with data even more challenging. To extract open-source military information from tweets, we initially need to train a Named-Entity Recognition (NER) model to recognize military-type entities. For this purpose, we use the spaCy NER model as a base and fine-tune and train it (train split = 70%, validation split = 30%) with the only open source military dataset[14] from the Defense Science and Technology Laboratory of the UK. The Entity Schema of the NER model is in Table 3. As shown in Table 3, we achieve our best performance in epoch 42. The training of the NER model is based on the following parameters: warm-up steps = 250, total epochs = 71, and initial rate = 5e-5. We create a pipeline that can filter our dataset and extract military entities, with the following steps:

1. The XLM-RoBERTa model for zero-shot classification using the label "military" with a threshold > 0.7 (range 0-1),
2. Our implemented NER model to extract entities,
3. Filtering of 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.

5 Experimental Results

In this chapter, we provide the results of our developed analysis. The results are separated, similarly as in the methodology section, by each category of analysis: sentiment, topic, toxicity, and military intelligence. It is important to note that some literature suggests the presence of automated accounts, or "bots," on the platform. These bots can potentially influence the overall landscape of social media discourse. A recent study by [36] introduces a novel approach for bot detection on Twitter and detected bot accounts during the Russo-Ukrainian War

Table 3: Performance of Spacy's NER training on [14] and Entity Schema

Epoch	Step	Accuracy	Entity Schema
14	200	0.66	CommsIdentifier, DocumentReference,
28	400	0.73	Frequency, Location, Money,
42	600	0.74	MilitaryPlatform, Nationality,
57	800	0.73	Organization, Person, Quantity,
71	1000	0.73	Temporal, Url, Vehicle, Weapon

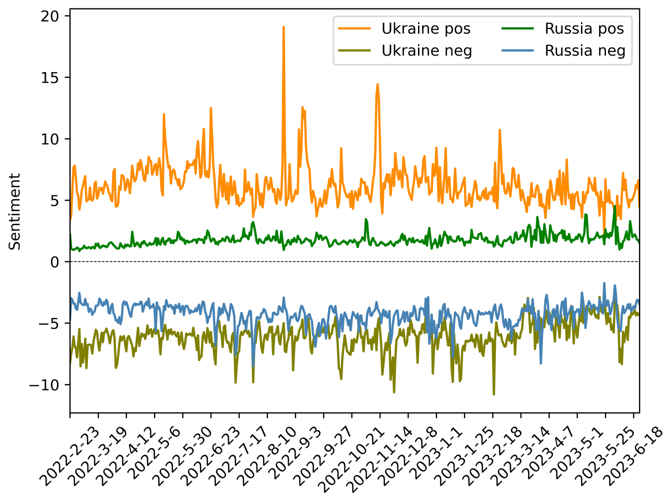

Fig. 3: Daily positive and negative sentiments towards each country.

5.1 Sentiment Analysis

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

Regarding the sentiment analysis of the countries, as illustrated in Figure 3, the general sentiment trend tends to exhibit a higher positive sentiment toward Ukraine (with higher values indicating greater support from Twitter users). Although we notice some spike on the negative axes the overall positive sentiment towards Ukraine is higher.

Furthermore, we examine the sentiment vectors of country presidents, as presented in Figure 4. Our analysis indicates that President Zelenskyy receives a significantly higher positive sentiment. This observation can be attributed to the substantial support expressed by Twitter users toward Ukraine and President Zelenskyy during the Russo-Ukrainian War.

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

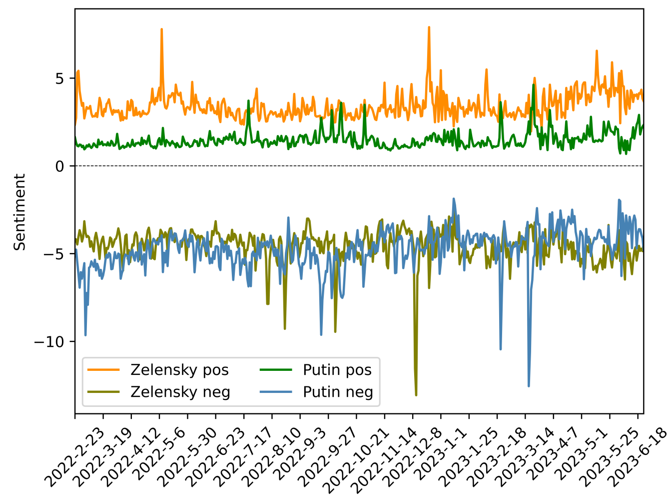

Fig. 4: Daily positive and negative sentiments towards each president.

Table 4: Most popular topics for dates with high user activity.

Date	**Topics**
8 May	bono, kyiv, ukrainian, rt, edge, conference zoom, resists azovstal, commanders regiment, plant press, killed city, btc humanitarian, gc13
14 May	ukraine, putin, eurovision, russie, stereotypes, rt, rt mavkaslavka, mavkaslavka, kerziouk today, deepl, city, battle, kharkiv axis, threat city, kharkiv
14 July	ukraine, fighting, forget, european, ukrainians fighting, recognize russia, recognize, world recognize, call world, russia terrorist, fuck, vinnytsya, including dead, area casualties, dialing

5.2 Topic Analysis

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

An example is a surge in positive sentiment towards Ukraine on 14 May 2022. On this day, the mainstream media reported that Ukraine had won Eurovision 2022, contributing to the overall increase in positive sentiment. Furthermore, the Ukrainian military continued its counteroffensive in the northeastern region of Kharkiv [31]. Our topic analysis ranked these significant events as the top discussion topics (1st and 3rd) as shown in Table 4.

Another noteworthy instance from our dataset is a significant increase in negative sentiment on July 14, 2022, as evident in Figure 3. On this date, Ukrainian officials reported that at least 23 people died from a Russian strike in Vinnytsia, central Ukraine, according to reports in the mainstream media [4]. The results of our topic modeling, which ranked this tragic incident as the third topic (Table 4), align with the observed sentiment trends and the coverage in the mainstream media. Moreover, this topic was associated with user discussions calling for the recognition of Russia as a terrorist state.

Furthermore, we examine the user discussions on 8 May, when President Zelenskyy experienced a positive sentiment peak. According to reports from the main media, President Zelenskyy had invited Bono and Edge musicians to a concert in Kyiv, coinciding with his address for the Day of Remembrance and Reconciliation [32].

As indicated in Table 4, 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 identify each day 20 topics, including those that are reported by mainstream media. These findings suggest that Twitter users tend to follow the narrative presented by the mainstream media. The remaining topics, not covered by mainstream media, often include references to Twitter accounts mentioning the War (e.g., @mavkaslavka), indicating that a significant number of users incorporate events reported by other Twitter users into their conversations.

In addition, we identify topics related to cryptocurrencies and NFTs posted by spam accounts attempting to exploit popular hashtags, which is also supported by related work [35].

5.3 Toxicity Analysis

Using Detoxify [19], a toxic classification model, we analyze 1,883,507 tweets originating from suspended accounts. We examine this part of the dataset 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 suspended users is low (2.1%), so we conclude that toxicity is not necessarily the main factor in Twitter suspension for our dataset.

5.4 Military Intelligence

Our analysis, reveals that the collected dataset contains a significant volume of military intelligence content, with 879,232 tweets with military intelligence over the whole period. This distribution of identified content closely mirrors the volume of user activity between registered users. Through manual inspection, we confirm that the identified content contains military-related information directly correlated with the conflict. Table: 5 provides a selection of random examples of these identified tweets containing military content. Upon further investigation, we discover 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

Table 5: Examples of tweets with military information

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 Kyiv op mostly), and mercenaries to cut off #Bakhmut - #Severodonetsk highway. They were unsuccessful, but it made UA ops in the area more difficult.
A Russian mortar position was located and destroyed by the Ukrainian 20th Separate Special Regiment of the Ukrainian SOF near Sievierodonetsk, Luhansk Oblast.#Russia #Ukraine

volume and entity filtering (e.g., Location = Kyiv) to monitor military events and movements.

6 Conclusion

In the current study, we use the Twitter API to obtain a dataset of 127.2M tweets originating from 10.9M users over a period of 16 months 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-Ukrainian war creates a surge of activity on social networks with a generally negative attitude. Although the negative sentiment is high on both sides, the positive sentiment is higher towards Ukraine and Zelenskyy, leading to the deduction that the negativity disagrees with the war rather than Ukraine and Zelenskyy 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, several spam accounts are active and post in large volumes, often referring to cryptocurrencies, NFTs, and other similar products that have no connection to the war.

Furthermore, we show that a combination of state-of-the-art AI models allows us to identify military intelligence content over social media, making possible further implementation of intelligent technology for monitoring battles, making command decisions, and interfacing with computers. We include in our plans military-named entity recognition as a key part of military data extraction, to provide the basis for the intelligent handling of military information from social media. Furthermore, we make the collected dataset available to the research community in two formats: tweet IDs for those with API access and anonymous tweets via the Zenodo data sharing platform, ensuring the protection of user privacy.

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References

1. Antonakaki, D., Fragopoulou, P., Ioannidis, S.: A survey of twitter research: Data model, graph structure, sentiment analysis and attacks. Expert Systems with Applications **164**, 114006 (2021)
2. Barbieri, F., Anke, L.E., Camacho-Collados, J.: Xlm-t: Multilingual language models in twitter for sentiment analysis and beyond. arXiv preprint arXiv:2104.12250 (2021)
3. BBC: Twitter blue accounts fuel ukraine war misinformation. https://www.bbc.com/news/world-europe-66113460 (2023), accessed: 2023-09-09
4. BBC News: Ukraine war: 23 killed in russian rocket attack on vinnytsia. https://www.bbc.com/news/world-europe-62163071 (2022), accessed: 2022-07-15
5. Caprolu, M., et al., S.: Characterizing the 2022-russo-ukrainian conflict through the lenses of aspect-based sentiment analysis: dataset, methodology, and key findings. In: 2023 32nd ICCCN. pp. 1–10. IEEE (2023)
6. Carchiolo, V., Longheu, A., et al., M.: Terrorism and war: twitter cascade analysis. In: International Symposium on Intelligent and Distributed Computing. pp. 309–318. Springer (2018)
7. Chakriswaran, P., et al., V.: Emotion ai-driven sentiment analysis: A survey, future research directions, and open issues. Applied Sciences **9**(24), 5462 (2019)
8. Chen, E., Ferrara, E.: Tweets in time of conflict: A public dataset tracking the twitter discourse on the war between ukraine and russia. In: Proceedings of the International AAAI Conference on Web and Social Media. vol. 17, pp. 1006–1013 (2023)
9. Chibuwe, A.: Social media and elections in zimbabwe: Twitter war between pro-zanu-pf and pro-mdc-a netizens. Communicatio: South African Journal of Communication Theory and Research **46**(4), 7–30 (2020)
10. Conneau, A., et al., K.: Unsupervised cross-lingual representation learning at scale. arXiv preprint arXiv:1911.02116 (2019)
11. Conneau, A., et al., R.: Xnli: Evaluating cross-lingual sentence representations. In: Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics (2018)
12. Curiskis, S.A., Drake, B., Osborn, T.R., Kennedy, P.J.: An evaluation of document clustering and topic modelling in two online social networks: Twitter and reddit. Information Processing & Management **57**(2), 102034 (2020)
13. Dashtipour, K., et al., P.: Multilingual sentiment analysis: state of the art and independent comparison of techniques. Cognitive computation **8**(4), 757–771 (2016)
14. Defence Science and Technology Laboratory UK: Relationship and entity extraction evaluation dataset. https://github.com/dstl/re3d (2017), accessed: 2022-05-15
15. Dos Santos, C., Gatti, M.: Deep convolutional neural networks for sentiment analysis of short texts. In: Proceedings of COLING 2014, the 25th international conference on computational linguistics: technical papers. pp. 69–78 (2014)

16. Fan, H., et al., D.: Social media toxicity classification using deep learning: Real-world application uk brexit. Electronics **10**(11) (2021). https://doi.org/10.3390/electronics10111332
17. Giachanou, A., Crestani, F.: Like it or not: A survey of twitter sentiment analysis methods. ACM Comput. Surv. **49**(2) (jun 2016). https://doi.org/10.1145/2938640, https://doi.org/10.1145/2938640
18. Grootendorst, M.: Bertopic: Neural topic modeling with a class-based tf-idf procedure. arXiv preprint arXiv:2203.05794 (2022)
19. Hanu, Laura and Unitary team: Detoxify. Github. https://github.com/unitaryai/detoxify (2020), accessed: 2022-05-15
20. Haq, E.U., et al., T.: Twitter dataset for 2022 russo-ukrainian crisis. arXiv preprint arXiv:2203.02955 (2022)
21. Hardeniya, T., Borikar, D.A.: Dictionary based approach to sentiment analysis-a review. International Journal of Advanced Engineering, Management and Science **2**(5), 239438 (2016)
22. Infosec Resources: Social media use in the military sector. https://resources.infosecinstitute.com/topic/social-media-use-in-the-military-sector/ (2013), accessed: 2022-05-15
23. Kok, A.e.a.: Named entity extraction in a military context. In: 2019 International Conference on Military Communications and Information Systems (ICMCIS). pp. 1–6 (2019). https://doi.org/10.1109/ICMCIS.2019.8842722
24. Kumar, A., Albuquerque, V.H.C.: Sentiment analysis using xlm-r transformer and zero-shot transfer learning on resource-poor indian language. Transactions on Asian and Low-Resource Language Information Processing **20**(5), 1–13 (2021)
25. Lample, G., Conneau, A.: Cross-lingual language model pretraining. arXiv preprint arXiv:1901.07291 (2019)
26. McInnes, L., Healy, J., Astels, S.: hdbscan: Hierarchical density based clustering. The Journal of Open Source Software **2**(11) (mar 2017). https://doi.org/10.21105/joss.00205, https://doi.org/10.21105%2Fjoss.00205
27. Öztürk, N., Ayvaz, S.: Sentiment analysis on twitter: A text mining approach to the syrian refugee crisis. Telematics and Informatics **35**(1), 136–147 (2018)
28. Pierri, F., Luceri, L., Jindal, N., Ferrara, E.: Propaganda and misinformation on facebook and twitter during the russian invasion of ukraine. In: Proceedings of the 15th ACM Web Science Conference 2023. pp. 65–74 (2023)
29. Qayyum, A., Gilani, Z., Latif, S., Qadir, J.: Exploring media bias and toxicity in south asian political discourse. In: 2018 12th International Conference on Open Source Systems and Technologies (ICOSST). pp. 01–08 (2018). https://doi.org/10.1109/ICOSST.2018.8632183
30. Reimers, N., Gurevych, I.: Sentence-bert: Sentence embeddings using siamese bert-networks. arXiv preprint arXiv:1908.10084 (2019)
31. Reuters: Ukraine presses counteroffensive on key russian line of assault - governor. https://www.reuters.com/world/europe/ukraine-presses-counteroffensive-key-russian-line-assault-governor-2022-05-14/ (2022), accessed: 2022-05-15
32. Rolling Stone: See u2's bono and the edge play surprise set in kyiv bomb shelter following invitation from president zelensky. https://www.rollingstone.com/music/music-news/u2-bono-the-edge-acoustic-set-kyiv-bomb-shelter-1350428/ (2022), accessed: 2022-07-15
33. Saarinen, M.J.O., Aumasson, J.P.: The BLAKE2 Cryptographic Hash and Message Authentication Code (MAC). Internet-Draft draft-saarinen-blake2-06, Internet Engineering Task Force (Aug 2015), https://datatracker.ietf.org/doc/draft-saarinen-blake2/06/, work in Progress

34. Severyn, A., Moschitti, A.: Twitter sentiment analysis with deep convolutional neural networks. In: Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval. pp. 959–962 (2015)
35. Shevtsov, A., Antonakaki, D., et al., L.: Russo-ukrainian war: Prediction and explanation of twitter suspension. In: Proceedings of the 2023 IEEE/ACM ASONAM. p. 348–355. ASONAM '23, Association for Computing Machinery, New York, NY, USA (2024)
36. Shevtsov, A., Antonakaki, D., Lamprou, I., Pratikakis, P., Ioannidis, S.: Botartist: Generic approach for bot detection in twitter via semi-automatic machine learning pipeline (2024), https://arxiv.org/abs/2306.00037
37. Shevtsov, A., Oikonomidou, M., Antonakaki, D., Pratikakis, P., Ioannidis, S.: What tweets and youtube comments have in common? sentiment and graph analysis on data related to us elections 2020. Plos one **18**(1), e0270542 (2023)
38. Shevtsov, A., Tzagkarakis, C., Antonakaki, D., Ioannidis, S.: Identification of twitter bots based on an explainable machine learning framework: The us 2020 elections case study. In: Proceedings of the International AAAI Conference on Web and Social Media. vol. 16, pp. 956–967 (2022)
39. Smart, B., Watt, J., Benedetti, S., Mitchell, L., Roughan, M.: # istandwithputin versus# istandwithukraine: The interaction of bots and humans in discussion of the russia/ukraine war. In: International Conference on Social Informatics. pp. 34–53. Springer (2022)
40. Sufi, F.K., Khalil, I.: Automated disaster monitoring from social media posts using ai-based location intelligence and sentiment analysis. IEEE Transactions on Computational Social Systems (2022)
41. Taboada, M., Brooke, J., Tofiloski, M., Voll, K., Stede, M.: Lexicon-based methods for sentiment analysis. Computational linguistics **37**(2), 267–307 (2011)
42. Vayansky, I., Kumar, S.A.: A review of topic modeling methods. Information Systems **94**, 101582 (2020). https://doi.org/https://doi.org/10.1016/j.is.2020.101582, https://www.sciencedirect.com/science/article/pii/S0306437920300703
43. Wallach, H.M.: Topic modeling: Beyond bag-of-words. In: Proceedings of the 23rd ICML. p. 977–984. ICML '06, Association for Computing Machinery, New York, NY, USA (2006). https://doi.org/10.1145/1143844.1143967
44. Wang, X., Yang, R., Lu, Y., Wu, Q.: Military named entity recognition method based on deep learning. In: 2018 5th IEEE CCIS. pp. 479–483 (2018)
45. Williams, A., Nangia, N., Bowman, S.: A broad-coverage challenge corpus for sentence understanding through inference. In: Proceedings of the 2018 NAACL-HLT. pp. 1112–1122. Association for Computational Linguistics (2018)
46. Yang, S.H., et al., K.: Large-scale high-precision topic modeling on twitter. In: Proceedings of the 20th ACM SIGKDD. p. 1907–1916. KDD '14, Association for Computing Machinery, New York, NY, USA (2014). https://doi.org/10.1145/2623330.2623336, https://doi.org/10.1145/2623330.2623336
47. Zhang, Y., Li, X., Zhang, X., Li, Y.: Sentiment lexicons and non-english languages: a survey. Knowledge and Information Systems **63**(3), 707–736 (2020)