Characterizing the 2022- Russo-Ukrainian Conflict Through the Lenses of Aspect-Based Sentiment Analysis: Dataset, Methodology, and Key Findings

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Abstract—Online social networks (OSNs) play a crucial role in modern society by supporting free expression, information sharing, and social movement organization. However, they are also the tool of choice to spread disinformation, hate speech, and support propaganda. As such, it is crucial to analyze OSNs, particularly during critical events such as elections, pandemics, and conflicts, when disinformation campaigns may seek to undermine the democratic values of a nation.

This paper analyzes the general-public perception of the first phases of the 2022- Russo-Ukrainian conflict on Twitter. To this end, we developed a general methodology consisting of several steps. We built a dataset of 5.5+ million tweets related to the subject, generated by 1.8+ million unique users. Then, we cluster users into five categories, and combining statistical analysis and aspect-based sentiment analysis (ABSA), we quantitatively and qualitatively investigate the spread of information during the conflict. Our analysis revealed several important insights, including anomalies in the behavior of specific user categories and their sentiment trends and a spike in the daily account creation rate before the conflict. Other than being interesting on their own, our findings also have significant implications for future research on how disinformation campaigns are executed and on developing effective strategies to mitigate their impact.

Index Terms—2022-Russo-Ukrainian Conflict, Online Social Networks, Disinformation, Propaganda, Fake-news, Aspect-Based Sentiment Analysis, Twitter, Data Mining, Data Analysis.

I. INTRODUCTION

Online Social Networks (OSN) were born to connect users so that they could share their emotions, desires, happiness and interests as an important aspect of their socialization. While this is still true, OSNs have also evolved towards platforms where political opinions are formed and discussed, and where groups organize themselves in order to achieve shared objectives. Hence, on the one hand OSNs play a key role in forming the public opinion about almost any event. On the other hand, they are the ideal platform for spreading fake news and disinformation [1].

In this paper, we conduct a detailed study on the perception of the 2022- Russo-Ukrainian conflict on Twitter. Our main goal is to characterize the spread of information and its impact on user sentiment regarding the escalation of the conflict. Moreover, we also searched for digital clues that could suggest possible disinformation campaigns and investigated the collected data to highlight possible anomalies in the analyzed accounts. To reach these objectives, we built a massive dataset on the subject by collecting 5,583,168 tweets shared by 1,858,605 different users between January 27 and March 23, that is, one month before and one month after February 24, 2022. On that day, the Russian president Vladimir Putin announced the start of a special military operation in Ukraine. Our working hypothesis is that if there was a disinformation campaign aimed at manipulating the public opinion of English-speaking countries on the conflict in Ukraine, as suggested by several mainstream media1, its traces should be captured by our dataset. Therefore, we performed an exploratory analysis to discover any hidden abnormal pattern that might suggest such a disinformation campaign. In particular, we applied quantitative and qualitative analysis on the collected data using statistical analysis techniques and an advanced Natural Language Processing (NLP) technique, called Aspect-Based Sentiment Analysis (ABSA). ABSA, also known as fine-grained opinion mining or target-based sentiment analysis, provides significantly detailed and in-depth insights for the existing aspects, features and topics in an input text. Using the cited techniques, we compute the evolution over time of the sentiment for 5 main keywords: “Putin”, “Zelensky”, “NATO”, “Ukraine” and “Russia”, respectively, identifying them as the main ABSA aspect terms expected to provide meaningful insights for the conflict at study. The analysis over time of these data unleashed a trove of insights on the public perception of the conflict and its actors, providing some confirmations of current believes on the conflict, together with new important observations. In particular, as per confirmations, it appears that the negative sentiment related to President Putin increased after the escalation of the conflict, the neutral sentiment towards him decreased by roughly the same amount, while the positive one remained stable. A specific insight is that this negative sentiment does not appear pegged to

1https://www.theguardian.com/world/2022/apr/07/propaganda-social-media-surge-invasion-ukraine-meta-reports
the whole concept of Russia, signaling the fact that users are somehow able to distinguish between the action of a government and the subjected people. [2].

**Contributions.** The major contributions of this research are as follows:

- We built a dataset for the 2022- Russo-Ukrainian conflict by collecting more than 5.5 million tweets related to the subject. Although we cannot publish it due to Twitter’s policies, we reported the methodology and the query we used for this purpose in Section III-A, allowing any Twitter Developer Account to easily download and reconstruct exactly the same dataset.
- We classified user accounts into five different categories, and we analyzed them according to several metrics.
- We performed an exploratory analysis of our dataset, studying the volume of the data and the tweets distribution over time and users. Then, resorting to ABSA, we characterized the sentiment about the conflict shared on Twitter in the English-speaking world.
- We discussed our results revealing statistics and sentiment trends for the major players involved in the conflict and provided valuable insights for future investigation on disinformation and bot detection related, but not limited to, the Russo-Ukrainian conflict.

**Roadmap.** The rest of this paper is organized as follows. In Section II, we discuss the related work. In Section III, we present our proposed approach in detail. We show our results in Section IV, and we conclude in Section V with some insights for future research.

**II. RELATED WORK**

During the last decade, OSNs have been used for various applications, such as detecting cyber threats, characterizing social events (e.g., elections and pandemics), advertising goods, etc. [3].

The 2022- Russo-Ukrainian conflict is a recent event at the time of writing. Nevertheless, several studies have already leveraged the OSNs to gain insight on some aspects of the conflict, demonstrating the need to identify a dataset for supporting different research directions on this topic. Although existing work shared the same goal, i.e., to build a dataset of OSN contents on the Russo-Ukrainian conflict, methodologies and results are pretty different. In [4], the authors provide a collection of tweets (in English language only) built by using a set of keywords that changes over time according to the main events of the conflict. A similar work is reported in [5], with static keywords and a small post-processing phase to discard tweets non-related to the subject. A collection of raw data extracted from Twitter was proposed also in [6], where authors conducted a small analysis on data volume. In [7], instead, the authors pursued the same goal, but targeting information shared in Russian language, retrieved from both a Russian state-affiliated platform (VK) and Twitter. In [8], the authors investigated the account moderation on Twitter during major geopolitical event, with the 2022- Russo-Ukrainian conflict among them. They provided interesting insights, uncovering patterns of platform abuse that may lead to account suspension. In [9], the authors investigated the propaganda on Facebook and Twitter related to the Russian Ukraine conflict. They estimated the prevalence of Russian propaganda on social networks, identified super-spreaders of unreliable contents, and revealed how OSNs are still vulnerable to abuse, particularly during crisis. To the best of our knowledge, we are the first to build a dataset with more refined data, e.g., original contents only, and extensive post-processing, e.g., user categorization, sentiment analysis, data correlation, etc. and to provide data-based insights on the general sentiment (for different cohorts of users, for several subject terms) over this terrible crisis.

Recently, several researchers employed ABSA to conduct advanced natural language analysis [10] [11] [12]. Some pioneering works leveraged ABSA for analyzing OSN data on various domains, such as education [13], medicine [14] [15], and e-commerce [16] [17] [18]. Sivakumar et al. in [13] utilize ABSA to analyze students feedbacks collected from OSNs in order to improve students studies and teacher’s teaching quality. Bhata et al. in [15] use a weakly supervised ABSA technique [19] to investigate people opinions in OSNs regarding COVID-19 vaccination process in Canada. The results are shared with healthcare experts to improve their knowledge and performance toward optimizing the vaccination process. Consolia et al. in [18] introduce Fine-Grained Aspect-based Sentiment (FiGAS) that is a novel lexicon-based sentiment analysis approach developed particularly for the economic and financial domains. In the proposed approach, the sentiments are calculated only for the terms that are directly related to the topic of interest providing detailed insights.

However, to the best of our knowledge, we are the first to apply ABSA to the Russo-Ukrainian conflict and, more in general, to detect abnormal patterns in sentiment trends that may suggest disinformation activities.

**III. METHODOLOGY**

The methodology we used to characterize the 2022- Russo-Ukrainian conflict on Twitter is depicted in Figure 1. The first step is data collection. To build our dataset, we collected tweets related to the target topic via the Twitter API. Next, after pre-processing our data as detailed in Sec. III-B, we analyze the collected tweets from both the quantitative and qualitative perspectives. In particular, we evaluated the volume of our data, and we investigated the user’s sentiment over time by leveraging Aspect-Based Sentiment Analysis, as described in Sec. III-C. Each analyzed dimension produces different insights and results, that we analyzed in Sec. IV, while also providing exploratory findings.

**A. Data Collection**

To build our dataset, we collected tweets related to the Russo-Ukrainian Conflict via the Twitter API v2. Specifically, we queried the “tweets/search/all” Twitter endpoint\(^2\), which returns the complete history of public tweets matching a search
query, from the very first tweet in the platform (March 26, 2006) to the last one (query execution time)\(^3\).

To select only the tweets that would best highlight changes in the public sentiment, first, we have narrowed the search space to two months, one month before and one month after February 24, 2022. On that day, the Russian president, Vladimir Putin, announced the start of a special military operation in Ukraine. Then, we have selected several keywords, reported in Listing 1, to define our area of interest.

```
zelensky, ukraine, ukrainian, russia, russian, putin
```

Listing 1: The selected keywords for data collection.

As we explore the topic of the Russo-Ukrainian conflict, we are also interested in the perception of the reference users over the North Atlantic Treaty Organization (NATO). However, we did not directly use the “NATO” keyword for data collection because it is not directly involved in the topic under study. In fact, by including the NATO keyword alone, we would also have collected tweets that do not refer, neither directly nor indirectly, to the Russo-Ukrainian Conflict. On the contrary, by excluding the “NATO” keyword from the data collection, we collected, in any case, all the tweets mentioning the Atlantic alliance along with at least one other keyword reported in Listing 1, ensuring the correlation to our topic of interest. Then, we considered the “NATO” keyword in the data analysis by verifying both the volume and sentiment of the collected tweets that named the Atlantic alliance in our dataset.

Finally, we used some operators to refine further the results returned by the Twitter endpoint. In particular, we decided to target original content only, avoiding retweets, replies, and quotes. This choice ensures that every (original) tweet is analyzed only once. Moreover, as we are only interested in textual content, we excluded tweets containing links and media in the tweet body. In this way, we are sure that all the context needed to comprehend the tweet is within the tweet itself and in textual form. Indeed, if part of the tweet is not in textual form, e.g., a picture or video, or located outside the Twitter platform via URL, the ABSA analysis, not having the full context available, may produce incomplete or unreliable results. Also, considering this research’s tools and scope, we analyzed only tweets in English. The query we used to build our dataset is reported in Listing 2.

We inserted two parameters in the GET request to restrict the time space of the search from January 27 to March 23, i.e., 1 month before and 1 month after the triggering of the conflict (lines 1 and 2). Our keywords are in OR logic to catch all tweets that contain at least one of them (lines 4 and 5). We excluded retweets, replies, and quotes by using the “is” operator prepended by a dash to negate it (line 6). Similarly, we used the (negated) “has” operator to exclude tweets that include any link or share any media (line 6). By executing the query above described, we collected 5,583,168 tweets from 1,858,605 different users.

```
start_time = "2022-01-27T00:00:00.000Z"
end_time = "2022-03-23T00:00:00.000Z"

(zelensky OR zelenskyy OR ukraine OR ukrainian OR russia OR russian OR putin)
-has:links -has:media -is:retweet -is:reply -is:quote lang:en
```

Listing 2: The query we sent via GET request to the Twitter API v2, “tweets/search/all” endpoint.

B. Pre-processing

After building our dataset, we first cleaned up the data returned by the Twitter API to remove tweets that fall outside the scope of this research, or contain anything other than English text that could undermine subsequent analyses. We removed a total of 1144 tweets, 856 of which, although returned by the Twitter API, did not actually contain any of the keywords used in the query—this latter behaviour was duly noted down for further analysis in future works. Then, we categorized Twitter accounts based on different metrics to understand the user profiles that are more interested on the topic. In particular, we divided all the users included in our dataset into the following five categories:

\(^3\)https://developer.twitter.com/en/docs/twitter-api/tweets/search/api-reference/get-tweets-search-all

Fig. 1: Research Methodology
• **Trusted Accounts**: This category includes all the accounts for which the owner’s real identity is, somehow, publicly known. We put in this category accounts flagged as “verified” by Twitter and/or accounts with a high number of followers. Specifically, we considered users with celebrity status, i.e., $> 9.0M$ followers, and very popular account, i.e., $900K$ to $1.1M$ followers [20].

• **Baby Accounts**: This category includes all accounts that can be considered “young” during this study, i.e., account generated from September 2021 onward. We consider this category interesting as it may include a subset of accounts explicitly created for tweeting about the escalation in the Russo-Ukrainian conflict.

• **Abnormal Accounts**: This category contains accounts that do not behave similar to regular users. Such accounts are suspected to be managed by bots, trolls, and possibly other unconventional users. To identify this type of account, we used a standard metric in the literature, the Friend Ratio (FR) [21], which leverages two of the few user metrics provided by Twitter—the number of followers and the number of following. In particular, for each account, we compute the Friend Ratio (FR) as the ratio of follower/following. Then, we considered as “abnormal” three different situations that we believe are unlikely to occur in accounts managed by private citizens: (i) accounts with zero following; (ii) accounts with an extremely low FR, i.e., less than or equal to 0.02, as considered bots with high probability by existing works\(^4\); and, (iii) accounts with a fair FR, i.e., $\geq 0.99$ and $\leq 1.1$, as normal users tend to have a higher number of followers with respect to their following, since they follow celebritites or other popular accounts that don’t follow them back. Users who fall into this category but were also created after September 1, 2021, have been included in the baby accounts category.

• **Unknown Accounts**: This category includes accounts for which Twitter did not return information because the user was suspended or deleted from the platform at the time of the data collection.

• **Regular Accounts**: This category includes all remaining accounts that do not fall into the categories above discussed.

### C. Aspect-Based Sentiment Analysis

Aspect-based sentiment analysis (ABSA) helps identifying fine-grained opinion polarity toward a specific aspect associated with a given target. Unlike general sentiment analysis, ABSA can provide more detailed information helping to accomplish more advanced analysis [22]. Figure 2 illustrates how ABSA works for a sample sentence.

In this example, the result of general sentiment analysis is “Mixed” as there is one negative sentiment and one positive sentiment. However, as the figure illustrates, the sentiment for the ABSA aspect term “Zelensky” is positive while it is negative for “Putin”.

General sentiment analysis would allow us to identify only the prevalent sentiment of a single tweet. ABSA, instead, allows us to extract the different sentiments related to subject-aspects identified in a single tweet, hence enabling a more comprehensive, fine grained analysis.

![Fig. 2: An example of ABSA analysis](image)

**Tools.** Considering that ABSA is still an ongoing research topic in NLP field, there are not many open-source or third-party solutions providing this service in industry or academia. We considered two major solutions for this study: (i) A Python library called aspect-based-sentiment-analysis $2.0.3^5$ that has been developed based on BERT [23], a fundamental model for modern language understanding widely used in the literature [24] [25], and (ii) Amazon AWS Comprehend Targeted Sentiment Analysis $6^6$ which has been extensively used by researchers [16] [14] [26].

In terms of offered features, *AWS Comprehend* provides more detailed results than the open source alternative, such as confidence scores, aspect term type, aspect term location, to cite a few. Moreover, *AWS Comprehend* is able to identify the aspects automatically, while the considered Python library needs the term to be analyzed as a user-provided argument. Lastly, it is worth mentioning that *AWS Comprehend* is able to identify and analyze n-gram aspects whereas the Python library does not provide this feature.

Even though AWS offers much more features and detailed results, we need to compare the two tools in terms of performance. To this end, we randomly selected 500 tweets (including 670 terms) from our whole dataset. Then, for each selected tweet, we manually identify the terms related to our scope and, for each of them, we manually assign a label representing its sentiment—either positive, neutral, or negative—from a human perspective, i.e., taking into account underlying context, sarcasm, etc. Finally, to complete our comparison, we analyzed our labeled dataset with both *AWS Comprehend* and the Python library. For the replicability of our experiment, we shared our labeled dataset [27].

Table I shows the results of this experiment based on a list of regression metrics. We chose regression metrics (not classification metrics) because there is an ordered relationship among the target classes (e.g., the distance between positive and neutral class is lower than the distance between positive

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4https://i.blackhat.com/us-18/Wed-August-8/us-18-Anise-Wright-Dont-@-Me-Hunting-Twitter-Bots-at-Scale-wp.pdf

5https://pypi.org/project/aspect-based-sentiment-analysis/

6https://docs.aws.amazon.com/comprehend/latest/dg/how-targeted-sentiment.html
TABLE I: AWS and the Python library - comparison

| Metric                  | AWS          | Python Library |
|-------------------------|--------------|----------------|
| mean_squared_error      | 0.4586       | 0.7805         |
| mean_absolute_error     | 0.4103       | 0.5447         |
| r2_score                | -0.006       | -0.7379        |
| explained_variance_score| 0.0945       | -0.5895        |
| mean_pinball_loss       | 0.2051       | 0.2723         |

Fig. 3: ABSA raw result showing aspect terms and corresponding sentiments

and negative class. The results show that AWS Comprehend slightly outperforms the Python library in all the regression metrics. In addition, from a manual analysis of the results, we observe that AWS Comprehend is very conservative in its decisions, leaning toward Neutral class when its confidence score is not very high for a specific aspect term. As a consequence, unlike the Python library, AWS Comprehend never misclassified a positive with a negative, and vice versa. Hence, in light of the better quality results, we chose to conduct our experiments with AWS Comprehend.

D. Post-Processing and Results Generating

The input dataset to the AWS Comprehend is a CSV file including the list of tweet texts to be analyzed. For each tweet, AWS Comprehend provides a raw JSON entity including several aspect terms (subjects, objects, nouns, etc.) of that tweet, their corresponding sentiments and the sentiment scores.

To process the raw results of the ABSA analysis, we use custom scripts in Python. In particular, for every tweet, we filter the aspect terms identified by AWS Comprehend to extract only the results, e.g., sentiments and the sentiment scores, related to our subjects (Listing 3). In this way, for each subject (aspect term), we have all the tweets that mention it with the related sentiment. Furthermore, in order to avoid multiple sentiments for one specific aspect in a single tweet, we define the following policies:

1) If there are 2 distinct sentiments for an aspect term:
   - Neutral and Positive: the result is Positive
   - Neutral and Negative: the result is Negative
   - Negative and Positive: discard the sentiments

2) If there are 3 distinct sentiments for a specific aspect, we discard the sentiments.

The policies above reported ensure that each tweet contributes to exactly one sentiment for each subject of our study (Listing 3), and that mixed sentiments for the same aspect term (in the same tweets) are discarded. As the last post-processing step, we sorted chronologically the results, and normalized the data to transform daily number of sentiments into a decimal between 0 and 1. The result is, for each subject, three variables (#neutral, #negative, #positive) reporting the daily percentage of the corresponding sentiment over the total number of tweets per day containing that subject.

As a further investigation, we studied the correlation between the sentiment evolution over time of different user categories. Specifically, we are interested in understanding if users across different categories show similar trends in sentiment change (positive or negative) towards a specific aspect term. To achieve this, we calculated the correlation coefficient for positive and negative sentiment of each user category across the five terms considered in our study (reported in Listing 1). First, we tested our data with the Anderson-Darling normality test [28], founding that only a small subset of our variables follow a normal distribution. Consequently, we selected Spearman’s rank correlation coefficient to measure the strength of the relationship between our data, as it is a suitable measure for variables derived from categorical data that do not follow a normal distribution [29]. For each aspect term, we computed Spearman’s rank correlation coefficient for the four most important user categories (abnormal, baby, trusted, and regular) and the two most representative sentiments (positive and negative).

The Spearman’s coefficient \( \rho \) is computed as described in Equation 1:

\[
\rho(a, b) = 1 - \frac{6 \sum d^2}{n(n^2 - 1)}
\]

where \( d \) is the difference between the ranks of the two variables, and \( n \) is the length of the variables. Additionally, for every coefficient \( \rho \), we computed its probability value, \( p-value \), as a measure of how likely the observed correlation is due to chance. The \( p-value \) is \( 2P(T > t) \) where \( T \) follows a \( t \) distribution with \( (n - 2) \) degrees of freedom, with \( t \) computed as follows:

\[
t = r \sqrt{n - 2 \over 1 - r^2}
\]

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Fig. 4: Word-cloud of bigrams computed on the entire dataset used in this study

where \( r \) is the sample correlation coefficient and \( n \) is the length of the variables, i.e., the number of samples. If the p-value is less than 0.05, the observed correlation is unlikely to be due to chance, and there is a high probability that the data are statistically significant and show a true relationship. Results are reported in Section IV.

IV. RESULTS AND DISCUSSION

This section shows the results of both the quantitative and qualitative analyses we applied to our dataset to investigate the 2022- Russo-Ukrainian conflict as perceived on Twitter and analyzed through the lenses of ABSA. In particular, we studied the volume of tweet messages related to the topic, both total and per user, to evaluate the impact of the conflict escalation on the Twitter community and to characterize the users involved. Then, we used ABSA to investigate the users’ sentiments about the considered subjects (reported in Listing 3) and how they evolved over time.

A. Quantitative Analysis

By executing the query described in Listing 2, we collected 5,583,168 tweets published by 1,858,605 different users on Twitter during the considered period, i.e., one month before and one month after the triggering of the armed conflict, that happened on February 24, 2022. We analyzed our dataset using several metrics. First, we counted how many times our keywords were used in the collected tweets to identify the most popular subjects. We reported our results in Table II, where the first column contains the overall number of tweets that include the reference keyword, while the second column contains the number of tweets where that keyword is used stand-alone, i.e., without the other six. Ukraine is, by far, the most used keyword in our dataset, both in combination with others (34% of the entire dataset), and alone (22%). Other keywords related to Ukraine are, instead, far less used. Zelensky, for example, was only named in 3% of the tweets collected (1% alone). Overall, keywords related to Ukraine were used (alone) in 1,429,296 tweets, 26% of the entire dataset, while keywords related to Russia were used in 1,720,073 tweets, 31%. NATO, instead, was named in 330,638 tweets, 6% of the total number of tweets, always in combination with other keywords. It is important to note that, by design, our dataset does not include any tweet with the NATO keyword alone, as discussed in Section III-A.

| Keyword | Number of Tweets | Number of Exclusive Tweets |
|---------|------------------|---------------------------|
| Ukraine | 1,907,016        | 1,202,640                 |
| Putin   | 1,594,509        | 712,669                   |
| Russia  | 1,364,853        | 512,946                   |
| Russian | 1,250,835        | 494,458                   |
| Ukrainian | 544,908       | 166,628                   |
| Zelensky | 193,683        | 60,028                    |
| NATO    | 330,638          | 0                         |

TABLE II: Number of Tweets returned by our keywords

After evaluating how often our keywords have been used on Twitter, it is interesting to understand how they are used and what are the other predominant keywords in our dataset. To this end, we generated a word-cloud of our whole database using the Python library wordcloud7, version 1.8.2.2. The resulting image, in which the size of each word indicates its frequency, is depicted in Fig. 4. Our keywords were mainly used in combination with each other, e.g., Russia and Ukraine, giving us no information about their context. However, when combined with other words, they give us clear insights into the trend topics. For example, several bigrams show support for Ukraine, e.g., help Ukraine, pray Ukraine, stand Ukraine, and support Ukraine. Regarding Russia, instead, the main topics involved the economy, e.g., Russian oil, Russian oligarch, and Russian sanctions, the army, e.g., Russian troop, Russian soldier, Russian force, and the war itself, e.g., war Russia, and Russian invasion. Among the other keywords, we can identify different trend topics/subjects. For example, United States, Joe Biden, and America show that the USA is somehow perceived as one of the main actors in this conflict. These keywords, in fact, are even more used than president Zelensky and Ukrainian president. Other recurrent bigrams, such as war crime, innocent people, stop war, war criminal, and Ukrainian refugees, reveal fear for the fate of civilians involved in the conflict.

The volume of tweets related to the 2022- Russo-Ukrainian Conflict and published during the studied period is reported in Figure 5. During the first month under consideration, the number of tweets per minute was steadily around 20, except for a few isolated spikes, as shown in Figure 5.a. Then, it started to rise about a week before a central event in our

7https://pypi.org/project/wordcloud/
Fig. 5: Volume of tweets related to the 2022- Russo-Ukrainian Conflict, from January 27 to March 23. Overall number of tweets per minute (a), and number of tweets per account (b) in logarithmically scaled axes. The red vertical line in Sub-figure (A) is February 24.

| Account Category | Number of Users | Number of Tweets | Tweets per User |
|------------------|----------------|-----------------|----------------|
| Baby Accounts    | 237,814        | 718,163         | 3.02           |
| Trusted Accounts |                |                 |                |
| Celebrities      | 50             | 2,075           | 41.50          |
| Very Popular     | 690            | 11,461          | 16.61          |
| Verified         | 7,601          | 80,400          | 10.58          |
| Abnormal Accounts|                |                 |                |
| Zero Followers   | 7,166          | 62,783          | 8.76           |
| Fair Friend Rate | 83359          | 285,023         | 3.41           |
| Low Friend Rate  | 26,723         | 55,821          | 2.07           |
| Unknown Accounts |                |                 |                |
| Suspended        | 1,358          | 3,366           | 2.48           |
| Deleted          | 2,074          | 4,048           | 1.95           |
| Regular Accounts | 1,489,940      | 4,360,028       | 2.93           |

TABLE III: Number of users, tweets, and average tweets per user for each category.

dataset: the press conference at which the Russian president announced the start of a special military operation in Ukraine. On that date, the number of messages posted on Twitter suddenly shot up to over 1300 per minute. Subsequently, in the following weeks, it gradually decreased until it settled between 20 and 100 tweets per minute.

The vast majority of the users published very few tweets in the considered time window, as depicted in Figure 5.b. This behaviour is perfectly in-line with what already noticed in the literature [30]. After the user categorization discussed in Section III-B, we looked at how much each category participated in the discussion about the escalation of the conflict. Table III reports the number of users, the total number of tweets, and the average number of tweets per user for each category—and sub-category, if any—identified in our study.

The users who contributed most to the discussion are the trusted accounts. Specifically, celebrities tweeted on average 41 times, while very popular and verified accounts tweeted 16 and 10 times, respectively. This observation is not surprising, given that many news agencies that fall into this category. Instead, regular accounts, which are supposed to be owned and managed by normal users, tweeted on average only twice, in line with what can be seen in Figure 5.b. It is important to mention how abnormal accounts, specifically those with low FR, differ significantly from regular accounts, having tweeted about eight times on average. These accounts could be involved in disinformation activities, and their analysis should be deepened in future work. Another particularly interesting category is baby accounts. As described in Section III-B, this category includes all the accounts created in the proximity of the considered time window, i.e., from January 27th to March 23rd. Therefore, it is very likely that a subset of those accounts was explicitly created for tweeting about the Russo-Ukrainian conflict.

Figure 6.A shows the number of accounts created over time. In the first period, around 1000 accounts were created per day. Then, the creation rate increases around 1 month before February 24—the grey vertical line in Fig. 6.A—to reach more than 5000 accounts created on that day. Then, the number suddenly decreases to values far less than the median before February 24. Figure 6.B, instead, shows the number of tweets per baby account. Similar to regular ones, the vast majority of baby accounts published very few tweets in the considered time window, following a power-law distribution.

B. Qualitative Analysis

Applying ABSA to the 2022- Russo-Ukrainian Conflict dataset (2 months tweets) provides an opportunity to extract and present hidden insights not easily achievable by other analytical techniques.

The main objective is to investigate the sentiment of Twitter users about the main players involved in the escalation of the conflict and how that sentiment has changed over time. Given the space constraints, we only report the most relevant results, i.e., related to a subset of keywords and user categories—the complete outcomes of our analysis will be included in a future extension of this paper.
Figure 6 illustrates our results for the “Russia” and “Ukraine” aspect terms over time, 1 month before and 1 month after the escalation of the conflict, i.e., February 24. Evolution of sentiments for the 2 considered aspects are quite different. For “Ukraine”, the number of positive sentiments significantly increases after February 24. Instead, the same sentiment for “Russia” seems relatively constant over the two months considered, without experiencing any modification around February 24—this point will be expanded at the end of this section. On the other hand, the number of negative sentiments increase for “Russia” after the escalation of the conflict, while for Ukraine the negative sentiment increase rate is lower—reasonably driven by a feeling of sadness for the fate of the civilians involved in the conflict, as emerges from Fig. 4.

For Abnormal Accounts, the graphs are significantly different. For the aspect term “Ukraine”, positive sentiment rate is very high while negative sentiment rate is very low. Then, starting the conflict, negative sentiment rate increases. Furthermore, it seems that all user categories have started to post more tweets supporting Ukraine after the conflict has begun. This fact may suggest that some of them, baby accounts in particular, have tried to obtain consensus and support for Ukraine, and partially for Zelensky, in Western public opinion.

Figure 8 illustrates the results for “Putin” and “Zelensky”
appear to be negatively correlated. For almost the entire period
peak on 24 February. Instead, the Negative and Neutral trends
constant throughout the considered period, with a very slight
Putin, shown in Figure 8. For each category of accounts,
regard, we can mention the sentiment trend for President
party, affecting public feelings, and possibly others. In this
campaign manipulating OSNs data, e.g., supporting a specific
manipulation, and, more in general, any disinformation cam-
logical sentiments that may suggest disinformation activities,
in Table II. The other values (positive or negative) can be interpreted
as follows: i) $0.01 \leq \rho < 0.19$: weak correlation; ii) $0.20 \leq \rho < 0.39$: weak correlation; iii) $0.40 \leq \rho < 0.69$: moderate correlation; iv) $0.70 \leq \rho < 0.89$: strong correlation; and v) $0.90 \leq \rho \leq 1.00$: very strong correlation. Abnormal and trusted users only have 3 out of 10 statistically significant coefficients. This is because, as showed in Table III, these categories have a low number of tweets compared to the others. A similar effect can be observed for “Zelensky” and “NATO”, the two terms with the fewest tweets in our dataset, as reported in Table II.

**Findings.** One of the main objectives of our qualitative analysis is discovering abnormal patterns within the chronological sentiments that may suggest disinformation activities, such as fake news and sentiments propagation, statistical manipulation, and, more in general, any disinformation campaign manipulating OSNs data, e.g., supporting a specific party, affecting public feelings, and possibly others. In this regard, we can mention the sentiment trend for President Putin, shown in Figure 8. For each category of accounts, it can be seen that the positive sentiment seems relatively constant throughout the considered period, with a very slight peak on 24 February. Instead, the Negative and Neutral trends appear to be negatively correlated. For almost the entire period considered, when one of the two rises, the other one falls by approximately the same quantity, and vice versa. This would suggest that strong supporters of President Putin remained of the same opinion throughout the studied period, while neutral sentiments turned mainly negative following the escalation of the conflict. Though, it is very difficult to argue that there has been a massive campaign, by bot, paid collaborators, or trolls in support of the Russian initiative, as it was stated in a few outlets, at least in the English speaking word. Another finding is the fact that President Zelensky, while having a constant exposure over standard media (TV, newspaper), has not been able to match the popularity on such media over Twitter. Indeed, while the general sentiment towards him is positive, it does not reach remarkable heights. Finally, it is worth noticing that, while the sentiment for President Putin has overall turned negative, the sentiment towards Russia has not suffered an equal decay in popularity. By looking at the results of our correlation analysis, showed in Table IV, we can see a strong correlation for negative sentiment of the term “Putin” among all the user categories, showing a sort of consensus on this subject. In two cases, abnormal/regular and baby/regular, the correlation is very strong. These two pairs of user categories show a moderate to strong correlation on all the aspect terms, highlighting their tendency to react similarly to events related to the conflict. Trusted users, instead, appear less correlated to other user categories, often with relations not statistically significant. These findings may question the ability of celebrities to influence regular users, who appear much more related to abnormal and baby accounts, the main suspects of disinformation. Finally, NATO is the term with the least correlation between users. This means that users’ emotions follow a different trend over time, suggesting that this term is perceived discordantly among the various users.

**Limitations and Future Work.** This study also carries some limitations that can be addressed in future works. First, since our analysis aims to identify disinformation in English-speaking countries, we considered only tweets in English. Including data in other languages will enable the characterization

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TABLE IV: Correlation coefficients for user categories and aspect terms used in our study. NA means that $p$-value is greater than 0.05 for the corresponding coefficient, meaning that the data are not statistically significant and that the observed correlation is likely to be due to chance.

| Abnormal, Regular | Putin, Positive | Putin, Negative | Zelensky, Positive | Zelensky, Negative | Ukraine, Positive | Ukraine, Negative | Russia, Positive | Russia, Negative | NATO, Positive | NATO, Negative |
|-------------------|-----------------|-----------------|-------------------|-------------------|------------------|------------------|-----------------|-----------------|---------------|---------------|
| Abnormal, Baby     | 0.680155        | 0.932604        | 0.756315          | 0.581345          | NA               | 0.806357         | 0.528922        | 0.882537        | NA            | 0.479912      |
| Abnormal, Trusted  | 0.29866         | 0.854751        | 0.632177          | 0.376522          | NA               | 0.469993         | 0.380013        | 0.676954        | NA            | 0.490596      |
| Abnormal, Trusted  | 0.576394        | 0.892003        | 0.722899          | 0.513172          | 0.811141         | 0.560492         | 0.621531        | 0.661773        | NA            | 0.320703      |
| Regular, Baby      | NA              | 0.650923        | 0.664276          | NA                | NA               | NA               | NA              | NA              | NA            | NA            |
| Regular, Trusted   | 0.71285         | 0.528564        | NA                | 0.54641           | 0.238893         | 0.285753         | 0.485874        | 0.268604        | 0.510535      |
| Baby, Trusted      | NA              | 0.7162          | 0.522957          | NA                | 0.419879         | 0.091593         | 0.295671        | 0.45498         | NA            | -0.11086      |
of the information flows in other countries, such as Russia and Ukraine, that can be compared with the results of this study. Second, existing ABSA techniques are not able to discriminate different emotions of the same sentiment, e.g., madness and sadness, love and joy. As a result, if a specific tweet is, for example, negative for both Russia and Ukraine, our analysis does not reveal if the author is mad at Russia but sad for Ukraine, or vice versa. An interesting future work includes the discrimination among different feelings of the same sentiment, refining the results of this study and providing novel insights.

V. CONCLUSIONS

In this paper, we characterize the general-public perception of the first phases of the 2022 Russo-Ukrainian conflict by collecting and analyzing data from Twitter. In particular, we investigated the public perception of the conflict by leveraging statistical analysis and ABSA.

We identified several anomalies in users’ behavior and sentiment trends for some subjects that call for further research in the field. In particular, accounts with a low Friend Rate (FR) tweeted much more than other user categories, with a sentiment trend for some keywords that diverged from other users. Also, the baby accounts daily creation rate suggests that a subset of them was created specifically for tweeting about the conflict. As per the correlation analysis, it shows that all categories of users have similar perceptions of the term “Putin”, with a strong correlation on the negative sentiment. In addition, the sentiments of regular users are correlated to both abnormal and baby accounts, suggesting that they tend to react similarly to conflict-related events.

To the best of our knowledge, we are the first to use ABSA to analyze the Twitter sentiment on the Russo-Ukrainian conflict. The replicability of the experiments and the novel techniques adopted, joined with the gained insights and the highlighted future work, pave the way for further research on the comparative strength and weaknesses of ABSA, and its possible use to study the flow of information on OSNs during high-impact events.

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