Semantic Analysis of Russo-Ukrainian War Tweet Networks

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ABSTRACT

Millions of people around the world continue to express their view on various topics on Twitter everyday. Such data is frequently used to generate and analyze networks of users, tweets and hashtags based on specific actions, such as tweets, retweets, mentions etc. In our study we focus on tweets related to the Russo-Ukrainian conflict. We combine sentiment and network analysis approaches to produce various important insights into the discussion of the conflict. We focused on the most influential actors in the debate as well as uncovering communities of users or hashtags which correspond to either side of the conflict. We discovered that the vast majority of users express support for Ukraine, and that the most important accounts belong to political leaders (e.g. Volodymyr Zelenskyy), relevant organizations (NATO) or media outlets, who actively report on the conflict (Kremlin News). Similarly, most of the relevant hashtags are used predominantly in a pro-Ukraine context, while many of them appear in tweets supporting Russia as well (e.g. #war, #Russia). We have identified numerous communities within the networks, which belong to discussions about the conflict being held in various languages or about various aspects, that the war indirectly affects (e.g. finance & cryptocurencies). Apart from a few very evidently pro-Russia communities, all the groups express support for Ukraine to at least some degree. Future research should focus on more thoughtful data collection and consequently thorough analysis of various aspects of the networks.

KEYWORDS

Network analysis, war in Ukraine, sentiment analysis.

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INTRODUCTION

Twitter has become one of the most important platforms for public response to current affairs. People join in on debates by tweeting, retweeting, hash-tagging, replying to or mentioning other users. In such ways, people tend to form like-minded groups or communities.

Since the beginning of Russia's invasion on Ukraine at the end of February 2022, the conflict has become the prevailing talking point of many mainstream as well as social media outlets. On Twitter, millions of tweets are still made in regards to the conflict every day. This provides an excellent opportunity for in-depth analysis of various social aspects of the conflict. By constructing networks from Twitter data, e.g. as in Figure 1, based on users, tweets, hashtags etc., this study provides answers to important questions about social aspects of the conflict, namely: who are the most important users and what is their role in the debate? Are there specific users or hashtags that are pro-Russia or pro-Ukraine and do they form clear communities, or do communities correspond to some other semantic property? Are there notable differences in tweets being posted before and after the ban of Twitter in Russia?

With the help of modern sentiment and network analysis approaches, this study provides an important high-level view into the conflict. The questions listed above are answered in the following sections. The results are not only interesting to the general public and social scientists for future research, but also to PR professionals, media outlets, and perhaps even world leaders.

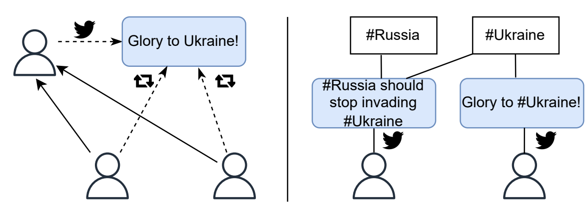

Figure 1: Diagrams of two models of graphs, constructed for our analysis. Left: projected directed user graph based on retweet connections. Right: tri-partite graph between users, tweets and hashtags.

RELATED WORK

Today, social networks play a critical role in online social discourse, particularly during major events such as elections, public affairs, COVID-19 and wars. The authors of [9] and [8] analyzed the elections in the United States and Italy using Twitter data. Study [9] looked at the evolution of the retweet graph over time, focusing on the two main entities. They identified fluctuations in sentiment and measured the volume around each entity. In [8] they used network analysis techniques such as triadic closures, degree-degree correlations, k-core decomposition, and core periphery structure detection to analyze complex semantic structures, prominent topic connections, similar topics within different communities, and how topics animate the discussion over time. They noted that connecting users with tweets using retweets models user preference better than using mentions or replies. In [13] authors analyzed the *who is following who* network to highlight users whose position is particular – important entities. Specifically, they showed that linguistic groups are key factors to explain certain clusters. The authors of [6] used network analysis techniques to visualize different network models on COVID data and used centrality to find the network's most influential hashtags. The authors of [5] used sentiment classification to enhance community detection and vice-versa. Different supervised techniques for sentiment analysis on Twitter, such as Naive Bayes, max entropy, and SVM, are proposed in [14], but those methods are usually used for positive and negative sentiment. With the rise of deep language models, such as *RoBERTa* [10, 11], more complex data domains can be analyzed, e.g., news texts, where authors typically express their opinion and different topic analysis can be done (e.g. republican vs democratic). Authors of [7] used similar models to investigate target-dependent sentiment classification in news articles. A recent study by [16] looked into tweets about the crisis between Ukraine and Russia. They found that most popular hashtags are `#Ukraine`, `#Russia`, `#StandWithUkraine`, `#Putin`, `#UkraineRussiaWar`, and `#StopPutin`. Additionally, they conducted sentiment analysis and tracked daily positive and negative sentiment between Zelenskyy and Putin and between Ukraine and Russia. They verified that the majority of Twitter users support the Ukrainian side and that Putin is the subject of the majority of negative tweets.

RESULTS

General analysis. Using RoBERTa, we first assign a probability (referred to as **pro-Russia score** or **PRS** in the following) of supporting Russia instead of Ukraine to each tweet. The distribution on both datasets is shown in Figure 2. As expected, we observe significant support for Ukraine in the analyzed tweets. On the 65D sample, data collection is less biased (see Data). However, these models can struggle with sarcasm and produce indecisive scores when content is complex or cannot be directly connected to the predicted classes, which explains the peak at 0.5 and heavier right tail on aforementioned dataset. We also found no noticeable difference in distributions of pre- and post-ban PRS. We constructed 4 main networks for our analysis: a projected hashtag network, two projected user networks based on different types of connections (mentions and retweets) and a tri-partite user-tweet-hashtag network. Basic statistics of the networks are seen in Table 1.

Hashtag network connects hashtags that co-appear, with edge weight representing the number of co-appearances. Each node has two attributes: the number of tweets it appeared in and it's PRS, calculated as the mean of these tweet PRSs. The network is scale free and small-world. Mean PRS in LCC equals to 0.29, while mean PRS of nodes outside of it is 0.42.

Table 1: Network statistics.

network type	data	n	m	$\langle k \rangle$	LCC
hashtag	65D	17k	79k	9.16	84%
user (retweet)	25M	167k	189k	2.26	62%
user (mention)	25M	79k	115k	2.91	76%
tripartite	25M	571k	924k	3.24	83%

n - number of nodes, m - number of edges, $\langle k \rangle$ - average node degree, LCC - largest connected component

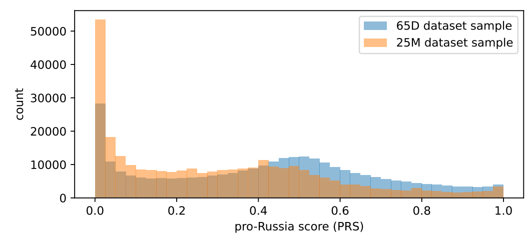

Figure 2: Distribution of tweet pro-Russia score (PRS) on 300k data samples.

We ran PageRank on the network, separated hashtags into pro-Ukraine (PRS below 0.4) and pro-Russia (PRS above 0.6) and selected the most important ones in each group. It turns out that most important pro-Russia hashtags are `#istandwithputin`, `#csto` (post-Soviet intergovernmental military alliance) and `#notmypresident` (references Biden), while the most important pro-Ukraine hashtags are `#ukraine`, `#standwithukraine` and `#nato`.

To see how hashtags form groups on Twitter, we used Infomap on the LCC, filtered out small clusters (less than 15 hashtags) and calculated their average PRS. The largest cluster includes common hashtags like `#ukraine`, `#russia`, `#nato`, `#putin` and has average pro-Russia probability of 0.38. The most pro-Russia cluster, with mean PRS of 0.58, is clearly representing American republicans. The second one, with similar PRS is connected to Kazakhstan protests. Five out of ten top pro-Russia clusters tweet about different types of investments: stock market, cryptocurrencies, commodities, forex, etc. with average PRS around 0.5. The most pro-Ukraine clusters are heterogeneous, but some talk about transport, helping refugees, or represent different languages (German, Ukrainian) or groups (tech, fashion, art) showing their support.

In Figure 3 we can see the main core of the network, obtained with k-core decomposition, where $k = 51$. All 89 hashtags in it have less than 0.5 PRS, with a mean PRS of 0.29. We conducted a permutation test as we hypothesized that the main core is significantly more pro-Ukraine than a random subgraph of the same size. We estimated the average PRS of 10,000 randomly selected subgraphs and compared it to the PRS of the main core. It was lower in 25%, indicating that it is not completely random, but with a p-value of 0.25 we are unable to confidently claim that it is significantly pro-Ukraine.

User retweet network is a directed, scale free network, which we tried to visualize and find different clusters on (similar as in [13]). Figure 4 shows a sub-network of the retweets network; we filtered out nodes with $k < 5$ before taking only nodes in the largest connected component. There are four well-defined clusters, each of which was annotated based on it's distinguishable topic. The

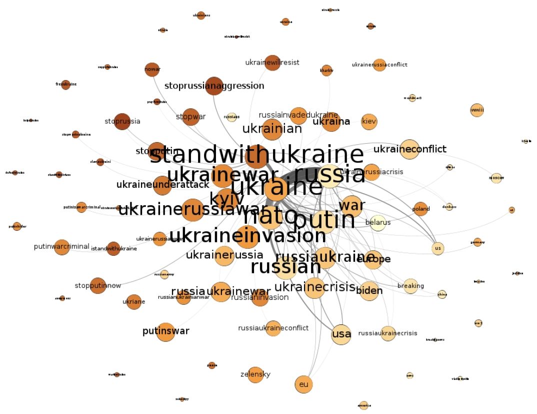

Figure 3: Main core (k=51) of hashtag network. Edge thickness is proportional to hashtag co-appearance and node size to number of appearances. Some thin edges are hidden. Lighter color of nodes represents higher PRS. From **`#stoprussia`** (0.06) to **`#belarus`** (0.47). We can observe a strong connection between **`#ukraine`** and **`#russia`** that appear together in many tweets and a well defined color gradient over the network.

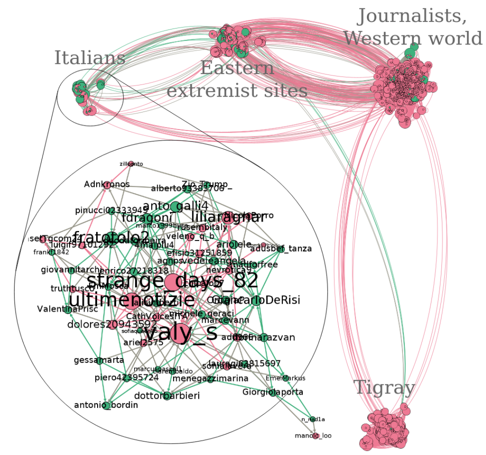

Figure 4: Sub-network of retweets network, consisting of nodes with $k \geq 5$ and nodes within LCC ($n = 8575$, $m = 47851$). Red color represents pro-Ukraine users and green color represents pro-Russia users. Size represents in-degree of the node.

cluster on the left is zoomed in at the bottom. This is the only cluster that is dominantly pro-Russia and it represents a group of Italian-speaking users. After digging deeper into this data, we discovered that it is annotated as pro-Russia, because their tweets are interpreted as slightly pro-Russia by the model, e.g. (translated): *"Of which side should we take sides now? From Italy and the Italians who will pay more..."*, but they do not strongly side with Russia, with mean PRS 0.56. We observe a high density of edges between the "Eastern extremist" and "Journalists and the Western World" clusters, which is a result of the fact, that Eastern sites occasionally post explicit content, which the other cluster frequently retweets. The Tigray cluster is particularly interesting because the main topic of discussion is not the Ukraine war, but rather the Tigray war. Users in this cluster frequently express their belief that the Western world only reports on and aids in the fight against wars in Europe, but is unconcerned about the war in Ethiopia.

On the same network, we used the PageRank algorithm to determine the most influential pro-Ukraine users: `lesiavasylenko` (member of the Ukrainian parliament), `HannaLiubakova` (Belorussian journalist), `nexta_tv` (the largest Eastern European media) and pro-Russia users: `MauriceSchleepe` (Russian news), `ejmalrai` (veteran war journalist) and `Charles_Lister` (Syrian reporter).

Mentions network is a scale free network, on which we tried to find most influential users. PageRank returns the following pro-Ukraine users: `zelenskyyUa`, `POTUS`, `nato` and pro-Russia users: `createimagic` (suspended account), `kevjmclaughlin` (suspended account) and `needlesineyes` (misclassified by the model as a pro-Russian).

Additional analysis. On above user networks, we were unable to find similar core-periphery structure results as with hashtags, using k-core decomposition. However, we have found significant assortativity based on PRS, with a coefficient of 0.37 on the user (retweet) network.

On the tri-partite network, the 5 largest communities found by Infomap cover 35% of the network and contain the main discourse about the conflict in English. However, the communities which follow by size have an immediately distinguishable property, such as language – Spanish (16k nodes), Thai (11k), French (9k), German (8k), Italian (7k), Indian (6k) etc., or other topics such as hackers (6k), NFTs and Cryptocurrency (6k), etc. These communities are notably pro-Ukraine with average PRS 0.3. Only the 26th largest community with 3k nodes has been found to be noticeably pro-Russia with PRS 0.68 and popular hashtags such as `#istandwithputin`.

DISCUSSION

To summarize, we analyzed two Twitter datasets and found similar results. The majority of tweets are in favor of Ukraine, with many being falsely labeled as pro-Russia as a result of the nature of our process of semantic inference. Here we highlight the community of Italian users, which are mostly labeled as slightly pro-Russia, although this is not apparent from the tweets. However, we have identified a few communities of pro-Russian accounts, many of which have been suspended.

Nevertheless, we observed no differences in the ratio of pro-Russia to pro-Ukraine tweets between pre- and post-ban of Twitter in Russia, as we might have expected. This is likely to be due to the specifics of data collection in our case. When it comes to the most important actors in either side of the debate, we identified important politicians such as Zelenskyy and the US President as well as NATO to fill that role for the pro-Ukrainian side, as we might have expected. Important supporters of the Russian side include local media outlets and influential independent journalists. As expected, we found that most users tend to retweet posts from users with a similar stance on the conflict.

When it comes to hashtags, we found that all the most popular ones are primarily used in a pro-Ukraine setting, even e.g.

`#Russia`, which frequently co-appears with `#Ukraine`. Clusters in the hashtag network show that American republicans tend to be pro-Russia. They use `#notmypresident` in reference to Joe Biden, making them side with Trump and consequently (on average) with Russia. While the core hashtags are noticeably pro-Ukraine, others from the periphery are more neutral as they do not directly address the conflict.

Unfortunately, aside from identifying various linguistic communities (most of which were found to be pro-Ukraine), location data was mostly lacking and thus inappropriate for analysis. This could be further looked into in future research alongside a more in depth temporal semantic analysis. A shortcoming of this analysis was the data collection process, which was here bypassed and should be addressed appropriately (considering e.g. balance, completeness).

We suggest using information from various platforms, for example *VKontakte* and *Weibo* (considered as Russian and Chinese Twitter respectively), for a potential future work. In a sense, the data would be less biased in this way, since it would broaden the scope of the research onto those who don't use Twitter.

METHODS

Data. We found two datasets connected to the conflict. The first dataset [2], was gathered from Jan 1, 2022 to Mar 5, 2022, using certain keywords for the search, such as `ukraine war`, `russian troops`, `ukraine troops`, etc. The second one [3], has over 25 million tweets and has been updated on a daily basis since February 27, 2022. It contains tweets whose geolocation was found to be in Ukraine or they contained hashtags such as: `#SlavaUkraini, #Russia, #RussiaUkraineWar, #Putin, #ukraineunderattack`, `#StopPutinNow`.

For our analysis, we constructed random subsamples of the two datasets of size 300k, in order to decrease computational complexity while preserving structural properties we were interested in analyzing. We label these two samples as 65D and 25M respectively.

Because information about retweets is only contained in the 25M dataset from Apr 23, 2022 onward, we prepared an additional 300k sub-sample which contains only such data to construct our retweet-based user network.

We argue that the results reported on these subsamples are representative of the full data and that they retain the structural properties of interest. By sampling multiple graphs of the same size and calculating the standard deviation for the average node degree ($\sigma_{\langle k \rangle} = 0.003$) and the largest connected component ($\sigma_{LCC} = 1.5\%$), we validated that different randomly sampled subgraphs retain these properties.

The structure of the graphs was also examined by computing the Jaccard index, which is a statistic used for gauging the similarity and diversity of sample sets. When looking at nodes with degree > 50, we discovered that 80% of nodes overlap between different samples. We also assessed the degree difference for each node that appears in both graphs at the same time and discovered that the difference is modest ($diff = 12.5 \pm 0.2$), implying that local structure is preserved across all samples. Because the standard deviation of the aforementioned statistics across different samples is failry small, we realized that the global and local structure of the graphs matched across samples.

Methods & algorithms. In order to perform semantic analysis, we use a 0-shot pre-trained multilingual model [1], based on BERT. This transformer-based state-of-the-art language model has been successfully used in different fields of Natural Language Processing and especially for the task of Twitter data classification [17]. The model used for our analysis takes as input query text (e.g. a tweet) and a possible set of labels. In our analysis, we used the labels "support Russia" or "support Ukraine". The model semantically interprets the inputs and computes a probability distribution over the set of labels. The probabilities represent the likelihood of the query text being associated with the respective labels. This is a simple but effective technique of labeling our data, which allows us to also assign probabilities to users or hashtags, based on tweets they are directly connected to by averaging. By using a different set of labels for our tweets, namely: "pro Russia" and "pro Ukraine", we observed a high Pearson correlation coefficient of 0.83, showing the model's semantic understanding capabilities.

For the rest of our analysis, we resorted to Infomap for community detection and k-core decomposition for analysis of the networks' core and periphery, PageRank centrality for measuring importance of nodes, Pearson correlation for evaluating assortativity based on PRS and permutation test for evaluating PRS significance of subgraphs. For our flexible visualizations, we relied on Gephi software. We selected Infomap for community detection, because it proved to be a reliable method during our previous work. In [12] they show its consistent performance over synthetic and real datasets. K-core and PageRank were selected because their algorithms (described in [4] and [15]) simulate the behaviour of Twitter users. PageRank simulates how a user would surf over Twitter, by clicking on users mentioned in tweets of the user whose feed he is scrolling (similarly with hashtags). K-core shows the most important users/hashtags by iteratively deleting those that are connected to least others, and thus have lower probability that someone would click on them.

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