The University of Hong Kong

BSDS3002 Social Computing Methods and Applications

Group 4 Project Report

Computational propaganda in the Russo-Ukraine War:

A network analysis

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Abstract

Since the outbreak of the Russo-Ukrainian War in 2022, an information war that consists of computational propaganda and misinformation has also occurred to fight for support from the public and damage the credibility of the opposing side. In this research, a data-driven approach has been adopted to investigate the network characteristics of pro-Ukrainian and pro-Russian tweets. The tweets and users are differentiated based on their political stances regarding the war. We manually classified popular hashtags into 'Pro-Ukrainian', 'Pro-Russian', and 'Neutral' to determine users' political stances. While the trends of pro-Ukrainian tweets and tweets with non-identifiable hashtags remained consistent throughout the investigated period, the number of pro-Russian tweets only peaked on Twitter a few days after Russia declared war on Ukraine and before the domestic block of Twitter in Russia. In addition to network attributes, we also found different propaganda strategies employed by the two sides, with Pro-Ukrainian tweets using more explicit hashtags and political bots, and Pro-Russian tweets leading the propaganda narrative but using more neutral hashtags to gain exposure.

1. Introduction

1.1. Background

Since 2014, Russia has annexed Crimea. Russia has been occupying areas of the south-eastern regions of Ukraine. Russia has waged many conflicts over the years (Global Conflict Tracker, 2022). Until October 2021, Russia sent over 190,000 troops to the Ukrainian border and began to spark the Russian-Ukrainian crisis. On 24 February 2022, Russia launched a full-scale assault on Ukraine, and the Russian-Ukrainian War began. In the following days, Russia's offensive continued to heat up (The Economist, 2022; Bloomberg, 2022). In addition to armed attacks, many cyberattacks and computational propaganda have happened (Goldenziel, 2022). The online information war is another battlefield.

According to the PropOrNot Team (2016), Russian attempts at computational propaganda are nothing new. They usually attempted computational propaganda in three steps. Firstly, Russian affiliated media outlets create false or misleading content. Secondly, Russia used force multipliers, such as trolls and bots, to disseminate and amplify these contents, adding fear-mongering commentary. Finally, Russia used mutually reinforcing digital entities to pick up and perpetuate the narrative. Russia usually achieves three goals by using computational propaganda, and the goals are affecting public opinion, elections and political events. Therefore, in the current war, Russia is likely to employ similar propaganda techniques (Trauthig, 2022).

1.2. Theoretical Framework

The aim of this research is to investigate the role of social media in the Russo-Ukrainian War by looking into our two research questions:

Research Question 1 (RQ1): How do the network characteristics differ on the pro-Ukrainian and pro-Russian sides?

Research Question 2 (RQ2): How do the network dynamics of users change before and after Russia banned Twitter domestically?

To answer our research questions, a data-driven approach has been adopted. Specifically, to characterise the networks of users with the classification approach to determine their polarisation regarding the Ukrainian War based on popular hashtags that show support for one side (e.g. #IstandwithUkraine/#IstandwithRussia; #Putinisawarcriminal/#Zelenskyisawarcriminal).

By comparing the network between different groups of users with comparative network analysis, it can provide insights into the core questions in social and political science, such as understanding the behaviour and role of the users in a group (Siegel, 2011).

With the advancement of information technology, the internet can be easily accessed by billions of people around the globe and become part of our lives. Recent research has indicated that more than half of the American population (57%) receives their news and information from social media platforms, namely Facebook and Twitter (Walker & Matsa, 2021). As opinions are freely exchanged on the internet, computational propaganda and internet misinformation is emerging to be a tool for different groups and organisations to manipulate people. Compared with fact-checked information, social media users tend to share polarised and false information related to politics more (Vosoughi et al. 2018). It shows that the flow of fake news on social media platforms could pose a great threat to the public easily.

Since the outbreak of the Russian-Ukrainian war, the Russian government has been pushing their agenda and fake information regarding the war with their State-affiliated media on various western social media platforms. Meta, a parent company of Facebook, announced they uncovered a network of Russia-backed new entities and fake personal accounts that spread disinformation across different social media platforms (Milmo, 2022a).

According to Sanovich (2017), the Russian government is known to use bots and trolls on the internet as propaganda tools to support Putin's leadership from being challenged and sabotage the political credibility of the West for their gains. In the first research question on examining the the difference in the network characteristics between pro-Ukrainian and pro-Russian users on Twitter, our the goal is to find out the differences in user activity between the two groups and the implication of different propaganda strategies used by the two sides.

To combat the disinformation flow regarding the war, Twitter and Facebook have since banned numerous state-affiliated news entities from Russia. In response to the ban and the overwhelming amount of positive news and anti-Russian government information on the said social media platforms, the Russian government banned most popular western social media platforms, including Twitter, Facebook, and Instagram, restricting the access for all the Russian citizens (Milmo, 2022b). Our second research question aims to investigate the difference in networks for both sides between the period before and after the ban of Twitter issued by the Russian government.

2. Methodology

The code of the below-described analysis can be accessed in this Github repository: https://github.com/Yvonne27Jin/BSDS3002GP_Computational_propaganda_Ukraine.

2.1 Data source

2.1.1. Twitter API

First, we tried scraping tweets via the application programming interface from Twitter ("Twitter API"). However, this method has technical constraints for three reasons: (1) Twitter restricts users to 180 requests per 15-minute time window, thus we managed to collect only a relatively small dataset; (2) Without a researcher's access, it is not possible to collect data older than 7 days; (3) As Twitter reacts to fake news, some tweets and users may be determined as disinformation and were labelled or even removed (McSweeney, 2022; Khalid, 2022). Therefore, a pre-collected dataset scraping tweets in real-time and updated daily in Kaggle was used as the data source.

2.1.2. Kaggle Dataset

The Kaggle dataset, named *'Ukraine Conflict Twitter Dataset (27.59M tweets)'*, was contributed majorly by 'BwandoWando', 'stpete_ishii' and 'oliver' and was released per the CC BY-NC-SA 4.0 Licence. Starting on 27 February 2022, the team started to scrape tweets using Anaconda notebooks running on Microsoft Azure ML in real-time, extracting tweets every 15 mins monitoring relevant hashtags pertaining to the Ukraine-Russia conflict. The hashtag list was updated with new datasets in the meantime. The advantage of this dataset is that it is up-to-date, and comprehensive, containing information on tweet content, hashtags and user information. Hence, it captured politically sensitive tweets that were deleted or censored. The details of data processing will be indicated in the next section.

2.2. Data preprocessing

2.2.1. Data Sampling

We sampled 2% of the Kaggle dataset with tweets for the duration of 18 days counting from 24 February 2022. The selection of duration is decided based on the day when the Russo-Ukrainian War officially started (24 February) and the day when Twitter was blocked by the Russian government (4 March) (Psaropoulos, 2022). We chose to investigate the information landscape for an equal time range of 9 days before and after the domestic ban of Twitter. Hence, the two-time range is "Pre-blocking" (24th Feb to 4th Mar), and "Post-blocking" (4th Mar to 13th Apr) respectively.

The sampled dataset contains 161,628 tweets with user information on user id, username, location, user-created timestamp, following count, followers count, total tweets count, and tweet information on language, tweet id, tweet created timestamp, retweet count, hashtags, and the text content.

2.2.2. Hashtags processing and User categorization

We extracted the list of hashtags and their occurrences in the dataset. From the list, we chose the most frequent 507 hashtags which appeared more than 45 times in the dataset. These criteria were determined by a reasonable number of hashtags to manually label the political orientation. Each hashtag was assigned True/False values per category: pro-Russia, pro-Ukraine, or Neutral. Categorization was done in a liberal way so the side stance was given to those hashtags which have a literal meaning of supporting aside. After the first attempt, there were 5 pro-Russia, 108 pro-Ukraine, and 394 neutral hashtags. After the in-group cross-checking and external consultation with a political science master's student, some hashtags were relabelled. Finally, the dataset was concluded with 2 pro-Russia, 93 pro-Ukraine, and 412 neutral hashtags (see examples in Table 1).

Pro Russian	**Pro Ukrainian**	**Neutral**
#IStandWithPutin	#StandWithUkraine	#Ukraine
#istandwithrussia	#StopPutin	#Russia
	#SafeAirliftUkraine	#Putin
	#UkraineUnderAttack	#UkraineRussiaWar

Table 1. Examples of hashtags' categories after manual labelling

Each tweet in the dataset was assigned a political stance based on the hashtags in the tweet test: Pro-Russia, Pro-Ukraine, Both, or Neutral. Category "Both" was given for those users which had both sides' hashtags, and category "Unknown" was given to the tweets with no labelled hashtags. We then summed up the tweets of the same user by assigning pro-Russia tweets a -1 score, and pro-Ukraine tweets a +1 score. The final score, named as political orientation index, was used in the subsequent analysis and visualisation.

2.2.3. Text ID creation

In order to create bipartite users-tweets networks and for easier nodes' management in the analysis we created text ids by extracting unique tweets (n=105,158), generating a unique index and assigning it to the tweet text.

2.3. Bot Identification

We used Botometer API which "checks the activity of a Twitter account and gives it a score based on the extent to which it matches accounts that use automation. Higher scores indicate activities that are more bot-like". This API provides 500 free account checks per day (without requiring a credit card) and provides the scores for 6 bot types: **fake_follower** (bots purchased to increase follower counts), **self_declared** (bots from botwiki.org), **astroturf** (manually labelled political bots and accounts involved in following trains that systematically delete content), **spammer** (accounts labelled as spam-bots from several datasets), **financial** (bots that post using hashtags), and **other** (miscellaneous other bots obtained from manual annotation, user feedback, etc.) (Sayyadiharikandeh et al., 2020).

The scores by the API are given considering both: the English and the universal language of the Twitter account, thus each account receives 12 different scores, as well as 2 Complete Automation Probability (CAP) values, which are the conditional probabilities that account with a score equal to or greater than this are automated. Comparing the overall bot score with CAP value we categorised an account as a bot or not.

Because of API limitations, we used it on sampled data. Small number sampling and checking with the API process were repeated several times instead of sampling a bigger number and checking one time because the latter approach took too long (>400 minutes) and did not produce results. In total, 570 accounts were sampled of which 522 were unique.

2.4. Network Construction

We divided the database into two-time frames (24th February 2022 to 4th March 2022 and 5th March 2022 to 13th March 2022) as aforementioned. The methodology for network construction and analysis is identical for two-time frames to allow direct comparison.

For each time range, we constructed a bipartite network in which the two types of nodes represent users and tweets respectively, and undirected edges represent the action that the user tweeted or retweeted the tweet content. We then project the bipartite network onto user nodes and tweet nodes respectively. For the one-mode projected user network, the (undirected) weighted edges represent that the two users shared the same tweet content, with the weight representing the number of same tweets they both shared. Notably, the edge does not represent a direct retweet action, nor that they are connected on Twitter. But a higher weight represents a higher likelihood of the two users sharing and consuming similar political information sources and sharing a similar stance.

We visualised the networks using Gephi (Bastian & Jacomy, 2009). For positioning nodes, we applied the Fruchterman Reingold layout algorithm, a layout with efficient processing time and a clear presentation.

3. Results

3.1. Discussion trends by political stance

Figure 1 plots the most frequent words in tweets for 2*2 two comparisons: time range (before and after Russia blocked Twitter domestically) and political stance (pro-Ukrainian or pro-Russian hashtags used in the text).

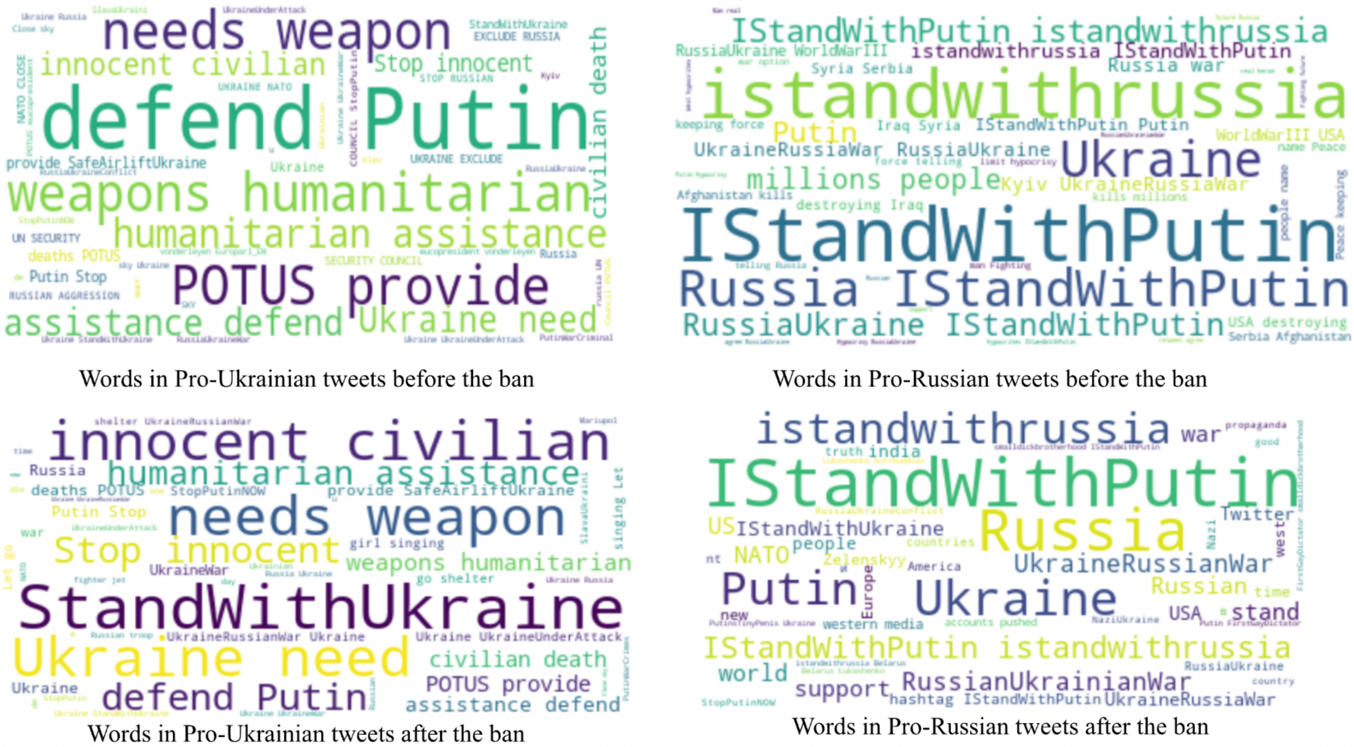

Figure 1. Word Clouds of the most frequent words in tweets

Table 2 shows the number of tweets before and after the ban of Twitter issued by the Russian government. Comparing the number of tweets between the two periods, the overall number of tweets has increased after the ban (+20.4%). As for the number of Pro-Ukrainian tweets, a 61.19% increase has been recorded after the ban. On the other hand, the number of pro-Russian tweets has significantly decreased from 393 tweets before the ban to 166 tweets after the ban (-57.96%).

Tweets containing	Before the ban (24th Feb - 4th Mar)	After the ban (4th Mar - 13th Apr)	Difference
Pro-Ukrainian hashtags	10375	16723	+6348 (+61.19%)
Pro-Russian hashtags	393	166	-227 (-57.76%)
Hashtags of both stances	38	34	-240 (-10.53%)
Neutral hashtags	62527	71372	+8845 (+14.15%)
Total No. of tweets	73333	88295	+14962 (+20.4%)

Table 2. Change in discussion prevalence by political stances

Figure 2 displays the distribution of tweets throughout the whole time frame by our classified political stance. Just before the Russian government issued the ban of Twitter on 4th March, there was a sudden increase in the number of pro-Russian tweets from 1st March to 2nd March but drastically decreased afterward. After 4th March when Twitter was officially banned in Russia, the number of pro-Russian tweets steadily decreased while the number of pro-Ukrainian tweets increased progressively.

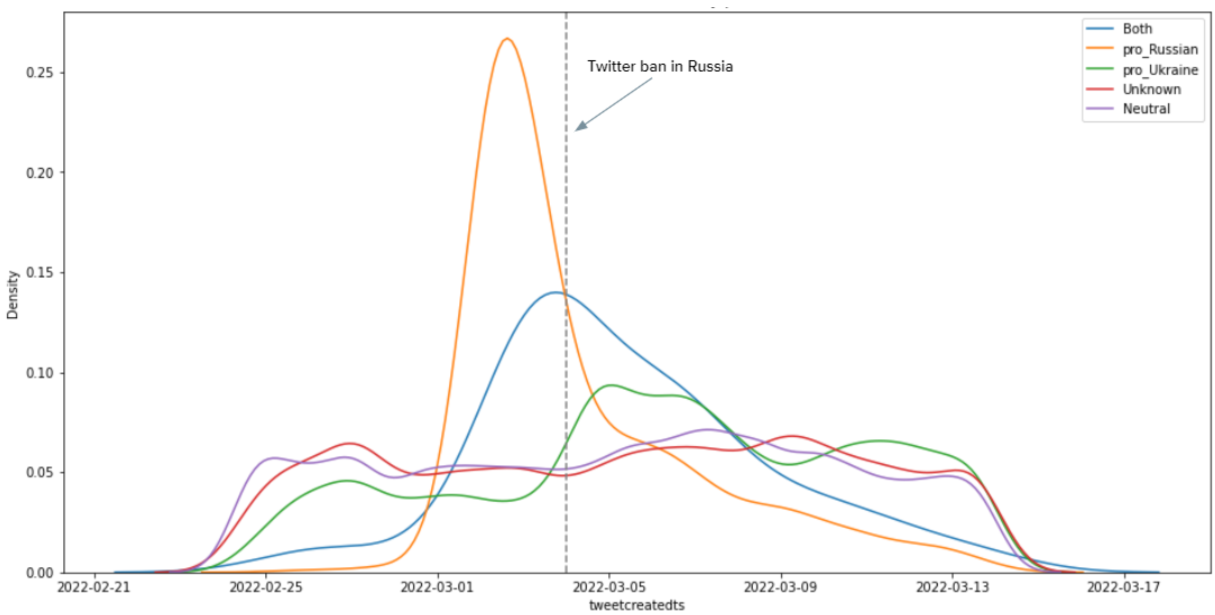

Figure 2. the distribution of tweets over time

By further looking into the distribution of tweets created over time, figure 3 shows that since 24th February, the day Russia declared war on Ukraine, the pro-Ukrainian tweets have increased and remained steady at an average of 750 to 1000 tweets per day. Since 3rd March, right before the ban, the pro-Ukrainian tweets skyrocketed from 1000 tweets to 2250 tweets. Unlike the pro-Ukrainian tweets, the number of pro-Russian tweets remained very few or none on the first few days after the declaration of war, but only started increasing on the 1st March to around 200 tweets and soon decreased to 50 to 100 tweets afterward (figure 4). After the ban, the number of pro-Russian tweets remained under 40 tweets per day and continuously decreased, although there was a slight increase on 9th March, generally, the number of tweets kept decreasing to lower than 10 tweets a day at the end of the time frame.

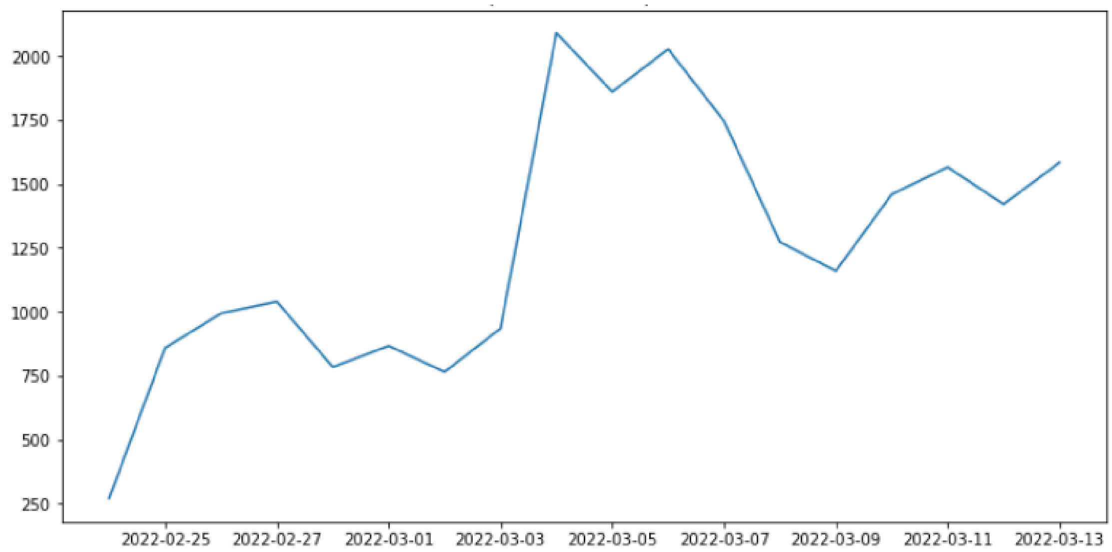

Figure 3. Tweets timestam distribution in pro Ukrainian tweets

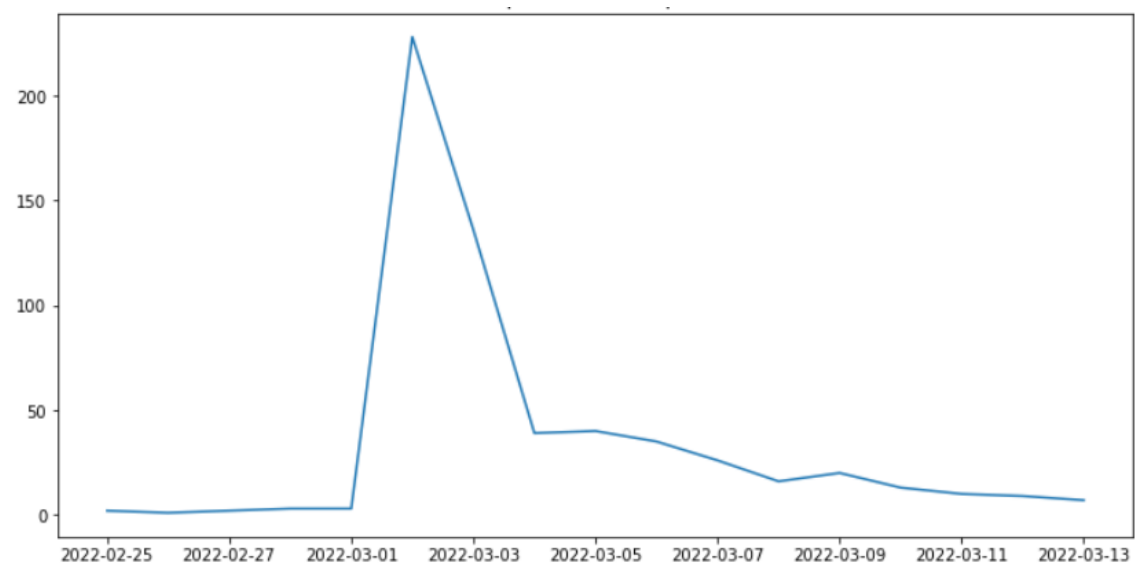

Figure 4. Tweets timestam distribution in pro Russian tweets

3.2 Network analysis

3.2.1. Bipartite Network

We constructed a bipartite network with 130,608 user nodes, 105,158 tweet text nodes and 161,429 edges for the sampled dataset. To facilitate further analysis, we sliced the dataset into pre-blocking (24th February to 4th March 2022) and post-blocking (5th March to 13th March 2022) subsets and performed an identical analysis. Table 3 summarises the size of the two bipartite networks.

	Pre-blocking Network (24th Feb - 4th Mar)	Post-blocking Network (4th Mar - 13th Apr)
No. nodes (Unique Users)	66530	72022
No. nodes (Unique Edges)	49702	56463

Table 3. Size of the pre-blocking and post-blocking bipartite networks.

3.2.2. Projected User Network

The projected bipartite network of users before and after the ban was both weighted, undirected and unconnected. The network properties are listed in Table 4. The density statistics of either of the networks are low and represent the proportion of possible relationships in the network that are sparse and less cohesive. Furthermore, the network diameters and clustering coefficient presented that the network is relatively low in proximity and graphs are less compact.

	Pre-blocking *(24th Feb - 4th Mar)*	Post-blocking *(4th Mar - 13th Apr)*
No. of Nodes (Users)	66532	72025
Isolated nodes	37012	36454
No. of Edges	403244	959639
No. of connected components	6011	4934
No. of nodes in the largest component	3066	18048
Density of the largest component	0.0467	0.0056

Diameter of the largest component (lower bound)	35	16
Global clustering coefficient	0.3338	0.3823
Global number of Triangles	114207915	422158848
Average degrees	142.9987	101.1282

Table 4. Global properties of one-mode projected networks

In the degree centralities part, since the limitation of algorithms, only the largest connected components from both networks were analysed respectively. For the result from the pre-ban network, we may find that nodes have a little different ranking in different degree centralities. We may see that there are three prominent nodes: node #1317819683169574913 (i.e. user 'rshafagatov') which has the highest degree of centrality and eigenvector degree centrality, node #3084343625 (i.e. user 'MadBaltic') has the greatest betweenness degree centrality and node #278893199 (i.e. user 'PebbleGreen2') has the highest closeness degree centrality. That represents that the tweet from 'rshafagatov' had been very actively retweeted which is also evidenced by the retweet counts of two posts. 'MadBaltic' might influence the community and take control of the communication between other humans in the social network which can be shown in the increasing number of tweets. The measure also shows that 'PebbleGreen2' had the best place of influence among all other nodes, which can be testified by his or her follower numbers. The common identity of all three users is that they posted pro-neutral and informative tweets instead of pro-Ukraine or pro-Russian: only one tweet from 'MadBaltic' has emotional wordings to express his or her view on the excellence of such news. This condition changed after the social network was banned in Russia, as we found that the prominent nodes have been changed to node #1277603521261522946 (i.e. user 'angel16802919'), node #278893199 (i.e. user 'PebbleGreen2'), node #3084343625 (i.e. user 'MadBaltic') and node #391167104 (i.e. user 'BrandiLynn4Ever'). The news shared, although it is still neutral, became more about issues happening to individuals in Ukraine and the choice of words became more emotional (e.g., 'Nice', '100%', 'Fucking'). The unchanged one is that people still seem to prefer news sharing.

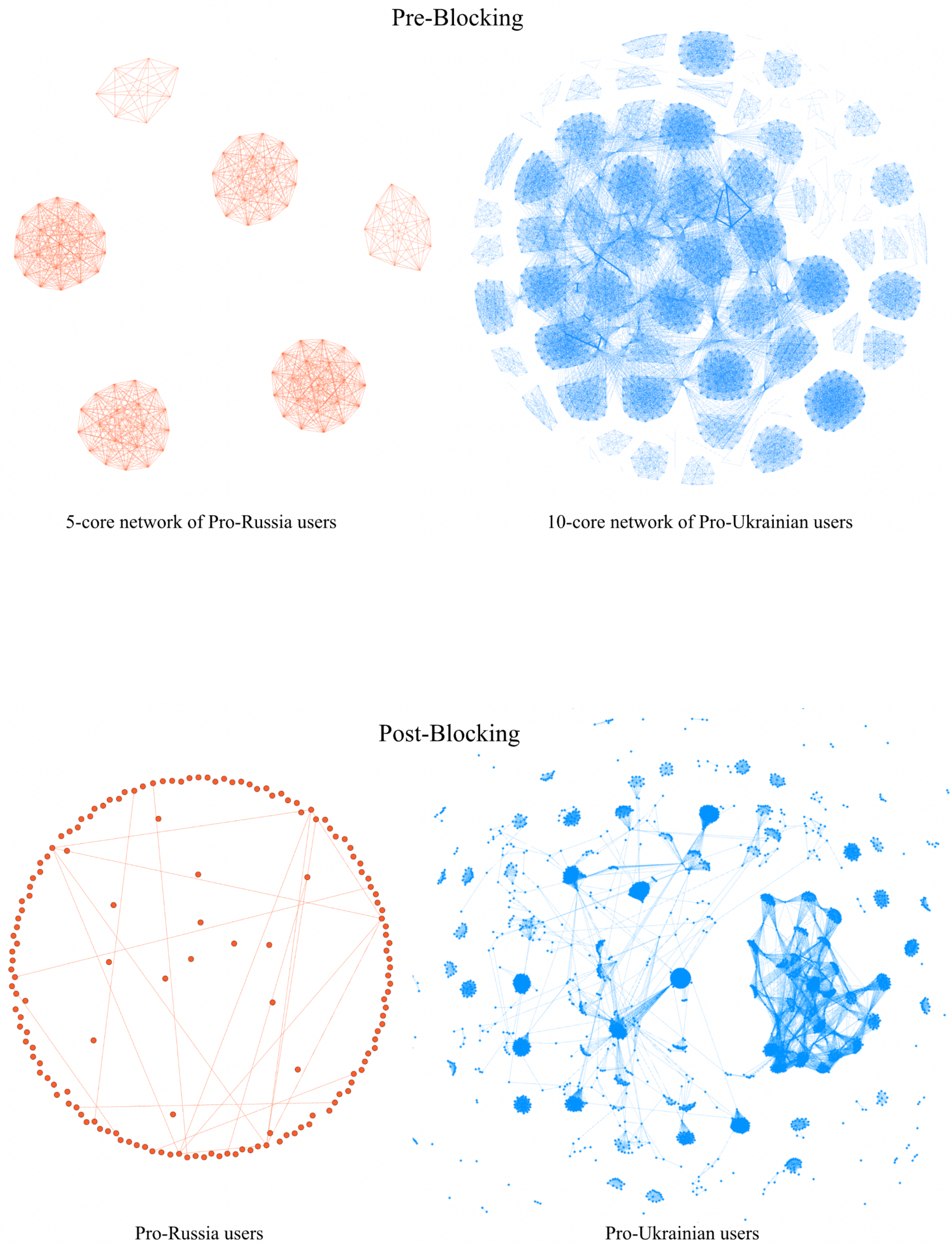

Figure 5. Pro Russian and Pro Ukrainian networks before and after the Twitter ban

3.3 Bot detection

The total number of checked accounts was 522. The numbers of checked accounts per group were: 126 Pro Russian before the ban, 120 Pro Russian after the ban accounts, 137 Pro Ukrainian before the ban, and 139 Pro Ukrainian after the ban. (Table 5.) The percentage of bots in the pro-Russian group during the post-ban time has increased by 55,56% compared to pre-ban time from 7 % bot-like accounts to 12 % bot-like accounts. The percentage of bots in the pro-Ukrainian group has increased by 13,64% from 16 % bot-like accounts to 18 % bot-like accounts.

Group	N		Number of Bots (%)		Mean (EN)		Mean (UNI)	
	Before	After	Before	After	Before	After	Before	After
Pro Russian	126	120	9 (7%)	14 (12%)	0.421	0.386	0.374	0.375
astroturf			0	10				
fake_follower			6	2				
other			3	2				
Pro Ukrainian	137	139	22 (16%)	25 (18%)	0.446	0.461	0.372	0.359
astroturf			3	7				
fake_follower			5	3				
other			7	8				

Table 5. The number of bots in Pro Russian and Pro Ukrainian group samples before and after the ban

An increase in **astroturf** (manually labelled political bots and accounts involved in following trains that systematically delete content) bots by 10, decrease in **fake_follower** (bots purchased to increase follower counts) bots by 4, and decrease in **other** (miscellaneous other bots obtained from manual annotation, user feedback, etc.) bots by 1 are seen in Pro Russian group after the Twitter ban.

In the pro-Ukrainian group, there was an increase in **astroturf** bots by 4, **other** bots by 1, and a decrease in **fake_follower** bots by 2. In neither of the groups, there were no **self_declared, spammer,** or **financial** bots.

The overall increase of bot-like accounts in the pro-Russian groups suggests that posting from real users decreased, potentially because of the domestic Twitter ban in Russia. However, this implication needs a more in-depth analysis of user locations.

3.4 Propaganda narrative

To understand how the propaganda narrative affected public opinion on Twitter, we filtered tweets with the keywords frequently used in Russian propaganda, and plotted the trend of tweets by political stance identified from hashtags.

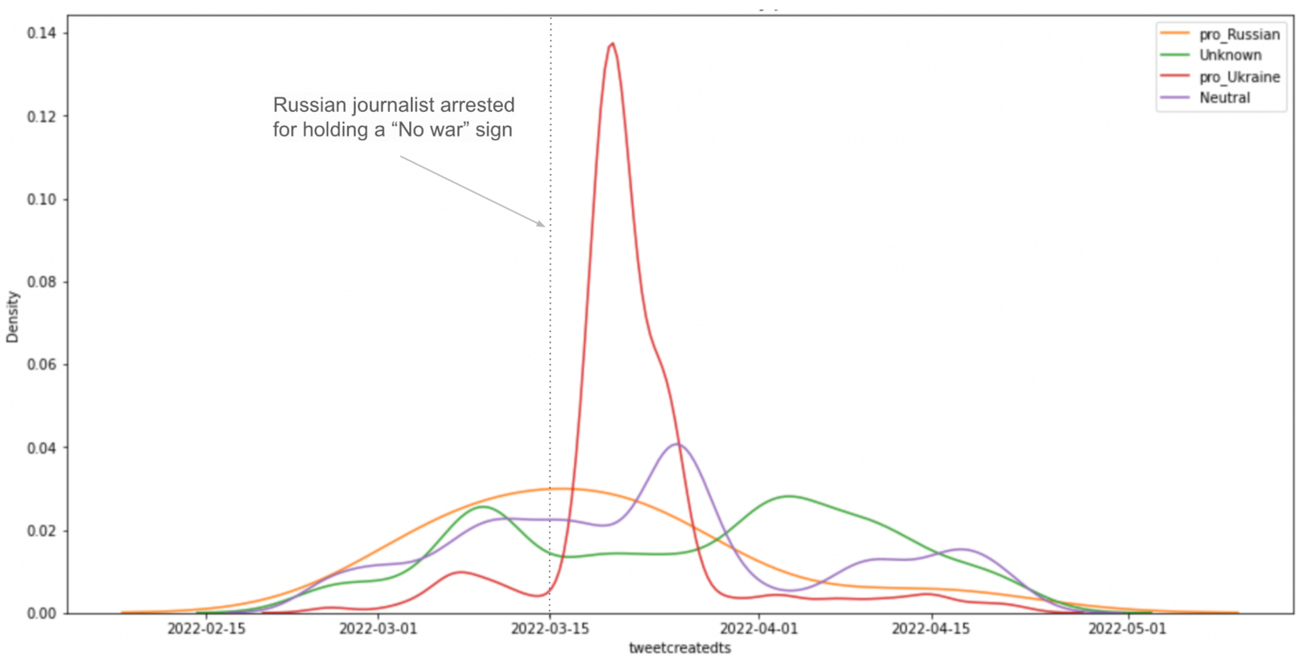

Figure 6. Tweets with keywords "Special military operation" distribution over time

For tweets containing the keyword "special military operation", a term coined by Putin in the press conference on 24th February 2022, the day that Russia launched a military attack. Initially, Pro-Russian tweets used the term most frequently. On 15th March, a Russian journalist and editor working for State-controlled Channel 1 protested by holding a "No war" sign on TV and was arrested, detained, and interrogated for 14-hours. The term "special military operation" peaked in pro-Ukraine tweets in astonishment at Russian enforcing a law prohibiting citizens from calling the conflict a "war" or "invasion". Many tweets used the term in quotation as a direct reference in rebuttal.

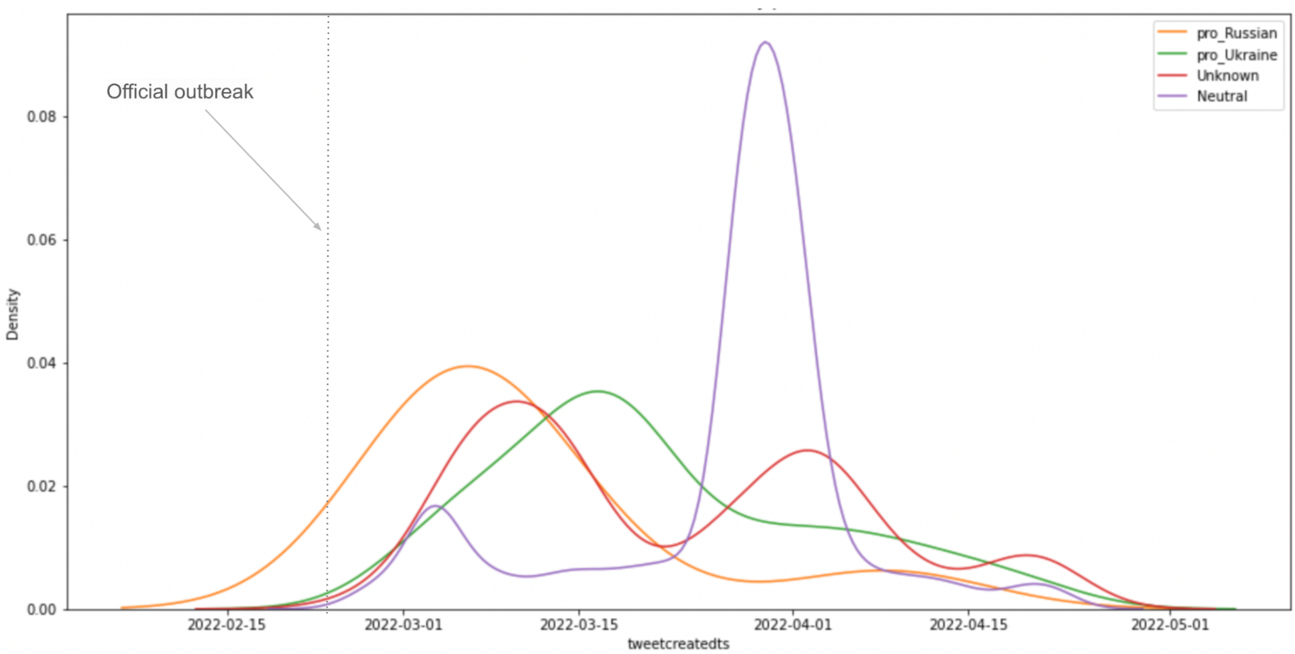

Figure 7. Tweets with keywords “Neo-Nazi” or “Fascists” distribution over time

For tweets containing the keyword “Neo-Nazi” or “fascists”, another term frequently used in Russian propaganda to justify the invasion as saving Russian speaking citizens from the “fascist” treatment by the Ukrainian government, it is clear in the graph that pro-Russian tweets are the first to use this term, even before the outbreak of the war, when the situation was tense in early February. For

the peak in late March with tweets using Neutral hashtags, we see a repeating pattern of pro-Russian arguments using neutral hashtags, such as the example:

“Max Blumenthal: the US is Arming Neo-Nazis in #Ukraine https://t.co/uDspTHpH4Q”

Hence, this signifies a different propaganda strategy from the pro-Ukrainian stance of using explicit hashtags. Rather, pro-Russian tweets are more likely to use neutral hashtags in the text while expressing anti-Ukrainian arguments. By doing this, they gain more exposure than using explicit hashtags.

4. Discussion

4.1. Strengths and limitations

By utilising the well-maintained and organised dataset from Kaggle, the time required to collect primary data was saved. However, as it is not tailor-made for our discussion, the data processing time would be longer due to excessive data. Also, it is too time-consuming to contrast a full network of retweets, therefore, only part of the data was sampled. In addition, by manually clustering the tweets into pro-Ukrainian and pro-Russian with the classification of the hashtags, although it could save time from collecting samples and training a classifier, it is still hard to objectively determine the polarisation as the hashtags could be irrelevant or used by both sides. Besides, some data might be left out of the discussion in Ukrainian and Russian. People in Russian may use their own social platforms like VK. Moreover, as we only identified English tweets, the native language in Ukraine and Russia is not English.

We have also adopted the use of 'Botometer' API, a tool that is trained by a machine-learning algorithm to calculate the score of the likeliness of an account for being a bot. By using a tool that is trained by a well-maintained algorithm, it provides us with a more objective and accurate way to locate the bot accounts. But according to Herring and Delwiche (2018), a machine learning algorithm may still be deceived by some 'obvious' bot or human accounts, such as categorising "organisational accounts" as bots.

4.2. Directions for Future Research

Firstly, this study only sampled and analysed the part of the dataset from Kaggle of public discussion on Twitter related to the event. It would be more meaningful and interesting to know the comprehensive sampling in various online discussion platforms over the world. Therefore, further studies could explore and investigate deeply and comprehensively, such as different online social media platforms like Facebook, Instagram, Reddit, Weibo, YouTube, etc. The above research results could be more representative, comprehensive, and convincing as they can include as much data as possible.

Secondly, this study only used hashtags to categorise the comments of the user belonging as pro-Ukrainian, pro-Russian, or natural. It could reduce the chance of analysis errors if the sampling also includes the comments' contents in various languages instead of just hashtags. Therefore, further studies could adopt ML multiclass categorization to learn from data, identify patterns and make decisions with minimal human intervention to examine more accurate results.

5. Conclusion

In this research we aimed to investigate computational propaganda trends in the Russo-Ukraine war by analysing war-related tweets. First, we wanted to identify general differences and/or similarities in Pro-Russian and Pro-Ukrainian side networks (RQ1). Second, we tried to find out network differences after Russia banned Twitter domestically on the 4th of March, 2022 (RQ2). To answer the questions we conducted data analysis on the Kaggle dataset "*Ukraine Conflict Twitter Dataset"*. We sampled 2% of the data within 9 days before and 9 days after the Twitter ban in Russia. In total, 161,628 tweets and retweets were analysed.

Political stance categorization based on the literal meaning of the hashtags in tweets identified only 2 pro-Russian, but 93 pro-Ukrainian, and 412 neutral hashtags which produced disproportional group sizes. In total, our dataset contained 96,528 Neutral, 37,371 Unknown, 27,098 Pro-Ukrainian, 559 Pro-Russian, and 72 Both (users who used both, pro-Ukrainian and pro-Russian hashtags) categorised users. We have found that the number of pro-Ukrainian tweets greatly outnumbered the number of pro-Russian tweets, meaning that there are more pro-Ukrainian users on Twitter. And before the declaration of war, while there were already pro-Ukrainian tweets exchanged on Twitter, pro-Russian tweets only appeared on Twitter a few days after Russia declared war on Ukraine. It could be interpreted that pro-Ukraina users are more active on Twitter compared to pro-Russian users.

“Botometer” API was used to check Twitter accounts. The amount of bot-like accounts has increased in both, pro-Russian and pro-Ukrainian, groups after the Twitter ban. The increase of bot-like accounts on the pro-Russian side was higher (+55,56%) than on the pro-Ukrainian side (+13,64%). The significant increase of bots in the pro-Russian groups might be explained by the Twitter ban which potentially reduced the number of real user accounts.

The majority of bot-like accounts in pro-Russian groups before the Twitter ban were classified as fake followers, whereas after the banned number of astroturf - manually labelled political bots and accounts involved in following trains that systematically delete content - bots increased. In the pro-Ukrainian groups before and after the ban, the majority of bot-like accounts were classified as “other”. No self_declared, spammer or financial bots were found in the samples.

After Russia officially banned access to Twitter on 4th March, the number of pro-Ukrainian tweets continuously increased while the number of pro-Russian tweets decreased, which could contribute to the assumption that most pro-Russian tweets are made by Russian people. In addition, a sudden increase in the number of pro-Russian tweets right before the ban could be noticed. This phenomenon cannot be easily justified and requires further socio-political analysis.

Although the network analysis shows that people on Twitter also seem to be more likely to view and retweet the news sharing posts, the preference for news has been changed to those with more emotional wordings and focusing on specific individuals after the ban.

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