Social Media and Network Analysis

Assignment 2

"Tracking Propaganda on Twitter During the Russian Mobilisation, and annexation of Ukrainian territories"

Table of Contents

Contents

List of Figures

List of Tables

Introduction

On the 20th of February 2022, the Russian Federation invaded Ukraine. With large amounts of resources available to both governments, a considerable amount of political propaganda has been deployed via the internet. The Russian government has its fit for purpose department dedicated to online political propaganda [1], called the 'internet research agency', which has previously been indicted in the US for attempts at influencing the 2016 election [2]. The Russian propaganda model has been described as a 'firehose of falsehoods', characterized by high intensity repetitive false posts with no commitment to consistency, designed to overwhelm the recipient rather than convince them [3]. Pro-Ukrainian propaganda has tended to be more focussed on improving military morale, with examples such as the false "ghost of Kyiv" war hero story, refuted by the Ukrainian military itself. In between the opposing sides lies civilians and organizations from around the world.

Multiple investigations have been made into patterns of twitter activity regarding the war. Shevtsov and colleagues [4] collected a large dataset of tweets regarding the war, and found that most tweets were in English, with a more positive sentiment towards Ukraine than Russia. Smart and colleagues [5] found a large influx of bot accounts at the start of the war, and that there was a high information flow between these accounts and authentic ones. They found a correlation between the average sentiment of bot and non-bot accounts, and that bot accounts tended to drive conversations towards topics of angst, work and governance.

The data collected on this event is vast and large, and so this report dives into not just the broader war's social media state, but also focuses in on the event of the annexation of 4 territories of Ukraine when Vladimir Putin signed "accession treaties" [6] on the 30th September 2022. This report will focus on a few research questions; What are the central areas of influence geographically? Who are the most influential figures or entities on the war? What are their backgrounds? What communities exist on this topic? What are the communities' backgrounds, views, and beliefs? What side are they most like affiliated with? These 5 questions will be the basis for exploring propaganda reach, and the influence impact of said propaganda. To find answers to these questions, many methods were employed to achieve these goals, which we further discuss below. We hypothesize that this topic will contain significant amounts of propaganda and/or inauthentic activity, and that individual authentic activity will be highly polarized.

Methods

Data Scraping

The Twarc python library [7] was used to scrape 2 datasets. The first, which we will refer to as the 'mobilisation' dataset, was collected with the streaming API and contained 494,473 tweets from the 22nd of September (the day of the Russian mobilisation announcement). This dataset was obtained for the purposes of detecting communities in the overall conversation surrounding the war, and thus keywords that broadly covered the topic were chosen. The specific keywords used were:

"Russia OR Ukraine OR Donbass OR Luhansk OR Crimea OR Kherson OR Kharkiv OR Putin OR Zelensky OR Zaporizhzhia"

Another dataset to do with the "illegal" annexation (according to international law) [8] was created with the following keywords: "Putin annex Ukraine". This produced a dataset containing over 33511 tweets over the course of 3 days. The dataset is called the "Annex Dataset" for the remainder of this report.

Data Pre-processing

Tweets in the dataset were translated into English using the google translate API via the deep-translator library [9]. All URL's, tags and non-alphanumeric characters were removed. For graph analysis, an edge list was created using twarc2 network [10]. The edges of the graph were weighted according to the number of replies, retweets, quotes, and mentions between two twitter users in the network, which were represented as nodes. Networks were also created using both tweets as nodes, and hashtags as nodes. The graph was spaced using the force atlas 2 algorithm in Gephi [11]. Visualizations of the mobilisation dataset can be seen in Figure 3. Pre-processing the tweets to be used in a word cloud for topic analysis required the text to be tokenised, and the hashtags to be removed. This also included removal of URLs and links.

Data Analysis

The Sklearn library was used for decomposition, and feature extraction, and the wordcloud library was used to produce word clouds from the sklearn model. The CountVectorizer feature extractor model was used to fit, transform and vectorize the tweets. The feature number was 1500, which produced the model using the decomposition Latent Dirichlet Allocation (LDA) to further fit the vectorizer using the online method, and a max iteration of 10 to then produce a single topic. This topic was visualised into the word clouds. The NDLib library was used to model information diffusion across the whole network. Both independent cascades and general threshold models were implemented.

Three community detection algorithms were attempted using the NVIDIA rapids library for GPU accelerated analysis [12]. These were Spectral Modularity Maximization Clustering (SMMC), Spectral Balanced Cut Clustering (SBBC), and Ensemble Clustering for Graphs (ECG). ECG [13], an extension of the Lovain algorithm, was chosen as the final method due to its ability to determine communities without arbitrarily specifying the number of groups to be returned.

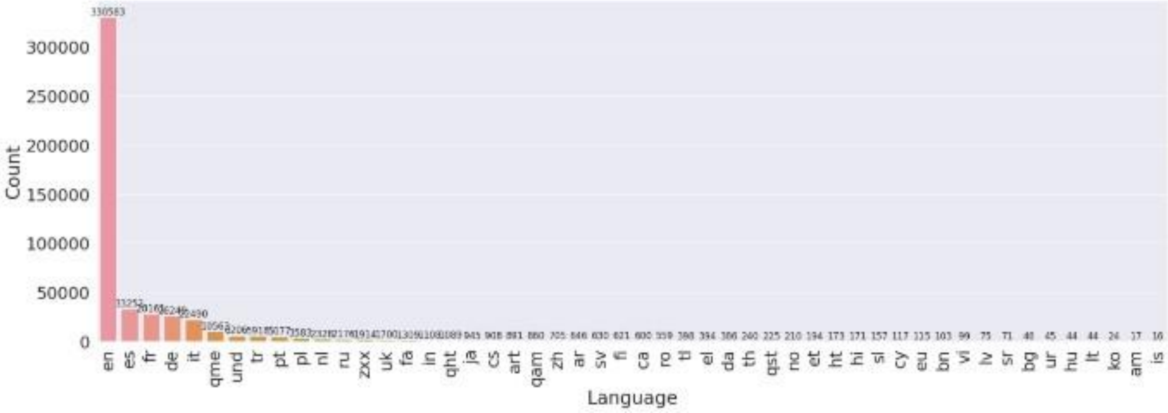
The average propaganda score for a random sample of communities was calculated using a distil-RoBERTa model [14] fine-tuned on 19 classes of propaganda, which were consolidated into 2 classes; a propaganda score and a non-propaganda score. Additionally, the average amount of days since account creation was calculated for these communities. The resultant scores were sorted to determine which communities likely contained the most sockpuppet accounts and/or propaganda.

Results – Mobilisation dataset

Exploratory Data Analysis

Results confirmed Shevtzov and colleagues' findings that most tweets regarding the war were in English. The second most common language was Spanish, followed by French, German and Italian. Russian was the 12th most spoken language, and Ukrainian was 14th. The distribution of languages can be seen in Figure 1. Figure 2 shows the distribution of account creation dates.

Figure 1. Distribution of languages spoken in the mobilization dataset



The distribution is positively skewed with approximately 100,000 accounts created less than a year before data collection. Visualizations of the mobilisation dataset graph can be seen in Figure 3. Top k hashtags and a hashtag graph can be found in Figure 4.

Figure 2. Distribution of days since account creation for the mobilization dataset

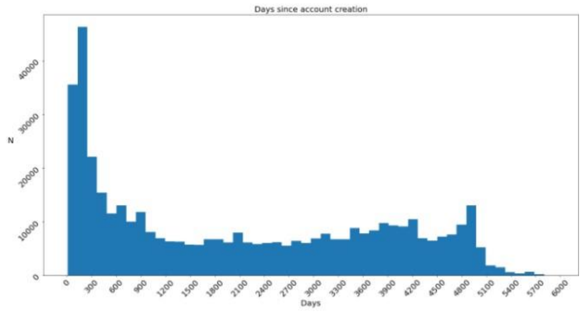
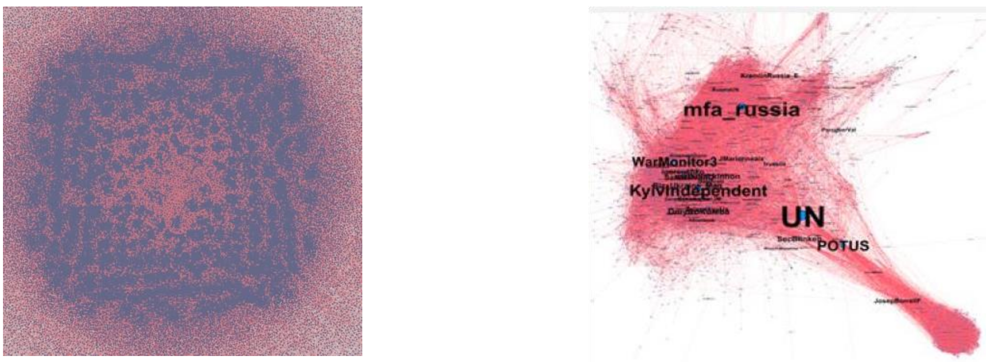


Figure 3 Visualizations of the mobilisation dataset

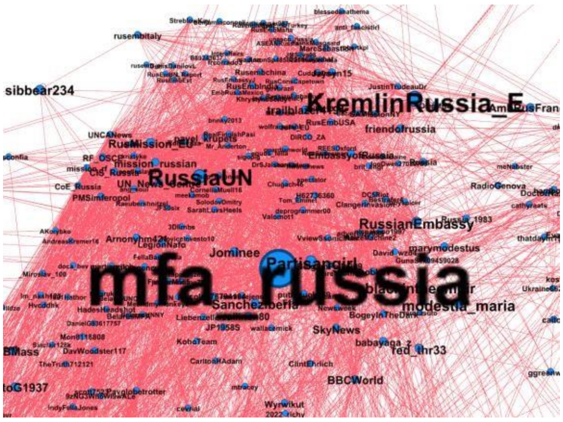
(A)
Full network graph, with 240,981 nodes represented in blue and 512,862 edges represented in red.

(B)
The graph filtered to 4296 nodes with a degree of 23 or more (40,392 edges). Node text size based on total degree



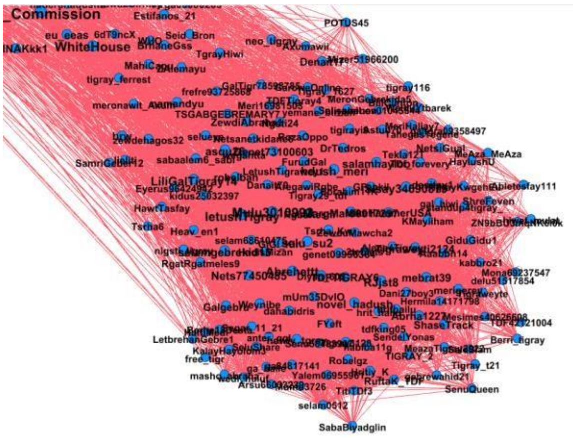
(C)

Subset of the filtered graph dominated by Russia supporting accounts



(D)

Subset of the filtered graph dominated by accounts advocating for Tigrayans in Ethiopia



(E)

A subset of the overall graph dominated by Ukraine-supporting accounts

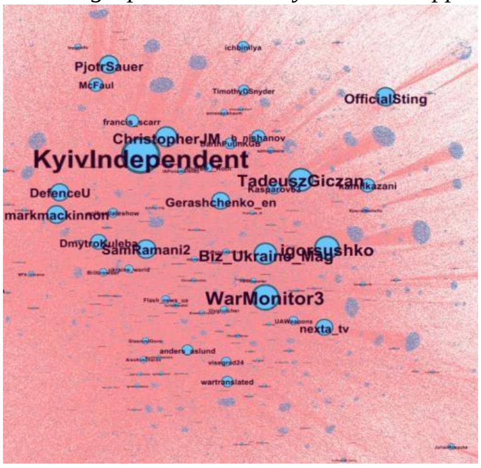
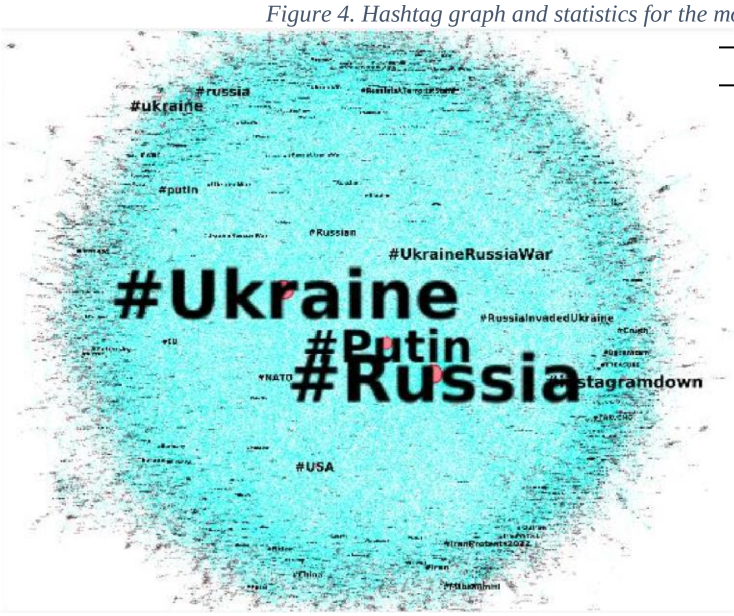


Figure 4. Hashtag graph and statistics for the mobilization dataset



Hashtag	Count
#Ukraine	24,036
#Russia	16,174
#Putin	9,863
#StopWarOnTigray	7,201
#TigrayUnderAttack	5,860
#UkraineRussiaWar	3,583
#MahsaAmini	2,642
#OpIran	2,233
#UNGA77	2,070
#Tigray	1,792
#Zelensky	1,760
#Russian	1,616
#UNGA	1,613
#Iran	1,585

Centrality Measures

Betweenness centrality was calculated over the entire dataset with a k of 100,000. The results (See Table 1) correspond with the larger nodes in the graph visualizations (Figure 3). Apart from official accounts for the UN, the US president, Kyiv Independent and Russian foreign ministry, various independent influencers can be seen. “Igor Sushko” is a proukrainian independent individual with a large reach. “TadeuszGiczan”, “PjotrSauer” and “MarkMackinnon” are journalists covering events in the war. “WarMonitor3” is a war reporting account that forwards information such as frontline maps and videos, created in March 2022.

Table 1. Most central accounts in the mobilisation dataset, calculated with betweenness centrality (k = 100,000)

Username	Centrality
KyivIndependent	0.0597
TadeuszGiczan	0.0330
UN	0.0314
WarMonitor3	0.0302
igorsushko	0.0272
Biz_Ukraine_Mag	0.0271
POTUS	0.0271
mfa_russia	0.0268
PjotrSauer	0.0244
markmackinnon	0.0239

This result was contrasted with results of the HITS algorithm, which returned many of these central accounts, albeit with others including SamRamani2, a pro Ukrainian professor of internation relations; DmytroKuleba, the Ukrainian minister for foreign affairs; ChristopherJM, a journalist with the financial times; and Geraschenko_en, an advisor for the Ukrainian minister of internal affairs.

Table 2. Hub and Authority Scores resulting from the HITS algorithm

Username	Hub Score	Authority Score
KyivIndependent	0.002593	0.002593
WarMonitor3	0.001619	0.001619
Biz_Ukraine_Mag	0.001304	0.001304
SamRamani2	0.001207	0.001207
DmytroKuleba	0.001117	0.001117
Igorsushko	0.001112	0.001112
markmackinnon	0.001109	0.001109
Mfa_russia	0.001102	0.001102
ChristopherJM	0.001078	0.001078
Gerashchenko_en	0.001063	0.001063

Information Diffusion

Experiments with information diffusion showed a strong resistance to information cascades. This is to be expected given the distribution of interaction weights (See Figure 8). 69% of weights (N = 352,065) had only one interaction. Results of the independent cascade model can be seen in figure 5, and the general threshold model is visualized in figure 6. We consider ‘infected’ to mean an interaction along the chain of an information cascade including replies, quotes, mentions, or retweets. Even a threshold of 0.01 only resulted in 40% of nodes being present in the cascade.

A search was conducted over the graph, between relevant central accounts (POTUS, VlodomyrZelensky, VladamirPutin) to see which accounts mostly mediated between them. A breadth first search revealed that none of the accounts had a direct interaction with each other. The inverse of the edge weights was calculated, and a shortest path was calculated between each pair. This shortest path represented the path with the most interactions between the two accounts due to the inverted weights. The account ‘anupkradhan’ was the biggest mediator between the accounts of Putin and Zelensky. Anupkrpradhan turned out to be a proselytizer who regularly tagged multiple world leaders in their preachings. After excluding this account from the graph, the path returned was through; (1) 'sibbear234', a strongly prorussian propagandist account; (2) 'guerini_lorenzo', the Italian minister of defence, and (3) 'Luigi65810766' a suspended account, accused by others of having been a bot.

POTUS and Zelensky had a single largest mediator, ‘onestandard4all’, a proukrainian account. The path between Putin and Potus was longer, involving; ‘MarcSebastion’ an account that had been banned for hateful conduct; ‘Mfa_russia’, the Russian ministry of foreign affairs, and ‘MartinEkvonu’, a Nigerian activist who regularly tags world leaders.

Figure 5. Independent cascades model; initial infected = 0.1, threshold - 0.5

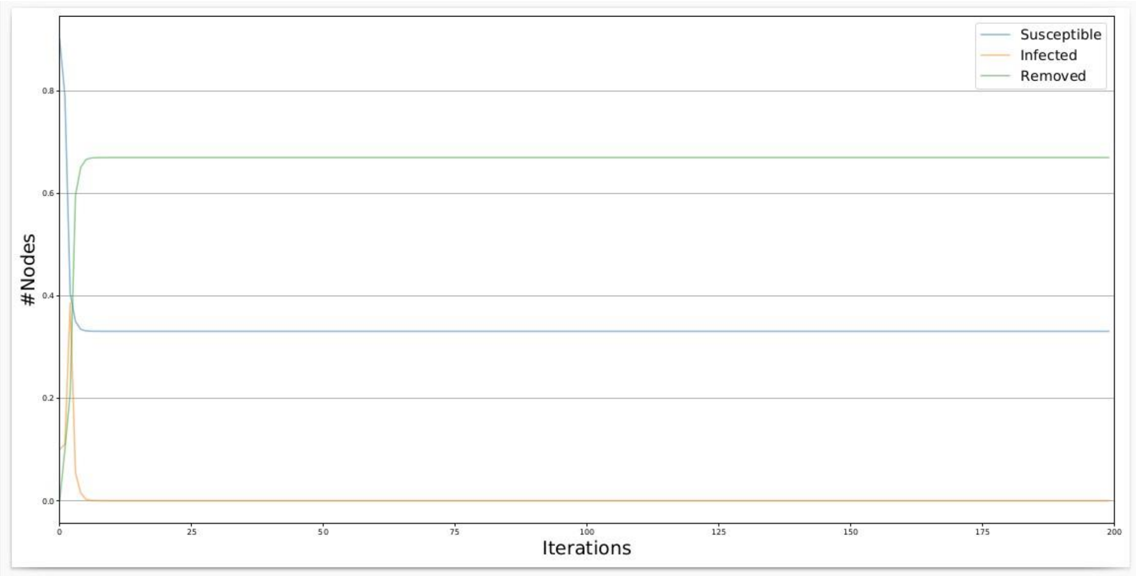
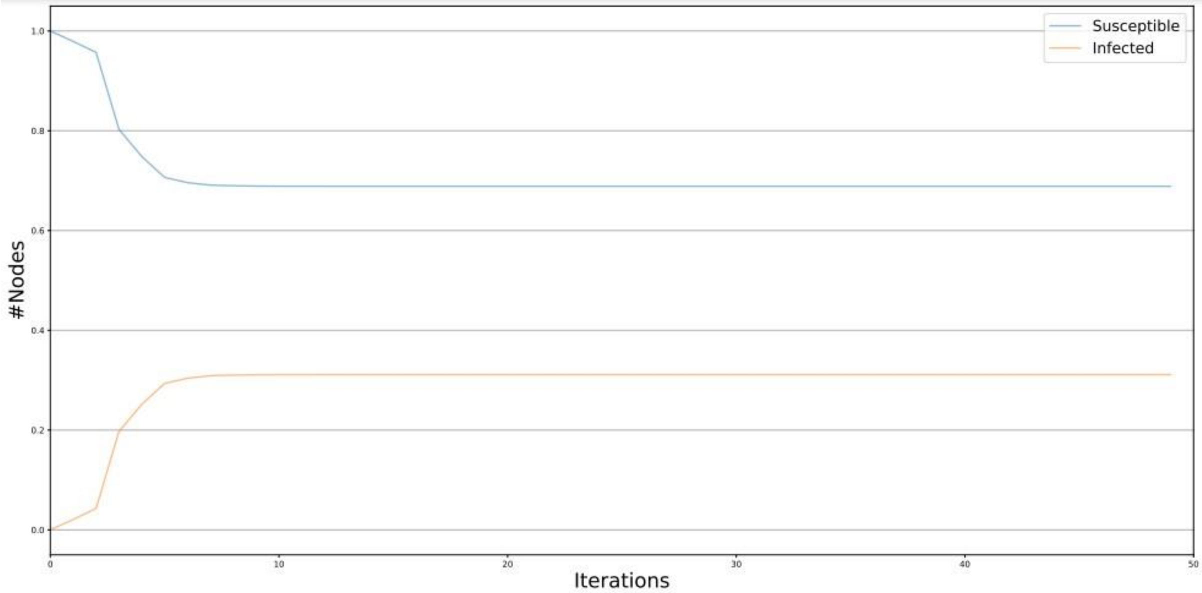
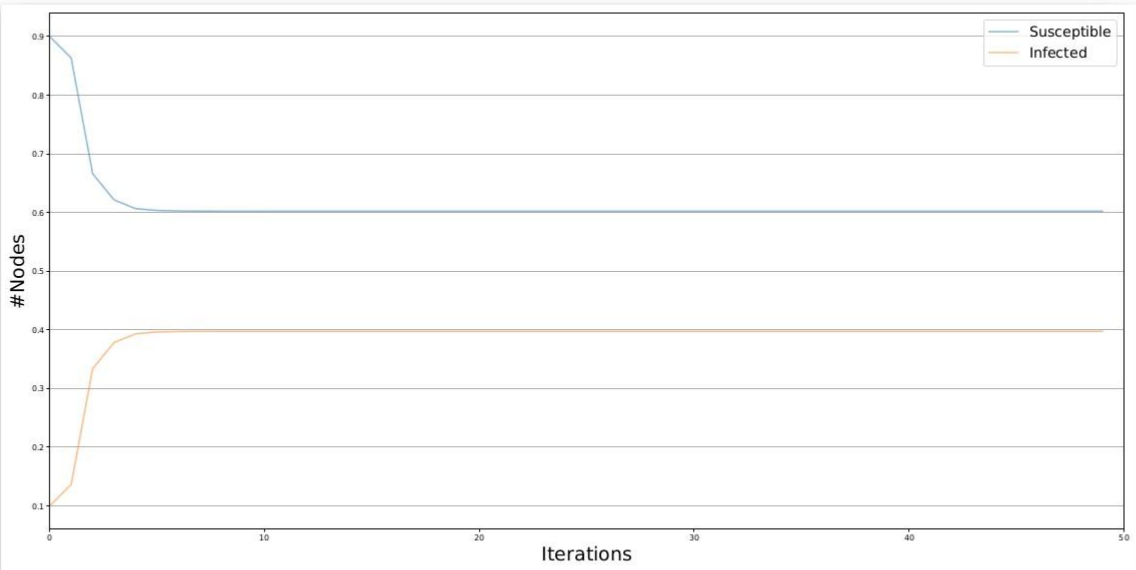


Figure 6. General threshold model; initial infected = 0.1, threshold = 0.01



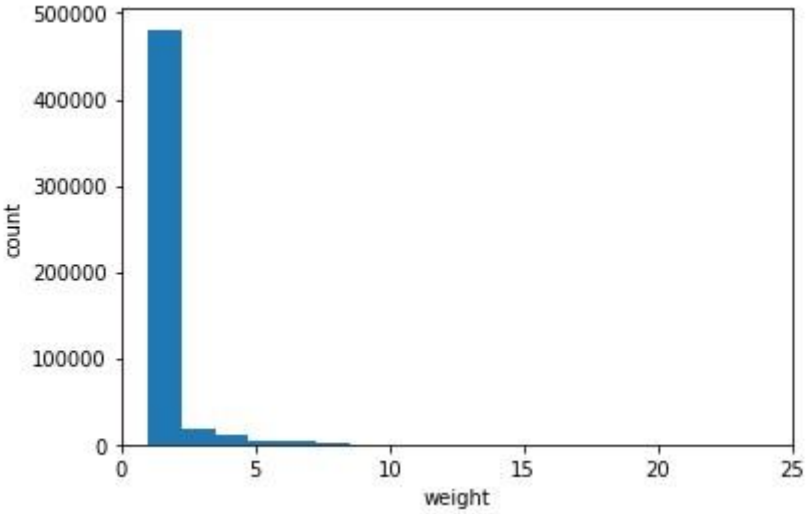
The models modelled an outbreak with 1% of all accounts, or 2,409 accounts in the dataset. Another simulation was performed with the general threshold model, and threshold of 0.01. However the initial infected population was set to the union of the top 10 hubs/authorities, and accounts with the top 10 centrality scores. As can be seen in figure 7, the top 14 accounts almost reached the same spread as 2409 picked at random.

Figure 7. General threshold cascade from the top 14 accounts; threshold = 0.01



Community Detection

Figure 8. Distribution of interaction weights over the full mobilisation dataset



518 communities were returned by the ECG algorithm. Communities with the highest propaganda score can be seen in figure 9. Communities with the smallest average amount of days since account creation are visualized in figure 11. The most propagandist (community 111), and least average days since creation (community 51) communities were further analysed. Hashtag graphs of these communities can be found in figure 12.

There was a statistically significant, mild correlation (R = 0.15, $p = 0.0003$) between a community's propaganda score, and average days since creation, such that accounts that had existed for longer had higher propaganda scores. See figure 10 for a scatterplot of this result

Figure 9 Top 4 most propagandist communities

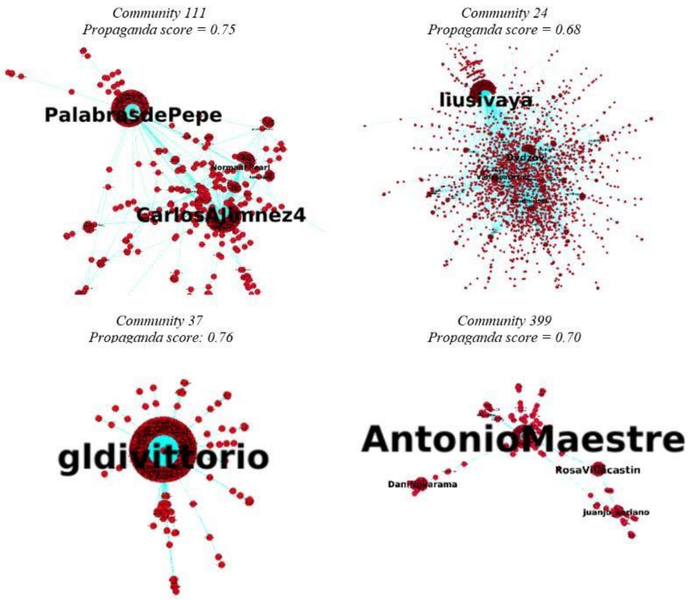


Figure 10. Scatterplot between average days since creation and propaganda score over a random sample of communities

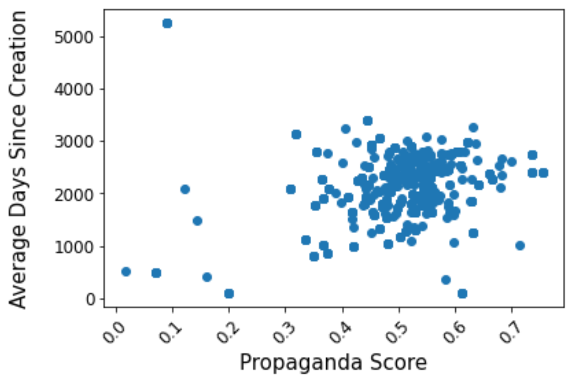
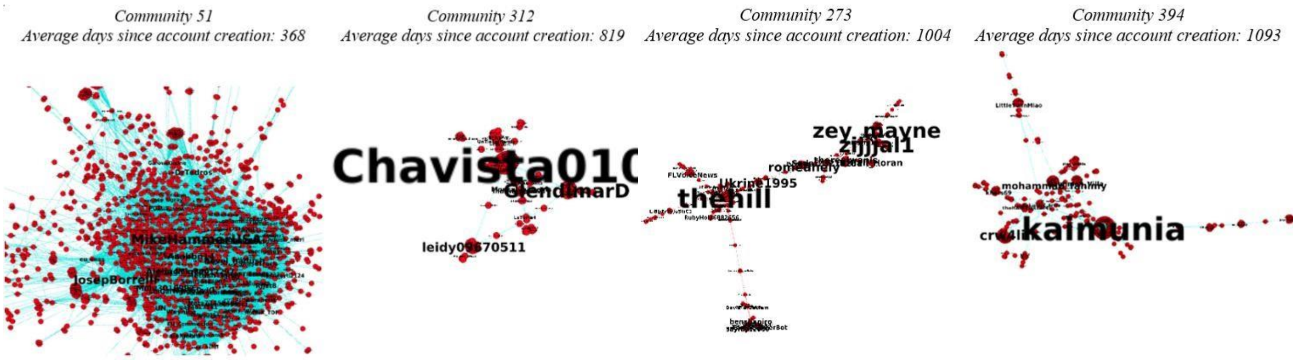
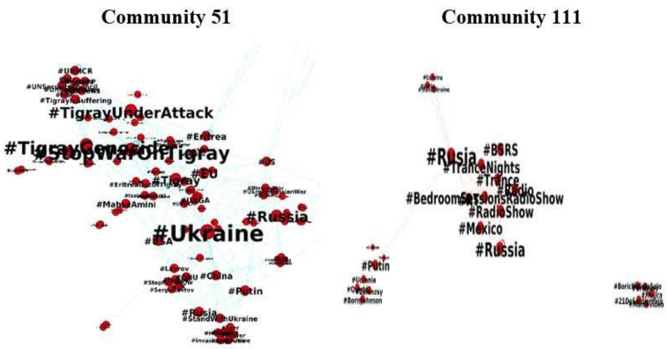


Figure 11. Top 4 communities regarding recent account creation



The most central accounts in community 111 were PalabrasPepe; a media personality from Uruguay,and carlosajimnez4; an pro-trump influencer from Mexico. The most central account in community 24 was liusivaya; a pro-russian war correspondent in the Donbas oblast. Community 37 was centered around gldivittorio; a liberal influencer from the US. Community 399 centered around AntonioMaestre; a journalist from spain.

Figure 12. Hashtag graphs for the top two most suspicious communities, determined by propaganda score/average days since account creation



Regarding communities with a high proportion of recently created accounts, community 51 was centered around MikeHammerUSA; a diplomat for the US democrats. Community 312 centered around Chavista0101; a reporter from Venezuela. Community 273 had multiple accounts with high centrality. TheHill is a political news organization from the USA; zey_mayne, an account from Iran, is likely a bot account, due to its repeated posts of duplicate messages (mostly containing the hashtags #we_wont_sell_iran_to_russia and #we_wont_sell_iran_to_china). The same was likely true of Zijjjal1, given it had been banned by the time it was investigated. As can be seen in Figure 12 the most common hashtags used in community 51 were regarding the war in Tigray; it is likely that this community is a subset of the isolated outcrop which can be seen in the filtered graph in Figure 3B, and 3D.

Discussion – Mobilisation Dataset

Despite the short 24 hour collection time, this dataset was large, with 240,981 accounts participating in the conversation. Although communities often had a small majority from one location on earth, they were generally composed of accounts from all over the world. The inhibition found in attempts at information diffusion, and the large amount of communities found, point to a large amount of diverse, insular conversations occurring. Central accounts had a lot of reach, however not enough to reach even half of all participants. Although there are hubs, the distribution is positively skewed by a large margin. The vast majority of account pairs only had a single interaction.

The majority of communities did not have a significant amount of propaganda (as assessed by the finetuned distilBERT model). It is not known how language translation would affect propaganda scores, as the model used was trained specifically on English. An interesting finding was the mild, statistically significant correlation between average propaganda and days since creation over the community's. At first glance, this may seem to be related to news organizations/government officials, who can be argued to have longer lasting accounts, and output more propaganda. However, the propaganda score and days since creation would be averaged over their audience as well, which is a larger population, and thus this is unlikely.

Multiple inauthentic and/or propagandist accounts were found in the conversation including but not limited to; sibbear234, zey_mayne, Zijjal1, MarcSebastion, and 'Luigi65810766'. Additionally, there were many accounts using the topic to draw attention to other causes, such as the Tigray genocide, or religion. The account sibbear234 was most indicative of the Russian propaganda model. This account joined in September 2022, was highly connected to Russian accounts, despite speaking Italian; it had a photo of a bear, with no personal information, and posted conspiratorial tweets. For example, this tweet on the 19th of October:

> *"Dear @EnricoLetta*
> *you are ambiguous! Italy has always been a partner of Russia on an energy and economic level in general! In particular we are not in favor of a Nazi like @ZelenskyyUa also a pedophile! So no ambiguity! Forza Russia* RU *@mfa_russia @rusembitaly"*

Sibbear234's followers followed a similar pattern; with the majority of accounts having no personal information and inauthentic profile photos.

Discussion - The Annexation

The annexation event occurred on the 30th of September 2020, and consisted of Putin declaring the annexation of 4 territories of Ukraine which sparked outrage on social media, due to its illegality according to international law [6]. The annexation was scraped for tweets for this sub event in the major war to see the community's reaction.

Figure 13. A map of the 4 territories of Ukraine that are supposedly annexed by Kremlin Putin, from The Guardian

The data spanned over 2 days, and it was found that there were not that many tweets in total being 32770. The communities gathered were of a minimal size of three users. ECG was used on the Annex dataset as well to generate 614 communities. The main analysis for the communities was to see what the tweets subtopics/consensus were on the main topic of the annex, and to analyse the top 5 most influential users', in each group, background and beliefs, and interests.

Figure 14. A visualisation of the network of tweets contained in the dataset and their connection to other tweets

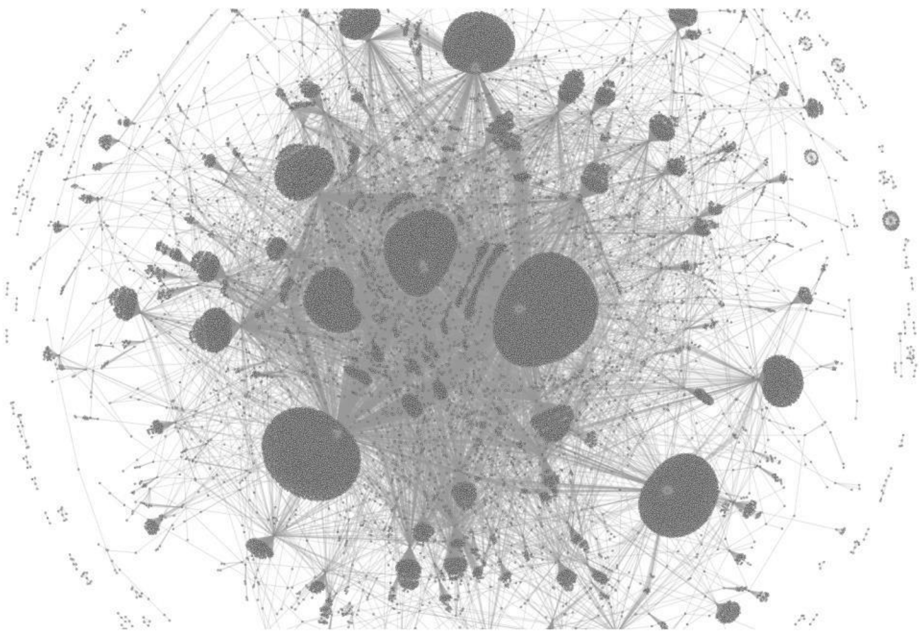
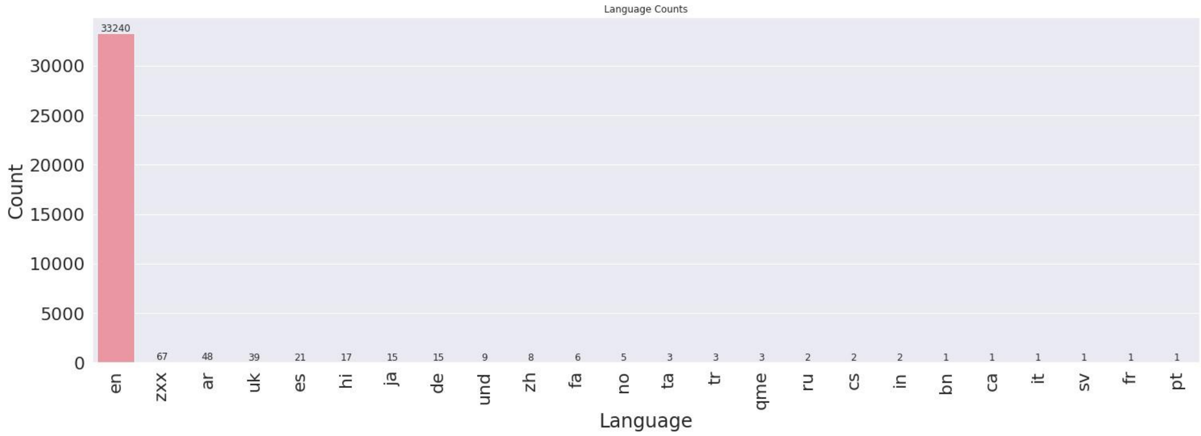
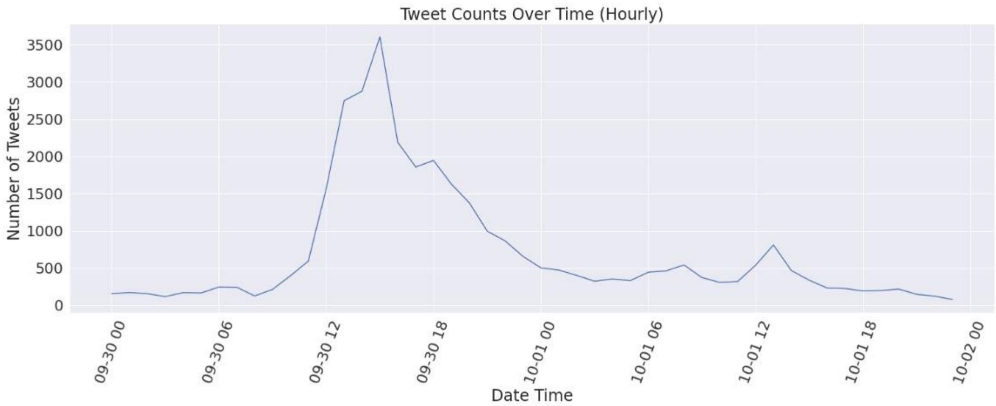


Figure 15. A histogram of languages detected in the tweets, overwhelmed by English



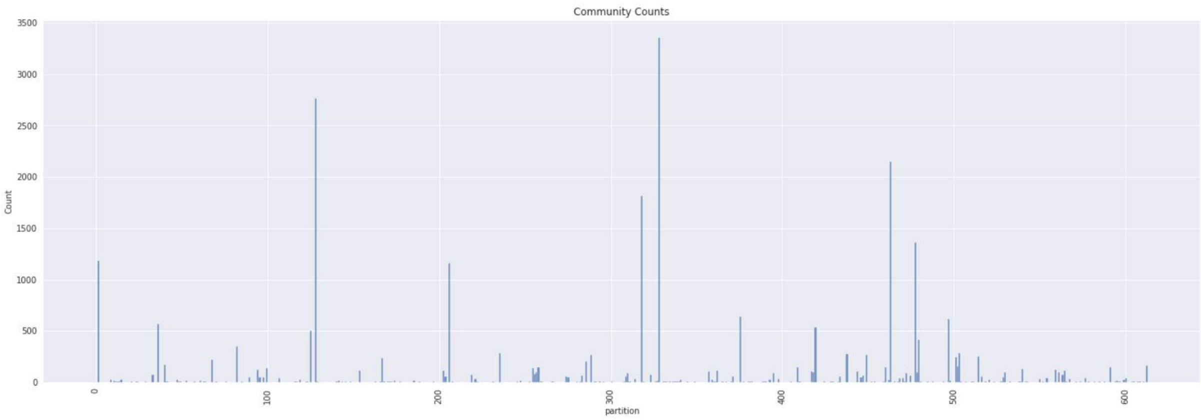
There was little to no tweets that were non-English and so it is likely that there will be little pro-Russian tweets to be seen in the dataset.

Figure 16. This contains the count of tweets per hour over the time of 2 days



In the above we can see that the tweets spanning from the event that occurred on September 30 peaked at a height of 3500 tweets in the single hour this created a taper off or slight decline going forward over the next 18 hours. The heightened event was between midday Sept 30 and the end of September 31st and so this was the moment that the bulk of the tweets were collected.

Figure 17. A histogram of the partitions (communities)



Given the above figure you can see that there are many small sub communities that were less than 400 members in size and the larger communities reached approximately 2300 users in size. The analysis was made on the top five largest communities because there was a lot more information to perform topic analysis on compared to the other communities and analysing all the smaller communities would be overwhelming and not informative. This is also shown in the table below.

Table 3 - The top 5 largest communities detected for the annexation of Ukraine.

GROUP / PARTITION ID	USER COUNT
128	**2764**
463	**2149**
318	**1817**
478	**1361**
2	**1182**

After analysing the groups of tweets detected by the ECG community detection method, it was found that the communities were large groups of retweets of the same tweet. This meant that the communities were a collective mind that was surrounding a single belief or tweet that was then a good indication of what many users agreed with and could then be extracted to what they believed on the topic. This was why we performed topic analysis on the groups of tweets to give us a word cloud of the more common words that the users would agree with. Because of this phenomenon the communities were not of great variety instead it meant that there were only a few unique beliefs within each community. This prompted the topic analysis of retweets versus non retweets. The analysis between the retweeted groups and the non-retweeted groups we're really an analysis on the vocal community sharing their own opinions versus the silent community that would only retweet (agree with) existing vocal members.

Summary of Top 5 ECG Groups – Vocal (Non-retweet) vs Non-Vocal (Retweet) Beliefs

As previously stated, the vocal sub-group of each community is considered the individuals who’s tweets that are original. The non-vocal participants that make up the community are considered the ones that are only retweeting existing tweets; therefore, they are not showing their own vocal opinions but rather sharing that they agree with the existing ones stated. Below are the top 5 largest community of tweets analysed by topics.

Figure 18. Partition 128's topics/beliefs on the Ukraine annex event

Partition 128 believe that Vladimir Putin’s war machine causing an annex against Ukraine is illegal and violating international law. This is a pro Ukraine stance against the Russian forces. There is not much change between the retweeted tweets and the nonretweeted/original tweets. ‘Nwe’ is viewed as a spelling error as there was nothing that was found on the Internet relating to it as an acronym for anything relevant. The two sub-groups of the community are in agreeance with each other.

Figure 19. Partition 483's topics/beliefs on the Ukraine annex event

Partition 483’s non-retweet vocal group believe that Russia attempts to take parts of Ukraine is a sham. The USA’s spokesperson secretary Blinken has been looked up to as a person responsible for further comment on the matter. The non-vocal group in petition 483 believes that the regions being taken over is a clear sham as well and a political stunt by Putin and is a violation of international law. This is again a similar pro-Ukraine story with partition 128. The two subgroups are unified in beliefs.

Figure 20. Partition 318's topics/beliefs on the Ukraine annex event

Petition 318 is also sharing a similar belief to the previously mentioned partitions, with the non-vocal group expressing how Vladimir Putin’s action against Ukraine is violating international law there needs to be discussions about imposing sanctions and if that could cripple the war. This non vocal group seems to expect further retaliation from those that are on Ukraine’s side, whereas the other communities are purely expressing just the belief that the annexation is wrong rather than the actions to retaliate with. The vocal group has a different focus being the signing of documents that Vladimir Putin of Russia has illegally made and how that is some of the biggest news for the world so far. It is unknown what “chant” specifically refers to, but it could imply that there needs to be protest such signing of documents.

Figure 21. Partition 478's topics/beliefs on the Ukraine annex event

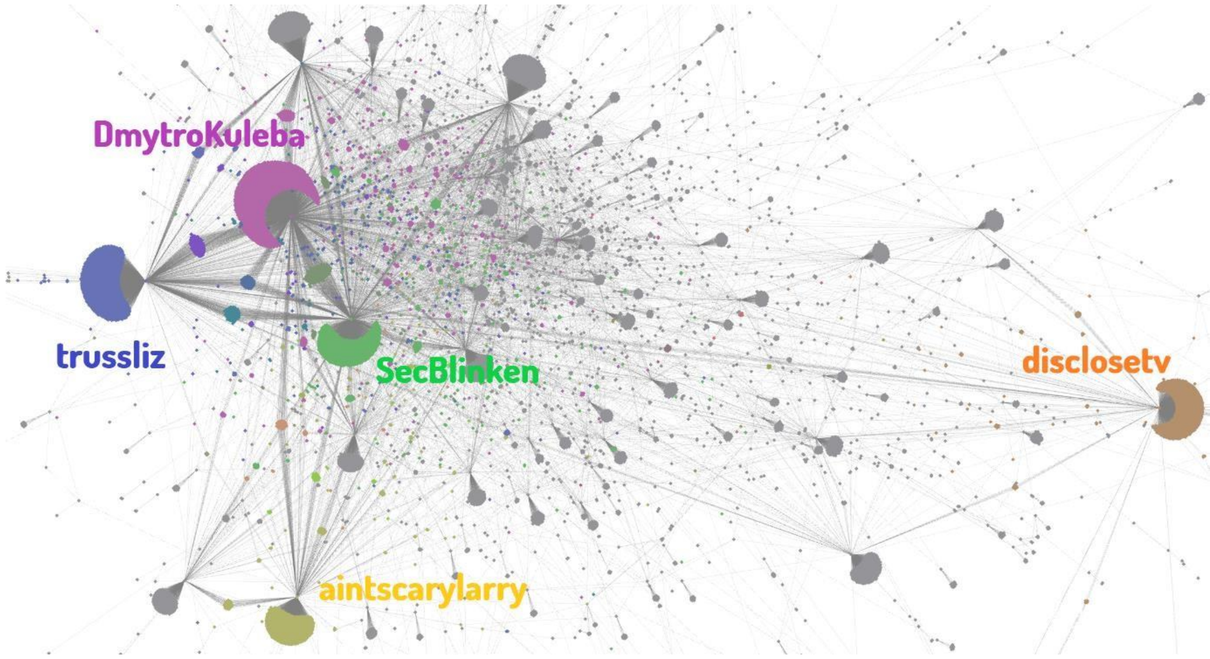
It is unknown what Republican Party the tweets in Group 478 are referring to, but nevertheless there is discussions on liberating the regions of Ukraine as well as mention of the word ‘restoring’, ‘control’, and ‘easily’, with Vladimir Putin being the centre of the stage. This gives the impression that group 478 doesn't necessarily have a negative belief on the annexation on Ukrainian soil. This begs for further investigation of this community and the most influential people of this community. The vocal group in the community didn't have a lot at all regarding unique content and so it means that most of the tweets in Group 478 are retweets and so it is a community of people that simply share the same interests but they're not their own opinions.

Figure 22. Partition 2's topics/beliefs on the Ukraine annex event

Partition #2 have had their non-vocal group retweet about the word Mordor, which comes from the Lord of the ring’s movies. The most likely explanation for this would be because the Russian Federation was referred to as Mordor by Ukrainians back in 2014 when Russia Annexed Crimea. Google Translate translated the Russian Federation to be Mordor in 2016 as an error that was introduced because of the Ukrainian to Russian translation service automatically updated based on the terminology the Ukrainians were using [15]. As you can see the non-vocal group in this community are also using the word Mordor in the same context of this recent annexation news. The vocal group of unique tweets was of very few numbers in this community being only a mere 7 words they discuss how Putin has had a military setback against the Ukrainians. The vocal and non-vocal groups in the community seem to be like minded against Russia.

Most Influential People - Background and Beliefs.

Figure 23. A graph showing all the connections and interactions twitter account holders had with each other. The coloured groups represent the effect of the top 5 most influential individuals on the annex dataset.



The network created was a graph of accounts whose interactions were replies, retweets, quotes, and mentions. This generated the graph above using the Force Atlas 2 layout and Gephi to visualise the network. It was through this network that the most influential individuals were found on the annexation topic.

Table 4 A table of the top 5 most influential twitter accounts over the annex dataset

Target	Weight
DmytroKuleba	5006
trussliz	3464
SecBlinken	2918
disclosetv	1948
aintscarylarry	1593

The most influential individuals were calculated by summing up all the weights of all the immediate interactions of other accounts to the individual's tweets. Dmytro Kuleba had the highest influence waiting being 5006 followed closely by trussliz with a weight following of 3464. SecBlinken, disclosetv, and aintscarylarry, we're also amongst the top five most influential individuals. More interestingly Secretary Blinken was also a point of topic in partition 483 shown in figure 19, suggesting the interactions were through mentions and not retweets or replies, because mentions are placed into the tweet, and replies and retweets are not. This also further indicates that secretary Blinken was a person expected to comment on the matter as a person of authority as it is common for mentions to desire reply from the mentioned.

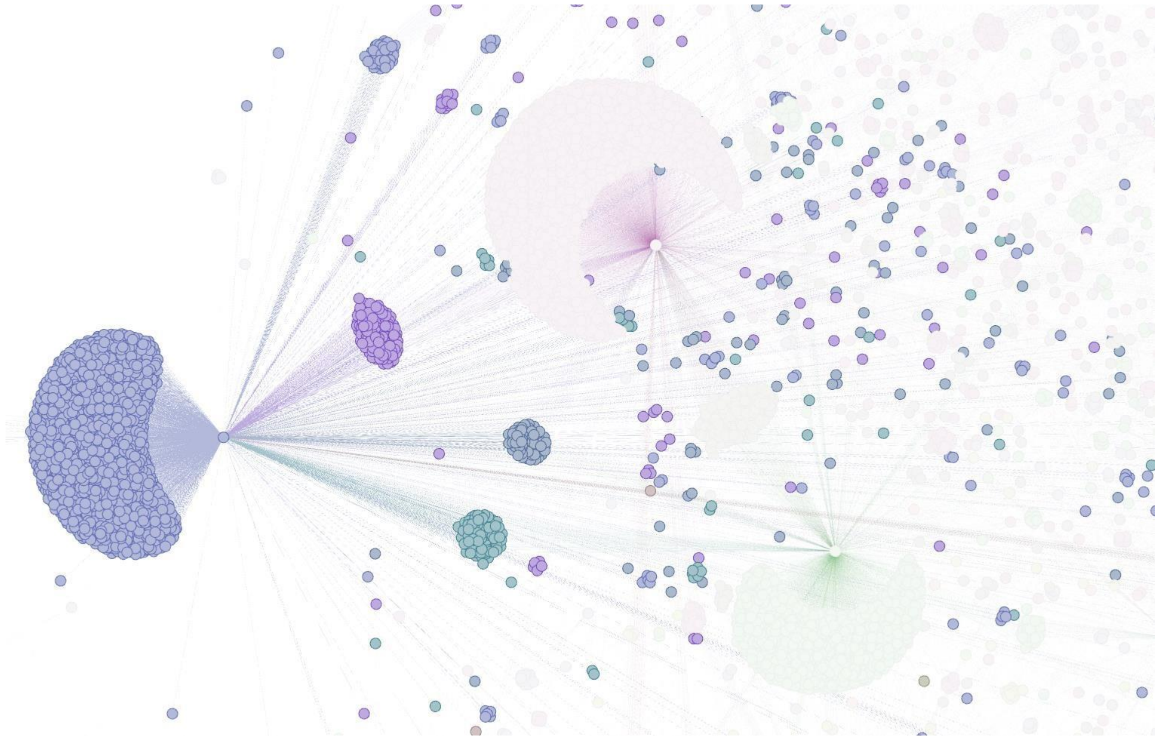
DmytroKuleba

Figure 24. A graph showing the outreach DymyroKuleba had on the annex dataset with the reached accounts being the connections to red dots.

Dmytro Kuleba is a “Minister of Foreign Affairs of Ukraine” [16] and had the most influence on the network with a vast outreach to small micro echo chambers and the largest echo chamber. They shared 4 subgroups amongst the other influencers, trussliz and secblinken, but also had a lot of influence on individuals that did not follow these large influencers, but instead micro-influencers. Dmytro has over 1 million followers on Twitter, so he has a tremendous outreach as proven by the collected dataset and network. Given from his professional position, he is against Russia and for the protection of the Ukrainian people. Dmytro received a propaganda score of 73%, which implies a non-neutral state, and so the positive state is for Ukraine.

Trussliz

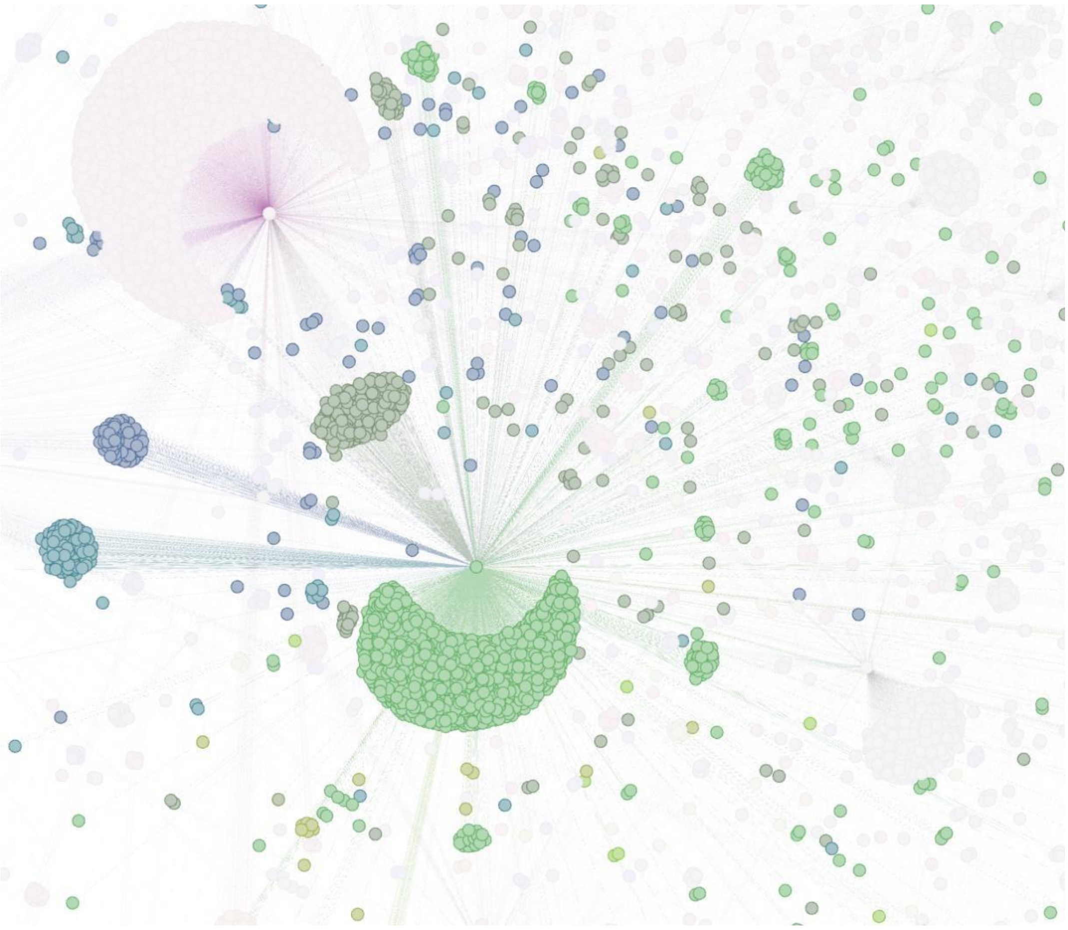
Figure 25. Graph of trussliz’s immediate influence from tweets



Trussliz is Liz Truss, the Prime Minister of the United Kingdom of Great Britain, and Northern Ireland. Leader of the Conservative and Unionist Party. MP for Southwest Norfolk. [17]. Liz has ~700K followers on Twitter which also shows why she has had so much influence on the network highlighted in blue in the figure above. Liz Truss' tweet that creates this impact on the network was "Vladimir Putin is once again violating international law with his threats to annex more of Ukraine. We will not hesitate to take further action, including imposing more sanctions to cripple Putin's war machine. We will ensure he loses this illegal war.". This tweet produced a propaganda score of 88%, signifying a strong one sided piece against the Russian decisions. This informs that the interactions with the tweet in the form of retweets show agreeance with the tweet and then represents the group as a pro Ukraine community. The interactions around the tweet was of a size of 3464 (node in degree).

SecBlinken

Figure 26. Graph of SecBlinken's immediate influence from tweets



Secretary Antony Blinken who is an official from the United States government. According to his biography he, is a Husband, dad, (very) amateur guitarist, and the 71st Secretary of State serving under the leadership of Biden. [18] The tweet that caused the community around SecBlinken reads "Today, we took swift and severe measures in response to President Putin's attempt to annex regions of Ukraine – a clear violation of international law. We will continue to impose costs on anyone that provides political or economic support for this sham.". This generated a propaganda score of 79%, leading to a positive look on supporting Ukraine and the interactions with the tweet also suggesting those agree with him. The interactions totalled a 2918 node in degree, being the 3rd most influence amongst the other twitter accounts in the dataset.

Aintscarylarry

Figure 28. Graph of Aintscarylarry's immediate influence from tweets

Aintscarylarry'so says, "You may have followed me in a past life. One thing's for sure, if you're fighting to defeat fascism and save our democracy, then I am your friend" [20]. He is a left-wing believing individual, and hates the previous president, Donald Trump. He has 30,000 followers, and so his reach compared to the other individuals is impressive given his follower count comparatively. He is new to the Twitter platform, only having joined in June 2022. Previously, group 478 was confused to know what sentiment it showed towards the war, but after investigating it further, it was aintscarylarry whose tweet went viral, being politically loaded against the republican party whilst also showing support for Ukraine, stating "Someone tell Vladimir Putin that he can't 'annex' Ukraine as easily as he annexed the republican party" [20]. This shows that group 478, is aligned with aintscarylarry's antirepublican political beliefs as well as an anti-Putin belief. The propaganda score for this tweet was the highest seen at 88%.

Disclosetv

Figure 27. Graph of Disclosetv's immediate influence from tweets

Disclosetv is a Twitter account that is a news source for many individuals having over 1 million followers [19]. They had a node in degree total of 1948 interactions with their tweet, “NOW - People chant "Russia, Russia, Russia" after Putin signed documents to annex occupied Ukraine lands.”. This resulted in the lowest propaganda score of the top 5 most influential accounts found on the topic of the annex, being 66%.

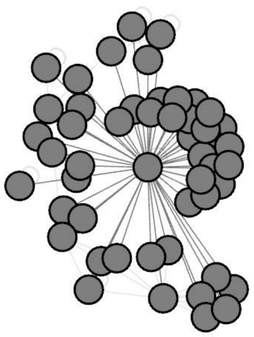
A look into Pro-Russia Twitter Accounts and Influence

Due to the analysis of the top 5 most influential accounts’ tweets and beliefs to all be pro-Ukraine freedom, and against the annexation, finding individuals that are for the annexation was search for to see what the influence levels are like. The main individuals found in the Mobilization dataset for pro-Russia viewpoints was Sibbear234, kitty_b88, and LPNH. We will analyse an example tweet and dive a bit deeper into commonly held viewpoints.

Sibbear234

With Sibbear234 found in the dataset, an example tweet was “She had to go get the Nazi @ZelenskyyUa and push him for peace! We see there are different interests between church and peace” [21]. Sibbear234 holds to the idea that Zelensky is a Nazi, and you will find that it is a common view of Zelensky, being the leader of the Ukrainians.

Figure 24a A Graph showing the node influence of sibbear234 in the middle with the nodes around it.



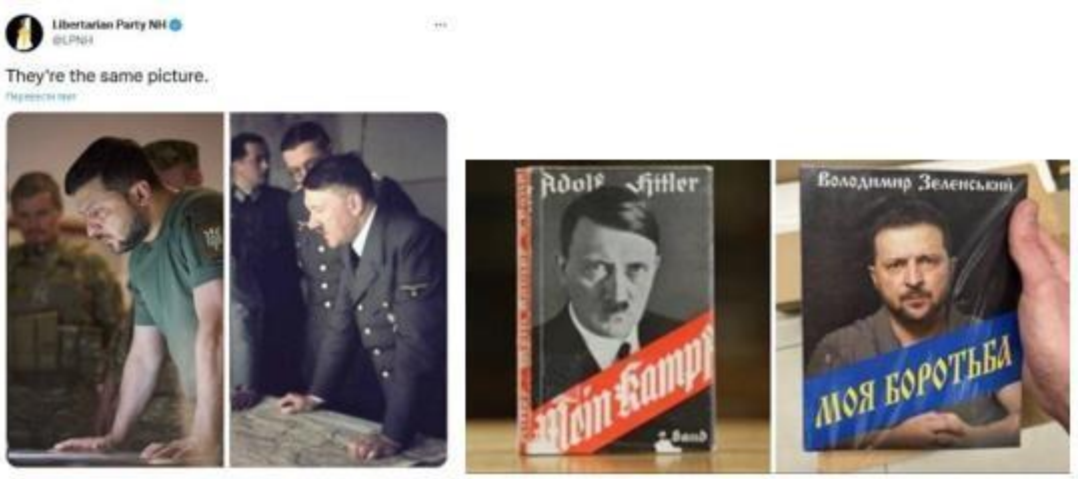
Sibbear234 has a small influence in the annex mobilization dataset, which is the reason why it is difficult to find pro-Russia nodes in the network, but from this we found 2 more individuals that also hold similar beliefs to sibbear234.

Kitty_b88

Also known as Cristina, they follow and retweet Sibbear234, and so is a direct connection.

Their reply to ZelenskyyUa's tweet of "Had a phone conversation with the Prime Minister CA @JustinTrudeau. Emphasized the importance of a strong #G7 reaction to the Russian missile terror. Ukraine needs an air shield to protect civilians and critical infrastructure.", was Kitty_b88's reply, "Go Putin <3" [22] Ironically, Kitty_b88's bio states, to "Love everyone, believe in a few and do no harm to anyone". [23] With that said, the only conclusion of Kitty_b88 to be consistent with their views of loving everyone, whilst supporting a war front, would be to believe that the Ukrainian leadership is evil, and so the good thing to do would be removing them. This view that Ukraine is evil is known to be believed by kitty_b88 after they retweeted this following image:

Figure 24b A picture comparing Zelensky to Hitler



Given this however, kitty_b88 tweet in the dataset was milder talking about how '10 thousand volunteered to be enrolled in the offensive in Ukraine before receiving the official call', having a propaganda score of 32%. There is little emphasis on pro Russia in this tweet leading to the lower propaganda score. From the figure above kitty holds the same view as Sibbear234 with the belief that Ukrainian leadership is a Nazi movement.

After being retweeted by kitty_b88, the LPNH bio reads, "Official Twitter of the Libertarian Party of New Hampshire. Set yourself free.", and from the figure above they are partly spreading the information that Zelensky is the modern day, Hitler. Given this, it would make sense why Kitty_b88's view of Putin is so positive whilst also believing to 'Love Everyone', leaving the 'do no harm to anyone' aside for now. LPNH received a propaganda score of 25% having only a short reply in the dataset collected being 'And Israel. And Ukraine. And Saudi Arabia. And everywhere else.'. So again, like kitty_b88, the data collected on the individuals wasn't enough to bring an accurate propaganda score for their views.

Pro-Russia Summary

There needs to be a reason for mobilizing a war, and that motivation needs to come about from something that is described as morally good to accumulate support and doing so to have the public eye on your side. It grows from an idea of a world that does not deal with evil, is a world that is unjust and worse off, and so that line of reasoning can be exploited to be one where, without the war, things would become worse. This line of reasoning is why the Hitler and Zelensky comparison is so prevalent with those that are for the war against Ukraine. Remove the Ukrainian brainwashing and the world will be a better place, very altruistic. This goes to show why finding the facts of the matter is so important today. Without the evidence and facts, propaganda can be spread that can turn even the most intelligent minds to do things that were once shunned, i.e., somehow holding the belief of do "no harm to anyone", whilst supporting a war effort that harms thousands. It seems that is the position of kitty_b88 is that compromise is needed when conducting a war effort.

Dataset Comparison

It was difficult to compare the datasets, both with imbalances in subtopics and dataset size. The intersection of both datasets had 10,064 accounts: about a third the size of the annex dataset (26,541). There was no overlap in the top five accounts (See Table 5). However, SecBlinken and trussliz were in the top 20 accounts in the mobilisation dataset.

Table 5. Top five accounts regarding out-degree and in-degree over both datasets

Mobilization				Annexation			
Name	Out	Name	In	Name	Out	Name	In
yammerapple	1361	KyivIndependent	8713	StevenG15689824	143	DmytroKuleba	5006
FrankGeurts3	1264	WarMonitor3	5794	EPPGroup	69	trussliz	3464
BogeyInTheDark3	1153	Mfa_russia	5647	kevinoler	51	SecBlinken	2918
OM_VA_SH	1043	KremlinRussia_E	4235	PaulStetson	51	disclosetv	1948
cathyjolly12	992	igorsushko	4113	kurtmac	39	aintscarylarry	1593

An interesting finding was the larger number of communities (614) returned in the smaller annex dataset, compared to 518 returned in the mobilisation dataset. This may be due to the difference in queries used; the mobilisation dataset used more queries, and specified the union of all queries, thus returning all tweets that contained any of the central topics related to the war. The Annexation dataset returned the intersection, and many of the possible connections may have been left out due to not fulfilling all criteria.

Using the union of search queries when scraping had its drawbacks; notably including many tweets from bots, or that were irrelevant to the main topic. This aided in detecting bot activity/propaganda, however made the task of deducing authentic opinions more difficult. The highest interaction path between world leaders tended to return inauthentic accounts, who had tagged both to obtain a higher reach.

Sentiment Analysis

VADER Sentiment Analysis was performed on the whole corpus of tweets initially, to find how the general public reacted to the Russian mobilization on Ukraine. A total of 494,473 tweets from users was analyzed. VADER (Valence Aware Dictionary for sentiment Reasoning) is a model used for text sentiment analysis that is sensitive to both polarity (positive/negative) and intensity (strength) of emotion. [24]

The general sentiment from the tweets resulted to be neutral from the VADER sentiment analysis, which constituted up to 71.15% of the tweets, but when the positive and negative tweet numbers are compared, the number of negative tweets are almost double to the number of positive tweets, showing that the general public was against the Russian mobilization on the whole.

Figure 25: Number of positive, negative, and neutral tweets in the Mobilization Dataset

	Counts	Percentage
Category		
0	3	0.000607
Negative	98507	19.921614
Neutral	351803	71.147060
Positive	44160	8.930720

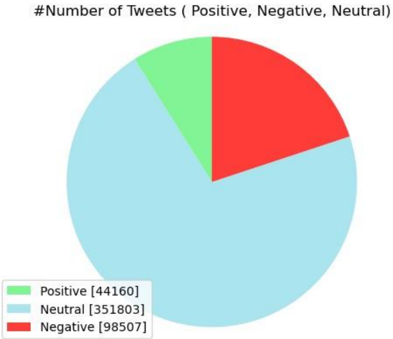


Figure 27: Negative tweet

Figure 28: Positive tweets

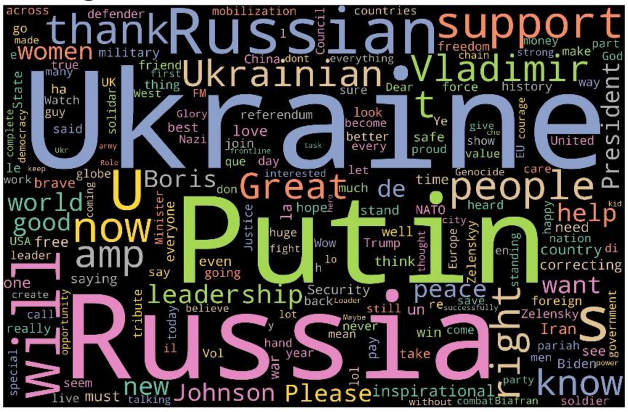
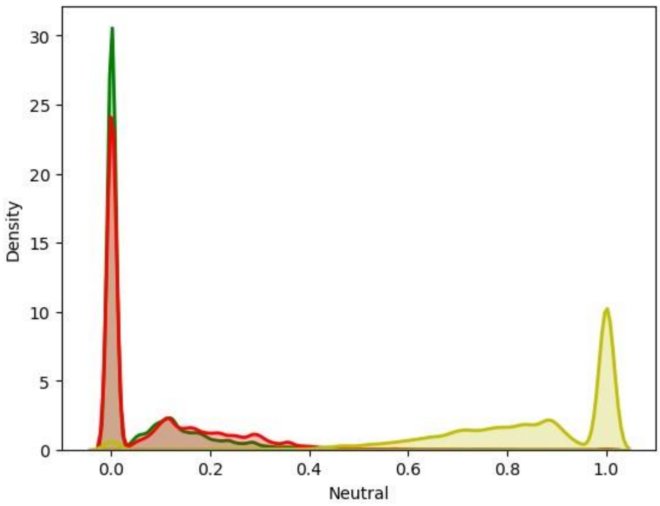
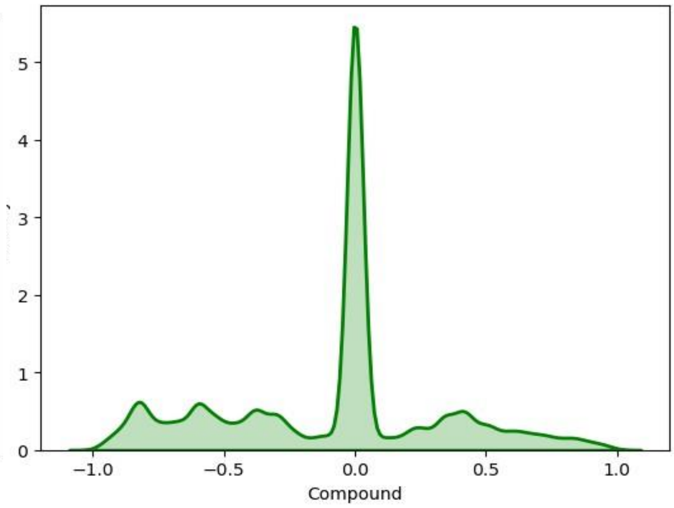


Figure 26: Neutral tweets vs Density and Compound vs Density Graphs





Word Clouds from the group of positive, negative, and neutral tweets was visualized to fight the most frequent words used. From the word clouds, words like “DIE” and “SOLDIER” comes up, showing how extreme the tweets really are. Words like “Support”, “Peace” and “Leadership” comes up in the positive tweets word cloud, showing how the users was peace.

Sentiment Analysis filtered by Location

To analyze tweets from a specific location, the whole dataset containing 494,473 tweets, which was initially in Jsonl format was converted into CSV – so as to get values from each field in the json file. A filter was applied on the “author.location” field to get exact location from where the tweets were coming from, and then analysis were done after grouping them. Tweets from these countries were the most in number, and hence analysis was done on the same – USA, UK, France, Ukraine, Australia.

For this sentiment analysis, a more advanced model was selected, i.e., SentiWordNet Sentiment Analysis. WordNet is a lexical database composing English words, grouped as synonyms into what is known as synsets. While WordNet can be loosely termed as a Thesaurus, it is said to be more semantically accurate, since it stores synonyms of words put together is specific contexts. All the words are linked together by the ISA relationship (more commonly, Generalisation). SentiWordNet operates on the database provided by WordNet. The additional functionality that it provides is the measure of positivity, negativity, or neutrality as is required for Sentiment Analysis [25].

Fig 29: Number of tweets per category for USA

Category	Counts	Percentage
Negative	2344	39.897872
Neutral	1748	29.753191
Positive	1783	30.348936

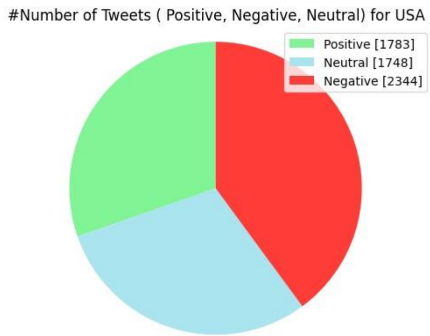


Figure 30: Number of tweets per category for UK

Category	Counts	Percentage
Negative	2451	43.838312
Neutral	1412	25.254874
Positive	1728	30.906815

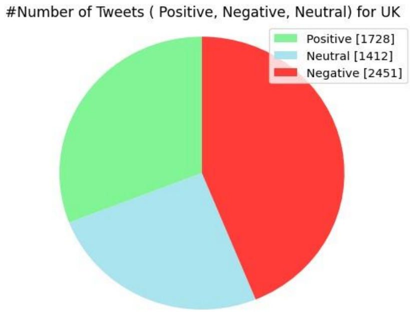


Figure 31: Number of tweets per category for France

Category	Counts	Percentage
Negative	990	46.698113
Neutral	827	39.009434
Positive	303	14.292453

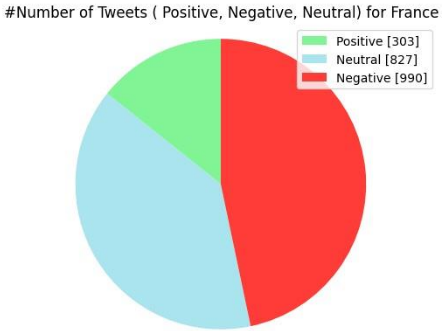


Figure 32: Number of tweets per category for Ukraine

Category	Counts	Percentage
Negative	569	31.734523
Neutral	703	39.208031
Positive	521	29.057446

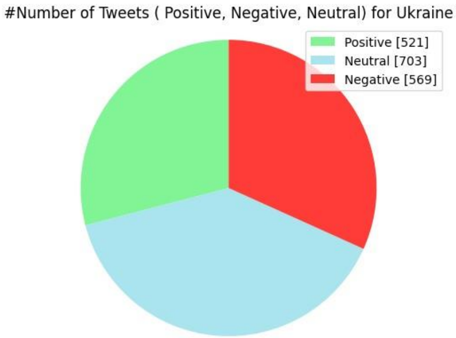
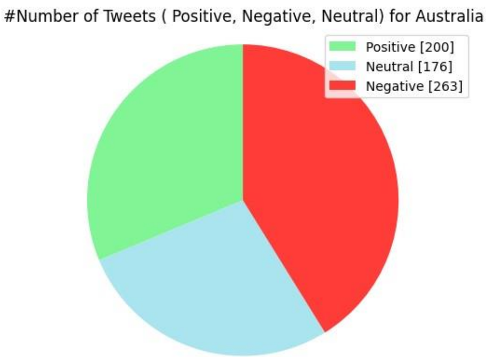


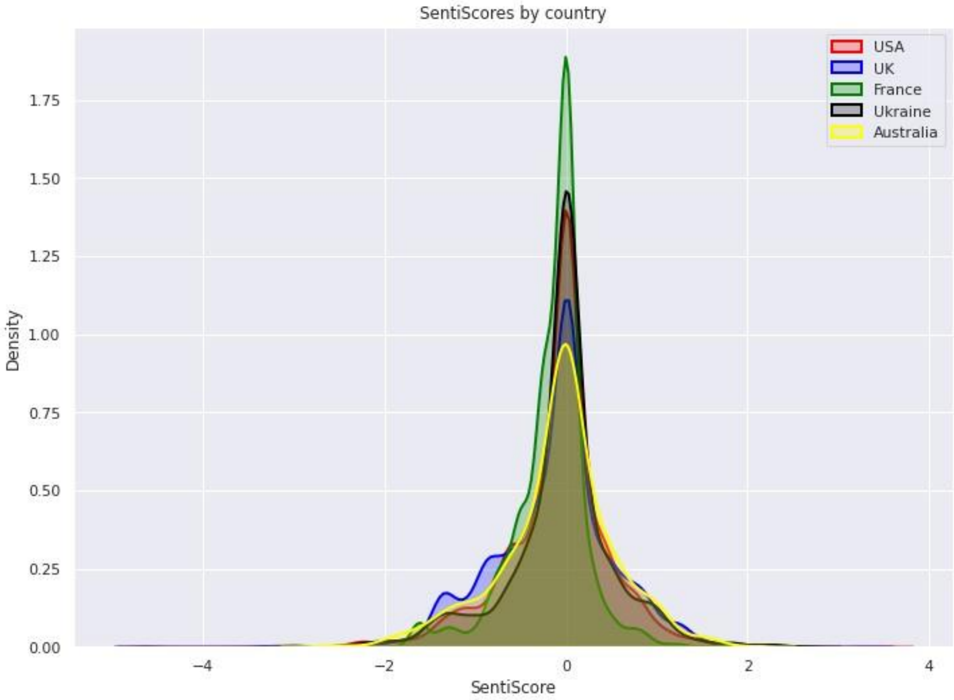
Figure 33: Number of tweets per category for Australia

Category	Counts	Percentage
Negative	263	41.158059
Neutral	176	27.543036
Positive	200	31.298905



From all the charts above, although most of the tweets from all the countries are categorized as Neutral, if we consider a ratio between the positive and negative tweets, all countries be inclined towards a negative sentiment, showing that none of them supported the Russian mobilization, and have a negative reaction towards it. The same also be seen in the graph below

Figure 34: SentiScore vs Density for all countries

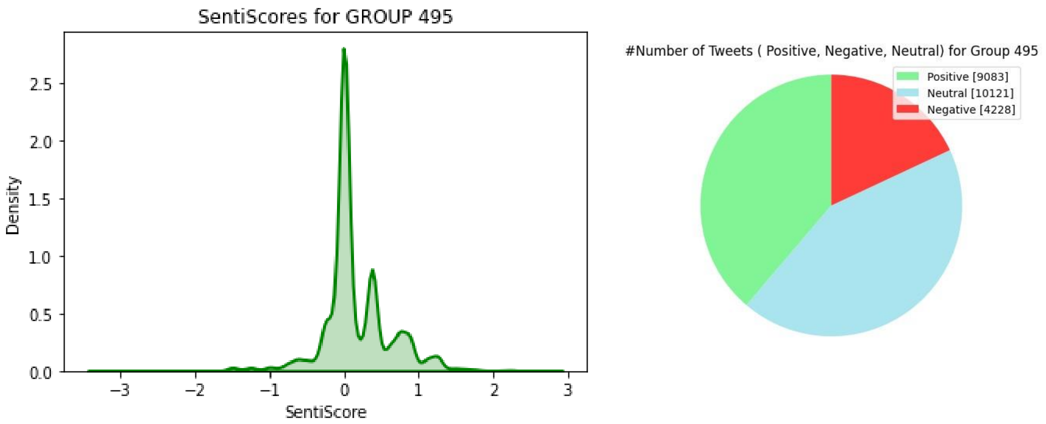


Sentiment Analysis for Top 5 Communities

ECG (Ensumbling Clustering for Graphs) algorithm was used to get groups of users from the whole network of dataset who are similar. The top 5 communities from these were selected, (518 communities for Mobilization Dataset and 608 communities for annex dataset) and sentiment analysis was done on the same to find if any of these top 5 communities were pro-Russia or pro-Ukraine.

After extracting sub-communities from the ECG algorithm, it doesn’t contain the actual tweet from the user, just the Username (Vertex) and which group they belong to. To get their respective tweets, it was necessary to join it with the mobilization dataset and extract the same from it. Again, SentiWordNet was used for sentiment analysis. Each tweet was ran through a POS tagging function which tagged each word in the tweet, used for the sentiment analysis. Following were the results for the top 5 communities:

Fig 35: Sentiment Analysis for Group 495



From the above graphs, it is clear that Group 495 has a more positive sentiment score than negative, indicating that they are more inclined towards the Russian Mobilization moment (pro Russian).

Figure 36: Sentiment Analysis for Group 138 (total tweets = 21,611)

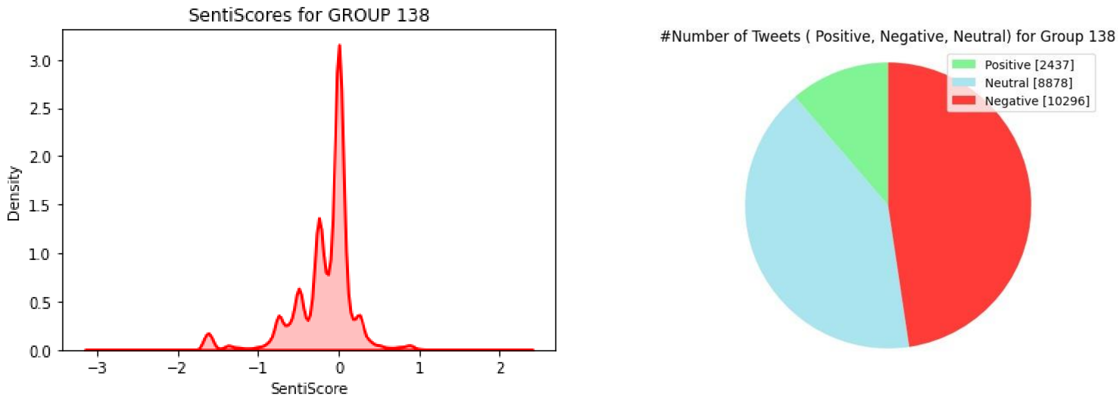


Figure 37: Sentiment Analysis for Group 205 (total tweets = 21,693)

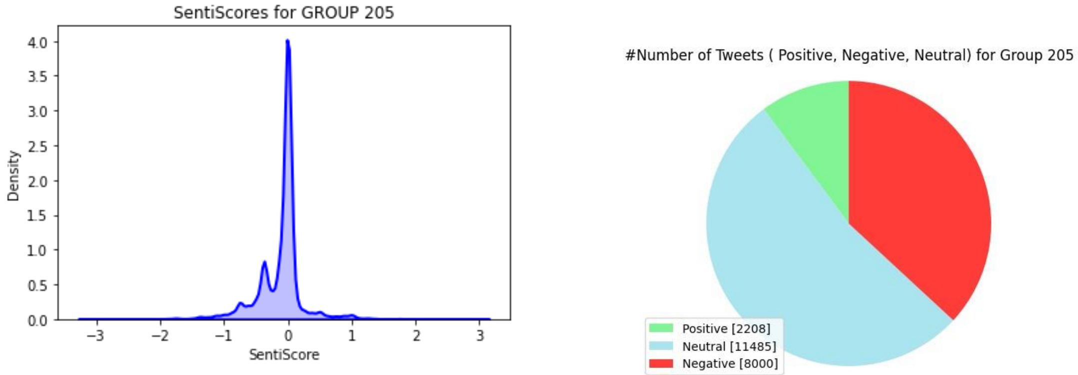


Figure 38: Sentiment Analysis for Group 326 (total tweets = 12,794)

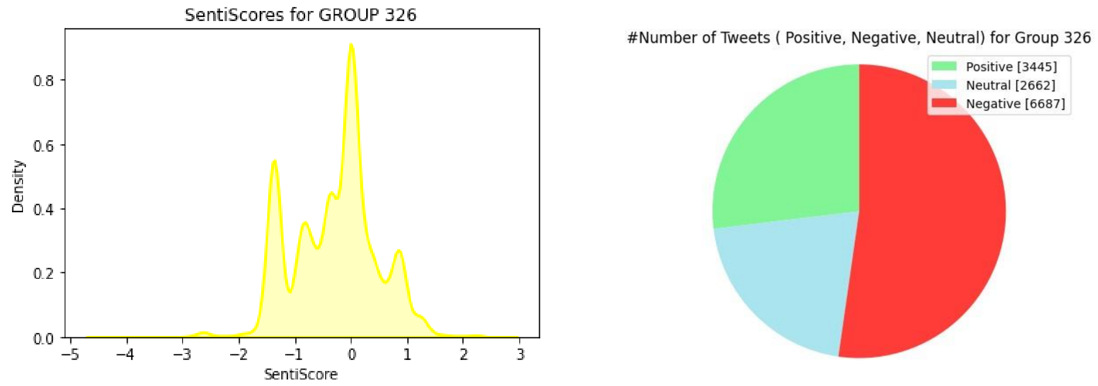
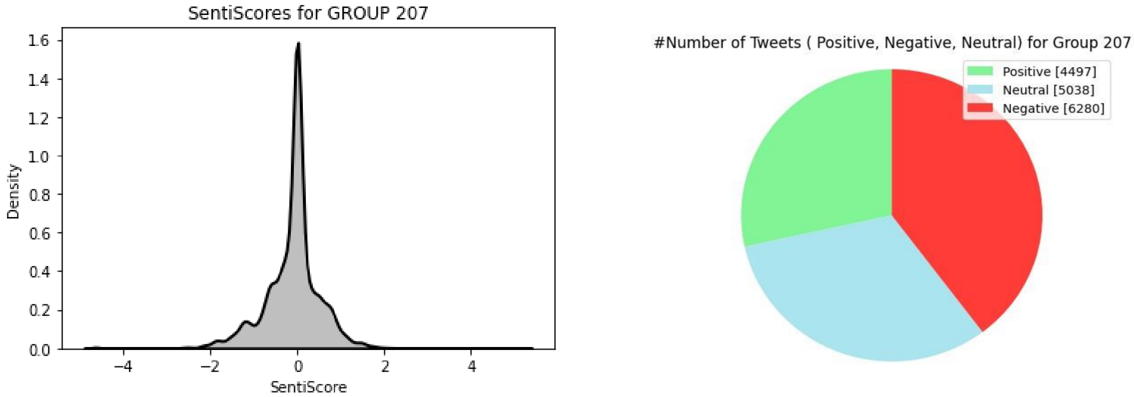


Figure 39: Sentiment Analysis for Group 207 (total tweets = 15,815)



From the above graphs, Groups 236, 207, 205 and 138 has a more negative sentiment score than negative, indicating that they are more inclined against the Russian Mobilization moment. Overall, group 495 was discovered to be pro- Russian community, making it standing out from the rest of the groups found from the Russian mobilization dataset.

Conclusion

We set out to investigate the patterns of activity and opinions of a large amount of accounts discussing the war. In the process, we discovered a network structure that was vast, yet highly insular. The vast majority of account pairs interacted only once. Account pairs with a high number of interactions were generally from many single accounts interacting with hubs. News organizations and politicians formed the majority of central accounts. A large amount of communities were returned, with lots of crossover between countries of origin. We found a mild positive correlation between how long an account has existed, and how much propaganda they output.

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Appendix

Project Plan

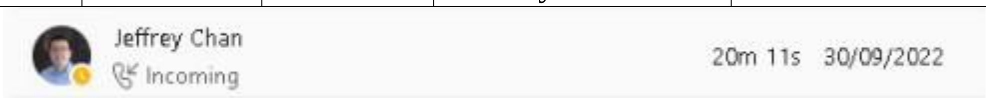
The main plan was first to come up with an idea that we agreed on to investigate. Next it was to get data about the topic via scraping the internet. Next was to do a simple data exploration into what we have found. Then the plan was to detect the communities in the data after generating the network. This required investigating the different community detection techniques. From there the tasks could be split into the individual areas from community beliefs analysis, individual reach, and influence rating, to graph network distance calculations, propagation, and reach. Propaganda was a desire of the team but unknown to whether it was within the scope and was left to an individual who had time to implement. After these were done it was then visualising the results and presenting it into a report format.

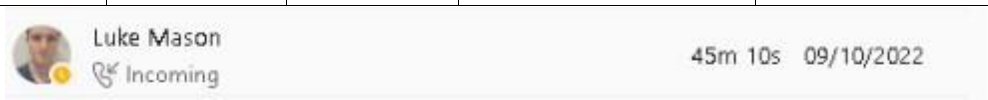
List of Tasks

Order - Week #	Task Name	Assignee
1	Annexation Sub Event Twitter Scraping	Luke Mason
1	Ukraine-Russia War Data Scraping	Arlo Rostirolla
3 **Blocker**	Community Detection – **Needs to be done before team can continue in parallel.**	Arlo Rostirolla
4	Community Belief Topic Analysis	Luke Mason
5	Propaganda detection (Optional)	Arlo Rostirolla
2	Exploratory Data Analysis - Annex	Luke Mason
2	Exploratory Data Analysis - Mobilisation	Arlo Rostirolla

5	Twitter Account Influence Analysis	Luke Mason
4	Information Flow	Arlo Rostirolla
	~~Tweet Image Content Analysis~~	~~Rohit Natesh~~
3	Sentiment Analysis - Mobilisation	Rohit Natesh
1,2,3,4,5	Report Writing	Luke Mason, Arlo Rostirolla

Meeting History – Teem Sheets

#	Time	Participants	Location	Meeting Minutes	Conclusion
1	20/09/2022 – 1:30pm	Arlo Rostirolla, Luke Mason	University, B10, L13	Topics we would like to do. Choosing between a dataset of gigs performed in the Melbourne music scene over 2019, and the Russia/Ukraine conflict.	Decided to pursue the Russia Ukraine conflict.
2	30/09/2022 1:30pm	Jeffrey Chan, Arlo Rostirolla, Luke Mason	Microsoft Teams	Our topic, plan, and thoughts on algorithms to use. Jeffrey suggested we choose to do one of the techniques discussed in the second half of semester, and optionally NLP, but not only NLP.	Chose to do graph analysis, and topic NLP analysis on communities. And not do CNNs.
					
3	01/09/2022 1:30pm	Luke Mason, Arlo Rostirolla	University B10, L13	We discussed our intention to study two topics, mobilization, and annexation, and collect datasets for both. We discussed in dealing with the large mobilization dataset, and how we could get cugraph working to speed up our analysis on it.	Arlo planned on running propaganda/sockpuppet analysis over communities to further analyse suspect ones. Luke planned on performing LDA analysis to find and analyse the opinions of authentic accounts.

<table>
<tr><td>4</td><td>09/10/2022 3pm</td><td>Luke Mason, Arlo Rostirolla</td><td>Microsoft Teams</td><td>talked about implementing information diffusion, to measure how insular/cosmopolitan the overall network was. We discussed how we were going with community detection on both datasets, and what insights we had found so far.</td><td>Sharing code to reduce individual workloads and encourage teamwork. Community detection was to be done once and then applied on both datasets, not done individually. Decided to conduct meetings every 2 days, Tuesday, Thursday, and Sunday.</td></tr>
<tr><td colspan="6">
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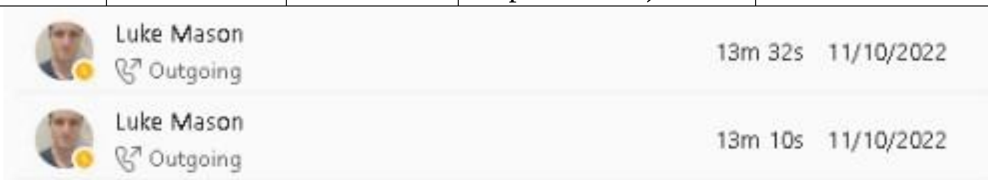
<tr><td>5</td><td>11/10/2022 3pm</td><td>Luke Mason, Arlo Rostirolla</td><td>Microsoft Teams</td><td>Discussed how we should go about integrating our findings, and what further analysis we should do. Started work on report, discussed how we should format it (merged? Or Experiment 1 then Experiment 2).</td><td>For analysis over the coming days. Luke planned to scrape followers of central accounts, and Arlo planned to implement information diffusion. Chose to merge.</td></tr>
<tr><td colspan="6">
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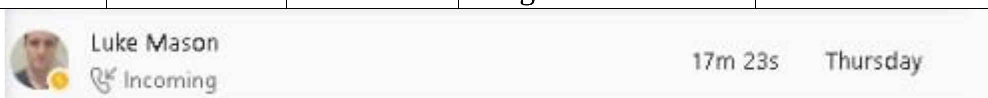
<tr><td>6</td><td>13/10/2022 3pm</td><td>Luke Mason, Arlo Rostirolla</td><td>Microsoft Teams</td><td>We discussed how we should perform analysis on both datasets. Discussed how this would be an issue, due to the significant imbalance in number and interactions weights.</td><td>Back tracked on merging and kept report sections separate to make it easier to read. Decided to combine both edge lists and take the intersection.</td></tr>
<tr><td colspan="6">
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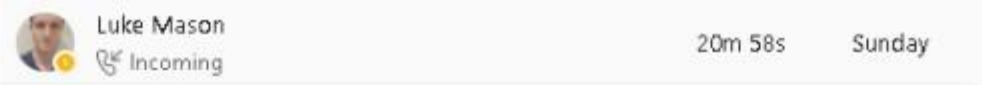
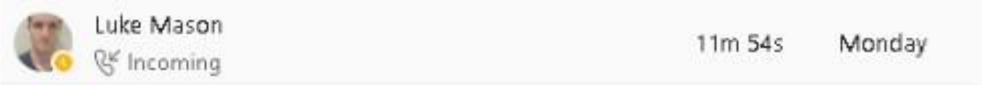
7	16/10/2022 3pm	Luke Mason, Arlo Rostirolla	Microsoft Teams	Both working on report and powerpoint. Discussed how we should organize the powerpoint, as we had enough analysis to be able to fit in 15 minutes. Discussed when we are free to do the presentation, and about how we should book another meeting with teaching staff to discuss our direction/team issues.	Decided to somewhat merge them together. Both aimed to have the powerpoint done by the following Wednesday.
					
8	17/10/2022 11:45am	Jeffrey Chan, Luke Mason, Arlo Rostirolla, Rohit Natesh	Microsoft Teams	Discussed what Luke and Arlo had done, and what Jeffrey thought about synthesizing the findings. Jeffrey and Rohit discussed what he should do as he had not started.	Rohit was going to do computer vision on the datasets twitter links. Luke was going to find top 5 most influential individuals in annex dataset.
					
	18/10/2022 1pm	Luke Mason, Arlo Rostirolla	Microsoft Teams	Shared that Rohit was not going to do Computer vision due to time constraints,	Rohit was going to do Sentiment analysis on the datasets.
9	20/10/2022	Luke Mason, Arlo Rostirolla Rohit, Natesh	Microsoft Teams	Discussed the presentation and how we should structure it. Moved parts around so that it flowed well