Ukraine-Russia Conflict in the Realm of Twitterverse

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Code Link:
https://www.kaggle.com/shriyamurthy/tad-project
https://colab.research.google.com/drive/1ss7V3oITR8t-nO2hXuoZeqTq05BUH-yR?usp=sharing
https://colab.research.google.com/drive/14Fny03jcVAmX1al83H2bLBAbVno_RWnh?usp=sharing

Introduction

The agitation between Russia and Ukraine has been on a rise in the past few decades since the dissolution of the Soviet Union. On February 24th 2022, Russia invaded Ukraine. In the days that followed, tales of a confrontation turning into war continued to pour in from laymen to news anchors.[1] Russia was met with criticism and condemnation from throughout the world. While the war continues to worsen Ukraine's humanitarian and refugee crisis, a new warzone has formed in the internet realm, both in terms of using social media to rally support for both sides of the conflict and in terms of information warfare. In this paper we aim to analyze the trends of tweets posted during the war. To understand the shifting sentiment among people we are taking tweets for a 3-day period in the beginning of the war and 3-day period from a month later. Our aim is to understand public sentiment in the Twitterverse about the ongoing war/conflict and the evolution of the conflict on a daily basis based on the micro trends of the topics by analyzing the Tweets. We also aim to comment on the shifting support based on the influence of politics. In the end we are interested in comprehending how social media's pervasiveness has altered how modern conflict is fought both online and on the ground.

Dataset

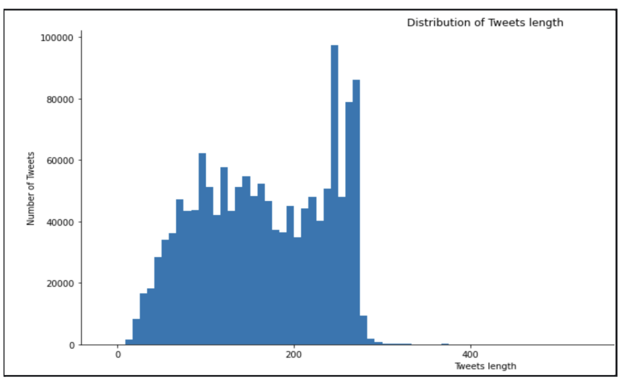
The dataset we are using is Kaggle's "Ukraine Conflict Twitter Dataset ". This dataset is updated on a daily basis and contains tweets related to the ongoing Ukraine-Russia conflict. It scrapes tweets that are related to the conflict using Tweepy and Azure ML with a small compute running Anaconda notebooks running 24/7. These notebooks extract tweets every 15 mins monitoring certain hashtags pertaining to the Ukraine-Russia conflict.[2] The dataset contains columns pertaining to 'userid', 'username', 'acctdesc', 'location', 'following', 'followers', 'totaltweets', 'usercreatedts', 'tweetid', 'tweetcreatedts', 'retweetcount', 'text', 'hashtags', 'language', 'coordinates', 'favorite_count', 'extractedts'. A few limitations of using this dataset are that we are confining our analysis to the English language only which could mean that we are missing out on crucial information/sentiments in regional languages. We are also using an unstructured form of text, which makes our analysis quite difficult. We are using a small subset of the dataset (2million tweets from about 30million tweets) which makes our data prone to some amount of bias since it might not be completely representative of the population.

Literature Review

“Twitter Dataset for 2022 Russo-Ukrainian Crisis” studies the Russo-Ukrainian conflict through over 1.6 million tweets during the first week of the crisis. The paper particularly analyzes the frequency of the tweets over a period of time and the key words in the tweets and the hashtags and how it explains the escalation of the conflict.[3] “Using Structural Topic Modeling to Detect Events and Cluster Twitter Users in the Ukrainian Crisis” studies how topic modeling evolves with time. They explore how STM can be used to cluster Twitter users that are sympathetic to Ukraine versus Russia, as well as to cluster accounts that are thought to belong to the same individual.[4] “Machine learning model to project the impact of Ukraine crisis” studies war effects using Linear Regression. They explore empirical experiments on economic indices datasets to evaluate and predict the war tolls and its effects on main economics indexes. [5] “Empirical study of topic modeling in Twitter” explores the problem of using standard topic models in micro-blogging environments. They propose methods to train a topic model and evaluate their performance. They discuss how Author-Topic models fail to establish hierarchical relationships between entities in Social Media.[6]

Exploratory Data Analysis

27th February- 1st March



19th April- 21st April

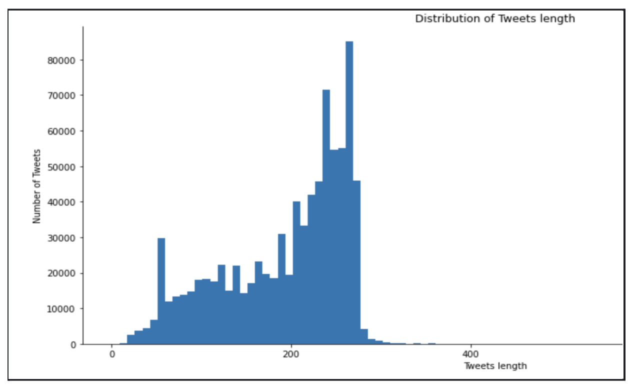


Fig1: Distribution of Tweet length vs Number of tweets

First, we have tried to analyze the number of tweets and their lengths right after the conflict and a month after the conflict. We can see through the distributions that the number of tweets have considerably decreased after a month. An important question that this poses is “Have we become increasingly immune to the war after a month?

27th February- 1st March   19th April- 21st April

Fig2: Word Cloud of the English Tweets

Here we are visualizing the word-clouds for both our 3-day periods. We can see that the first 3 days of the conflict the tweets are centered around support for each of the sides whereas after a month the tweets are more informative in nature. They are primarily reporting the cities impacted and the amount of deaths.

27th February- 1st March   19th April- 21st April

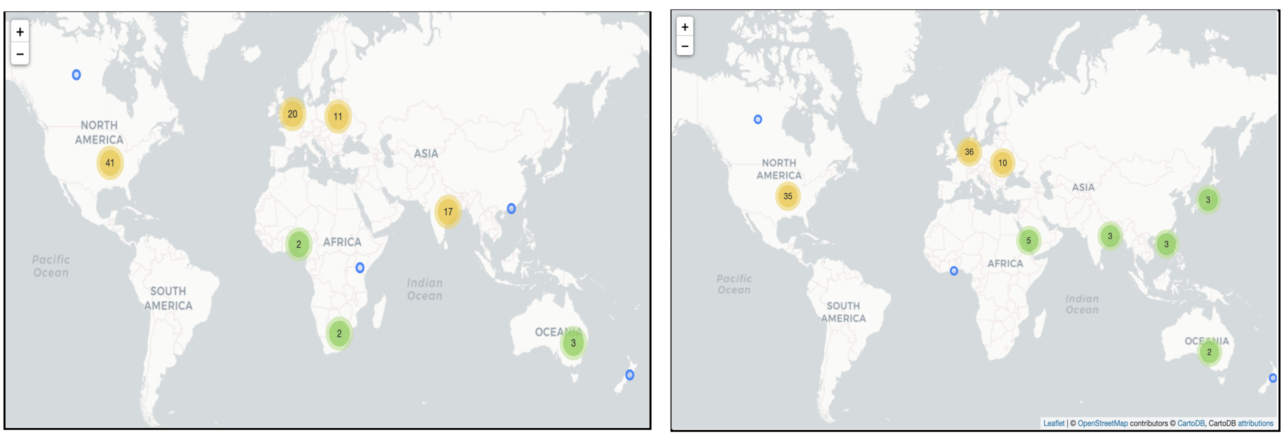


Fig3: World Map for Top 100 places with maximum Tweets

Here we are trying to visualize the top 100 places that had the maximum number of tweets during each of the periods. The graphs show the number of places in a particular country that are tweeting regarding the conflict. We can see the shift in the places that tweeted the most as the political scenarios changed. For instance, India was one of the top contributors in graph 1 and after a month when India refused to take a stand, we can see that the number of places tweeting regarding the conflict decreased there. Another notable change is the involvement of Japan after they announced their support for Ukraine. All in all, we can see a shift in the involvement around the world as the political landscape changes.

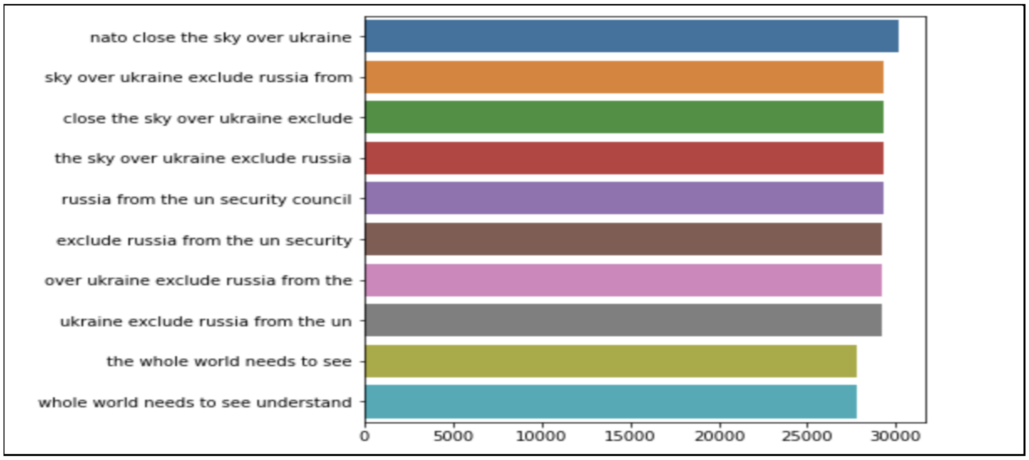


Fig 4: Ngram for 27th Feb-1st Mar

When we look at the top ngrams from both the aforementioned periods, we see the political sentiment conveyed during different periods of the conflict. It is really interesting to analyze ngrams as they paint a very accurate picture of the world politics at different points in time.

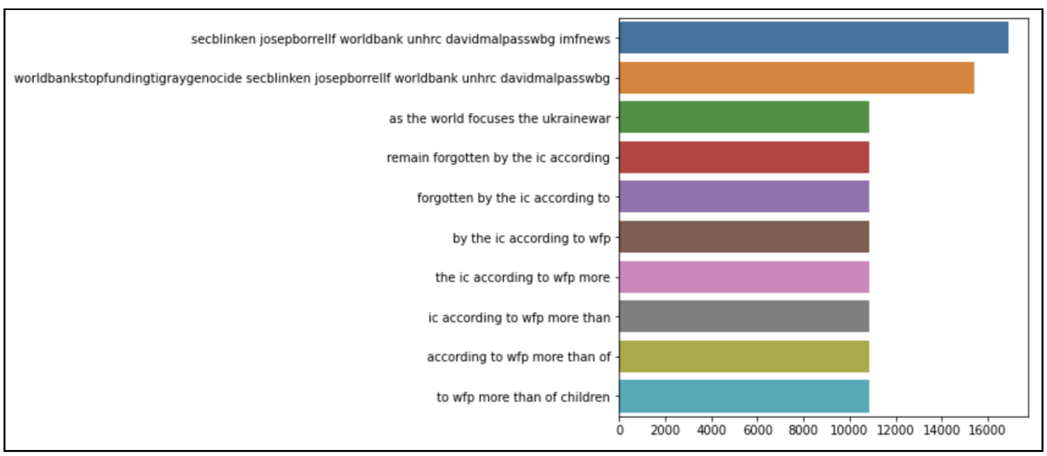


Fig 5: Ngram for 19th April-21st April

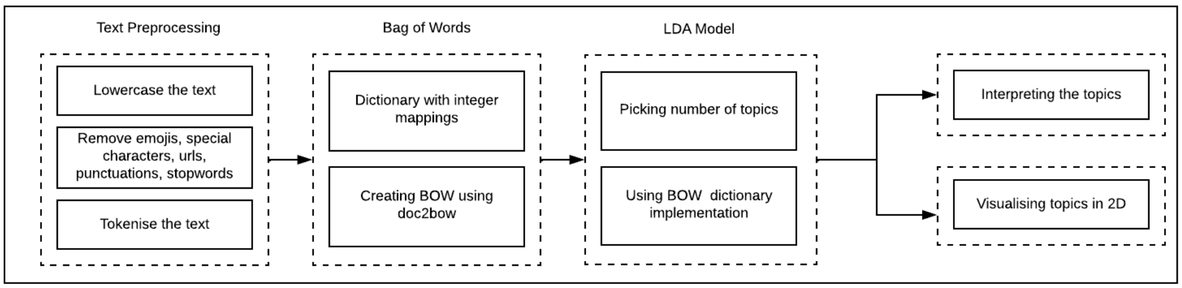
Topic Modeling

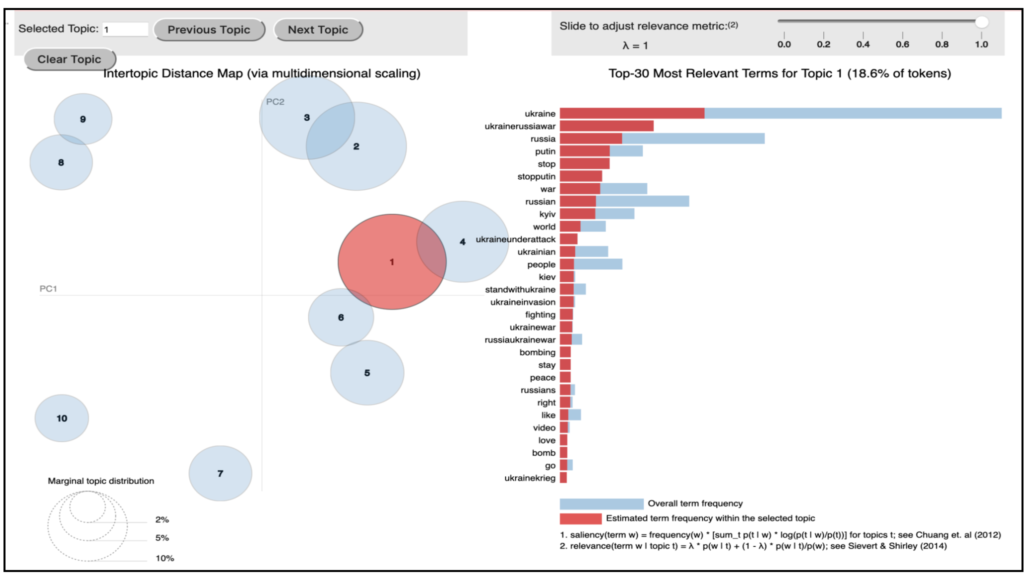
We have a huge corpus of text which consists of close to 2million tweets (in english) over the course of the 6-day period we are analyzing. Topic modeling helps us interpret and summarize huge amounts of textual information. We have made use of Latent Dirichlet Allocation for our topic modeling. LDA is a hierarchical probabilistic model that describes each subject as a term distribution and each document as a mixture of topics. The topics explain the contents of a collection of documents, and the topic proportions establish a low-dimensional representation of each.[7]

We make use of the LDA model module from gensim. The algorithm is fairly straightforward, it includes:[8]

- Training documents may be accessed in any order; random access is not necessary.
- Runs in constant memory regardless of the number of documents: the size of the training corpus has no bearing on memory footprint, and it can handle corpora larger than RAM.
- Uses a cluster of machines to speed up model estimation if possible.

The basic workflow of our LDA modeling is as follows [9]:






```
[(0,
  '0.042*"president" + 0.038*"’" + 0.033*"one" + 0.029*"zelensky" + 0.027*"country" + 0.026*"international" + 0.024*"reach" + 0.021*"sister" + 0.020*"injuries" +
0.020*"deprivation"'),
 (1,
  '0.089*"ukraine" + 0.057*"ukrainerussiawar" + 0.038*"russia" + 0.031*"putin" + 0.030*"stop" + 0.026*"stopputin" + 0.025*"war" + 0.022*"russian" + 0.022*"kyiv"
+ 0.013*"world"'),
 (2,
  '0.057*"ukraine" + 0.024*"people" + 0.023*"russiaukraine" + 0.023*"amp" + 0.011*"poland" + 0.011*"help" + 0.010*"ukrainian" + 0.010*"support" + 0.010*"media" +
0.009*"’""'),
 (3,
  '0.044*"ukraine" + 0.031*"un" + 0.025*"war" + 0.024*"council" + 0.022*"russia" + 0.021*"’" + 0.016*"“" + 0.016*"”" + 0.015*"putin" + 0.012*"palestine"'),
 (4,
  '0.064*"kharkiv" + 0.033*"kyiv" + 0.024*"shelling" + 0.021*"freezing" + 0.019*"city" + 0.018*"million" + 0.016*"nuclearwar" + 0.015*"—" + 0.014*"appeal" + 0.01
3*"control"'),
 (5,
  '0.052*"russian" + 0.034*"ukraine" + 0.029*"russia" + 0.029*"military" + 0.026*"kyiv" + 0.022*"forces" + 0.019*"russias" + 0.017*"vonderleyen" + 0.016*"army" +
0.016*"ukrainian"'),
 (6,
  '0.076*"ukraine" + 0.061*"russia" + 0.035*"nato" + 0.027*"russian" + 0.026*"close" + 0.025*"stoprussia" + 0.024*"security" + 0.022*"sky" + 0.020*"exclude" + 0.
019*"amp"'),
 (7,
  '0.033*"’" + 0.024*"trying" + 0.022*"ukriane" + 0.021*"racism" + 0.019*"sleep" + 0.017*"trapped" + 0.016*"dead" + 0.014*"get" + 0.014*"photo" + 0.014*"today"')
,
 (8,
  '0.051*"tv" + 0.046*"world" + 0.033*"see" + 0.025*"belarusian" + 0.020*"whole" + 0.020*"speech" + 0.020*"house" + 0.019*"message" + 0.018*"spent" + 0.017*"life
"'),
 (9,
  '0.042*"ukraine" + 0.028*"anonymous" + 0.022*"european" + 0.018*"indian" + 0.016*"tower" + 0.013*"law" + 0.012*"expect" + 0.012*"government" + 0.011*"decided"
+ 0.009*"india"')]
```

Fig 6: Topic Modeling for 27th Feb-1st Mar

We can see from the results above that most of the topics spoke about the conflict and the conditions of the people during the war. Topics such as StopRussia StopPutin were also quite common. Tweets were used to spread awareness and information regarding the state of the people in Ukraine and the progression of the invasion. We can see that the tweets were centered around support and had an informative tone during the first few days.

```
[(0,
  '0.064*"ukraine" + 0.031*"russia" + 0.018*"nato" + 0.017*"war" + 0.015*"still" + 0.015*"weapons" + 0.014*"us" + 0.011*"president" + 0.010*"time" + 0.010*"heavy
"'),
 (1,
  '0.057*"ukraine" + 0.051*"russian" + 0.028*"ukrainian" + 0.021*"russia" + 0.016*"putin" + 0.015*"forces" + 0.011*"tank" + 0.010*"one" + 0.009*"said" + 0.009*"t
oday"'),
 (2,
  '0.029*"amp" + 0.022*"stopputinnow" + 0.022*"support" + 0.018*"us" + 0.017*"armukrainenow" + 0.016*"ukraine" + 0.015*"biden" + 0.014*"siege" + 0.013*"senate" +
0.013*"government"'),
 (3,
  '0.048*"amp" + 0.034*"tigray" + 0.032*"aid" + 0.030*"secblinken" + 0.029*"’" + 0.023*"people" + 0.022*"un" + 0.021*"ethiopian" + 0.020*"josepborrellf" + 0.020*
"crimes"'),
 (4,
  '0.104*"tigray" + 0.048*"ethiopia" + 0.030*"humanitarian" + 0.029*"ic" + 0.029*"women" + 0.025*"children" + 0.024*"“" + 0.023*"”" + 0.022*"world" + 0.022*"wfp"
'),
 (5,
  '0.044*"ukraine" + 0.040*"glory" + 0.039*"“" + 0.030*"”" + 0.028*"✊" + 0.021*"worldbank" + 0.021*"man" + 0.021*"fighting" + 0.020*"russias" + 0.020*"russians"
'),
 (6,
  '0.020*"services" + 0.020*"peace" + 0.019*"act" + 0.019*"must" + 0.017*"mayor" + 0.016*"access" + 0.015*"essential" + 0.015*"demand" + 0.014*"would" + 0.013*"r
egion"'),
 (7,
  '0.047*"’" + 0.035*"putin" + 0.025*"help" + 0.023*"russia" + 0.018*"please" + 0.016*"standwithukraine" + 0.015*"ukraine" + 0.015*"mariupol" + 0.014*"armukraine
now" + 0.014*"people"'),
 (8,
  '0.081*"mariupol" + 0.026*"azovstal" + 0.020*"city" + 0.016*"civilians" + 0.015*"soldiers" + 0.014*"reconnecttigray" + 0.014*"ukrainian" + 0.010*"amp" + 0.010*
"russians" + 0.010*"people"'),
 (9,
  '0.050*"standwithukraine" + 0.042*"stoprussia" + 0.034*"never" + 0.020*"ukraine" + 0.019*"tanks" + 0.018*"bucha" + 0.013*"turret" + 0.013*"europe" + 0.012*"win
ner" + 0.011*"melitopol"')]
```

Fig 7: Topic Modeling for 27th Feb-1st Mar

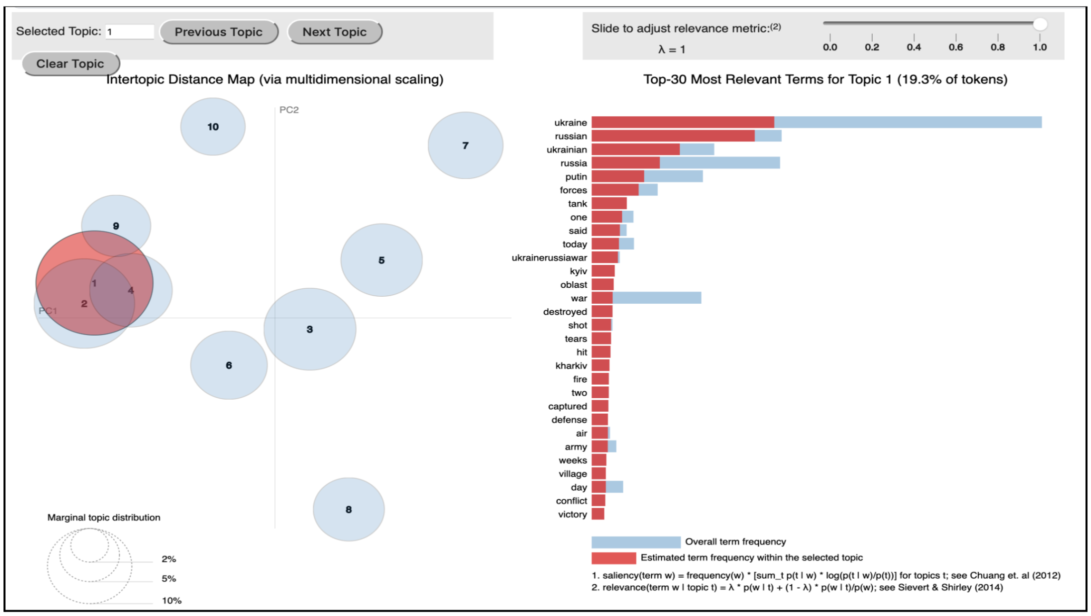


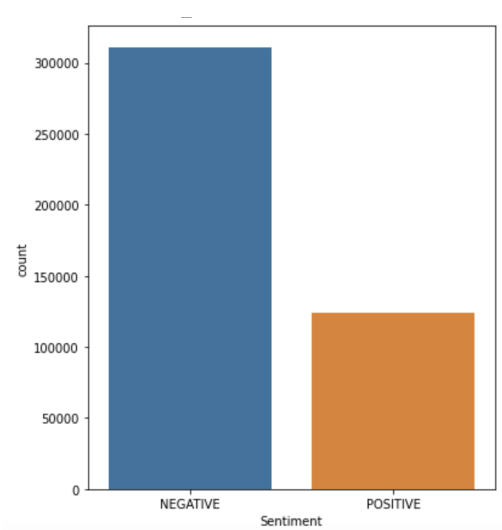
Fig 8: Topic Modeling for 19th April-21st April

Taking a look at the tweets a month after the advent of the war, we can see a shift in the topics that are usually tweeted about. One of the topics mentions words like ‘Biden’, ‘senate’, ‘government’ alluding to the political influence of the USA in the Ukraine-Russia conflict. Another topic mentions ‘Josep Borrell’, a representative of the EU, which again shows the influence of world politics in the tweets related to the conflict. Other topics also mention Tigray which is also facing a humanitarian crisis. We can see the stark difference between the sentiment of the tweets in both the 3-day periods.

Sentiment Analysis

We have studied the sentiment of the users through their tweets over a 6-day period. This helps us analyze the opinions of the people towards the Russo-Ukrainian conflict and how it changed over a period of time as there were developments in the war. For the purpose of text classification we have used the Flair library. Flair is a Natural Language Processing library that is used for poS tagging, text classification and entity recognition, developed and open-sourced by Zalando Research.[10] It supports the combination and stacking of different embeddings such as GloVe, BERT, ELMo for various tasks.[11] It provides an embedding called “Flair Embeddings” that uses the concept of contextual string embeddings. We have used the pretrained text classification model trained on the IMDB dataset, that uses the pretrained flair embeddings for our sentiment classification application. The setup for the sentiment analysis consisted of predicting a label “positive” or “negative” on each of the tweets depending on a sentiment score. This task was performed only on a sample of preprocessed English tweets (0.33) of each of the 3-day periods to analyze the overall sentiment of the twitterverse. Here is the summary of our results.

27th February- 1st March



19th April- 21st April

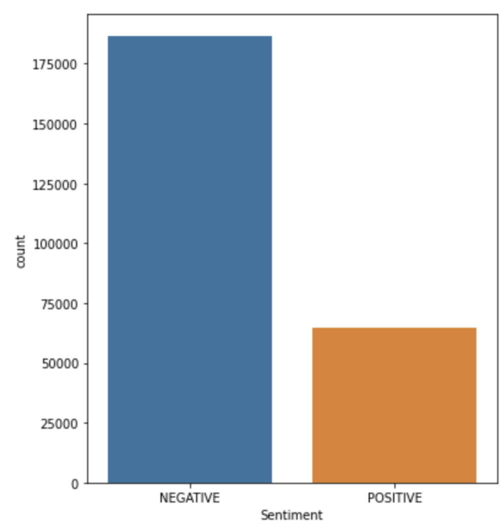


Fig 9: Distribution of Sentiment Labels

We can see from the above bar graphs that the number of tweets that had a positive sentiment to them were close to 25% of the total tweets in both the cases. The total number of tweets decreased in the later 3-day period but the overall sentiment resembled the one of the former 3-day period. Here’s an example of the most retweeted tweet that was classified as negative - “Dear God:\nWhy have you allowed such an evil being (#Putin) to roam this earth allowing thousands of innocent people to be taken from their families by the hands of such a murderous beast? Please, if there truly is a God, remove this evil now so innocent people can live!”

27th February- 1st March 19th April- 21st April

Fig 10: Word Cloud of Positive Labeled Tweets

Taking a look at the word cloud of the positive tweets over the 6-day period we can see that for the former 3-day period the tweets were centered around the President of Ukraine - Volodymyr Zelensky and his address to the people of Russia calling for peace and to motivate the people of the world to join the fight against Russia. These positive labeled tweets, with the mention of the word "catholic" point towards the statement by the Pope and his prayer for peace in Ukraine. In the later 3-day period the tweets similarly talk about President Zelensky and his address to his people. A woman, named "Iryna", as appearing in the word cloud, a maternity doctor, became yet another unsung Ukrainian hero. Iryna Filkina, a Ukrainian mother, who was shot dead by the Russian soldiers. A drone video of her horrific death was captured around this 3-day period. Chairman of the Foreign Affairs Committee of the Parliament of Estonia Marko Mihkelson said in his address at the Inter-Parliamentary Conference on the Common Foreign and Security Policy and the Common Security and Defense Policy in Paris that it was time to grant Ukraine the status of a candidate country for membership in the European Union. The above world cloud depicts these events.

27th February- 1st March 19th April- 21st April

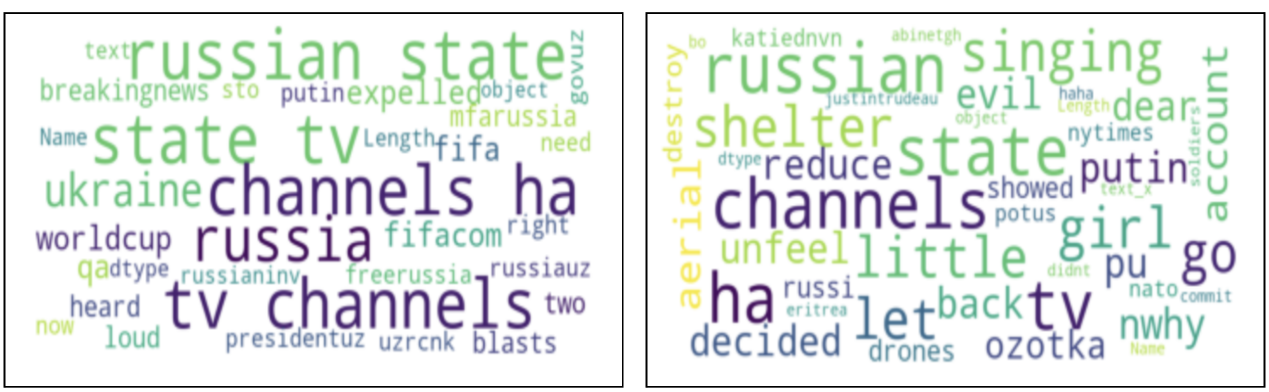


Fig 11: Word Cloud of Negative Labeled Tweets

The word cloud of negative tweets shows similar words in both of the 3-day periods, namely "Putin", "Russian", "Channels". The negative sentiment seems to be directed towards the

Russian government, Ministry of Foreign affairs of Russian Federation and the Russian invasion. The mention of “President UZ” , “Russia Uz” and “Gov Uz” in the negative labeled tweets in the first 3-day periods seems to be stemming from the conversation between Putin and Uzbekistan President Mirziyoyev who “expressed understanding of Russia’s activities in Ukraine” but took a neutral stance in the later part of the war. The mention of the word “girl” in the later 3-day period seems to be pointing at the young girls who were killed or injured by the Russian soldiers or the crimes against women that emerged in Ukraine after a month being occupied by the Russian military. The negative sentiment seems to be directed towards heinous crimes such as aerial attacks, drone captures.

27th February- 1st March *19th April- 21st April*

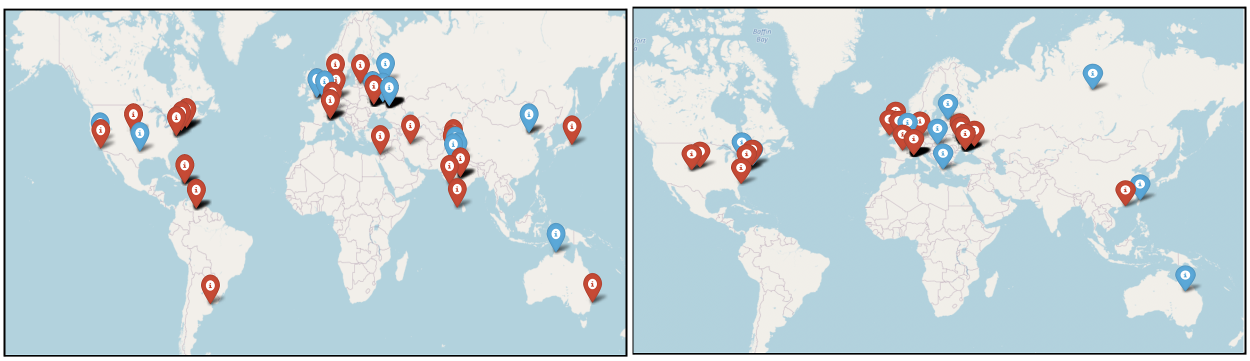


Fig 12: World Map of Top 100 Tweets with Maximum Favorite Count

The above two visualizations show the involvement of the world and its sentiment towards the Ukraine- Russia conflict. The red marker is an indicative of a negative label whereas the blue marker is an indicative of a positive label. We have visualized the top 100 most favorite tweets of the two 3-day periods. Initially India seems to have tweeted against the events in Ukraine, later it proceeded to take a neutral stand. The overall negative sentiment also seems to shift from the whole world to only be concentrated in certain countries.

Conclusion

Through this paper we have tried to understand the sentiments among people regarding the conflict. We have tried to analyze the text to look for prominent cues that can help us understand human interactions and opinions during humanitarian crises. We were able to observe the political influence on the responses to the on-going conflict. An interesting question that we were able to explore through our research is the evolution of the conflict on a per day basis based on the micro trends of the topics under the Ukraine conflict, using topic modeling. We were also able to assay the public sentiment in the Twitterverse about the ongoing conflict using Flair. Our research was based on a very small subset of tweets but we were able to get satisfactory results from the same.

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