Coursework 2: SMA for Russia-Ukraine Conflict
COMP61332 Text Mining

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Abstract

Social Media Analytics (SMA) is becoming prevalent in gauging the interest and opinions on a product or topic of discussion. Based on Twitter debates, this research investigates the use of SMA approaches to analyse the Russia-Ukraine conflict. The results demonstrate that the majority of Twitter's English-speaking user base sees the war unfavourably, and the discussion topics revolve around the idea of stopping the conflict and strategies to accomplish this (sanctions, intervention and foreign support). Furthermore, NER revealed that the most frequently named entities are the countries engaging in the conflict alongside the US (and NATO), while the most frequently mentioned people are the leaders of those countries.

1 Introduction

Since Russia invaded Ukraine on 24th February 2022, social media networks have served as a primary source of information regarding the conflict. Twitter, in particular, has been used to raise awareness, share critical information in real time and document public opinion. In this report, we develop a Social Media Analytics (SMA) pipeline to analyse the vast amount of public discourse on this conflict that is freely available on Twitter. We propose three preliminary research questions to guide our exploration:

1. What are the **main topics** discussed by tweets related to the Russia-Ukraine conflict?
2. What is the **dominant sentiment** towards the Russia-Ukraine conflict?
3. Which **countries and people** are involved in the Russia-Ukraine conflict?

2 Background

Social media has become the de facto public town square, allowing people to express their opinions, concerns, and beliefs regarding different topics. The widespread adoption of social media platforms generates massive amounts of data, which can be analysed to infer valuable information in the context of marketing, politics, and finance. This section explores existing work in the field of Social Media Analytics (SMA) and provides an overview of NLP techniques used to analyse the stream of social media data.

2.1 Social Media Analytics

Social Media Analytics (SMA) is concerned with leveraging the massive amounts of social media user-generated content (e.g., posts, comments, forum chats) to acquire relevant insights into public opinion, as well as understanding who provides the content and who the most influential agents are [1].

The large amounts of data can be utilised in a wide variety of fields for a range of purposes. Through SMA, it can be used to generate business insights and trends [2], monitor brand loyalty [3], target audience [4], and more [5]. Political discussions have also become prevalent on social networks, with one study suggesting social media fosters political participation [6]. However, mixing politics with data collection and analysis presents several ethical concerns and dangers, such as data privacy and public opinion manipulation during major political events like elections [7].

The main challenges faced by SMA are the large volumes of data that come in different structured or unstructured formats, and the increasing difficulty of information extraction. Use of slang, sarcasm, un/intentional misspellings, and other elements relating to personal writing style also present a problem. Biases in information supplied by users of the platform and willingness to discuss also affect the general presentation of opinions on the platforms.

2.2 SMA Techniques

Sentiment Analysis is a Natural Language Processing (NLP) task that quantifies the sentiment expressed in a piece of text. Knowledge-based techniques compute sentiment based on the presence of certain words with predefined unambiguous polarity (e.g., happy, sad, or fearful), whereas statistical methods employ machine learning. Due to the complexities of natural language, sentiment analysis remains a difficult undertaking.

Topic Modelling aims to discover the hidden semantic structures in a corpus of documents. Given that a document is about a specific topic, one would expect certain words to appear in the document more or less frequently: "midfielder" will appear more frequently in football related documents. In this sense, topics are clusters of similar words. Topic modelling captures this intuition by examining a set of documents and, based on the statistics of the words in each, discovers what the topics are. The most common approach used for topic modelling is Latent Dirichlet Allocation (LDA). LDA is a generative statistical model that assumes each document is a combination of a set of topics and each word's existence is traceable to one of the topics.

Named Entity Recognition (NER) is an essential step in Information Extraction that aims to discover named entities in unstructured text and categorise them (e.g., people, locations, times/dates, events, products). **Spacy**, an NLP library that provides a quick statistical entity recognition system, was used for experiments.

(a) Word Cloud for data extracted directly from Twitter API with preprocessing applied and stopword removal.

(b) Word Cloud for *Ukraine Conflict Twitter Dataset* [8] with preprocessing applied and stopword removal.

Figure 1: Word clouds representing tweet text data weighted by word frequencycy, where text size represents their frequency.

3 SMA Text Mining Pipeline

Making Twitter API query requests is the primary approach for obtaining tweets required for SMA. However, the number of API query requests that can be made in a 15-minute window is limited. As an alternative, a publicly accessible dataset titled *Ukraine Conflict Twitter Dataset* [8] with 15.15 million tweets is used. However, data received from direct Twitter API calls are still used to test SMA pipeline components because the smaller data takes less computational time to process.

3.1 Data Retrieval and Cleaning

The following preprocessing methods were employed to clean the tweets before they could be used for further analysis:

- **Removal of artefacts**: remove usernames, URL links, hashtag symbols ('#'), and emojis.
- **Lowercasing**: lowercase all alphabetic characters from the corpus.
- **Punctuation removal**: remove punctuation tokens from the corpus.
- **Blank characters**: remove line breaks, leading, trailing, and replacement of inner spaces.
- **Redundancy removal**: remove duplicate tweet text with first occurrence kept.
- **Stopword removal**: remove stop words when creating a dictionary and corpus to be used by the LDA model.

The hashtag symbols were removed, but the words themselves were retained because Twitter users frequently use the hashtags as part of sentences or to carry information pertinent to the tweet.

The word clouds are created as an exploratory analysis to ensure preprocessing has cleaned up text appropriately, as shown in Figure 1. Word clouds visually represent tweet text data weighted by word frequency, where text size is proportional to their frequency. The preprocessing steps were successful, as shown in Figure 1a and Figure 1b.

3.2 Sentiment Analysis

The general sentiment towards the Russia-Ukraine conflict is measured using VADER [9], a lexicon and rule-based tool for sentiment analysis, which computes the polarity of a piece of text using four scores (positive, negative, neutral, and compound). In our experiments, the compound score represents normalised sum of valence scores of each word in the lexicon and is used as a threshold to assign a sentiment label.

$$\text{label} = \begin{cases} \text{Positive} & C_{\text{compound}} \geq T_{\text{thold}} \\ \text{Negative} & C_{\text{compound}} \leq -T_{\text{thold}} \\ \text{Neutral} & T_{\text{thold}} > C_{\text{compound}} > -T_{\text{thold}} \end{cases} \tag{1}$$

Each tweet has been assigned a corresponding sentiment label based on the value of the compound score, as shown by Equation 1. The T_{thold} threshold value used is `0.05` as specified by the authors of paper [9]. In the paper, it is also mentioned that capitalisation and punctuation influence the intensity of sentiment. Our experiments reveal that retaining exclamation marks and preserving uppercase words results in very similar counts for tweets with positive and negative labels, respectively (Table 1).

Table 1: Sentiment analysis for various preprocessing steps.

preprocessing	Positive	Negative	Neutral
Keep exclamation points and uppercase words	198	429	125
Punctuation removal and lowercase conversion	196	431	125

3.2.1 Sentiment Analysis over Time

Figure 2 shows sentiment plotted over time, revealing that public opinion is predominantly negative throughout the conflict, with positive sentiment peaking around certain dates, as indicated by Table 2.

Table 2: Dates with over 3500 positive sentiment tweets.

Date	Number of Tweets	Normalised Average Compound Score
2022-03-08 10:00:00	4029	1.00
2022-03-08 13:00:00	3509	0.72
2022-03-08 15:00:00	3571	0.77
2022-03-08 16:00:00	3847	0.68
2022-03-08 17:00:00	3989	0.72
2022-03-08 19:00:00	3670	0.86
2022-03-17 13:00:00	3618	0.71

3.2.2 Sentiment Analysis with Geocoding

The Russia-Ukraine conflict has dominated social media, with people from all over the world sparking debates and sharing

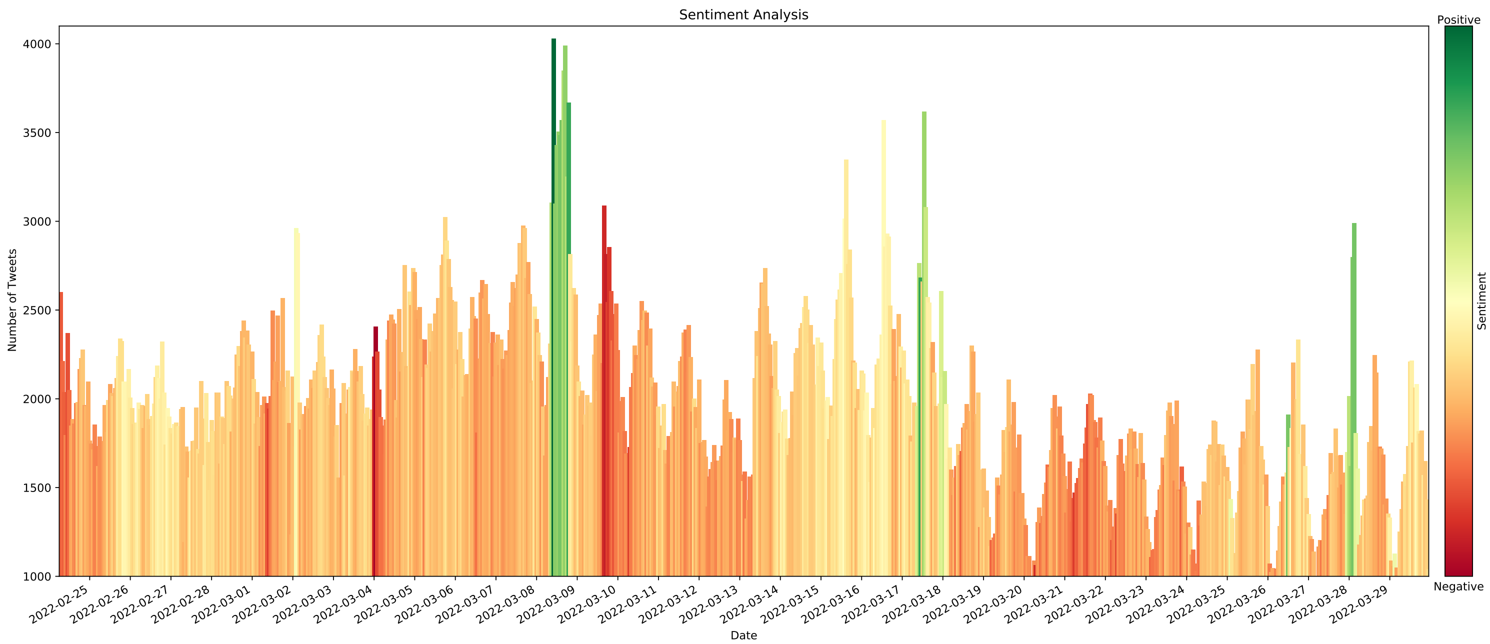


Figure 2: Sentiment analysis over time on *Ukraine Conflict Twitter Dataset* [8].

their perspectives on the conflict. Combining geocoding with sentiment analysis provides better insight into the sentiment on the Russia-Ukraine conflict from various parts of the world. OSM's Nominatim API has been used to precisely geocode tweets extracted from Twitter API, the results of geocoding with sentiment analysis is visualised in Figure 5. Due to the size of the *Ukraine Conflict Twitter Dataset* [8] and OSM's Nominatim API request limits, *Pycountry* was also used to identify tweet country location. The resulting geocoding with sentiment analysis is visualised in Figure 6.

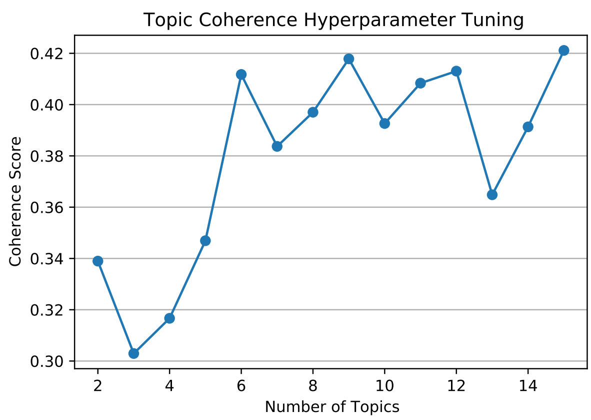


Figure 3: Topic coherence scores for *Ukraine Conflict* [8].

3.3 Topic Modelling

LDA requires defining K number of topics prior to building LDA model. An experiment is carried out to determine optimal k number of topics by computing coherence score for LDA models with a varying number of topics, as shown in Figure 3. The chosen optimal number of topics is $K = 6$, as the coherence score peaks at $K = 6$ and then flattens.

The word clouds visually representing tweet text data of six different topics as detected by LDA model weighted by word frequency, where text size is proportional to their frequency, is shown in Figure 4.

3.4 Named Entity Recognition

Geo Political Entity (GPE) and Person entity labels sorted by frequency in which they appear in $N = 10000$ randomly selected tweets are shown in Table 3.

Table 3: Top five unique identified entities of countries *(GPE)* and people *(PERSON)* from $N = 10000$ randomly selected tweets sorted by frequency.

Named Entity	**Frequency**	**Entity Label**
Ukraine	5039	GPE
Russia	3346	GPE
NATO	480	GPE
US	363	GPE
China	216	GPE
Vladimir Putin	1055	PERSON
Joe Biden	138	PERSON
Zelenskyy	131	PERSON
Donald Trump	29	PERSON
Lavrov	28	PERSON

4 Results and Analysis

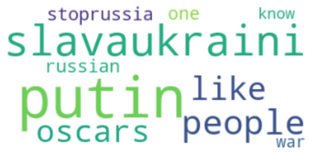
Three preliminary questions mentioned in Section 1 have guided the experiments discussed in Section 3. These questions are intended to better explain the public perspective of the conflict, as well as to identify the most relevant people and entities involved.

4.1 Analytical Question 1:

What are the main topic discussed by tweets related to Russia-Ukraine conflict?

There have been six distinct topics identified from the extracted data set, which can be observed in Figure 4. These correspond to the areas of concern surrounding the conflict.

- **Topic 1** mainly belongs to messages of support towards Ukraine, and those urging Russia to stop the hostilities.
- **Topic 2** contains discussions about NATO involvement in the conflict. This highlights the important role that the United States has played during the conflict.



(a) Stop Putin Russia

(b) NATO Intervention

(c) Cryptocurrency Support

(d) War Discussion

(e) Mariupol Incident

(f) Sanctions for Peace

Figure 4: Topic Modelling word clouds of 6 topics.

- **Topic 3** pertains to financial support for victims of the war, which also emphasises the significant role that cryptocurrencies and NFTs play in sourcing such support.
- **Topic 4** deals with developments on the frontline, with the port city of Mariupol being of significant interest, due to its strategic position.
- **Topic 5** focuses on the impact of the war on civilians, such as those in the besieged cities of Mariupol and Kyiv, and Poland, as an important country of refuge for civilians fleeing the conflict.
- **Topic 6** is around the discussion of western sanctions on President Putin and the Russian economy. This topic also showcases the importance of China in this regard, since the impact of the sanctions on Russia could be lessened with the support of the Chinese economy.

4.2 Analytical Question 2:

What is the dominant sentiment towards Russia-Ukraine conflict?

The results reveal insights into how the public perceives and reacts to the various developments of the conflict. While the general sentiment has been mostly negative since the start of hostilities, key events and developments have been observed to have a strong influence on the public sentiment, with significant increases in either positive or negative feelings. The address of Ukraine's President, Zelensky, to the British Parliament on *March 9*, was correlated with a strong increase in positive sentiment across the retrieved Twitter dataset. On the other hand, the release of the death toll after the bombing of a maternity hospital in Mariupol, on *March 10*, coincided with a strong increase in negative sentiment. These changes can be observed in Figure 2. Individual occurrences, particularly those of an emotional nature, can have a tremendous impact on public attitude, as evidenced by these examples.

4.3 Analytical Question 3:

What countries and people are involved in the Russia-Ukraine conflict?

The most commonly occurring entities are indicative of the main actors in the conflict. These can be viewed in Table 3. Among countries, both Russia and Ukraine are the most frequently mentioned entities. Other major players consist of NATO and the United States, which can be explained by the significant support that western nations have offered to Ukraine throughout the conflict. Despite not being an active supporter in the conflict, China is another commonly occurring entity. This could indicate the public perception of China as a potential deciding factor in the conflict since it has not fully committed to supporting either side as of yet.

Additionally, as demonstrated in Table 3, Russian President Vladimir Putin is considered as a prominent actor in the conflict, as he is the most mentioned person, far more than any Western leader. The Russian president is often mentioned in the context of major developments of the war, or in tweets referring to peace talks. This is likely because he is viewed as not only the principal architect of the war, but also as the one with the power to bring about constructive peace talks.

5 Conclusion

The findings indicate that there is a strong association between important developments in the conflict and public mood towards it. This is still the case even after a month of ongoing warfare, which is remarkable considering that we would anticipate the public become desensitised to the conflict and public interest to wane given the large stream of news. This demonstrates that how a conflict is reported plays a significant role in moulding public mood, which can alter quickly and unpredictably at times.

5.1 Further Work

All of the tweets examined in this paper were written in English, which may have resulted in unintentional bias because English speaking individuals prefer to hold Western ideals. However, non-English tweets account for 50% of the total tweets [10]. Therefore, the SMA pipeline should consider all tweets equally in the future.

Additionally, despite Twitter's popularity in the west, it does not represent the international public as it is only the 16th most popular social media platform worldwide [11]. Data from other platforms, such as the Chinese-based Weibo, which has 30% more daily users, may present different views and ideals. Therefore, any conclusions regarding public opinion should take such bias into account, and future improvements should use data from multiple social network platforms.

Sentiment analysis by itself cannot be utilised to distinguish between opposing sides in a conflict. Two tweets that employ tweets phrases linked to positive sentiment may support opposing viewpoints. Similarly, two tweets containing derogatory language could be directed at different entities (e.g., a tweet criticising the Ukrainian government vs. a tweet speaking out against the actions of the Russian army). As a result, rather than conducting a general sentiment analysis, each topic should have its own sentiment analysis.

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A Appendix : Sentiment Map Visualisation

Figure 5: Sentiment analysis map visualisation for data extracted from Twitter API. Sentiment(Green=Positive, Grey=Neutral, Red=Negative) with compound threshold of 0.05.

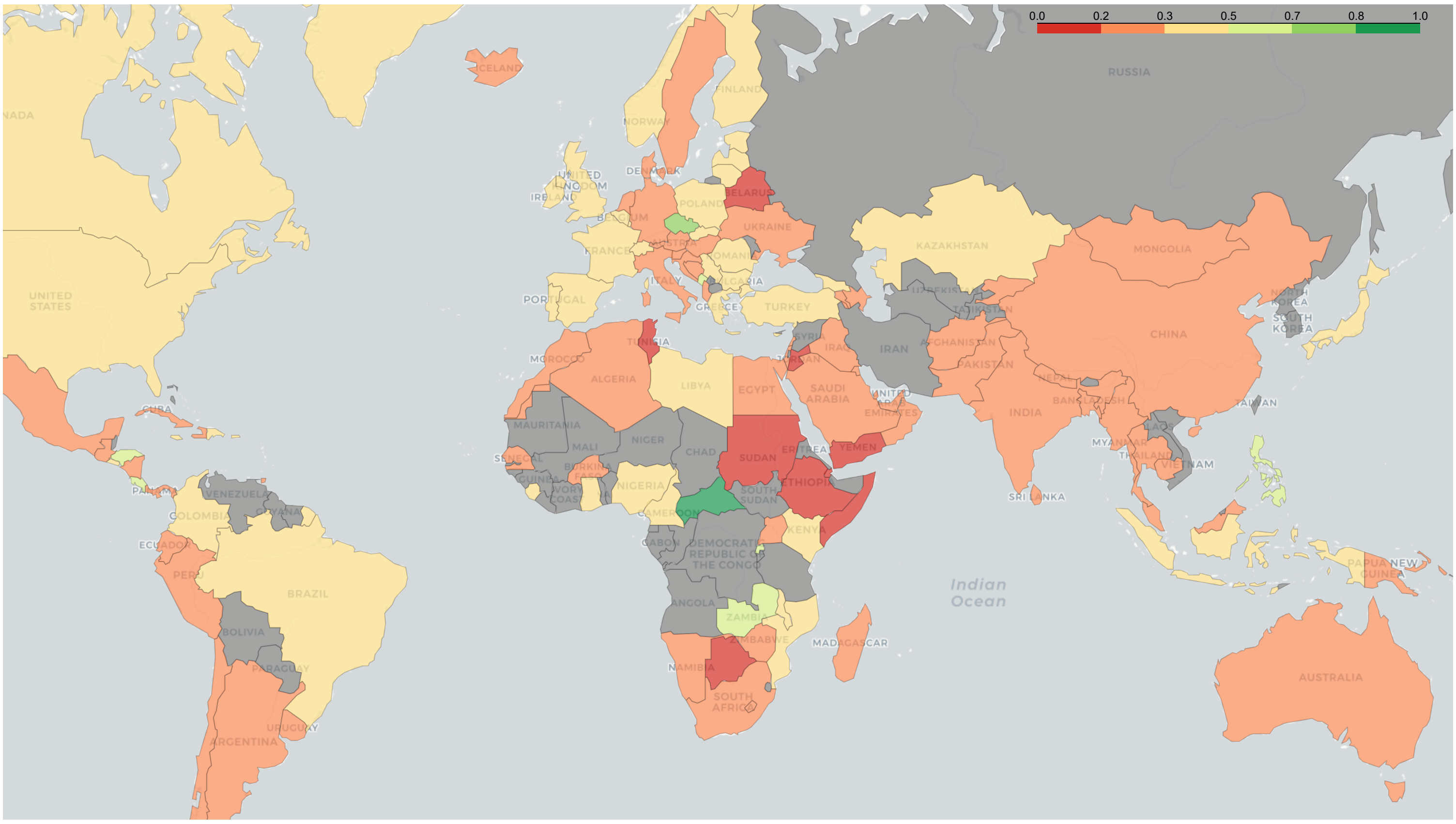

Figure 6: Sentiment analysis map visualisation for *Ukraine Conflict Twitter Dataset* [8]. Sentiment(Green=Positive, Red=Negative, Grey=Unknown(not enough data)) with normalised compound $(0.0 - 1.0)$.