Classification of Twitter posts regarding the Russo-Ukrainian war by emotion

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ABSTRACT

The rise of social media technology led to new possibilities of human communication. Platforms can be accessed worldwide to state opinions, discuss topics or self expression. Hence, a increased amount of traffic during disasters and crisis, enables further unintentional use cases. Analyzing the data, grants access to important real time crisis details, for instance used by governments or emergency organisations. Machine learning technologies create possibilities of using data to gain further knowledge, for example used by the field of Natural Language Processing. This study presents a sentiment analysis of the Ukrainian-Russo war based on Twitter data (Tweets). Therefore, we implement a BERT based sentiment classifier, fine tuned on emotion detection. The model is used to classify tweets containing Russo-Ukrainian war hashtags. Eventually, a selection of the most polarising war events is used to link peoples emotions to timestamps.

The results show, that certain events have a great impact on emotions. Furthermore, the public opinion clearly is shifted towards the Ukraine, facing Russia as an aggressor.

KEYWORDS

NLP, natural language engineering, emotion, twitter, text classification

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1 INTRODUCTION

The undeniable power of social media to connect people around the globe, through various social networking technologies is impacting daily life, whilst creating new opportunities for communication [18]. With a number of 4.6 billion users accounting more than half of the world's population, the access to consuming and sharing information leads to new possibilities for analyzing data, for instance on human behaviour or trends. [10] [27]

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Of adult Americans, 65% use social media frequently, hence the impact on politics, labour, and social life is significant. Furthermore, limiting the survey to young adults, results in a 90% use regarding American adults from the age of 18-29, underlining a upward trend of usage and importance over generations [22]. Apart from consumer side interactions, the enormous amount of users generates additional use cases for other organisations like companies sensing new marketing opportunities or governments exploiting for political propaganda [26] [16].

Facing crisis situations, many social media users tend to interact quickly, either in order to gather information or posting their current state and expressions. Due to the rapid emerge of information, organisations use social media data to assess situations and to collect relevant details [7]. People use social media during natural disasters, particularly Twitter, to get in touch with their social environment and afterwards for aid seeking and exchanging about the emergency[29]. The higher usage of social media during such events can be explained by the fact, that communication systems are likely to stop working during disasters, but social media services stay active.[29] For instance, in March 2011, during the great east Japan earthquake, twitter was used to reach the citizens due to power outages and less internet access. [13] Furthermore, social media is used not only during disasters, but also during war times, to obtain and exchange information [15]. During crisis, platforms like Twitter can also help with emotion communication. For instance during the 2014 Israel Gaza war, Israeli students of ages 13 to 18 years exchanged with their teachers via social media, mainly about emotional support.[21]

On the other hand, those platforms have to be analyzed critically. Twitter is not solely used for information sharing and self-expression, but also for spreading information about politics, for psychological operations and social cyber attacks to manipulate the population, for example during the 2014 Ukraine-Russia conflict [25] [16]. To reach a broader audience, messages containing emotional content are used, caused by the fact that political tweets with emotional content are shared more likely than political tweets with argument quality [12] [24] [31]. Additionally, tweets containing emotional messages are retweeted more frequently and rapid compared to neutral tweets [25] [12].

Incidents of social, political or economical nature disseminated over twitter, influence the public mood.[5] Collecting qualitative data daily, social media technologies can be used in several options to make assumptions about the public opinion on a certain topic. Particularly in crisis situations this data can be useful to spread awareness. Analyzing polarizing events is important in order to understand impacts and point out relations.

This work outlines emotional states of Twitter users during the Ukrainian-Russian war 2022, by creating a sentiment-classification model. Linking sentiments to relevant events, concludes interpretations regarding importance of events and the world-political view of the conflict. Through sentiment analysis by emotion, expressions of those affected can be highlighted and discussion can be cleared.

2 RELATED WORKS

As social media is included in daily life, those technologies influence human communication [18]. With 465.1 million recorded users, Twitter is ranked as one of the most influential social media platforms whilst numbers are growing daily [14]. In relation to growing user numbers, social media data available is rising. Hence, natural language processing (NLP) can be used to perform various tasks. Coppersmith et al. demonstrated the power of combining NLP and social media, by implementing a text classification model through use of word embeddings. Eventually, their classifier could recognize potential suicide risks in texts, highlighting the effectiveness of NLP and its potential force of spreading awareness in critical situations.

Regarding the field of NLP, sentiment analysis represents one of the most researched areas. Linked to the rapid emerge of social media technologies, researchers get access to users feelings when creating posts like current emotional states or opinions [36].

Connecting several users in real time, the micro-blogging technology Twitter is considered the most effective platform during disasters due to flat communication structures [20] [13] [6] and ease of use [29].

Akpatsa et al. presented a sentiment analysis of twitter data connected to the US-Afghan war to understand the public opinion on the crisis. To generate a data set for the created classifier, Twitter Streaming API was used by collecting relevant Twitter hashtags linked to tweets related to the conflict.

The Ukraine-Russian conflict hasn't come to an end, therefore it creates an ever-changing field to explore. Furthermore insights generated from sentiment analysis of up-to-date information, help to give a more in-depth look into the popularity's current emotional well-being.

A sentiment analysis (positive, negative and neutral) of more than 1.2 million english tweets on the topic of the Ukrainian-Russian-conflict was conducted, stating that 31.83% of the tweets were positive, 54.29% negative with 13.88% neutral.[11]

Looking at Ghosh and Roy (2022), tweets were only collected in the time span from 01.01.2022 to 06.03.2022, which doesn't cover the latest incidents. Tweets containing non English language were filtered out, which also narrows down the broadness of peoples opinions. This is especially problematic for analysing the tweets about the Russian-Ukrainian-conflict, since they can be written in their foreign languages.

We therefore present an emotion-sentiment analysis of the latest tweets about the Russian-Ukrainian-conflict, connecting them with timestamps of important events and comparing the emotional responses on the actions taken by Russia or the Ukraine. By analysing emotion, a more fine grained view regarding public opinion is possible, resulting from more assignable states than simply "positive" or "negative". Furthermore, linking event timestamps and emotion allows a general overview of the conflict through accessing immediate event reactions. A sentiment analysis of the different emotions on both war parties concludes the current world-political view of the war.

Table 1: Most popular hashtags related to Russo-Ukrainian war, according to Shevtsov et al.

Nr.	Hashtag
1	#Ukraine
2	#Russia
3	#StandWithUkraine
4	#Putin
5	#UkraineRussiaWar
6	#StopRussia
7	#StopPutin
8	#StopWar
9	#Kyiv
10	#NATO

3 METHODS

For our data-set generation we created a python script to crawl our tweets [34] and for classification and analysis a python notebook executed on google colab [35].

3.1 Data crawling

In the recent study of Ghosh and Roy, they used "Ukraine war", "Ukraine troops", "Ukraine border", "Ukraine NATO", "StandwithUkraine", "Russian troops", "Russian border Ukraine" and "Russia invade" as keywords to search for tweets, which represents one way of collecting tweets for a dataset.

Shevtsov et al. are collecting a data-set of tweets related to the Russo-Ukrainian War, starting at the 24. of February 2022, until now. By choosing the most relevant hashtags (Table 1), they are able to collect most of the tweets with minimal expense. The tweet id's, release date and month, are documented on their GitHub repository. Hence, this data-set already contains more than 79 million collected tweets from more than 8.6 million users. More than half of the tweets were composed in the English language, with a percentage of 61% when the paper was released.

We have chosen to sample tweets from this data-set, due to the tweet download limit per month of the basic Twitter API. For this reason our research depends on the Shevtsov et al. data-set tweets, that were already classified as tweets about the Russo-Ukrainian War.

3.2 Tweet preprocessing

To enable effective analysis of the tweets, pre-processing was applied. Removing URL's from tweet texts enhances the proportion of useful data in tweets, as those are no relevant feature for text classification. As the dataset from Shevtsov et al. is based on worldwide twitter data, languages differ. Therefore, Google-Translator was used to translate every tweet into the English language, on

Table 2: Important war events selected for data analysis.

Nr.	Date	Description
1	24.02.2022	Russia invades Ukraine
2	26.02.2022	Begin: siege of Mariupol
3	01.04.2022	Bucha Massacre
4	07.04.2022	Russian troops move back from Kyiv
5	16.05.2022	Russia completed control over Mariupol
6	06.06.2022	Missile strike on Kyiv

which the model is trained on. Out of many Deep-translation options, Google-Translator was the most handy, which influenced the decision, while others may propose a better accuracy of translation. In general, better translation would not imply a sufficient performance of the model, as it is based on BERT embeddings, which are robust therefore still efficient.

3.3 Finetuning

Huggingface is a company providing various pre-trained NLP models and datasets. Hence, Hugginface grants access to datasets like tweet_eval [3], consisiting of sentiment classified tweets. Furthermore, the dataset enables selection of different labeling, regarding tasks of sentiment classification like emotion recognition [19], emoji prediction [4] or irony detection [28]. We accessed a pre-trained sentiment classification model and fine tuned it with the tweet_eval emotion recognition dataset, in order to implement a tweet-emotion-detection classifier. Our text classification model is based on a RoBERTa model [17], as it has been proven to be a well performing model, especially on Tweets and when re-trained on Twitter [3]. As the datasets contain train, test and validation splits, tuning hyperparameters like batch size and learning rate leads to best performance results. In order to evaluate the classifier, precision, recall, accuracy and F1 metrics were used to distinguish performance differences when training the classifier.[1]

Finetuning the model, resulted in a precision of $P = 0.82$, a recall $R = 0.83$, an accuracy $ACC = 0.85$ and a F-Score $F1 = 0.82$.

3.4 Emotion prediction

Depending on the tweet_eval emotion subset, our text classifier labels tweets with one of four emotion labels. These are "Joy", "Sadness", "Anger" and "Optimism". Furthermore, those can be grouped into negative (anger and sadness) and positive (joy and optimism) sentiment classification labels. Therefore, our emotion classification model, is not only able to project users emotions, but concludes the general public opinion. Hence, emotion prediction is not only more fine grained, but more informative, when compared to standard sentiment classification, as multiple observations are possible.

Polarizing war events, which were analyzed as possible emotion influences, and important events are listed in table 2 [8]. When people are directly involved or the events lead to life changing actions, those are discussed by opinion exchange and emotion expressions, and therefore are spread on Twitter.

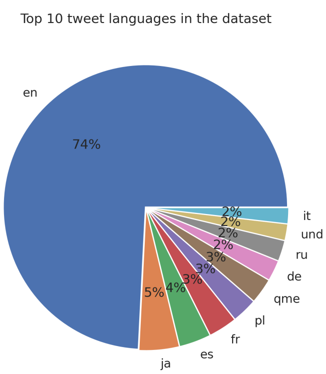
Important timestamps conclude emotional responses on events.

4 RESULTS

4.1 Data-set description

The data-set consists of $N = 21336$ tweets, which are object to classification.

Figure 1: Fractions of twitter classified languages used in data-set



Twitter classifies the language of the tweets. In this case our data-set mostly had tweets in the English language, as seen in figure 1 with a portion of 74%, before translating. Furthermore, other used languages did not exceed a 5% mark, like japanese (5%), spanish (4%), french (3%) and polish (3%).

As TwitterAPI hands multiple information about crawled tweets and the authoring user, we first expected to be able to link tweets to certain countries, in order to generate more detailed data on the conflict. Connecting emotions to countries over time would conclude world-political roles of countries and general positions regarding the war. But as figure 1 indicates, data generating country assumptions is poor, and therefore not useful. Apart from tweet languages, data fields like tweet-location (if specified by the user) and general origin of the user (not necessary, and can be filled with fictional information like "Hogwarts" from Harry Potter) did not conclude a successful and therefore precise country determination.

4.2 Data-set emotion analysis

The classification of the data-set resulted in a mean classification precision of $M = 0.86$ with a median of $Mdn = 0.94$. Results state a fraction of tweets labeled with "Anger" of 46% and "Sadness" with 23%. Positive emotions fall back with "Optimism" having 16% and lastly "Joy" at 15%, which can be seen in figure 2.

Figure 3 visualizes the fraction of emotions based on timestamps. For this chart, we combined the tweet data from the event plus the data of the following three days to get the direct impact of the events on the emotions.
It is recognizable, that the fraction of tweets, labeled with the emotion "Anger", is highest most of the time, ranging from 35% to 55%. "Joy" represents the lowest fraction regarding four out of six events,

Figure 2: Fractions of classified emotion-labels in data-set

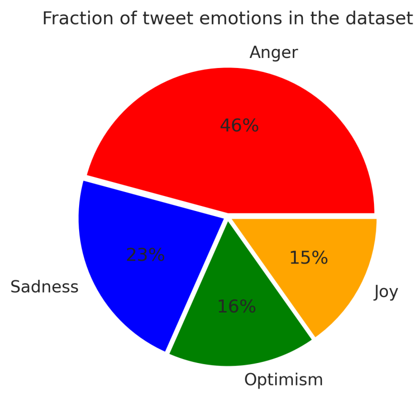
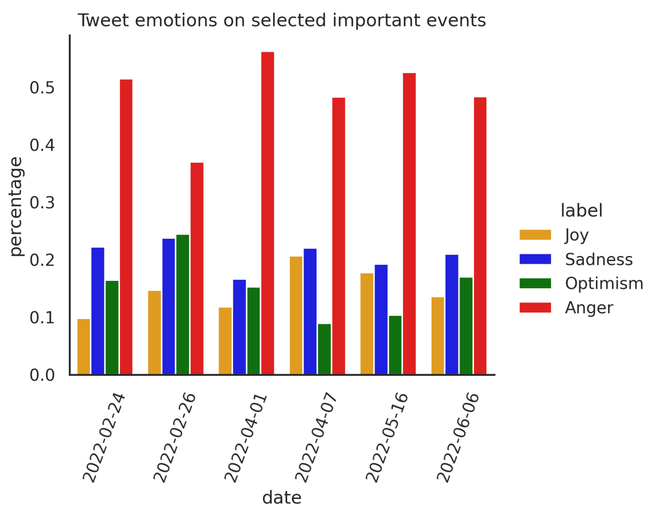


Figure 3: Tweet emotions around events

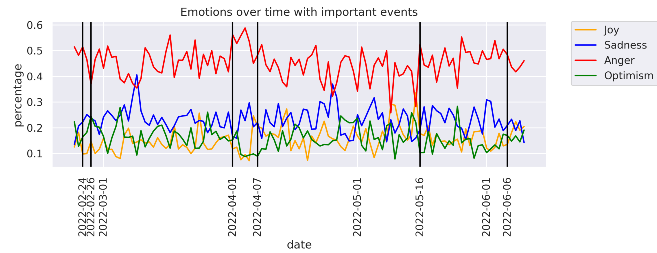


gathering 10% to 25% of tweets. The labels "Sadness" and "Optimism" mostly take up 10% to 25% of label proportions.

On the 24th of February, the fraction of anger labeled tweets is one of the highest of our selected events. This could be because of the starting invasion of the Ukraine by Russia, as well as the peaceful protests in Russia, where over 6000 people were detained for protesting.[32] The biggest "Anger" labeled fraction of our events, was on the first of April, where the Bucha Massacre took place. Looking at 16th of May, the fraction of "Anger" is above 50%. This can be related to the completed siege over Mariupol, resulting in new troop movement opportunities for Russia by using the Crimea land bridge.[30]

The highest level of optimism was on February the 26th. On the days around the 26th, the Ukrainians were succeeding in resisting the Russians.[30] High "Joy" levels were measured on 07.04.2022 where the Russian troops moved back from Kyiv.[8]

Figure 4: Tweet emotions per day



To show a bigger overview over all collected and classified tweets, figure 4 displays the percentage of labeled tweets by emotion per day. Hence, once again a glance at the relationship between labels is possible, as "Anger" mostly takes up the highest amount of labels, followed by "Sadness". In general, apart from a few outliers, the negative emotions are labeled most often, as they mostly occupy from 60% to 80%.

Figure 5: Tweet emotion fractions by country related hashtags

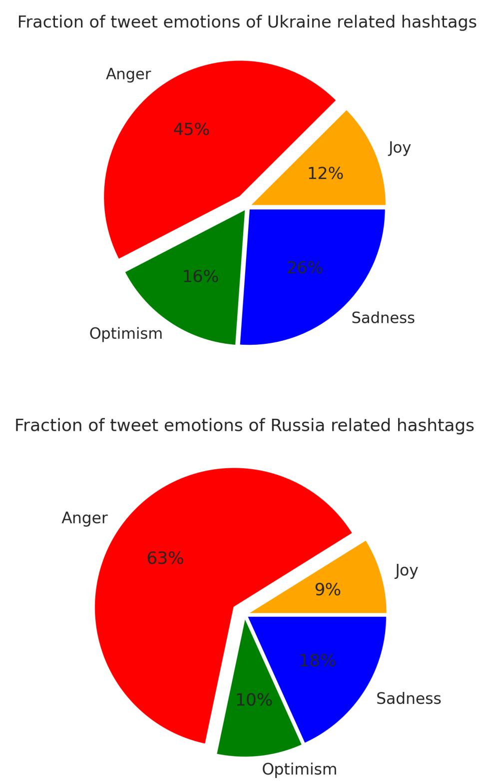


Figure 5 gives a closer look on the distribution of the labeled tweets. To filter for tweets containing opinions and emotions on Russian and Ukrainian movements, popular hashtags of the data-set

Figure 6: Tweet emotion fractions by country related hashtags over time

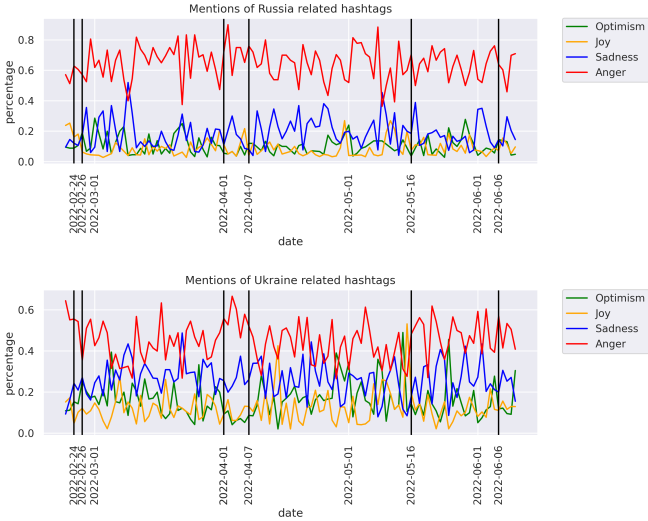


Table 3: Peaks of each emotion by parties

Emotion Label	Ukraine	Russia
Joy	15.05.2022	30.04.2022
Anger	03.04.2022	02.04.2022
Optimism	14.05.2022	01.03.2022
Sadness	22.03.2022	09.03.2022

were chosen. For Ukrainian tweets, the neutral hashtags #ukraine and #kyiv were chosen, for Russian tweets #russia, #putin. Looking at the distribution of labeled tweets, it is clearly visible that more tweets mentioning Russian hashtags are labeled "Anger" than the tweets mentioning Ukrainian hashtags. On the other side tweets mentioning joy, sadness and optimism are more frequent when containing Ukrainian hashtags. Tweets labeled as joy or optimism are relatively low regarding Russia related hashtags, when compared to Ukraine related ones.

We created two plots to analyze the fractions of emotions, associated with the tweets, by hashtags over time. In figure 6 it is visible, that the Russian related tweets containing anger emotion have a higher percentage than the Ukrainian related tweets. Also sadness fractions are lower in comparison to the Ukrainian ones.

4.3 Emotion peaks

Sorting all emotion fractions per party, we listed the events, as seen in table 3, with the highest peaks.
For Ukrainian tweets, Joy was the highest on 15. of May, which could be because of the statement of NATO Deputy Secretary General Mircea Geoana, that the Ukraine could win the war.[33] The "Anger" peak on 03.04.2022 is explained by the bucha massacre and the war crimes committed at that date. Optimism was the highest on 14th of May for Ukrainian related Tweets, a factor could be the announcement of the withdrawal of Russian troops from Kharkiv. The destruction of a laboratory at the Chernobyl nuclear power plant, could be the reason for the peak of Sadness. That is the case, because at this laboratory, they researched for new ways to deal with radioactive waste.[33]
Now looking at the Russian related tweets, we measured noticeable peaks of the labels "Anger" and "Sadness". "Joy" and "Optimism" fractions did not differ much between the highest peaks, therefore aren't further investigated. The twitter restriction of Russian users must be noted, therefore are tweets relating Russia mostly stated by non Russian citizens. On 02.04.2022 anger levels were at its highest with 90%. On that date, there were missile strikes on Ukrainian cities Poltava and Kremenchuk. Regarding the Russian related tweets, the label "Sadness" hat it's peak on 9th of March. The evacuation of 40.000 Ukrainian civilians could have been an influence.[33]

5 DISCUSSION AND CONCLUSIONS

Results conclude a general analysis of the public opinion regarding the Russo-Ukrainian war. In general, anger takes up the biggest fraction of emotions involved, followed by sadness, drawing a picture of suffering, incomprehension and antipathy facing the conflict. When comparing emotions regarding the two involved countries, people face Russia in a more aggressive way than the Ukraine, as 63% of tweets are labeled as anger, compared to the Ukraine, where the other emotions take up the majority. This fact states that users, and therefore the public opinion is clearly shifted towards the Ukraine as a sufferer and Russia as an aggressor.
Analysing emotions over time, states Ukraine related tweets as a "emotional roller-coaster", with certain events changing the ratio of emotions, while Russia related tweets were relatively constant regarding labeled emotions, concluding a stronger emotional bond to the Ukraine, hence again showing a shift towards the Ukraine regarding the general public opinion.
The analysis over time does not only conclude general emotion alteration and certain pre-selected event comprehension, but helps identifying the most relevant events statistically, and not by the evaluation of media-organisations.

Our research and analysis has given a first overview over the first incidents looking at the more fine grained emotion than just sentiment. Because of the ongoing conflict, there is still the need for more analysis, that also contains the newest information. Further research should be done incorporating more tweets over a larger time span.

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