Sentiment of the Tweets on Russo-Ukrainian War: the Social Network Analysis

Andrija Poleksić[1], Sanda Martinčić-Ipšić[1,2]
[1]Faculty of Informatics and Digital Technologies, [2]Center for Artificial Intelligence and Cybersecurity,
University of Rijeka,
Radmile Matejčić 2, 51000 Rijeka, Croatia;
Email: andrija.poleksic@student.uniri.hr, smarti@uniri.hr

***Abstract*—This paper presents the analysis of social network posts using standard natural language processing (NLP) methods and undirected graph representations. The Twitter data used in this work is based on two keywords: Ukraine and Russia in May, October, November and December 2022. After standard pre-processing of the raw data and sentiment classification using "Valence Aware Dictionary and sEntiment Reasoner" (VADER), we proceed to the construction of a weighted and undirected network with hashtags as nodes and hashtag co-occurrences as weighted edges. This representation enables topic extraction based on Louvain community detection. For the quantification of the polarity in the network–community, we propose the "stanciness" metric based on "pnlogratio". The results show that combining sentiment with community structures gives us a deeper insight into the polarity of public opinion on the Russian-Ukrainian war.**

Keywords*—*Sentiment analysis, Undirected graphs, Community detection, Natural language processing (NLP)

I. INTRODUCTION

Social networks are a valuable source of information and can serve as an important communication platform during global crises such as the COVID-19 pandemic [1], [2], wars [3]–[6], climate change [7], economic crises [6], [8], migration crises, etc. On one side social platforms can serve as the key communication platform that enables sharing of valuable information [1], but on the other, they can propel multiple negative effects: (i) foster negative emotions [5], [6], [9], [10] (ii) generation of insulting or hate speech [5], [11], (iii) spreading of fake news and misinformation [7], etc. Still, understanding how people post comments in online communication may shed light on the fundamental mechanisms by which collective thinking emerges in a social group [12].

Social networks analysis (SNA) and natural language processing (NLP) provide relevant methods for studying user-posted content and user behaviour in social networks, hence we engage both. Sentiment analysis (or opinion mining) is the field of NLP study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions toward entities such as products, services, organizations, individuals, issues, events, topics, and their attributes [13]. Sentiment analysis has been applied to identify attitudes, opinions and public perceptions on many topics, usually identified with topic modelling methods [10], [14]. Social network analysis provides a set of methods for analysing relationships and interactions between actors, explaining its underlying social structure, such as the communities of users, network hubs and central nodes, spreading patterns, etc. [15]–[17].

It is well-known that Twitter data can be used to study many phenomena like the growth mechanisms of social interactions, assessing user influence, monitoring trends, or sentiment analysis [18]–[21]. The goal of this work is to obtain insights into Twitter communication on the topic of the major global crisis caused by the ongoing war. We aim to provide insight into public opinion on the Russian-Ukrainian war by combining the polarity of tweets sentiment with analysis of hashtags graph structures.

Hence, we collect the dataset based on two keywords: Ukraine and Russia during May, October, November and December 2022. For the detection of the polarity of tweets (positive, negative and neutral) we use "Valence Aware Dictionary and sEntiment Reasoner" (VADER). Next, we construct an undirected weighted network with hashtags as nodes and hashtag co-occurrences as weights on the edges. This representation enables community detection for topic extrapolation. Finally, we propose a metric that quantifies the "stanciness" of the tweet based on "pnlogratio", which calculates the overall sentiment of the node based on the compound score of incident edges. The results show that "pnlogratio" can be used to obtain insights into the polarity of public opinion on the topic captured with hashtags.

Section II contains a short overview of the research of Twitter posts and hashtags analysis, specifically for the ongoing Ukrainian war domain. In Section III, we provide a brief overview of the methods for sentiment classification and graph analysis and define a novel "stanciness" measure. Section IV elaborates upon the data preparation, sentiment detection and network construction. The results are presented and discussed in Section V. In the last Section, we give some concluding remarks and plans for future work.

II. RELATED WORK

Twitter is a popular social network that enables publishing of short (i.e. up to 280 characters) publicly visible messages called tweets. Tweets typically consist of content (i.e. text), links (i.e. URLs), user mentions (with sign), retweet information (RT) and hashtags. Hashtags are marked with the # sign and are used for meta-tagging, which enables users to retrieve specific content. Hashtags do not follow a predefined structure, yet they can capture the essence of messages, much like keywords or keyphrases do [22].

The thorough report on the tweets hashtag networks construction principles and network analysis, along with the study of the growth mechanism via link prediction is reported in our previous work [22]. Therefore, here we focus on the overview of the related work centred around the sentiment analysis of tweets for the selected domain of the Russo-Ukrainian war.

Chen and Ferrara in [3] collect a large dataset of 63M tweets in many languages and report English for 72.58%, Spanish for 5.6%, and French for 3,77% tweets as the top frequent languages. Based on the simple occurrence frequency they report the top 15 hashtags: ukraine, russia, putin, standwithukraine, kyiv, ukrainerussiawar, stopputin, ukrainerussianwar, russian, ukraineunderattack, nato, stoprussia, kiev, ucrania, ukrainian. Finally, they also study the region of the tweet origin.

Garcia and Yabut in [4] perform lexicon-based tweet polarity detection with a report on the most frequently used hashtags: ukraine war, worldwar3, ukrainian, putin, ukraineRussaconflict, Russia, ukraineinvasion, ukraine, putin. The negative polarity and emotion of sadness prevail over fear and anger.

Sazzed in [5] goes a step forward and employs a methodologically similar setup to our work. The sentiment of 80,000 tweets is determined according to the VADER scores followed by LDA (Latent Dirichlet Allocation) and BERT (Bidirectional Encoder Representations from Transformers) topic modelling. The results suggest that although both positive and negative sentiments are present the negative prevails and topic modelling reveals a myriad spectrum of topics.

Polyzos in [6] conducts the meticulous sentiment analysis on 42M million tweets and calculates impulse response for 15 economic and financial indicators (stock markets, commodities, interest rates, currencies and cryptocurrencies). He shows that sentiment analysis determined with pre-trained deep learning model on an extended sample of 42M tweets can proxy the public's perception of the crisis situation, and influence the financial sector. The paper uses Vector AutoRegressive (VAR) model to quantify the response of stock markets, oil, gold and bitcoin prices, to Russo-Ukrainian War.

Finally, kindly note that we limit our study to isolated time periods and the English language, hence the generalization can be achieved only with extension to a broader set of languages (i.e. geographical regions) and the whole duration of the war. This remains a future challenge.

III. METHODOLOGY

This section gives a brief overview of the methods used for sentiment analysis and network construction and characterization.

A. Sentiment Analysis

The central part of the methodology focuses on the 3-dimensional sentiment analysis, which consists of a positive, neutral and negative dimension. To determine the sentiment, we use the Valence Aware Dictionary and sEntiment Reasoner (VADER) [23] due to its proven good performance when applied to Twitter data. VADER uses valence scores from -4 to 4 (extremely negative to extremely positive) to enrich a lexicon of words with their intensity. Compared to related work, VADER relies on 5 heuristics and an optimized human scoring method using the wisdom-of-the-crowd (WotC) approach [24]. The use of the 5 heuristics: punctuation, capitalization, degree modifiers, constructive conjunction "but", and a tri-gram strategy to resolve the effects of negation on polarity, as elaborated in [23]. VADER requires (works best with) raw, unprocessed microblog-like (i.e. short posts on social networks) data.

For the given input, (e.g. a tweet text), VADER computes 4 scores based on the valence scores of each word in the lexicon. The first three refer to the positive, neutral, and negative scores ("pos", "neu", "neg") as a ratio for the proportion of the text in each category. The compound score is calculated as the sum of the valence scores of each word in the lexicon (where unknown words have a valence score of 0). The sum is then normalized to fit the $[-1, 1]$ interval. The compound score is calculated with

$$\frac{s}{\sqrt{s^2+\alpha}}$$

where "s" is the sum of the valence scores of all words and alpha, as used by the author, is equal to 15. Using a recommended compound score threshold of 0.05, the data is sorted into three categories: "positive" for scores greater than or equal to 0.05, "neutral" between -0.05 and 0.05, and "negative" for less than or equal to -0.05.

B. Network analysis and construction

Next, we overview used network construction and characterization principles. Note that, we interchange the terminology between graph and network, both are accurate but stem from different scientific disciplines i.e. sociology and mathematics. The graph consists of nodes (i.e. vertices) representing the actor. We construct the weighted and undirected network: hashtags are nodes; undirected edges (i.e. links) represent the co-occurrence of hashtags in the tweet. The weights on the edges are derived from the co-occurrence frequency of the hashtags. With this setup, it is possible to calculate network characterization measures: centrality measures (e.g. degree, betweenness, eigenvector and closeness centralities) - metrics that quantify the importance of nodes - and community detection methods (e.g., Louvain clustering) - relevant for the revealing of the structure of communities or clusters. The details about complex network analysis can be found in [25], still, in continuation, we provide only the essential descriptions to ensure the integrity of the paper.

Degree centrality is computed as the total number of edges incident with a node normalized by the maximum degree in a network [25]. Betweenness centrality measures the extent to which a node lies along the shortest paths between other nodes. A node with high betweenness centrality acts as a bridge between other nodes, and information flow is more likely to pass through it [25]. Eigenvector centrality is similar to degree centrality and attributes the value of a node higher when connected to nodes with a high value. Hence, a node with a high eigenvector centrality value is incident to high-valued nodes [25]. Closeness centrality measures the average distance from a node to all other nodes, or a node with high closeness is close to all other nodes in the network [25]. The idea behind this measure is that the closer a node is to all other nodes, the more central it is, and the faster it can access and disseminate information to others.

Communities (i.e clusters of nodes) are groups of nodes that share properties and/or play similar roles within the network [26]. Detecting communities in complex networks is of particular interest when identifying nodes that share properties and dynamics [27]. In this research, we apply the Louvain algorithm [28] for community detection. As stated in [29], for analyzing network data where links represent not flows but rather pairwise relationships, it may be useful to detect the structural components - communities [26], [27]. The Louvain algorithm [28] is an unsupervised community detection method that consists of two basic steps: modularity optimization and community aggregation. In the first step, the modularity measure is iteratively maximized by comparing the modularity gain for combinations of different node partitionings. In the second step, each community discovered in the first step is abstracted into a single node. The algorithm is repeated until no further improvements are possible.

We propose a novel metric "stanciness" of tweets based on the "pnlogratio". "Stanciness" explains the amount or level of attitude present in a piece of text, which can be either positively or negatively polarized. Therefore, we use "stanciness" to approximate the total quantity of sentiment (both positive and negative) in texts. "Pnlogratio" quantifies the overall sentiment of nodes based on the compound score of each edge with which that node incidents. The formula is based on the ratio of the precomputed attributes *posc* and *negc* as follows:

$$pnlogratio = log_{10}(\frac{\sum posc}{\sum abs(negc)}),$$

where *posc* is a sum of all positive (>0) and *negc* is a sum of all negative (<0) compound scores of weights on incident links. The "pnlogratio" expresses the ratio between positive and negative nodes advantageously and centres the results around the value of zero to enable the best visualisation interpretability of the calculated values.

IV. DATA AND EXPERIMENTAL SETUP

A. Data collection

Aiming to analyze the content on tweeter posts on the crises caused by the Russo-Ukrainian war, collecting relevant data is a prerequisite. Therefore, we use the open-source alternative to Twitter's official API, the Twitter intelligence tool Twint [30]. Twint simulates Twitter search as a guest user obtaining tweets fitting the preset time span. For comparison purposes, we decide to gather 20000 tweets for each of the two selected keywords, Russia and Ukraine, on a daily basis. The selection of these two keywords is grounded on the frequency obtained on a large Twitter dataset [3]. Initial data collection conducted in May 2022 gathered a total of 134,297 and 120,038 tweets for Ukraine and Russia keywords respectively. During October, November and December, the data collection totalled 1,952,474 tweets (942,616 collected on the keyword Ukraine, 1,009,858 on Russia). The final dataset consists of two sets of 60 comma-separated values (csv) files (corresponding to a total of 60 days of data collection) containing 36 columns of various tweet metadata.

B. Data preprocessing

The data preparation resulted in two csv files (each per one keyword, and 60 days) containing eight filtered columns (out of 36): id, conversation_id, user_id, created_at, tweet, urls, hashtags, and language. Additionally, we filter the data by language to remove all non-English tweets. Note, due to the selected sentiment analysis method (see Section III), no further NLP preprocessing steps like stopwords removal or stemming are required.

Next, we proceed with assessing the polarity of tweets with VADER as defined in Section III. Tab. I shows two examples of Twitter data evaluated by VADER, where the first column is the text of the tweet and the second column is the evaluation score in the form of a 5-tuple. The tuple consists of the "pos", "neu", and "neg" mentioned above, a compound score, and the class to which it belongs (e.g. "negative").

Fig. 1 shows the overall distribution in two datasets where negative, neutral, and positive are red, blue, and green, respectively. As expected, higher overall negativity in the dataset is associated with the keyword Russia. And both parts of the dataset are leaned negatively (51% and 47% of negative tweets for Russia and Ukraine respectively).

TABLE I: Polarity of tweets with VADER scores

Tweet text	VADER Score
@JJcycles Trumpers in tears...now back to Russia and Ukraine war. Still think Putin will do something horrible soon.	(0.316, 0.684, 0.0, -0.8126, "Negative")
@Flingan67 Ukraine you are winning. There is no need to do that to POWs. Yes the ruzzians are terrible to Ukrainian POWs, but they are not Ukrainians. Be the better people.	(0.097, 0.692, 0.21, 0.6428, 'Positive')

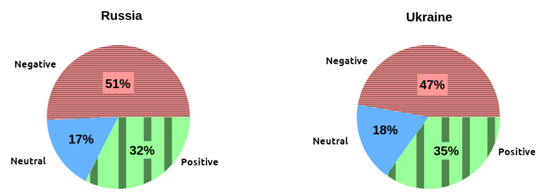

Fig. 1: Ratio of positive, neutral and negative classes in the dataset for Russia (left) and Ukraine (right)

C. Graph construction

Next, we proceed with the construction of hashtags network by merging two datasets (Ukraine and Russia) into one. By their nature, two sets are expected to overlap (e.g. contain both keywords), so we deduplicate the data, which resulted in removing a total of 197,499 rows and retaining 1,754,975 rows for the network construction. The data is then filtered by the number of hashtags to ensure that there are at least two in a tweet. Additionally, we normalize the case-sensitive variations of hashtags and remove emojis and unrecognized characters.

Graph (Network) construction is implemented with a Python package for creating, manipulating and studying the structure, dynamics and functions of complex networks, the NetworkX [31]. The first version of the network of hashtags consists of 50,522 vertices and 486,612 edges with "weight" and 4 more attributes:

- "posc": Sum of all positive (>0) compound scores of tweets in which the given "combination of hashtags" (from now on, edge) occurs,
- "poscount": Count of all positive (>0) compound scores of tweets in which the edge occurs,
- "negc": Sum of all negative (<0) compound scores of tweets in which the given edge occurs,
- "negcount": Count of all positive (<0) compound scores of tweets in which the edge occurs.

These attributes enable different calculations including averages, positive-negative ratios and weighted metrics. In the second version of the network, we filter out unconnected nodes, retaining only the largest connected component (LCC - i.e. the largest component of connected nodes in the network) with 47,395 nodes and 483,023 edges.

Fig. 2 shows a preview of the graph created from approximately 0.009% of the data, enabling the visualization. The colors of the nodes represent the overall sentiment of the incident edges: red, grey, and green indicating negative, neutral, and positive sentiment, respectively. Color is determined by comparing the values of "a" and "b": red (-1) if $a < b$, grey (0) if $a = b$, and green (1) if $a > b$. where

$$a = \sum posc, b = \sum negc$$

and *posc* and *negc* correspond to all edges incident to the particular node. The edge weights are visualised by the thickness of the edges.

D. Network analysis

Enriching nodes with numerical attributes such as centrality measures and sentiment averages allows us to gain a deeper understanding of public opinion on specific topics. Using the constructed graph, we can identify important nodes, their "stanciness", and the context in which they are mentioned. Therefore, we apply the proposed metric for measuring "stanciness" based on "pnlogratio" and add it to the node attributes.

In the second step, we compute four centrality measures: degree, eigenvector, betweenness, and closeness, to detect the most important nodes - prominent hashtags. The centrality measures can provide different insights as we have elaborated in [17], [32]. Therefore, here we examine several centrality values to detect the most prominent nodes, assuming that the majority of the important nodes will be closely related to the issues of the Russo-Ukrainian war.

The final step of analysis involves the detection of communities using Louvain clustering with a granularity of 0.75 while also removing communities containing less than 20 nodes. In the context of this analysis, we interpret the detected communities as a rough estimate of the topics related to the Twitter dataset we collected, which explains the underlying themes discussed in the context of the dataset. Still, whether detected communities really represent topics remain to be confirmed with topic modelling in future research.

V. RESULTS

In this section, we report the results of the combined network and sentiment analysis. First, we report the results of the centrality measures. Tab. II lists the top 15 nodes (hashtags), excluding the obvious russia and ukraine hashtags, based on each of the degree, eigenvector, betweenness and closeness centralities.

Different centrality measures detect different hashtags and derive different rankings, although as expected there

TABLE II: Top 15 hashtags according to the centrality value

Degree	Eigenvector	Betweenness	Closeness
putin	ukrainewar	urw	putin
usa	kherson	ukrainewar	usa
war	urw	ukrainewillwin	war
russian	putin	standwithukraine	russian
nato	nato	kherson	nato
ukrainewar	usa	crimea	ukrainewar
urw	war	etsyseller	urw
china	russian	ukrainianarmy	china
kherson	news	kharkiv	news
ukrainian	urwr	stopputin	urw
news	kyiv	dekorstyle	ukrainian
ruw	unitedstates	lgbtq	biden
urw	ruw	armukrainenow	ruw
biden	germany	nft	europe
iran	china	stoprussia	kherson

abbreviations: urw - ukrainerussi(an)awar; ruw - russiaukrainewar.

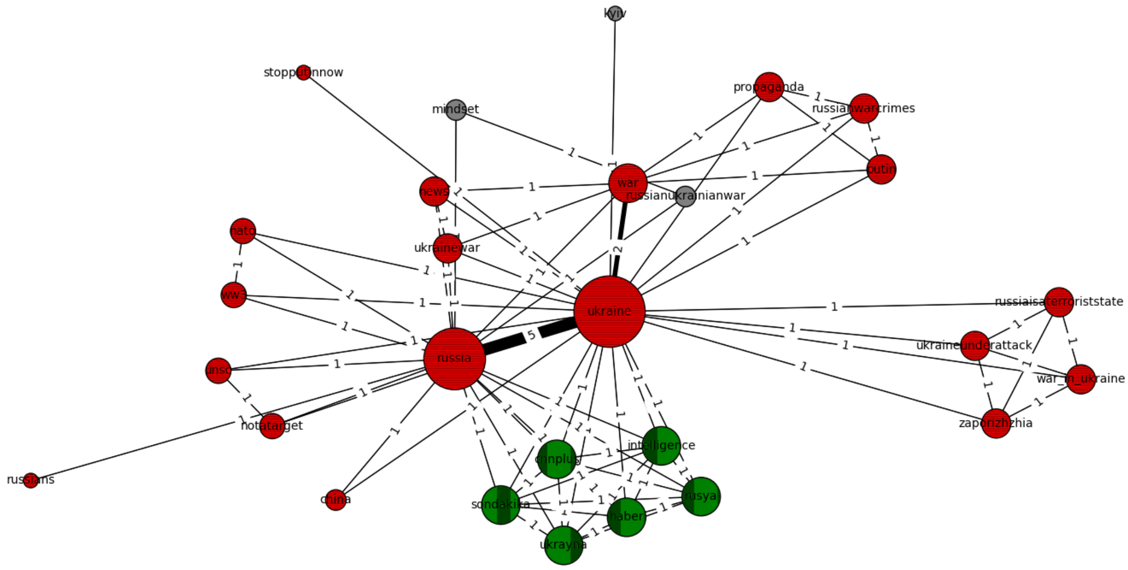

Fig. 2: Weighted graph example: negative hashtags-red-(horizontal lines), positive-green-(vertical stripes), neutral-grey-(no pattern)

is an overlap between ranked keywords (e.g. ukrainewar, putin, etc.). As might be expected, most of the detected keywords refer to or are directly related to recent events in the Russo-Ukrainian war. Betweenness centrality ranks the most out-of-the-domain hashtags in the top 15 (e.g. etsyseller, dekorstyle, lgbtq). Therefore degree, eigenvector and closeness are preferred centrality measures in this context. Moreover, it seems that centrality measures, regardless of which applied (with the exception of the betweenness) contribute to better extraction of representative hashtags in the domain (i.e keywords that capture meaning) compared to simple frequency calculation as also reported in [3], [4].

Second, we move on to the results of the sentiment analysis using the proposed "pnlogratio" metric. Fig. 3 shows the kernel density estimation (KDE) for estimating the probability density function of "pnlogratio" using Matplotlib [33] and Seaborn [34] Python libraries. The graph provides insight into the distribution of negative, neutral, and positive sentiments of the hashtags at the level of the largest connected component. It is possible to notice a slight tilt towards negative sentiment with the central peak around 0. The two opposing peaks (the first around -2 and the second around 2) indicate a large concentration of extremely negative and extremely positive hashtag contexts in the domain. Next, we compare the KDE density at the global (LCC) level with the KDE density at the level of identified communities.

The weighted Louvain clustering algorithm detected 39 communities of varying sizes. Fig. 4 and 5 illustrate the distribution of "pnlogratio" within a community. In the left top corner of the figures, we list the top-ranked nodes (i.e. hashtags) within the community, ordered by the value of degree centrality. The same can be reported for other

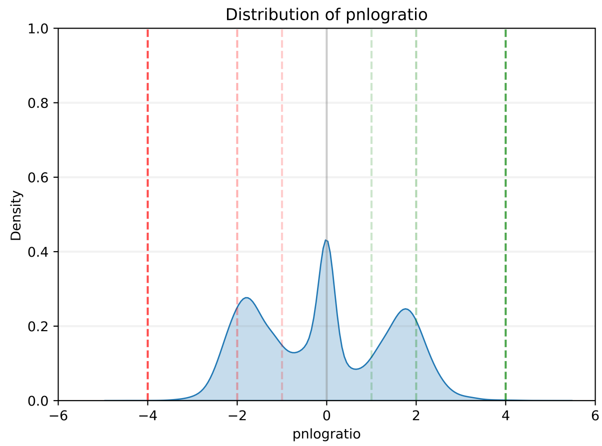

Fig. 3: The distribution of "pnlogratio" attribute at the level of the largest connected component

centrality measures, as well.

Examining the KDE curve in Fig. 4 compared to Fig. 3, one can notice a significant increase in the density of negative hashtags (nodes) and an overall decrease in positive and neutral "pnlogratio", indicating that the topic in Fig. 4 is connected to a more negative opinion and topic can be semantically defined as general war-related posts. The same holds for the community (or cluster) 5, which is related to energy as seen in Fig. 5. A similar shift towards positivity or negativity can be detected for all clusters, so in the Appendix, we provide additional examples of one positive (Fig. 6) and one negative (Fig. 7) cluster.

Please note, that it is possible to refine the proposed "pnlogratio" metric by including the weight attribute in the calculation and recalculating the metric at the local level,

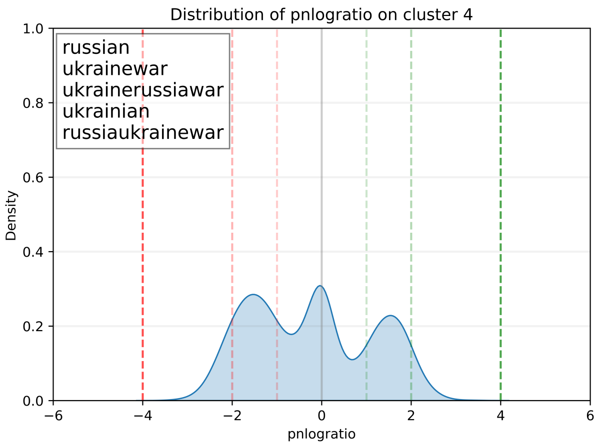

Fig. 4: The distribution of "pnlogratio" attribute in cluster 4: War related

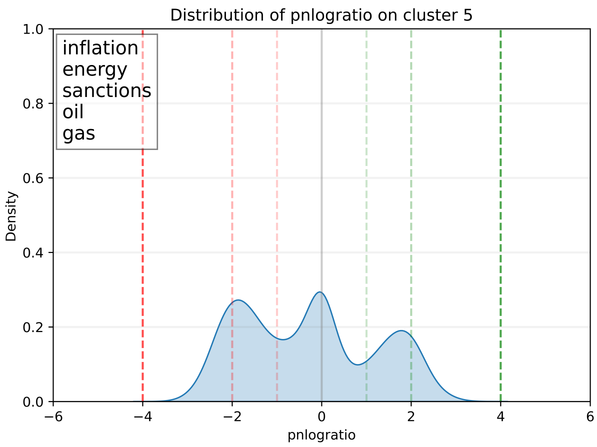

Fig. 5: The distribution of "pnlogratio" attribute in cluster 5: Energy related

e.g., within a community or cluster. In this way, the metric can assess the more or less context and possibly contribute to more or less fine-grained detection of the polarity. This mechanism still needs to be examined, but we assume that the proposed solution can be of help to detect the public-opinion polarity at different scales of granularity of topics, and subtopics extrapolated with communities of hashtags.

VI. Conclusion

In this paper, we combine methods of natural language processing, sentiment analysis, and network analysis to identify and explore the polarity of themes related to the recent event of the Russo-Ukrainian war. Initially, we collect and analyse Twitter data collected by two keywords, Ukraine and Russia. After preprocessing the data and determining sentiment polarity using the VADER dictionary, and constructing the undirected and weighted network of co-occurring hashtags, based on the value of centrality measures - degree, eigenvector, betweenness, closeness - we rank the top hashtags. Then, the Louvain algorithm detects communities that roughly extrapolate topics. Finally, we calculate the "stanciness" of topics based on "pnlogratio". "Stanciness" approximates the total quantity of both positive and negative sentiments in hashtags communities.

The obtained results confirm that cross-fertilization of NLP and social network analysis is of benefit to the gained insights. To conclude as expected and already reported in [4]–[6], we detect both positive and negative clusters of hashtags, but the negative polarity prevails. We show that proposed "stanciness" can quantify the overall sentiment of the hashtags community, being the alternative methodological solution to standardly applied topic modelling. Still, this remains to be further investigated and compared, especially in terms of the adequacy of obtained results and the potential limitations and biases of the measure. Still, the proposed measure of "stanciness", reveals many potentials and seems promising for further study.

Future work will include fine-graining of the Louvain clustering and/or using similar topic extraction methods for more accurate and thematically narrowed results at different scales of granularity. Next, it is also possible to extend the spectre of emotions extracted from the text and reach beyond the limited positive-neutral-negative perspective. Finally, detected communities need to be confirmed with topics determined with standard NLP - LDA techniques.

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VII. APPENDIX

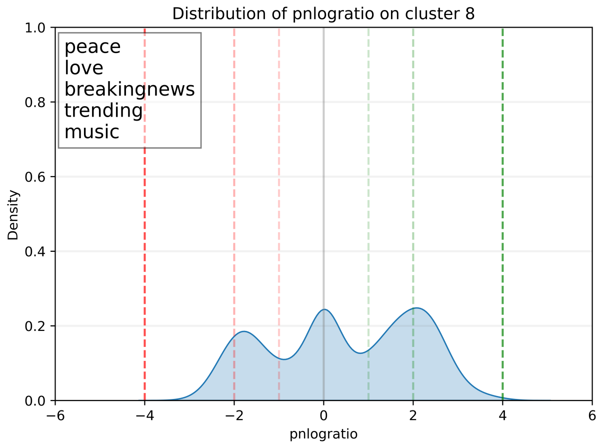

Fig. 6: The distribution of "pnlogratio" attribute in cluster 8: peace related

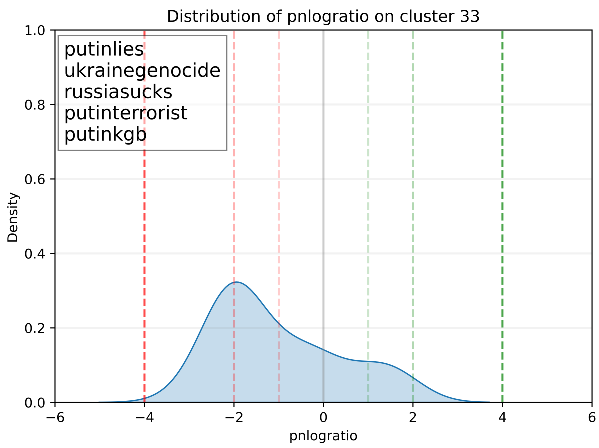

Fig. 7: The distribution of "pnlogratio" attribute in cluster 33: genocide related