Tweets about Ukraine during the russian-Ukrainian War: Quantitative Characteristics and Sentiment Analysis

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Abstract

The paper proposes the analysis of the tone and quantitative characteristics of posts about Ukraine on Twitter during the russian-Ukrainian war. It focuses on the growing importance of social networks due to the development of information and communication technologies and also characterizes sentiment analysis as one of the most widely used methods adapted to analyze data collected through social networks. With the help of LIWC-22 software, 111 tweets published by the leaders of the USA, Great Britain, Germany, France, and Poland shortly before and during the war have been analysed. The above tweets' frequency analysis and context research have been conducted (the most frequently used words and their collocations have been identified). Forecasting the tone differences of the next three tweets has been carried out. Thus, using the functionalities of interpreting the semantics and pragmatics offered by the automated systems, the research gives the key to understanding how the global community perceives the war events in Ukraine.

Keywords

Sentiment analysis, tweet, positive/negative/neutral tone, war, Ukraine, LIWC-22

1. Introduction

In modern linguistics, namely in the field of natural language processing, sentiment analysis belongs to the up-to-date areas of research. The rapid evolution of information and communication technologies has led to the active use of social networks, various forums, and other platforms that significantly impact the shaping of public opinions, assessments, and moods. If properly collected and analysed, network data makes it possible to understand and explain many complex social phenomena and even predict them.

Many research papers focus on the study of machine methods for classifying textual information and describing software applications designed for opinion mining [1, 2, 3, 4, 5]. The number of such studies is increasing; the area in terms of content has also changed over the years. Before the emergence of online textual arrays, the research relied mainly on survey methods and focused on public or expert opinions, rather than on the opinions of users or customers. In 2002, the use of online ratings marked the beginning of modern opinion mining. However, sentiment analysis as we know it today flourished later, as 99% of papers were published after 2004 [5]. Today, the sentiment analysis results are used in many areas: sociology (collection of data from social networks about people's likes and dislikes [6, 7, 8]), political science (collection of data on the political views of certain social groups [9, 10]), marketing (creation of product/company ratings [11, 12, 13]), medicine and psychology (identification of signs of mental illness or signs of depression in user messages [14, 15, 16, 17]), etc. Being completely dependent on customers, companies want to understand the attitude of consumers of their products to goods or services in order to support and develop their business. In fact, the results of sentiment analysis of goods and services are important and useful not only for companies but also for consumers in making purchasing decisions [5, 12].

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Opinion mining as a method has expanded and already involved semantic modelling of sentiments and emotions, irony and sarcasm as figures of speech and the difficulties for understanding they cause, detection of the opinion spam, summarisation of opinion-filled text, etc. [18, 19].

The primary source of sentiment analysis is data from social networks, messengers, online survey results, discussions of certain news, comments on online publications or video blogs collected automatically online. The constant growth in the number of users turns social networks into an environment of information interaction, which is increasingly used for advertising, propaganda, and psychological influences [18].

The paper is the continuation of the research [20], where the tones of the tweets about Ukraine, posted by the leaders of the USA, Great Britain, Germany, France, and Poland shortly before and during the russian-Ukrainian war, were identified and described using the LIWC-22 text analyser. Its main aims are to identify the words that are most often used in the above tweets, as well as to forecast the difference in tones of the next three tweets of the leaders of the USA, Great Britain, Germany, France, and Poland.

2. Related works

The term 'sentiment analysis' refers to a class of methods in computer linguistics designed for automated detection in texts and classification of "subjective information and affective states, such as opinions, attitudes, and emotions regarding a service, product, person, or topic" [3, p. 1]. It is worth noting that although sentiment analysis often contains an analysis of emotions, the latter is a specialised subcategory of opinion mining. Sentiment analysis is an assessment mainly in terms of the polarity of the positive and negative; the analysis of emotions involves a deeper study of specific manifestations, such as anger, anxiety, disgust, fear, joy, sadness, etc. [14].

Sentiment analysis can be carried out in various ways with their own features, advantages, and disadvantages [3, 5]. The lexicon-based method is interpreted as unsupervised machine learning. The clustering algorithm plays an important role here, placing data in different groups whose members are similar from a certain point of view. Thus, the data of a cluster have the maximum similarity, while the data of different clusters have the minimum similarity. The criterion for similarity is distance, i.e., samples located closer to each other are placed in the same cluster. For example, in document clustering, the similarity of two samples can be determined based on the number of common words in the two documents [2]. Clustering-based approaches can produce moderately accurate analysis results without any human involvement, linguistic knowledge, or learning time [21].

Techniques that "classify the texts in the test dataset into one of the predefined sentiment categories based on the results of machine-learning from the training dataset" [3, p. 17] are treated as supervised machine-learning methods. The process of supervised machine learning is complex and is often reduced in sentiment analysis to the following steps:

1. Manually assessing the sentiment polarities.
2. Highlighting features based on the experience of researchers.
3. Training in the algorithm based on examples (creation of a so-called training dataset).
4. Using the algorithm for computing the target document sentiment [3, p. 17].

As many lexicons are publicly available, it is easier for researchers to use unsupervised rather than supervised machine learning methods. However, unsupervised methods have two drawbacks: a limited number of units in the lexicon and the invariance of the assigned value, which prevents the quality extraction of a sentiment from various contexts [21].

As for supervised machine learning methods, their advantage is the ability to develop new models for almost any purpose and context. However, supervised machine learning methods are associated with the difficulty of integrating common semantic knowledge that was not derived from learning data, as well as with the lack of easily accessible marked data for different areas of research [2].

Sentiment analysis is one of the most used methods adapted for analysing data collected through social networks. Researchers divide social networks by the types of content created by users into several categories:

1. Profile-based social networks: focused on users and their desire to express themselves and communicate with their subscribers (e.g., Facebook, MySpace).

2. Microblogging social networks: focused on a message that should be short and clear (e.g., Twitter). Twitter is the most famous and is often described as an ‘amateur journalism’ website where people share news, especially about specific and current events and situations.
3. Content-based social networks: focused on the content posted by users (for example, YouTube, Flickr, Instagram) [18].

Sentiment analysis on Twitter is an important area of research in the modern world, where public opinion dominates through social networks. This platform’s vast array of raw data provides valuable insights into people’s trends, preferences, and dispositions. This is a relatively new area of research, but its popularity and usefulness are growing rapidly.

3. Methods and materials

Tones in research [20] were identified using the LIWC-22 lexicon (Linguistic Inquiry and Word Count) [22], which is one of the most accurate among the software designed for text analysis (studying various samples of emotional, cognitive, structural, and technological text components [23]). LIWC has proven itself well and has undergone internal and external verification involving specialists in the fields of psychology, sociology, and linguistics. The programme analyses formal and informal texts, social media posts, books, and short stories. LIWC-22 uses its own dictionary of nearly 12,000 words, word stems, phrases, and select emoticons [23]. The words contained in the texts posted by users are called target words. The words in the LIWC-22 dictionary file are called dictionary words. Groups of dictionary words related to a particular area (for example, words with negative emotions) are called differently: subdictionaries, word categories, or simply categories [23].

The programme contains a basic text processing module that compares units of given texts with the LIWC-22 dictionary. The above module counts all the words in the target text and then determines the percentage of the total number of words represented in each of the LIWC-22 dictionaries. The module also offers an option to select a dictionary based on which the analysis will be carried out. In addition to the main module, there are additional ones that provide such options as creating your own dictionary, calculating the frequency of use of words in the text, simulating the topic, comparing texts while determining their similarity, and identifying the style and context of the text. Thus, each of the above modules gives different information, which allows for a multiple-aspect analysis. Some modules present such results as tables, figures, and diagrams.

The material of our research was 111 English tweets about Ukraine by official representatives of states, of which: 39 tweets by the British Prime Ministers, 20 tweets by the US President, 18 tweets by the French President, 17 tweets by the German Chancellor, and 17 tweets by the Polish President.

At *the first stage* (partly covered in [20]), a sentiment analysis of tweets about Ukraine published by the leaders of the USA, Great Britain, Germany, France, and Poland was performed, which revealed the dominance of positive and negative tones. Before the war, tweets from representatives of only three countries (the United States, Great Britain, and Germany) were published, the posts on the pages of the Presidents of France and Poland were unrelated to Ukraine. Some tweets contained the same indicators of positive and negative tones, although most tweets were dominated by one tone. For example, the highest indicator of a positive tone of the United States President’s tweet was 5.71, while the lowest one was 2.38. The positive tone of German representatives was 5.13 (the highest), 2.33 (the lowest), the negative tone was 2.56 (the highest), while in the rest of the tweets, the negative tone indicator was 0. The highest and lowest indicators of the positive tone of the President of the United States were 4.26 and 2.17, respectively, and of the negative tone were 4.35 and 2.33.

During the first month of the war, the number of tweets increased significantly, as did the percentage of negative and positive tones. Thus, four tweets were published on the official page of the President of the United States, in which the positive tone prevailed, two tweets had a higher indicator of a negative tone, and two had a neutral tone. Among all the tweets published by the representatives of Great Britain in the first month of the war, positive tone prevailed in ten, four tweets had a higher indicator of negative tone and two were neutral. Unlike the tweets of the British representatives, the French President published most of the tweets (five) with a negative tone, three with a positive one, and two with a neutral one. A positive tone prevailed in three tweets of the German Chancellor, a negative one prevailed in two, and one tweet was neutral. The same number of tweets (six) was identified with positive and negative tones from the President of Poland. He also had two tweets with a neutral tone.

In September–November 2022, the number of tweets about Ukraine decreased. The French President's tweets were dominated by neutral and positive tones. Tweets of the President of the United States were mostly positive; the German Chancellor had as many tweets with a positive tone as he had with a negative one. The President of Poland published only three tweets about Ukraine in recent months, two of them were with a positive tone. Representatives of the British authorities published five tweets with a positive tone, five with a negative tone, and three with neutral tones.

The average indicators of positive and negative tones of each official representative for all periods of the war were confirmed. Before the war, the average positive tone of the US President was 2.34, the negative tone was 2.92; the average positive and negative tones of the Prime Minister of Great Britain were 2.47 and 2.26, respectively. The German Chancellor had a negative tone indicator of 1.97 and a positive tone indicator of 1.32. The analysis of the official tweets of representatives of Great Britain and the United States in the first month of the war suggests that the positive tone of the posts increased and amounted to 4.66 and 3.19, respectively, and the negative one decreased (1.86 and 1.2). In the tweets of the German authorities, the average indicator of a positive tone was 3.95, and that of a negative tone was 1.98. The representatives of Poland and France showed the following average indicators of a positive tone: 3.73 and 3.61, respectively, and the average indicators of a negative tone were 4.55 and 4.38. The analysis of posts published in September–November shows the following indicators: positive tone — 5.17 (USA), 5.13 (France), 4.69 (Great Britain), 3.94 (Poland), and 3.85 (Germany); negative tone — 4.69 (Great Britain), 4.31 (USA), 3.15 (Poland), 3.15 (Germany), and 3.66 (France).

We believe that the analysis of frequency characteristics of data is relevant and productive for the description of texts; therefore, at *the second stage*, the quantitative parameters of the tweets using the LIWC-22 programme were traced.

The third stage was forecasting the difference in tones of the next three tweets of official representatives of the United States, Great Britain, Germany, France, and Poland based on the data obtained using the LIWC-22 analyser in the first stage.

4. Results and discussions

4.1. Quantitative parameters of tweets about Ukraine

The quantitative analysis of tweets about Ukraine carried out with the help of the LIWC-22 programme predictably made it possible to record the most frequent use of the word *Ukraine*. For example, we find it 18 times in the tweets of the German Chancellor (Figure 1), while *Putin*, *Russia* occur six times, and the word *Germany* is found only five times. There are a significant number of units with a lower frequency: *integrity* (4), *international* (4), *law* (4), *territorial* (4), *sovereignty* (3), *accept* (3), *Putin's* (3), *situation* (3), *war* (3), *Russian* (3), *freedom* (3), *violence* (3), *side* (3), *sham* (3), *referendums* (3), *peace* (2), *invasion* (2), EU (2), *Russian's* (2), *President* (2), *weapons* (2), *stands* (2), *friends* (2), *call* (2), *partners* (2), *country* (2), *strength* (2), *generation* (2), *stronger* (2), *phone* (2), *violate* (2), *important* (2), *clear* (2). In addition to words, the programme calculates the frequency of phrases used in the text: *territorial integrity* (4), *sham referendums* (3), *international law* (2), *sovereignty territorial* (2), *Germany stands* (2), *phone call* (2).

Tweets about Ukraine by representatives of Great Britain suggest the following most frequent words (Figure 1): Ukraine (39), UK (14), Putin (12), stand (10), Ukrainian (9), people (8), freedom (8), security (8), united (7), Putin's (7), country (7), war (7), President (6), Russia (6), aid (6), international (6), support (6), Russian (6), fail (6), economic (6), right (5), invasion (5), sanctions (5), ensure (5), package (5), sovereignty (4), peace (4), Ukraini (4), thank (4), Ukraine's (4), Russian's (4), action (4), British (4), allies (4), continue (4), defensive (4), slava (4), NATO (4), illegal (4), spoke (3), diplomacy (3), resolve (3), choose (3), ensuring (3), sham (3), law (3), referendums (3), unity (3), Ukrainians (3), partners (3), nationals (3), eastern (3), destiny (3), supporting (3), crisis (3), sing (3), threats (3), vital (3), humanitarian (3), energy (2), violated (2), institute (2), committed (2), stage (2), leave (2), days (2), European (2), western (2), appalling (2), live (2), helping (2), cooperation (2), nothing (2), asks (2),

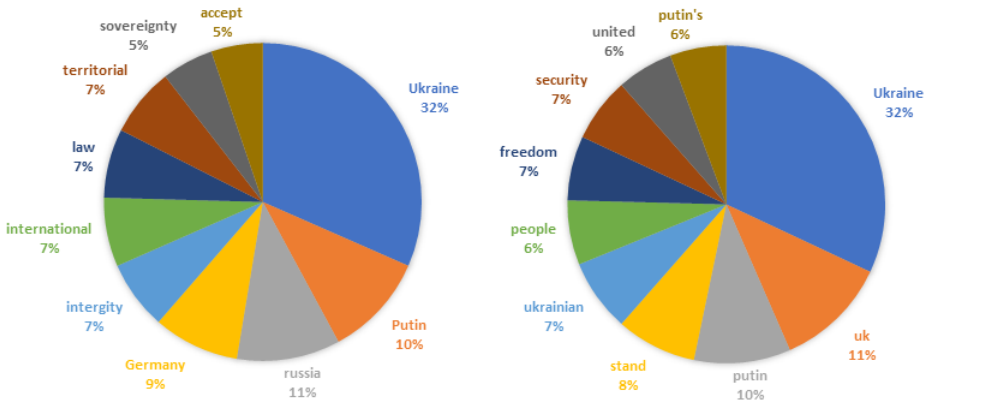

Figure 1: The 10 most frequent words of the German Chancellor (left) and the Prime Minister of Great Britain (right).

Britain (2), speak (2), discussed (2), candle (2), hostile (2), stands (2), high (2), border (2), months (2), friends (2), principles (2), incursion (2), hour (2), today (2), working (2), families (2), territory (2), counties (2), seek (2), attack (2), free (2), tragedy (2), military (2), sovereignty (2), look (2), allow (2), defend (2), step (2), troops (2), provide (2), law (2), protect (2), interests (2), welcoming (2), targeting (2), annex (2), clear (2), afternoon (2). Word combinations also include: invasion Ukraine (4), stand Ukraine (4), slava Ukraini (4), Vladimir Putin (3), President Putin (3), British national (3), people Ukraine (3), international law (3), sham referendums (3), Putin fail (3), choose destiny (3), violated Ukrainian (2), humanitarian aid (2).

The words most frequently used by the President of France include (Figure 2): Ukraine (12), President (9), continue (6), war (5). The rest of the words are used less frequently: Putin (4), support (4), Zelensky (4), spoke (3), morning (3), Ukrainian (3), Ukraine's (3), thoughts (3), avoid (3), Russian (3), stand (3), civilians (2), sovereignty (2), stop (2), union (2), days (2), minister (2), united (2), end (2), Russia (2), order (2), today (2), integrity (2), situation (2), tragedy (2), Zaporizhzhia (2), worst (2), freedom (2), protect (2), dialogue (2), prime (2), peace (2), Kramatorsk (2), attacks (2), nuclear (2), human (2), international (2), families (2), people (2), ensure (2), justice (2), security (2). The most frequent phrases are: President Zelensky (4), President Putin (3), spoke President (2), human tragedy (2), avoid human tragedy (2), protect human tragedy (2), war Ukraine (2), support Ukraine (2).

The Polish President most frequently used the following words (Figure 2): Ukraine (11), Zelenskyyua (11), defenders (8), support (5), Poland (5), Russian (5), civilians (4), ua (4), break (4), fight (4), Kiev (3), President (3), Russians (3), weapons (3), criminal (3), spirit (3), win (3), defenders Ukraine (3), stop (2), strong (2), Ukraine's (2), blockade (2), eu (2), killed (2), told (2), talked (2), women (2), together (2), difficult (2), bombing (2), determination (2), free (2), situation (2),

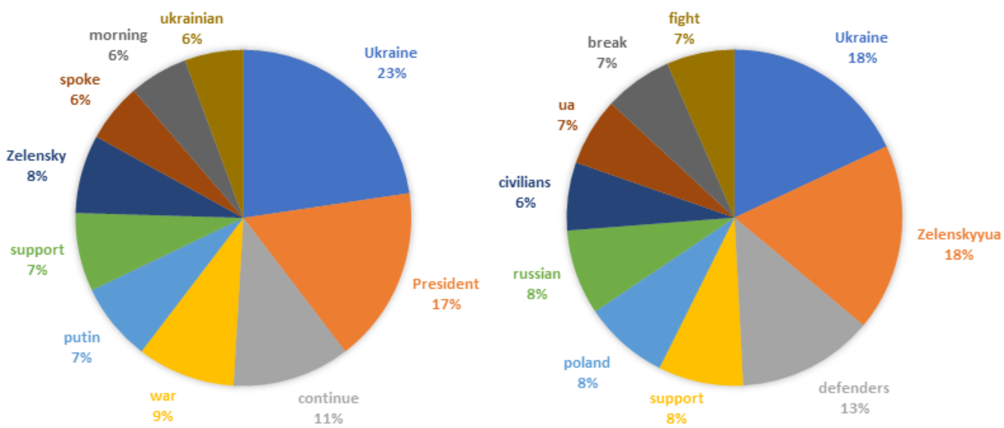

Figure 2: The 10 most frequent words of the President of France (left) and the President of Poland (right).

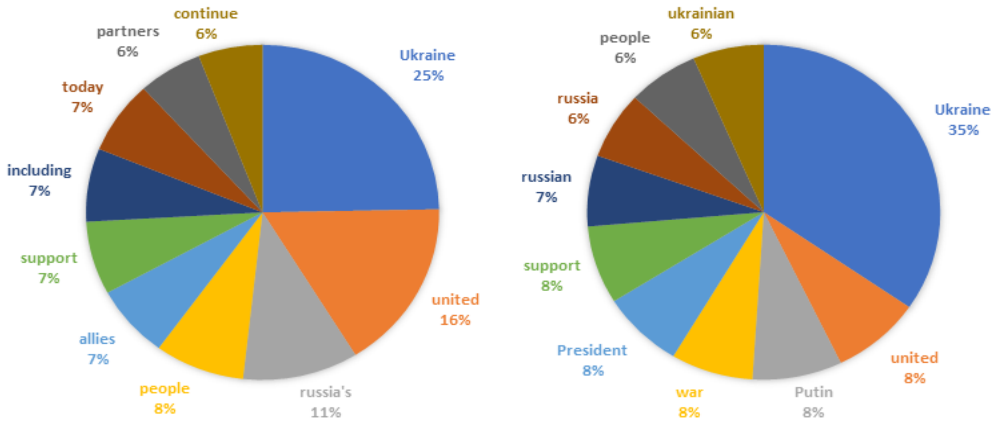

Figure 3: The 10 most frequent words of the President of the United States (left) and of the representatives from all the five countries (right).

residential (2), Ukrainian (2), towns (2), war (2), Kharkiv (2), compromise (2), children (2), give (2), justice (2), villages (2), membership (2), President Zelenskyyua (2).

An analysis of the US President's posts on Twitter revealed the following most common words (Figure 3): *Ukraine* (21), *united* (14), *Russian's* (9), *people* (7), *allies* (6), *support* (6), *including* (6), *today* (6), *partners* (5), *continue* (5), *war* (5), *security* (5), *prime* (4), *global* (4), *close* (4), *Ukrainian* (4), *minister* (4), *assistance* (4), *states* (4), *Russia* (4), *cooperation* (4), *challenges* (4), *spoke* (3), *continuing* (3), *stand* (3), *together* (3), *defend* (3), *Russian* (3), *ready* (3). The following word combinations are the most common: *allies partners* (5), *support Ukraine* (5), *war Ukraine* (4), *United States* (4), *people Ukraine* (3), *Russian's war* (3), *close cooperation* (3), *Ukrainian people* (3), prime minister Liz Truss (3), *Ukraine continue* (2), *global challenges* (2), *Russian's purported annexation* (2), *stand people* (2), *assistant package* (2), *united support* (2).

The following words made it to the top ten most frequent words in the tweets of official representatives of the countries under study (Figure 3): *Ukraine* (101), *united* (24), *Putin* (24), *war* (22), *President* (22), *support* (22), *Russian* (20), *Russia* (19), *people* (19), *Ukrainian* (19).

Contextual analysis of the most frequent units of the tweets studied, carried out using LIWC-22, shows that words *Ukraine, Ukrainian* are typically used with prepositions *of, on, in, to* and words *support, help, eastern, including, need, sovereignty, people, territory*. *Putin*'s colocations are *President, Vladimir, fail, is, must, has, that*. The word *war* occurs close to *Russian's, in, the, illegal, this*. Words like *Russia, Russian* are used mainly with units indicating negative emotions: *invasion, targeting*

Figure 4: Word cloud of the most frequent units of tweets.

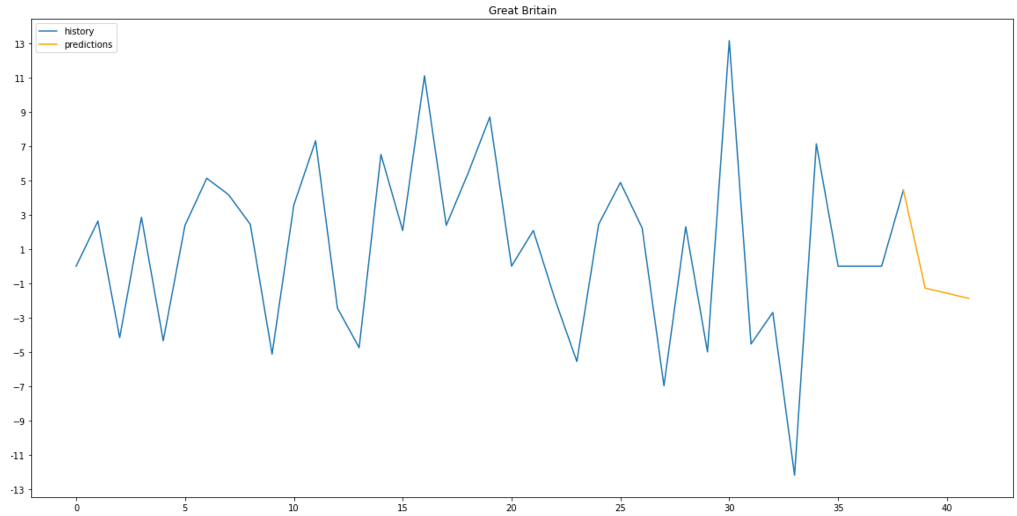

Figure 5: Forecasting tone differences (British Prime Minister).

economic, *aggression*, *rockets*, *cruelty*, *oligarchs*, *attack.* The ten most frequent words include those that indicate a positive and negative tone, such as *support* and *war*.

LIWC-22 presents the results not only in the form of a table, but also in that of a word cloud (the most frequent words are located in the centre of the image, Figure 4), and makes it possible to choose the number of words to be depicted, the colour of the text, and the colour of the background.

4.2. Forecasting tone differences

Considering the specifics of the representation of text tones by the LIWC-22 programme, the most effective and accurate way is to forecast the relative difference in the tones of tweets. As a result, it was revealed how large the difference would be between the positive tone and the negative one. The forecasting is made for each country separately while observing the existing posts' strict chronological order. For practical implementation, the pandas library was used to read Excel files and calculate tone differences, and the NumPy library was used to convert values and forecast differences (see https://github.com/RoksolanaNazarchuk/TweetAnalysis). Given the relatively small volume of data, we consider it incorrect to use complex machine learning models, because these models, having too many parameters relative to the number of observations, may be prone to overfitting. So we settled on the extrapolation method for forecasting. A high-degree polynomial will also cause overfitting and an

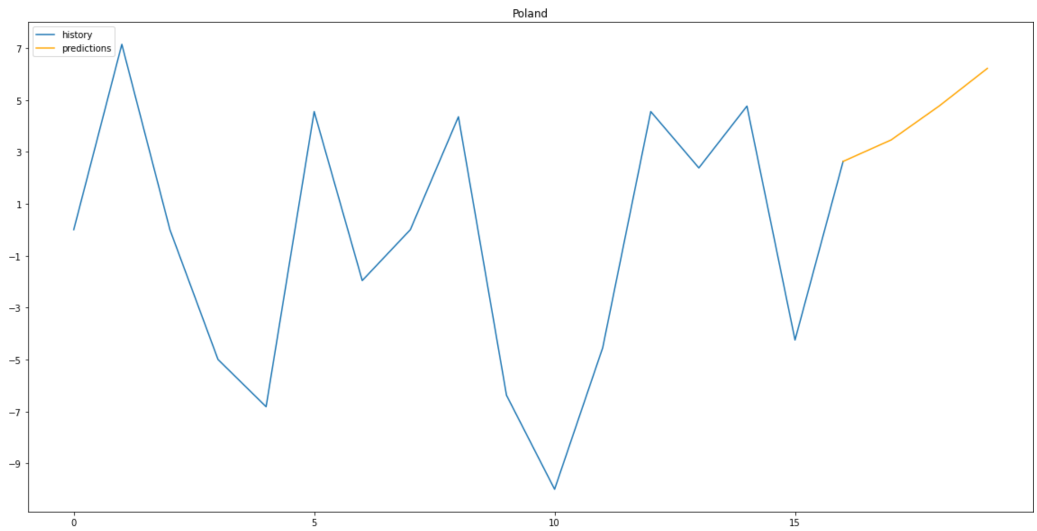

Figure 6: Forecasting tone differences (Polish President).

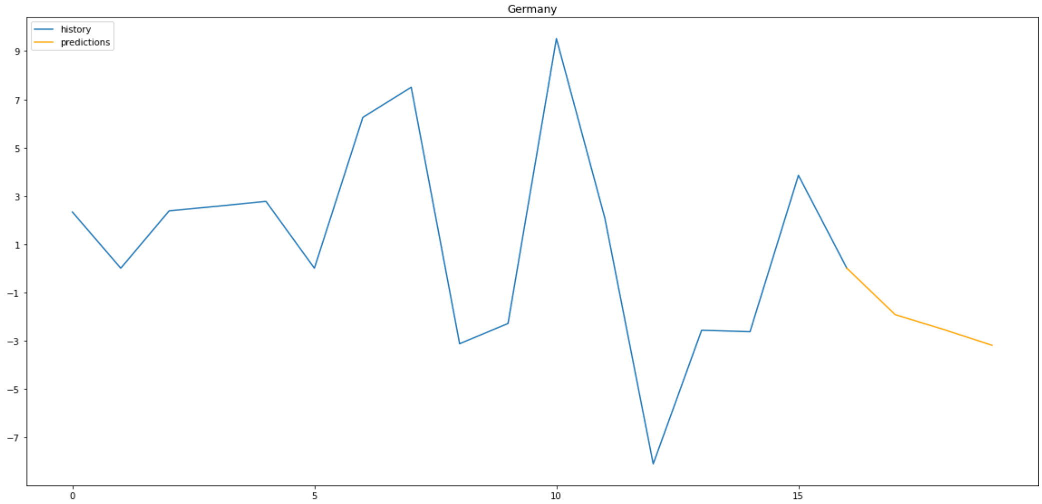

Figure 7: Forecasting tone differences (German Chancellor).

incorrect result, so we used the cross-validation method and found that a quadratic polynomial would provide the most accurate results. At the end, using the Matplotlib library, the results were graphically visualised and the diagrams were combined.

Since we aim to forecast the tonal difference of tweet texts, we use only positive and negative tones. The part of the diagram marked in blue shows the difference in tones of the already published tweets, the yellow indicates the difference in tones of tweets that will be published in the future. The difference between the positive and negative tones of the next three tweets of the British Prime Minister will be: - 1.28, -1.58, -1.88 (Figure 5), of the Polish President: 3.46, 4.77, 6.21 (Figure 6), of the German Chancellor: -1.93, -2.54, -3.19 (Figure 7), of the President of France: 0.56, 0.08, -0.49 (Figure 8), of the President of the United States: -1.18, -1.85, -2.58 (Figure 9). A minus sign in front of the numbers indicates that the positive tone indicator is less than the negative one.

5. Conclusions

The LIWC software product has been widely used to evaluate the tones in social network texts. The accuracy of the results is due not only to the functions of the programme, but also to the style of the posts studied, which involves the minimum use of language means that can mislead the analyser.

The frequency analysis of the tweets of the official representatives of the United States, Great Britain, Germany, France, and Poland predictably revealed the presence of the word *Ukraine* in almost every tweet. The total number of uses of the mentioned unit is 101; 39 of them belong to the tweets of the Prime Minister of Great Britain, 21 to the President of the United States, 18 to the Chancellor of

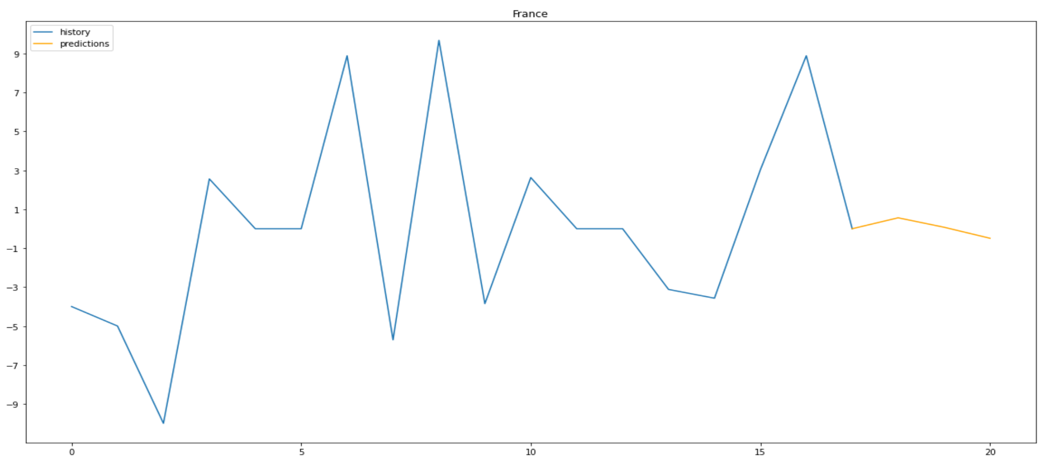

Figure 8: Forecasting tone differences (French President).

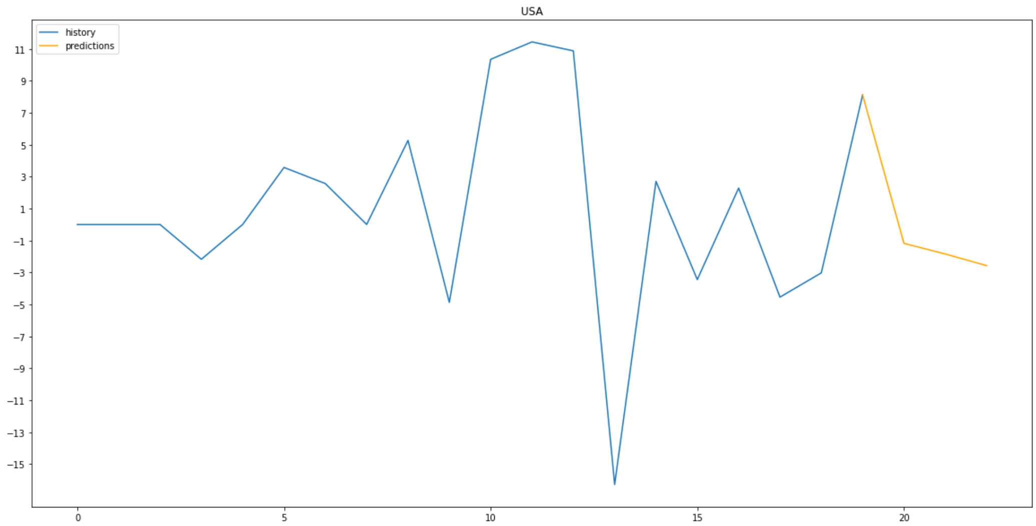

Figure 9: Forecasting tone differences (President of the USA).

Germany, 12 to the President of France, and 11 to the President of Poland. In other words, the following units were found to have a high frequency of occurrence: *united* (24), *Putin* (24), *war* (22), *President* (22), *support* (22), *Russian* (20), *Russia* (19), *people* (19), *Ukrainian* (19), *stand* (17), *Russian's* (16), *continue* (16), *security* (16), *ZelenskyyUa* (15), *UK* (15), *freedom* (14), *international* (13). The following frequent word combinations were also found in the tweets of the official representatives of the countries under study: *support Ukraine* (7), *sham referendums* (6), *war Ukraine* (6), *people Ukraine* (6), *international law* (5), *slava Ukraini* (4), *invasion Ukraine* (4).

Pandas and NumPy libraries were used to forecast the tone differences of the next three tweets of the leaders of the United States, Great Britain, Germany, France, and Poland. The difference between positive and negative tones of the next three tweets of the British Prime Minister will be: -1.28, -1.58, -1.88, the Polish President: 3.46, 4.77, 6.21, the German Chancellor: -1.93, -2.54, -3.19, the US President: -1.18, -1.85, -2.58, the French President: 0.56, 0.08, -0.49.

Sentiment analysis, with its significant potential for practical application and room for improvement, will continue to evolve along with the increased efforts of researchers to improve the quality of the interpretation of the material.

The suggested approach to the study of social network communication opens up a significant prospect for research of other texts within this framework.

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