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APPLICATION OF NEURAL NETWORK TECHNOLOGY FOR PUBLIC OPINION ANALYSIS

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Abstract. The research is devoted to studying and using neural network technologies, in particular algorithms and methods of natural language processing, to increase the efficiency of studying and analyzing public opinion of Ukraine's partner countries regarding the war in Ukraine. The research involved analyzing and processing databases consisting of messages about the war in Ukraine on the social network Twitter. The resulting datasets were used to train several neural network models. The best classification results were obtained with the GPT-3.5-turbo model. For a deeper understanding of the results of the public opinion analysis, we created their visualization. The results of the study have shown the high efficiency of the selected solutions. They may be of great practical importance for improving methods of analyzing public opinion and making informed decisions based on a deep understanding of global feedback.

Keywords: public opinion, neural networks, natural language processing, large language models, social networks, classification.

INTRODUCTION

In the context of war, the Ukrainian government has to make prompt decisions on how to interact with the governments of partner countries. These decisions should take into account the public opinion of partner countries in the course of the war in Ukraine. Therefore, monitoring changes in public opinion and the attitudes of people in different countries towards this war is a key aspect for further analysis of the prospects of these countries' assistance to our country, because public opinion can influence both the official positions of partner countries and their leaders. Of course, public opinion is reflected in social media, which can be used as an information base for this analysis.

To improve the efficiency of public opinion analysis, artificial neural networks can be used, so the purpose of this paper is to study the use of algorithms and methods of natural language processing based on artificial neural network models to improve the efficiency of studying and analyzing public opinion in Ukraine's partner countries.

To achieve this goal, the following tasks were solved: search, analysis, and preparation of datasets; determination of the dependence of the target variable on the input data for dataset annotation; dataset markup, cleaning, and verification; tokenization and vectorization of text; creation of training and test samples; determination of the effectiveness of solving the text classification problem using a Gaussian naive Bayesian classifier model and a multilayer perceptron to determine further the effectiveness of using large language models.

The peculiarity of solving the classification problem in this paper is to identify the types of classes and data that most affect the classification process. That is, it is necessary to analyze not the mood of people in its classical psychological sense based on the color of the message, but to determine which posts and messages on social media can be classified as useful or not useful for helping Ukraine. For example, messages about support, assistance, and texts about the success of our troops will be classified as positive, while posts approving of the Russian government's statements, which often turn out to be fake news and disinformation, and texts supporting the war or Russia will be labeled negative. The issues and problems of combating disinformation in social networks and news are discussed in Bergstrom C.T., West J.D. [1].

LITERATURE REVIEW

Literature analysis and selection of technological solutions. Many scientific works are devoted to the problem of using neural networks for analyzing public opinion. Thus, the work of Wordliczek Ł. [2] points out the need to use neural networks for sociological research. The works [3–5] discuss the technical aspects of using neural networks for analyzing public opinion. Gong M. [3] proposes a deep neural network (DNN) model for text sentiment classification, which, according to the author, makes it possible to better extract local and contextual information from the text. The article by Yang S. [4] proposes to use of a genetic algorithm to train a multilayer perceptron to increase the sensitivity of public opinion forecasting. The article by Chen X. et al [5] proposes the use of hybrid fuzzy neural networks. It should be said that the use of large language models is limited by their high computational complexity, which is a common disadvantage of connectionist neural networks [6].

The software model was developed in Python. All parts of the project, namely data aggregation, processing, analysis, model development, training, and testing, were carried out in Jupyter Notebook. The most common Python libraries were used in the work, such as Tensorflow, Keras, Pandas, Sklearn, RegEx, NumPy, Matplotlib, Seaborn, WordCloud, as well as the Gensim package for text processing and topic modeling. In this work, we used the Word2Vec model, which is one of the most popular models for vectorization and contextual word association.

We also conducted an experiment using the GPT-3.5-turbo model for text annotation and classification [7]. The choice of these technological solutions is due to their popularity, wide functionality, convenient interface, availability of multifunctional libraries, and support of the developer community. To work with this model we used the API of the OpenAI platform [8–10]. The use of OpenAI's GPT models is governed by license agreements, which may differ depending on whether the intended use is commercial or non-commercial. Users must also abide by certain terms of use and ethical considerations, such as avoiding harmful or malicious content and complying with privacy laws. However, these restrictions do not, in our opinion, prevent this task from being accomplished. It is likely that using a commercial version of GPT-4 would improve the quality of content analysis but would incur additional financial costs. There are also open-source models, such as LLaMA, whose use for this task also requires further research.

Data selection. Open datasets were chosen to analyze public opinion on the war in Ukraine: Unveiling Global Narratives: A Multilingual Twitter Dataset of News Media on the Russo–Ukrainian Conflict (in the future — Zenodo) [11], which contains 1.5 million tweets in 60 languages, and the dataset from the Kaggle platform — Ukraine Conflict Twitter Dataset (in the future — Tweets) [12], which contains 44 million tweets until June 2023 related to the war between Ukraine and Russia.

The Zenodo dataset was selected due to the presence of columns generated using the RoBERTa model [13]. These columns reflect the essence of the text and indicate its tendency towards being "in support" or "against" Ukraine, Russia, and the war in general. Each record in this dataset is represented in JSONL format. It was decided to use the Tweets dataset for data analysis and classification for the last two months using the GPT-3 model.

MATERIALS AND METHODS

Project structure and implementation. The project consists of three program code files. The purpose of each of the development files is shown in detail in Table.

Purpose of development files

File	File purpose
PartnerSentiment.ipynb	Data preparation and data analysis.
ClassifySentiment.ipynb	Processing text data and creating a process for using the OpenAI API
ModelingSentiment.ipynb	Text data processing, text vectorization, and modeling.

Data preparation. The project implementation begins with the creation of the PartnerSentiment.ipnb file, the main parts of which are provided on the GitHub platform [20]. All the necessary modules were imported and the functionality that iteratively transforms Zenodo data from JSONL to dataframe was implemented. Tweets data was also processed, a data frame was created using Pandas, and functionality was developed to concatenate certain columns, filter only English texts, and extract hashtags from the text using a Regex pattern.

Exploratory Data Analysis. After the data preparation was completed, we started analyzing it. To do this, we created a new column with a shortened date to the year-month format and grouped the data by this criterion to see how many unique text messages there were in each month from the beginning of the war until June 2023. The resulting distribution is shown in Fig. 1.

The next step was to analyze the number of tweets from each country per month. To do this, we used Regex to reduce all the locations of tweet authors to the country name, and the rest of the records were removed. The processing results are shown in Fig. 2.

Next, we analyzed the hashtags that users added to their messages. Using the WordCloud library, we created word distribution graphs for each month.

The analysis of the information shows that in the first months of the war, the country received significant support and the war in Ukraine became the most relevant topic of communication on the world's largest online platforms. It is worth noting that all war crimes were also noticed and brought to the public.

A more complete picture of the history of changes in the most popular topics of discussion can be obtained by creating a hashtag timeline. We also analyzed the hashtags of users with more than 500 thousand followers. This was done to see what topics are discussed by popular figures and whether they are in favor of Ukraine.

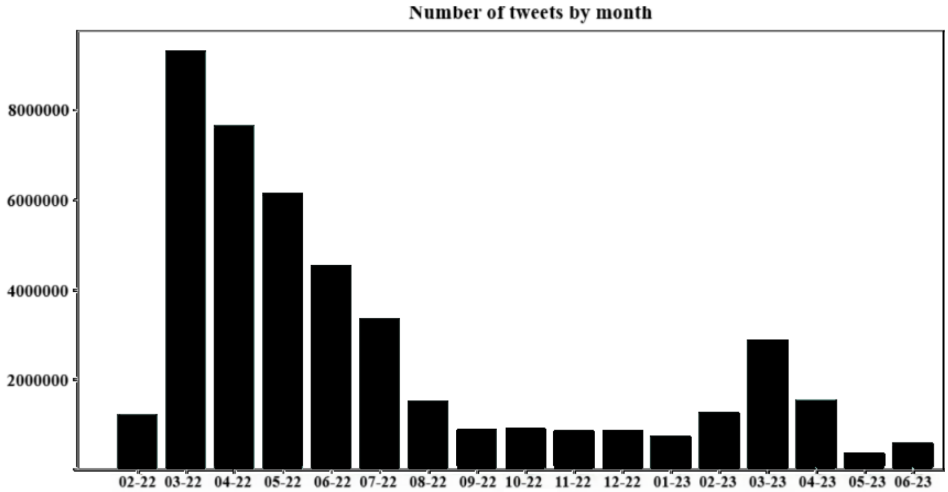

Fig. 1. Number of tweets per month

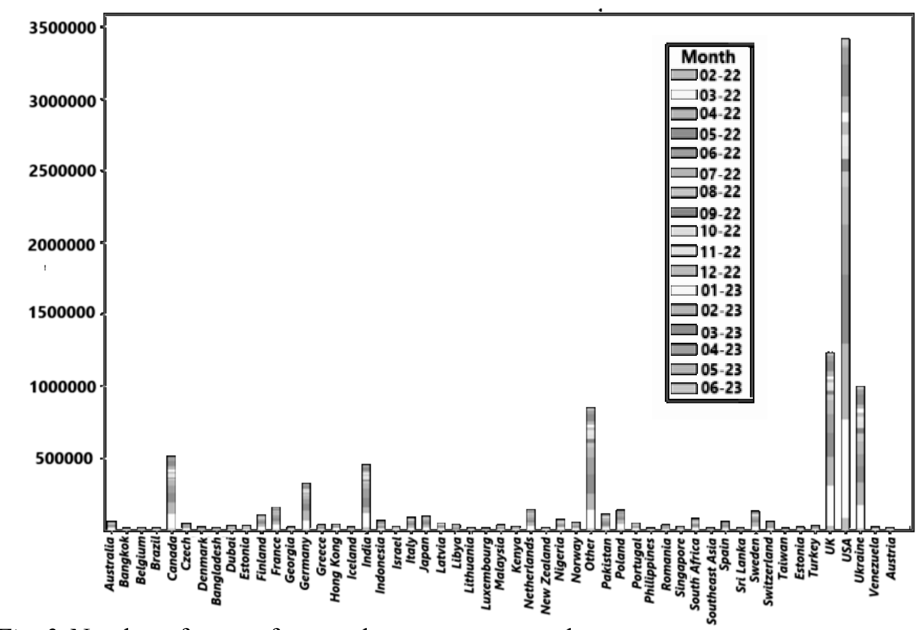

Fig. 2. Number of tweets from each country per month

EXPERIMENTS

Preparation of datasets. To experiment, we prepared the Zenodo dataset for training. The entire algorithm was implemented in the ModelingSentiment.ipynb file, the contents of which are available on GitHub [14]. To determine the target variables in the datasets that are necessary to solve the classification problem, the following rules were empirically derived:

IF $(A_1+A_2) > 2{,}5(B_1+B_2) \rightarrow$ Cl (True);

IF $1{,}7(A_1+A_2) < (B_1+B_2) \rightarrow$C2 (False);

Else → C3 (Unknown).

Where: A1 is the column "This statement is against russia" in the Zenodo dataset; B1 is the opposite column in terms of content; A2 — is the column "This statement is in favor of Ukraine" in the Zenodo dataset; B2 — is the opposite column in terms of content; C1 is a positive class; C2 — negative class; C3 — neutral (undefined) class.

Using the identified class labels, we checked the dataset markup. The markup results are shown in Fig. 3. Next, we created a function to clean the text from unwanted characters, and links, and convert it to lowercase. The text processing function is shown in Fig. 4.

```
[8]:   df.mySentiment.value_counts()

[8]:  mySentiment
      Neutral     1194233
      Positive     197985
      Negative     132614
      Name: count, dtype: int64
```

Fig. 3. Distribution of class labels

The text was vectorized using the Word2Vec model, which was trained on the full corpus of words after processing. Before converting the data to a numerical form, it is worth looking at the distribution of text lengths. To do this, we created a process for counting the number of tokens in a message. The process itself and the graph showing the distribution of text lengths are shown in Fig. 5.

```
def preprocess(text):
    text = str(text).lower()
    text = re.sub(r"< user_mention_1 >|< url_1 >",'', text)
    text = re.sub(r"\n|\r|\d", '', text)
    text = re.sub('https:[/a-z0-9.]+|&[a-z;]+|@[a-z]+','',text)
    return text
```

Fig. 4. Function for text processing

It was found that almost 900 entries were less than 5 in length and did not contain much meaning, so they were excluded from the dataset.

```
13  df['len_text'] = df['clean_text'].apply(lambda x: len(x.split()))
    df.len_text.value_counts().sort_index().plot()

13  <Axes: xlabel='len_text'>
```

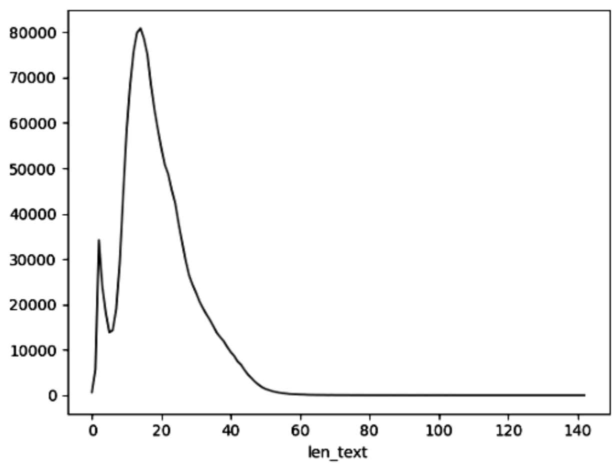

Fig. 5. Distribution of text lengths

The next step was to create a Word2Vec model by splitting all the values of the processed text into tokens and feeding them to the model for training. As a result, the model has a vocabulary of 44351 unique tokens and each vector has 100 values. The training result is shown in Fig. 6.

```
[21]:
model = Word2Vec(sentences=sentences.values,
                 sg=1,
                 workers=4)

model.wv.vector_size, len(model.wv.index_to_key)

[21]: (100, 44351)
```

Fig. 6. Word2vec model

The resulting dataset was divided into training and validation samples. The validation data accounted for 20% of the entire corpus. It was also foreseen that words not contained in the model's dictionary would appear. In such cases, instead of these words, a hundred-dimensional vector filled with values of 0.5 is added to the sum of vectors. The code for this function is shown in Fig. 7.

```
[23]:
import numpy as np

def text_to_vector(text):
    words = text.split()
    vectors = []
    for word in words:
        try:
            vector = model.wv.get_vector(word)
            vectors.append(vector)
        except KeyError:
            vectors.append([0.5 for i in range(100)])
    if not vectors:
        return None
    return np.mean(vectors, axis=0)
```

Fig. 7. The function of converting texts to vectors

Modeling. We first solved the classification problem using a Gaussian naive Bayesian classifier to evaluate the effectiveness of using large language models. The classification results are shown in Fig. 8.

In multiclass classification, accuracy is calculated by summing up the number of correct predictions for each class and dividing it by the total number of predictions made across all the classes. It is a commonly used metric to evaluate the performance of models in multiclass problems. In this study, the model's overall accuracy was calculated using this metric, and it was found to be 45%. The confusion matrix was also analyzed to understand the model's performance for each class. It was observed that the model performed well for the positive class, but it had a high false positive rate for the neutral and negative classes. A new model with four layers of neurons was developed, which improved the accuracy to 57%. However, even with this improvement, the model's accuracy was still not sufficient for practical applications.

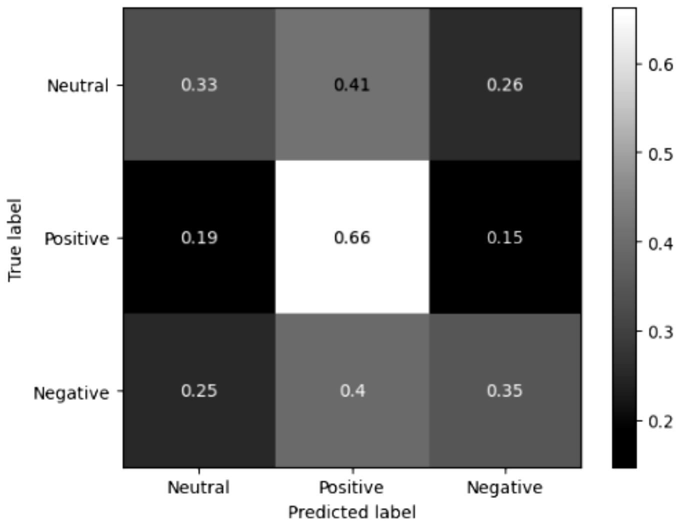

Fig. 8. Confusion matrix of Gaussian naive Bayesian classifier

Use of large language models for annotation. To work with large language models, we created the ClassifySentiment.ipynb file [14]. For the experiment, we chose the GPT-3.5-turbo model developed by OpenAI. It can be used using the API. The following restrictions were also used: data were taken only for May and June of 2023; duplicates were removed; location values were processed and tweets from Ukraine were removed.

Next, we created a dictionary called mySentiment and the functionality of working with the OpenAI API, the implementation of which is also given in [14]. The next step was to create functionality for sending queries to the GPT-3.5-turbo model, as well as the process of updating the dictionary. As a result, we obtained a dictionary with 59470 entries annotated with a large language model. They were saved and compared with the results of the multilayer perceptron. The results of the comparisons are presented in the file "ModelingSentiment.ipynb" on GitHub [14].

The GPT-3.5-turbo model demonstrates the best result of all the models studied. This is an expected result, but it demonstrates that the large language model GPT-3.5-turbo can effectively solve many problems with a fairly simple functionality using the OpenAI API.

RESULTS

The final stage of the experiment was the analysis of the results of public opinion classification based on the GPT-3.5-turbo model. First, the change in the distribution of forecasts for May and June 2023 was demonstrated. The results are shown in Fig. 9.

The public opinion score for Ukraine has both positive and negative ratings. The positive assessments are shown in Fig. 10. The negative, neutral, and positive grades are labeled as 0, 1, and 2, respectively. Thus, the average score from a country can range from 0 to 2.

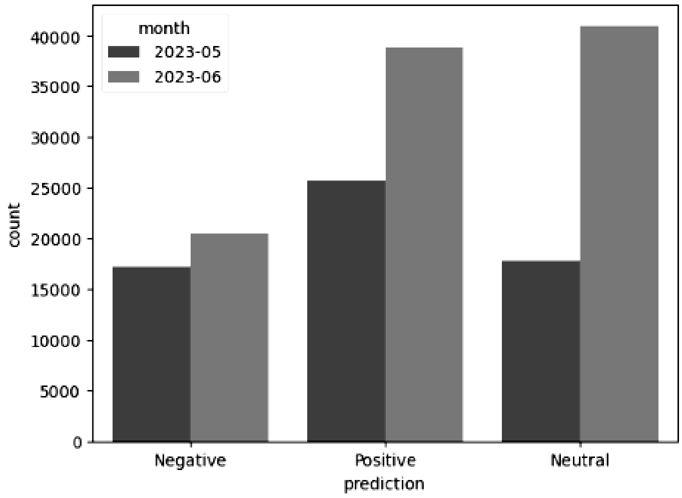

Fig. 9. Classification results

To improve the overall sentiment towards Ukraine, we need to analyze the factors contributing to negative public opinion and eliminate them. We can also highlight the positive aspects of the country, such as its rich culture, history, picturesque nature, and tourist attractions. By promoting these aspects, we can create a positive image of the country and improve its sentiment.

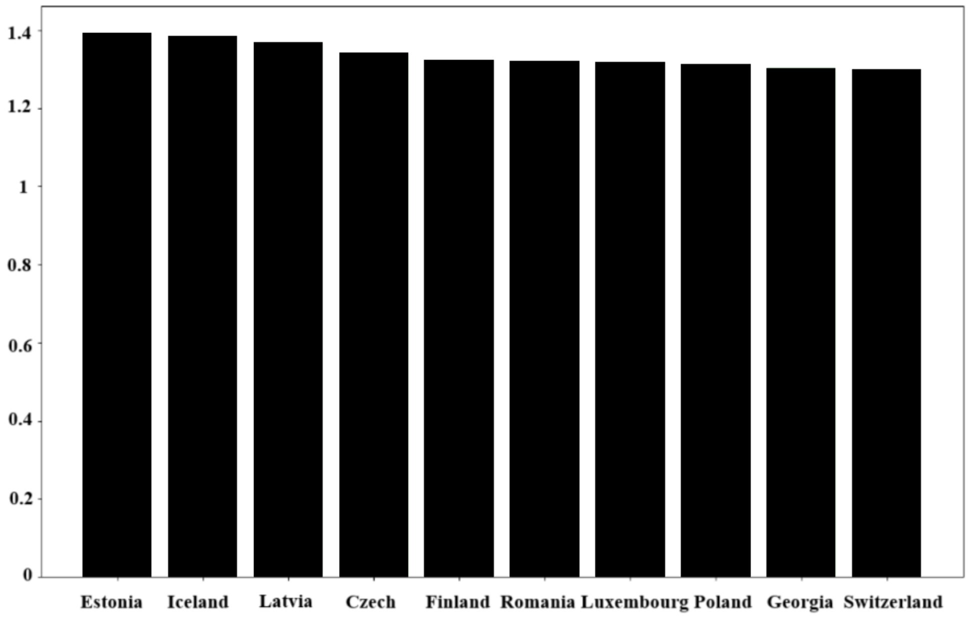

Fig. 10. Countries with the most positive attitude toward Ukraine

DISCUSSION

The results of classification using fairly simple models - Gaussian naive Bayesian classifier and multilayer perceptron - do not allow us to conclude that they can be practically used to process large data sets required for public opinion analysis. At the same time, the results of our work show that large language models with an open API can be effectively used both for analyzing public opinion and for solving other applied problems. To obtain qualitative results, an important step was taken in collecting and preparing a large amount of data, which amounted to an impressive 44 million tweets from the social network Twitter (X). This amount of data was one of the key indicators for determining an objective assessment of public opinion in many partner countries regarding the war in Ukraine.

As part of this work, a visualization of the results of the analysis of public opinion and sentiment regarding the war in Ukraine was created for a better and deeper understanding.

CONCLUSIONS

The results of the work show that its goal of studying the effectiveness of using algorithms and methods of natural language processing based on artificial neural network models to improve the efficiency of studying and analyzing public opinion in Ukraine's partner countries has been achieved. All the research and development tasks were solved, namely: a large amount of data was collected and prepared, which amounted to 44 million messages from the social network Twitter (X); two models were used to analyze the data: a Gaussian naive Bayesian classifier and a multilayer perceptron, and their comparative analysis was conducted, which made it possible to find out the advantages and features of each model; an experiment was conducted using a large language model GPT-3.5-turbo, which demonstrated the high efficiency of its extraction. In addition, to improve the evaluation of the analysis results, we created their visualization.

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INFORMATION ON THE ARTICLE

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ЗАСТОСУВАННЯ ТЕХНОЛОГІЇ НЕЙРОННИХ МЕРЕЖ ДЛЯ АНАЛІЗУ СУСПІЛЬНОЇ ДУМКИ / К.М. Перевозник, Ю.В. Паржин

Анотація. Присвячено дослідженню та використанню технологій нейронних мереж, зокрема алгоритмів та методів оброблення природної мови, для підвищення ефективності вивчення та аналізу суспільної думки країн-партнерів України щодо війни в Україні. У ході виконання досліджень проаналізовано й опрацьовано бази даних, що складалися з повідомлень стосовно війни в Україні у соціальній мережі Twitter. Отримані датасети використано для навчання декількох моделей нейронних мереж. Найкращі результати класифікації отримано на моделі GPT-3.5-turbo. Для більш глибокого розуміння результатів аналізу суспільної думки створено їх візуалізацію. Результати дослідження показали високу ефективність обраних рішень і можуть мати важливу практичну значущість для поліпшення методів аналізу суспільної думки та прийняття обґрунтованих рішень на основі глибокого розуміння глобальних відгуків.

Ключові слова: суспільна думка, нейронні мережі, оброблення природної мови, великі мовні моделі, соціальні мережі, класифікація.

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