Opinion Mining of Ukraine-Russia War publications on X social media Using Deep Learning

Verlon Roel Mbingui*
African Masters of Machine Intelligence (AMMI)
African Institute for Mathematical Sciences (AIMS)
Senegal
vrmbingui@aimsammi.org

Abstract

The primary goal of this study is to analyze public sentiment expressed in publications on X about the Ukraine-Russia war conflict. This involves using deep learning methods to extract and understand the nuanced opinions and emotions embedded in the text of these tweets. By harnessing the powerful capabilities of BERT and RoBERTa, this research aims to uncover insights into public sentiment trends, polarization, and emotional dynamics surrounding this significant geopolitical issue. In this study, we used data preprocessing, training and validation of the BERT and RoBERTa model with Literature, and model evaluation using the metrics of accuracy, precision, recall, and F1 score. The dataset collected in this study had 27.50% positive, 25.83% neutral, and 46.67% negative sentiments. The results of this study indicate that the BERT model with Literature can provide good results in sentiment analysis with a prediction accuracy of 80% and 67% with RoBERTa. from BERT on the datasets, we perform sentiment analysis with different hashtags.

Keywords: X Opinion Mining , BERT, RoBERTa, Natural Language Processing, kraine-Russia War

1 Introduction

The Ukraine-Russia conflict has sparked intense social media discussions since February 24, 2022, generating millions of daily publications on X social media. This project uses natural language processing (NLP) techniques to uncover public opinions on the conflict. The study comprehensively analyzes sentiment trends using advanced NLP methods. It employs an up-to-date dataset of conversations from the Ukraine Conflict X Dataset on Kaggle. Each publications on X entry includes important details such as text, language, posting time, user account creation date, and follower/following counts. Due to the difficulty of determining the location of publications, the study focuses on language, user account details, and publication content. It aims to uncover distinct perspectives among different groups and explore potential media influence and biases in the conversations [3]. By leveraging advanced NLP techniques, the study aims to reveal diverse viewpoints and expressions in the conversations related to the Ukraine-Russia conflict. By using innovative methodologies such as sentiment analysis, the research enhances understanding of public sentiment during this significant global event. In this project, we will examine the sentiment analysis of the 2022 Russo-Ukrainian War. Several Natural Language Processing (NLP) models that are widely researched for sentiment analysis include the BERT [1] and Robustly Optimized BERT Pre-training Approach (RoBERTa) [2]. Machine translation tools such as the googletrans python package to translate Russian language conversations into English.

*https://github.com/VerlonRoelMBINGUI/AMMI_Bootcamp_Project2023

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2 Methodology

2.1 Data preprocessing

To create a unified dataset for our analysis, we first selected several dates on which significant events happened during the Ukraine-Russia conflict. For example, we selected February 24, 2022, the day the war began, and March 4, 2022, the day a Ukrainian nuclear power plant was hit by a projectile missile. We thought these events would lead to more reactions on X social media and generate a wider user response.

We then merged the data from these dates and performed a series of data wrangling steps. We first dropped several columns that were not relevant to our analysis, such as location, publications ID, coordinates, and extracted timestamp.

To reduce the risk of selecting spam publications, we filtered the dataset based on some reasonable metrics, such as follower count, total tweet count, and user created timestamp. We also dropped duplicate publications (i.e., retweets) and kept the first occurrence of those duplicates, since the dataset was arranged in chronological order.

Since we wanted to analyze both English and Russian language publications, we filtered the dataset by language and used the googletrans package to translate Russian publications into English. We also reformatted the hashtags column to make it easier to filter publications by hashtag.

The final dataset contained over 800,000 unique English publications, and 10,000 of those were translated from Russian. When we performed sentiment analysis, we preprocessed the conversation texts by lowering the case, removing emojis and links, etc.

3 sentiment analysis using BERT and RoBERTa

Sentiment analysis is an NLP technique that uses computational methods to determine whether people's opinions or statements express positive, negative, or neutral sentiment. This report focuses on using BERT and RoBERTa for sentiment analysis. To determine the best approach, we randomly sampled 600 publications from days with significant war-related events and manually labeled each publication to evaluate the results. The goal is to determine the superior sentiment analysis method, with initial performance comparisons conducted on the dataset. In this project, we split the dataset into two parts, namely the Testing Data which is 10% and the Training Data which is 90%. There is also Validation Data that takes 10% of the Training Data.

3.1 BERT

The fourth strategy employed involves BERT, a novel language representation model that captures bidirectional context representation through Transformers. In contrast to conventional models, BERT focuses on pre-training profound bidirectional representations from unannotated text, influencing both left and right contexts across layers. Upon implementing BERT as a language model with a learning rate of 2e-5 and utilizing AdamW as the optimizer, we achieved the prediction accuracy of 80%.

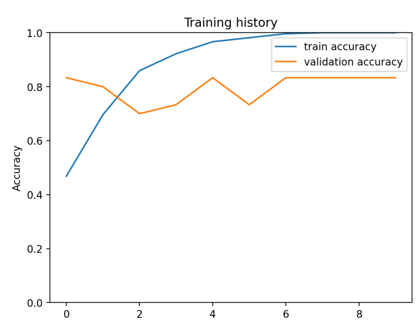


Figure 1: Report on Performance of BERT Training Process

The Training in Figure 1 is resembling Good Fit/Robust patterns with minor Overfitting seen in an Epoch 5 fluctuation. The training accuracy starts to approach 100% after 8 epochs.

Model Evaluation

The prediction output involves 3 sentiment classes: Positive, Neutral, and Negative. The Confusion Matrix, a 3x3 matrix, shows actual classes in rows and model predictions in columns. Evaluation with Testing Data in Figure 2 reveals 9 correct positive, 6 neutral, and 9 negative sentiment predictions, while the rest are BERT model's incorrect predictions.

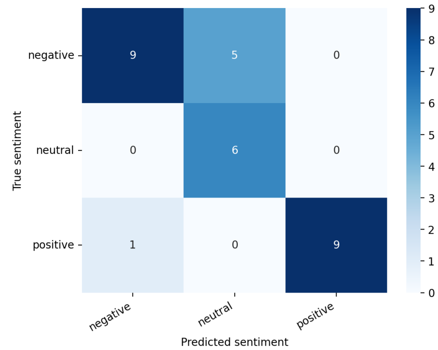


Figure 2: Confusion Matrix Data Testing BERT

Using the provided Confusion Matrix, we can determine the ratio of accurate predictions to the overall predictions. This calculation is as follows:

$$Accuracy = \frac{correct\ \ predictions}{Total\ \ predictions} \times 100\% = \frac{9+6+9}{30} = 80\%.$$

Discussions

BERT demonstrates strong sentiment analysis outcomes. Training and validation yield average accuracy above 73%, with a peak of 95%, indicating minimal overfitting due to similar performance across both stages. But most of training outcomes reveal insignificant differences between both values, suggesting the model avoids overfitting.

3.2 RoBERTa

RoBERTa is a state-of-the-art pre-trained language model that improves upon BERT by using larger batch sizes and more training data, achieving superior performance on various natural language processing tasks. Upon implementing RoBERTa as a language model with a learning rate of 2e-5 and utilizing AdamW as the optimizer, we achieved the prediction accuracy of 67%.

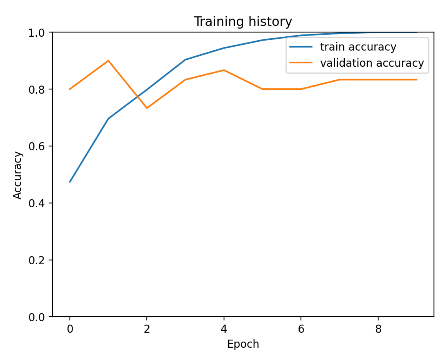


Figure 3: Report on Performance of RoBERTa Training Process

Model evaluation

The prediction output involves 3 sentiment classes: Positive, Neutral, and Negative. The Confusion Matrix, a 3x3 matrix, shows actual classes in rows and model predictions in columns. Evaluation with Testing Data in Figure 4 reveals 9 correct positive, 2 neutral, and 9 negative sentiment predictions, while the rest are RoBERTa model's incorrect predictions.

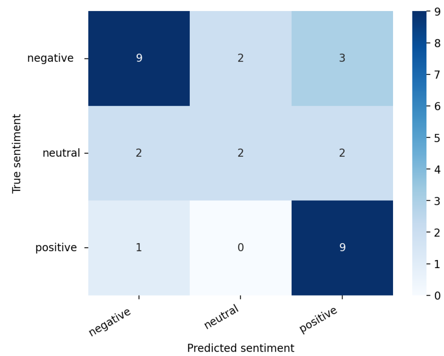


Figure 4: Confusion Matrix Data Testing RoBERTa

Using the provided Confusion Matrix, we can determine the ratio of accurate predictions to the overall predictions. This calculation is as follows:

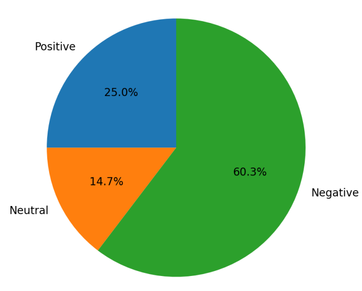
$$Accuracy = \frac{correct\ \ predictions}{Total\ \ predictions} \times 100\% = \frac{9+2+9}{30} = 67\%.$$

Discussions

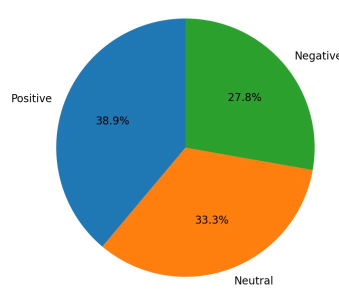
Four our case we remarque that, the model learns to perform exceptionally well on the training data but struggles to generalise to new, unseen data, resulting in a drop in performance on test datasets. This is because this model is too complex for our dataset. Therefore, We need to decrease model size or complexity to make it less prone to memorising training data and use se more Data.

4 Hashtag Sentiment Analysis

We extracted and selected between the sampled 600 publications four hashtags publications concerning "Putin," "Zelensky" "Ukraine" and "Russia" for sentiment analysis. Figures 5 (b) and 6 (c) illustrate that 41.7% of "Ukraine" hashtag publications and 38.9% of "Zelensky" publications hold positive sentiment. Additionally Figures 5 (a) and 6 (d) illustrate that 60.3% of "Putin" hashtag publications and 51.2% of "Russia" hashtag publications hold negative sentiment. However

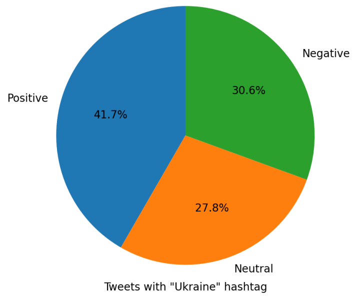


(a)

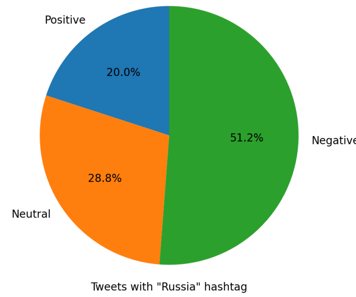


(b)

Figure 5: Hashtag Sentiment Analysis



(c)



(d)

Figure 6: Hashtag Sentiment Analysis

5 Conclusion

Our project delved into sentiment analysis publications centered around the Ukraine-Russia war's onset on Feb 24. Among multiple methodologies, BERT displayed notably superior performance in sentiment analysis. The results gleaned from applying BERT to datasets featuring distinct hashtags indicated a prevailing negative sentiment among X social media users regarding the ongoing war. This comprehensive analysis shed light on public sentiments in the virtual sphere and highlighted BERT's effectiveness in discerning emotions within this context. We gained valuable insights into the sentiments expressed on social media platforms throughout the conflic. We could conclude that people on X social media were mainly negative about the war.

Future work will be to use the Deep Learning Model for Opinion mining in X social media Combining Text and Emojis.

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