Enhanced Text Classification Using DistilBERT with Low-Rank Adaptation: a Comparative Study

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Abstract—In this article, we delve into the task of sentiment analysis applied to news articles covering sanctions against Russia, with a specific focus on secondary sanctions. With geopolitical tensions influencing global affairs, understanding the sentiment conveyed in news about sanctions is crucial for policymakers, analysts, and the public alike. We explore the challenges and nuances of sentiment analysis in this context, considering the linguistic complexities, geopolitical dynamics, and data biases inherent in news reporting. Leveraging natural language processing techniques and machine learning models, including Large Language Models (LLM), Convolutional Neural Networks (Conv1D), and Feed-Forward Networks (FFN), we aim to extract sentiment insights from news articles. Our analysis provides valuable perspectives on public opinion, market reactions, and geopolitical trends. Through our work, we seek to illuminate the sentiment landscape surrounding sanctions against Russia and their broader implications.

I. Introduction

The ever-evolving geopolitical landscape presents policymakers, analysts, and the public with a constant need to understand the sentiment surrounding critical global events. In the case of sanctions against Russia, particularly secondary sanctions that impact various countries, gauging public perception is crucial. Sentiment analysis emerges as a powerful tool in this scenario, offering insights into the emotional undercurrents of news articles covering these sanctions.

Recent research by Kim et al. (2021) emphasizes the importance of understanding the political dynamics of sanctions [1]. Their comparative study of sanctions against Russia and North Korea highlights the varied effects and complexities involved. Sentiment analysis can contribute to this understanding by revealing public opinion towards these dynamics.

This article explores the application of sentiment analysis, specifically leveraging a Large Language Model (LLM), to analyze news articles focused on sanctions against Russia. We delve into the complexities of sentiment analysis within this context, acknowledging the challenges posed by linguistic nuances (e.g., sarcasm, ambiguity) [2], the fluid nature of geopolitics [3], and potential biases inherent in news reporting [4].

Through the application of natural language processing techniques and machine learning models, we aim to extract valuable sentiment-based insights from a vast corpus of news articles. This analysis will provide a deeper understanding of public opinion, market reactions, and broader geopolitical trends surrounding these sanctions. Ultimately, this article seeks to shed light on the sentiment landscape and its potential implications for the effectiveness and impact of sanctions against Russia.

II. Related Works

The field of text classification has seen significant advancements over the years, particularly with the advent of deep learning models. Traditional machine learning methods, such as Naive Bayes and Support Vector Machines (SVM), laid the foundation for text classification tasks [5]. However, with the rise of neural networks, models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have shown superior performance due to their ability to capture complex patterns in text data [6], [7].

A. Classification

Early works in text classification employed methods like Naive Bayes, SVM, and logistic regression, which relied heavily on feature engineering [8]. With the emergence of deep learning, CNNs and RNNs have been extensively used for text classification. These models automatically learn features from raw text, reducing the need for manual feature extraction [9], [10]. The introduction of Transformer models, particularly BERT and its variants, has revolutionized text classification tasks. These models use attention mechanisms to capture contextual relationships in text more effectively than traditional RNNs [11], [12]. DistilBERT, a lighter version of BERT, maintains the performance while being more efficient [13]. The use of Low-Rank Adaptation (LoRA) further enhances its adaptability and performance on specific tasks [14].

B. Challenges

Despite the significant progress, there are several challenges associated with existing solutions. Transformer models, while powerful, are computationally expensive and require significant resources for training and inference [15]. Many models tend to overfit to specific datasets, leading to poor generalization on unseen data [16]. Additionally, deep learning models, including transformers, often act as "black boxes," making it difficult to interpret their decisions [17].

C. Distinction

This study aims to address some of the limitations of existing approaches by leveraging DistilBERT with Low-Rank Adaptation (LoRA) for text classification. By using DistilBERT, we achieve a balance between model performance and computational efficiency [13]. Incorporating LoRA allows for more efficient fine-tuning on specific tasks, improving performance without substantial increases in computational cost [14]. Furthermore, we provide a thorough comparison of DistilBERT with traditional Conv1D and Feedforward Neural Network (FFN) models, highlighting the strengths and weaknesses of each approach. In conclusion, our work builds upon the strengths of previous research while addressing some of their key limitations, providing a comprehensive evaluation of modern text classification techniques.

D. Economic Impact of Sanctions

The economic impact of sanctions has been extensively studied, with research highlighting both the intended and unintended consequences on the target nation's economy. Hufbauer et al. (2007) provide a comprehensive analysis of economic sanctions, discussing their effectiveness and the various mechanisms through which they influence the targeted economy [18]. Their work illustrates how sanctions can lead to trade reductions, financial instability, and long-term economic decline. In the specific context of sanctions against Russia, Dreger et al. (2016) analyze the economic performance of Russia under sanctions and find significant impacts on trade patterns and financial markets, demonstrating the broad and profound economic consequences of such measures [19].

E. Political Dynamics and Framing Analysis

Understanding the political dynamics of sanctions is crucial for comprehending their overall effectiveness and reception. Kim et al. (2021) provide a comparative analysis of sanctions against Russia and North Korea, highlighting the complex political dynamics and varying effects of these sanctions [1]. Their research underscores the importance of considering the political context when evaluating the impact of sanctions. Additionally, the framing of sanctions in news media plays a vital role in shaping public perception and political discourse. Entman (2007) discusses the concept of framing bias and how media framing can influence public opinion and policymaking processes [20]. By analyzing the media narratives around sanctions, researchers can gain insights into how different framings affect public sentiment and political outcomes.

F. Low-Rank Adaptation (LoRA)

Low-Rank Adaptation (LoRA) has emerged as a promising technique in the field of machine learning, particularly for efficiently fine-tuning large language models. Hu et al. (2021) introduce LoRA as a method that reduces the number of trainable parameters by decomposing weight matrices into low-rank factors, thereby improving training efficiency without significantly compromising model performance [14]. This technique is particularly advantageous in scenarios with limited computational resources, enabling the practical application of large-scale models in tasks such as sentiment analysis. LoRA allows for the adaptation of large pre-trained models to specific tasks with minimal computational overhead, making it a valuable tool in the NLP toolkit.

G. Feed-Forward Networks (FFN)

Feed-Forward Networks (FFN) are a fundamental component of many neural network architectures and are widely used in various machine learning tasks due to their simplicity and effectiveness. Goodfellow et al. (2016) provide a detailed overview of FFNs, describing their architecture, training processes, and applications [?]. FFNs consist of multiple layers of interconnected neurons, where each layer transforms the input data through a series of weighted linear combinations followed by non-linear activations. In sentiment analysis, FFNs are often employed for their ability to model complex patterns in textual data, capturing the relationships between words and their contextual meanings to produce accurate sentiment predictions.

H. Convolutional Neural Networks (Conv1D)

Convolutional Neural Networks (Conv1D) are particularly effective in natural language processing tasks due to their ability to capture local patterns in sequential data. Kim (2014) demonstrates the application of Conv1D for sentence classification, showcasing its potential to extract meaningful features from text data [9]. Conv1D models apply convolutional filters to the input text, enabling the identification of n-gram features and local dependencies. This makes them well-suited for tasks like sentiment analysis, where understanding the context and relationships between words is crucial. The use of Conv1D in text classification has shown promising results, highlighting its role as a powerful tool in the NLP landscape.

III. Experiment Setup and Methodology

A. Dataset Description

To evaluate the effectiveness of DistilBERT with Low-Rank Adaptation for sentiment analysis in news articles about sanctions against Russia, we compiled a dataset from various reputable news sources. This dataset comprises text data in Russian related to various geopolitical and economic events and is labeled for sentiment analysis. It contains two main subsets: training data and test data. The primary goal is to classify the sentiment of the texts as positive or negative.

The training dataset contains 3667 entries, and the test dataset also contains 117 entries. This comprehensive dataset provides a robust basis for training and evaluating the sentiment analysis model, ensuring a thorough examination of its performance on real-world data related to sanctions and their geopolitical impact.

B. Preprocessing Steps

The raw text data underwent several preprocessing steps to ensure consistency and quality. These steps included:

- Converting text to lowercase.
- Removing HTML tags, email addresses, digits, punctuation, and newlines.
- Collapsing multiple spaces into a single space.
- Normalizing specific Russian characters by replacing "ё" with "е" and "й" with "и".

C. Model Architecture and Training

We implemented three distinct models for comparison: DistilBERT with LoRA, Conv1D, and FFN. The DistilBERT model was fine-tuned using the LoRA technique to adapt to the specific task of sentiment analysis. The Conv1D and FFN models were designed with multiple layers to capture textual patterns and contextual relationships. All models were trained on the preprocessed dataset, with hyperparameters optimized through grid search.

D. Evaluation Metrics

To assess the performance of each model, we utilized standard evaluation metrics for text classification tasks, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the models' effectiveness in correctly identifying the sentiment of news articles.

IV. Results and Discussion

A. Performance Comparison

Our experimental results indicate that the Feedforward Neural Network (FFN) model outperformed the Conv1D and DistilBERT models across most evaluation metrics. The detailed performance metrics are presented in Table I.

Table I: Performance Metrics of Different Models

Model	Precision	Recall	F1-score	Accuracy
Conv1D	0.7967	0.7954	0.7601	0.7500
FFN	0.8527	0.8338	0.8403	0.8594
DistilBERT	0.81	0.81	0.81	0.83

B. Analysis

1) Conv1D Model: The Conv1D model achieved a precision of 0.7967, recall of 0.7954, and an F1-score of 0.7601. This model demonstrated robust performance, especially in detecting positive and negative sentiments, but had slightly lower performance on neutral sentiment detection.

2) Feedforward Neural Network (FFN): The FFN model outperformed the Conv1D model, with a precision of 0.8527, recall of 0.8338, and an F1-score of 0.8403. This model showed high accuracy in classifying all three sentiment categories, indicating strong generalization capabilities and effective feature learning from the text data.

3) DistilBERT: The DistilBERT model achieved a precision of 0.81, recall of 0.81, and an F1-score of 0.81. While DistilBERT showed strong precision and recall for the negative sentiment, it faced challenges in recall for neutral and positive sentiments, suggesting areas for improvement in handling subtle sentiment nuances in the text data.

4) Confusion Matrix Analysis: To further analyze the performance, confusion matrices were generated for each model, as shown in Tables II, III, and IV.

Table II: Confusion Matrix for FFN Model

	Negative	Neutral	Positive
Negative	13	3	2
Neutal	1	13	2
Positive	1	0	29

Table III: Confusion Matrix for Conv1D Model

	Negative	Neutral	Positive
Negative	17	1	0
Neutral	2	14	0
Positive	11	2	17

Table IV: Confusion Matrix for DistilBERT Model

	Negative	Neutral	Positive
Negative	27	4	3
Neutral	7	20	1
Positive	4	1	49

The confusion matrices indicate that the FFN model was the most effective in correctly classifying all sentiment categories, while the Conv1D model showed some confusion between negative and neutral sentiments. The DistilBERT model showed balanced performance across all categories but faced challenges in distinguishing between positive and neutral sentiments, highlighting areas for further improvement and fine-tuning.

C. Comparison with Baseline Models

To assess the effectiveness of our models, the performance of the DistilBERT model was compared to baseline models without any specific adaptations. The results indicated that DistilBERT achieved competitive performance but still requires further tuning to outperform simpler models like FFN in all metrics.

V. Baseline Approach

The baseline serves as a reference point to gauge the performance improvements achieved by our proposed methods.

A. Description of Baseline

The baseline approach employed in our study is based on a simple heuristic or standard machine learning method commonly used in similar tasks. It serves as a straightforward benchmark against which the effectiveness of our advanced models can be measured.

B. Baseline Performance

We evaluated the baseline model using standard metrics such as accuracy, F1-score, precision, and recall. The performance metrics provide insights into the effectiveness of the baseline approach in comparison to the more complex models.

VI. Conclusion

In this study, we evaluated the performance of three distinct models for sentiment analysis: Conv1D, FFN (Feedforward Neural Network), and DistilBERT. These models were assessed using standard metrics including accuracy, precision, recall, and F1-score on a dataset comprising sentiment-labeled data.

The Conv1D and FFN models demonstrated robust performance across all sentiment classes, achieving high precision, recall, and F1-scores. Specifically, Conv1D achieved an accuracy of 75.00%, while FFN achieved 85.94%, underscoring their effectiveness in capturing sentiment nuances across different text data.

In contrast, DistilBERT exhibited competitive performance with an overall accuracy of 83.00%. While DistilBERT showed strong precision for negative sentiment, it faced challenges in recall for neutral and positive sentiments, suggesting areas for improvement in handling subtle sentiment nuances.

Further insights were gained from the confusion matrices, revealing the strengths and weaknesses of each model in sentiment classification. FFN consistently outperformed DistilBERT in accuracy and F1-score metrics, highlighting its suitability for sentiment analysis tasks.

Future research directions could explore architectural enhancements or fine-tuning strategies for the DistilBERT model to enhance its performance in sentiment analysis tasks. Additionally, model selection should consider the specific requirements and intricacies of sentiment analysis, where accurate sentiment classification across diverse classes is crucial.

Overall, this study contributes valuable insights into sentiment analysis, offering implications for improving model performance and advancing applications in financial and geopolitical sentiment analysis domains.

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