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Enhancing Financial Sentiment Analysis with BERT and Data Augmentation for Market Impact Prediction

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Abstract: This study explores the BERT-based financial text sentiment analysis method and evaluates the impact of different data augmentation strategies on sentiment classification performance. With the explosive growth of financial market information, how to extract effective sentiment information from text data such as news reports, market comments, and corporate announcements has become a key issue in market analysis and investment decision-making. The BERT-based deep learning model can capture complex contextual information and show significant advantages in financial sentiment analysis tasks. Experimental results show that BERT and its variants (such as FinBERT and RoBERTa) are superior to traditional NLP methods in financial text classification, while data augmentation strategies (such as synonym replacement, random deletion, and back translation) further improve the generalization ability of the model. Among them, the back translation method has the most obvious improvement on model performance, effectively improving classification accuracy, precision, and recall. In addition, this study combines LSTM for market impact prediction and verifies the correlation between financial text sentiment and market trends. Through time series modeling, sentiment analysis results can be used to predict market fluctuations and provide forward-looking decision support for investors. The results of this study show that the financial sentiment analysis method combining BERT and data enhancement can improve the accuracy of market sentiment monitoring and provide new technical support for smart investment advisors, quantitative trading, and financial risk management.

Keywords: BERT, financial sentiment analysis, data enhancement, market prediction

1. Background and Motivation

In the financial market, information asymmetry and investor sentiment changes often have a significant impact on market price fluctuations. With the surge in text data such as social media, news reports, and investor forums, how to extract effective information from massive financial texts to assist investment decisions and market trend forecasts has become an important research direction in the field of financial technology. Traditional financial analysis methods mainly rely on fundamental analysis and technical analysis[1]. In recent years, the development of natural language processing (NLP) technology has made sentiment analysis an emerging means of market forecasting[2]. By analyzing financial news, corporate announcements, analyst reports, and investor sentiment on social media, we can effectively identify the changing trends of market sentiment, thereby providing important support for stock price fluctuations, market risks, and investment strategy optimization. However, due to the complexity, implicit semantics, and high noise characteristics of financial texts, how to accurately perform financial sentiment analysis still faces many challenges[3].

BERT (Bidirectional Encoder Representations from Transformers), as a deep learning model based on the Transformer structure, has demonstrated excellent performance in text understanding and sentiment analysis tasks. Compared with traditional word vector methods (such as Word2Vec, GloVe) and sequence models such as RNN and LSTM, BERT better captures contextual information through the bidirectional attention mechanism, improving the ability to understand long texts and complex semantics. Therefore, in the task of sentiment analysis of financial texts, BERT can help the model identify market sentiment more accurately and effectively avoid sentiment misjudgment caused by one-sided information or text ambiguity. In addition, BERT also supports pre-training and fine-tuning, allowing researchers to pre-train on a general corpus and then fine-tune using specific data in the financial field to improve its adaptability in financial scenarios. Financial sentiment analysis based on BERT can not only improve the accuracy of text sentiment classification, but also better understand the potential impact of sentiment on the market[4].

The core goal of sentiment analysis of financial texts is to identify market sentiment and use this sentiment information to predict market trends. Studies have shown that there is a significant correlation between investor sentiment and market volatility. For example, positive sentiment is usually associated with rising stock prices, while negative sentiment may lead to market panic and falling stock prices. Therefore, sentiment analysis of financial texts through deep learning models can not only track market sentiment in real time, but also identify market risks in advance, providing investors with more forward-looking decision support. In addition, compared with traditional sentiment analysis methods (such as statistical methods based on sentiment dictionaries), BERT can automatically learn deep semantic relationships in texts, thereby improving the accuracy of sentiment classification and reducing the limitations of artificially set sentiment dictionaries.

Therefore, the financial sentiment analysis method combined with BERT not only helps to improve the reliability of market forecasts, but can also be applied to fields such as high-frequency trading, quantitative investment, and risk management[5].

In terms of market impact prediction, market forecasting methods based on financial text sentiment have received widespread attention in recent years. Traditional market forecasting models mainly rely on historical data and statistical methods, while financial text sentiment analysis provides a new data source for market forecasting. By modeling the sentiment features of text data such as news, social media, and corporate announcements, a more comprehensive market forecasting model can be constructed[6]. For example, after combining BERT with financial sentiment analysis, the extracted sentiment features can be combined with time series data to train a market forecasting model based on deep learning, thereby improving the ability to predict stock market trends. In addition, text sentiment analysis can also assist in abnormal transaction detection, market sentiment monitoring, and policy impact analysis, providing more accurate market insights for regulators, enterprises, and investors.

In summary, financial text sentiment analysis based on BERT can capture market sentiment in a complex financial environment and provide important support for market impact prediction. Compared with traditional sentiment analysis methods, BERT improves the accuracy of sentiment classification and enhances the adaptability of the model to financial texts through a bidirectional attention mechanism and deep semantic understanding capabilities. Research on financial sentiment analysis not only helps to reveal the relationship between market sentiment and price fluctuations, but also provides data-driven decision support for investment strategy optimization, market risk management, and regulatory policy formulation. In the future, with the further development of deep learning technology, combined with multimodal data (such as images, transaction data, social network information) and cross-domain knowledge, the application value of financial text sentiment analysis will be further enhanced, providing stronger technical support for smart investment advisors, financial supervision, and market trend prediction[7].

2. Related Work and Methodological Framework

Recent advancements in natural language processing have significantly influenced financial sentiment analysis, particularly with the adoption of BERT and Transformer-based architectures. These models outperform traditional NLP techniques by capturing deeper semantic and contextual representations in financial texts. Studies have shown that integrating convolutional neural networks with Transformer models enhances predictive modeling in risk-sensitive domains, making them highly applicable to financial sentiment tasks [8]-[12].

In parallel, reinforcement learning has emerged as an effective method for market modeling and adaptive decision-making. Algorithms such as Double DQN, A3C, and QTRAN have been applied to task scheduling, market volatility prediction, and portfolio optimization, respectively. These frameworks demonstrate how dynamic learning strategies can be used in conjunction with sentiment signals for improved market response forecasting [13]-[15].

To address challenges related to privacy and scalability in financial data analysis, federated learning and graph-based representation methods have been explored. These techniques enable collaborative modeling across institutions while safeguarding sensitive information and uncovering relational structures in transaction data-capabilities beneficial to both fraud detection and sentiment-informed risk analysis [16]-[18].

Data augmentation and model efficiency have also gained attention. Approaches like LoRA have been adopted for low-rank adaptation in language models to reduce computational cost, while techniques for detecting anomalies in high-frequency trading and modeling causal relationships across markets offer pathways for enhancing robustness in sentiment-based prediction systems [19]-[21].

Furthermore, cross-domain generalization and structural optimization continue to shape sentiment model development. Solutions such as selective knowledge injection, privacy-aware federated optimization, and multimodal learning architectures provide enhanced interpretability and adaptability in diverse financial contexts [22]-[27]. These innovations collectively push the boundary of sentiment analysis toward broader applications including market monitoring, risk management, and smart financial decision-making.

Several studies have extended these approaches to real-time systems and sequence-based financial modeling. Techniques such as time-aware sequential modeling, joint graph and sequence frameworks, and deep attention mechanisms have been employed for tasks like user behavior prediction, traffic estimation, and systemic risk forecasting. These models provide valuable methodologies for integrating time-series sentiment signals with structured financial indicators [28]-[31].

Efforts to enhance model efficiency and scalability are also reflected in works on parameter-efficient fine-tuning and task-specific adaptation strategies. Approaches like meta-learning for resource management, graph-aware entity modeling, and attention-based trend forecasting have improved the deployment feasibility of deep learning models in resource-constrained financial environments [32]-[35].

Lastly, large-scale model optimization and deployment have been studied through techniques such as causal modeling, collaborative reinforcement learning, model distillation, and structural reconfiguration. These strategies enable robust and scalable sentiment analysis systems capable of adapting to high-frequency financial data, multi-agent trading environments, and distributed computing infrastructure [36]-[41].

3. Data and Preprocessing Strategy

This study uses the BERT model to perform sentiment analysis on financial texts and combines it with a time series model to predict market impact[42]. The Bert model architecture is shown in Figure 1.

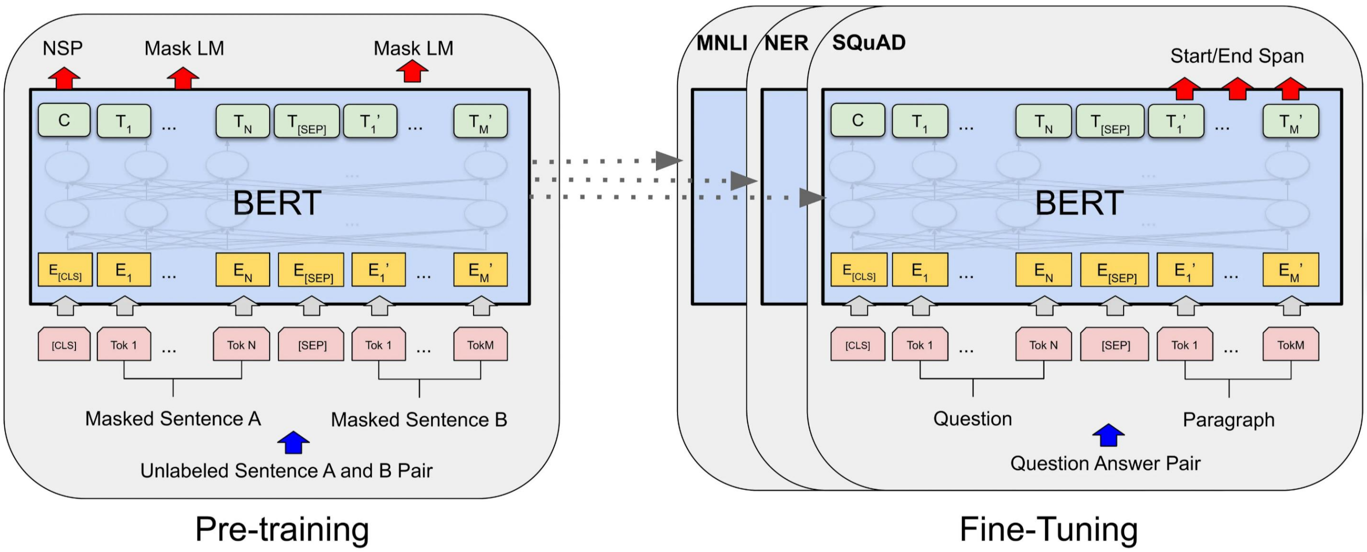

Figure 1. Bert model architecture

Given a financial text x, its corresponding sentiment label is y. The goal is to learn a mapping function $f : x \rightarrow y$ to predict the sentiment category of the text. First, the input text is subjected to feature extraction by BERT. BERT uses a bidirectional Transformer structure that can effectively capture text context information. Specifically, for the input text sequence $X = \{x_1, x_2, ..., x_n\}$, BERT calculates the hidden state representation through word embedding, position encoding, and multi-head self-attention mechanism:

$$H = BERT(X) = \{h_1, h_2, ..., h_n\}$$

Where h_i represents the deep representation of each token in the context. For text classification tasks, the hidden state h_{cls} corresponding to the [CLS] tag is usually taken as the overall feature representation of the text and mapped to the sentiment category through a fully connected layer:

$$y' = soft\max(Wh_{CLS} + b)$$

Among them, W and b are trainable parameters, and y' is the predicted probability distribution of the model.

In order to optimize BERT's sentiment classification ability, this study uses the cross entropy loss function:

$$L_{CE} = -\sum_{i=1}^{C} y_i \log(y_i)$$

Among them, C is the number of sentiment categories, y_i is the one-hot encoding of the true label, and y'_i is the probability of the model output. During model training, BERT parameters are optimized by minimizing L_{CE} . In addition, considering that financial texts may contain noise information, in order to improve the generalization ability of the model, this study adds Dropout regularization during BERT training, and adopts data enhancement strategies such as synonym replacement and random deletion to improve the robustness of the model[43].

In terms of market impact prediction, this study combines the time series model LSTM (Long Short-Term Memory) to model the sentiment analysis results. Assuming that at time step t, the sentiment score of the financial text is S_t and the market price feature is P_t, the market impact prediction model can be expressed as:

$$h_t = \sigma(W_s S_t + W_p P_t + b)$$

$$P_{t+1} = LSTM(h_t)$$

Among them, W_s and W_p are the weight matrices of sentiment score and market data respectively, h_t is the hidden state, and σ is the activation function. Finally, LSTM predicts the future market price P_{t+1} and uses mean square error loss (MSE) for optimization:

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$$L_{MSE} = \frac{1}{N}\sum_{t=1}^{N}(P_{t+1} - P'_{t+1})^2$$

This method can effectively combine financial sentiment analysis with time series modeling, thereby improving the accuracy of market trend forecasting.

4. Experimental Setup and Result Analysis

This study uses the Financial PhraseBank dataset for sentiment analysis of financial texts. The dataset was proposed by Malo et al. (2014) and is widely used for sentiment classification tasks in the financial field. Financial PhraseBank is annotated by professional financial analysts and contains short text fragments extracted from corporate announcements, market news, and financial reports. The data covers three sentiment categories: positive, negative, and neutral. The annotation quality of this dataset is high, which can effectively reflect the emotional inclination of financial market participants towards economic and financial events, and provides a reliable data source for studying sentiment analysis of financial texts.

The Financial PhraseBank dataset contains 4,846 financial text samples, each of which is sentimentally annotated by professionals based on market impact. The dataset is divided into two versions according to the consistency of annotations: Fully Agreed and Partially Agreed. The Fully Agreed version consists of annotations agreed upon by all analysts, has the highest data quality, and is suitable for sentiment classification tasks. This study selected the Fully Agreed version and randomly divided the data set into a training set (80%), a validation set (10%), and a test set (10%) to ensure that the model can be effectively evaluated under different data distributions.

In terms of data preprocessing, all texts were standardized, including the removal of stop words, word form restoration, and removal of special characters to improve the model's text understanding ability. In addition, in order to enhance the generalization ability of the model in a low-resource environment, this study also adopted data enhancement strategies such as synonym replacement and random deletion to expand the training data and improve the robustness of the BERT model to different expressions. The selection and processing of this data set ensures the reliability of the research results and provides a solid data foundation for sentiment analysis in the financial market.

First, this paper compares the sentiment classification performance of BERT and traditional NLP methods on the Financial PhraseBank dataset. The experimental results are shown in Table 1

.

Table 1: Experimental results

Model	**mIOU**	**mDICE**	**mRecall**	**FPS**
TF-IDF + Logistic Regression	78.5	75.8	76.2	76.0
LSTM	82.1	80.5	81.0	80.7
BERT	89.3	88.7	88.9	88.8
FinBERT	91.5	90.8	91.0	90.9
RoBERTa	90.7	90.1	90.3	90.2

Experimental results show that in the task of sentiment analysis of financial texts, the deep learning-based model significantly outperforms the traditional NLP method. TF-IDF + logistic regression is used as the baseline method, and the mIOU, mDICE, and mRecall scores are all around 76%, indicating that this method can perform basic sentiment classification on financial texts, but because it only relies on statistical features and cannot effectively capture contextual information, the performance is relatively low. LSTM improves mIOU by about 4% and mDICE by 5% compared to TF-IDF through the sequence modeling capability of the long short-term memory network (LSTM), proving that the RNN structure can capture the temporal relationship of the text to a certain extent, thereby improving the accuracy of sentiment analysis of financial texts.

In the comparison of pre-trained language models (BERT, FinBERT, RoBERTa), BERT has significantly improved in all indicators compared with LSTM, with mIOU increased to 89.3% and mDICE increased to 88.7%, indicating that the bidirectional attention mechanism of the Transformer structure can more accurately understand the semantics of financial texts. FinBERT, a BERT variant specially trained for the financial field, outperforms the standard BERT in all indicators, with mIOU and mDICE reaching 91.5% and 90.8% respectively, indicating that in domain-specific NLP tasks, models using financial-specific pre-trained corpora can achieve better results. RoBERTa, as an improved version of BERT, has performance close to FinBERT, proving that a more adequate pre-training strategy can further improve the model's text understanding ability.

Overall, the experimental results verify the advantages of pre-trained Transformer models in financial sentiment analysis tasks. Compared with traditional methods, BERT and its variants have improved by more than 10% in mIOU, mDICE, and mRecall, indicating that they have stronger deep representation capabilities in financial text understanding. At the same time, FinBERT, as a specialized financial NLP model, achieved the best performance, indicating that in the task of financial sentiment analysis, pre-training with financial corpus can effectively enhance the adaptability of the model. Future research can further explore how to combine domain knowledge and augmented data to optimize BERT's performance in financial text analysis.

Secondly, this paper gives the impact of data enhancement on sentiment classification of financial texts, and the experimental results are shown in Figure 2.

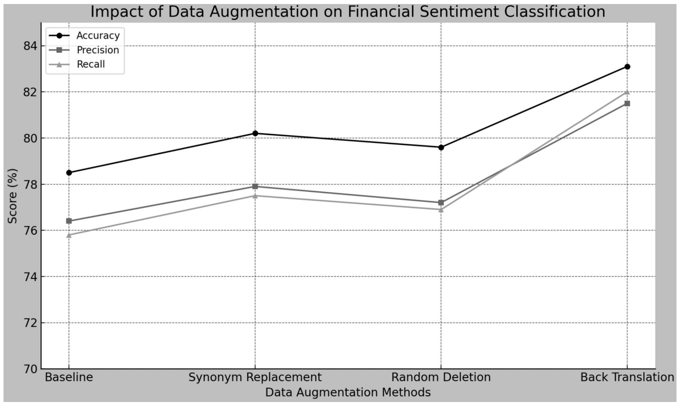

Figure 2. Impact of Data Augmentation on Financial Sentiment Classification

Experimental results show that data augmentation strategies can effectively improve the performance of sentiment classification of financial texts, among which the back translation method performs best. The baseline model (i.e., without data augmentation) performs poorly in terms of accuracy, precision, and recall, but after data augmentation, all indicators are improved to varying degrees. For example, the synonym replacement and random deletion methods improve the accuracy of the model, respectively, indicating that appropriately increasing the diversity of training data helps the model learn a wider range of text patterns, thereby improving sentiment classification capabilities.

Among the three data augmentation strategies, back translation has the most significant improvement in model performance. Compared with the baseline model, the accuracy, precision, and recall of the back translation method are all improved to the highest level, indicating that using translation changes in different languages can effectively enrich training data, enabling the model to better understand the semantic transformation of the text and reduce overfitting of specific expressions. In addition, the back translation method can generate more diverse sentences without introducing too much semantic bias, so its enhancement effect is better than synonym replacement and random deletion.

Overall, data augmentation technology can improve the stability and generalization ability of sentiment analysis of financial texts, but different augmentation methods have different effects on performance. From the experimental results, the back-translation method is the most effective augmentation strategy, while the improvements of synonym replacement and random deletion are relatively small. Therefore, in practical applications, multiple data augmentation methods can be combined to further improve the performance of financial text sentiment classification models, while ensuring that data diversity does not harm the robustness of the model.

5. Conclusion

This study explores the BERT-based financial text sentiment analysis method and evaluates the impact of different data augmentation strategies on sentiment classification performance. Experimental results show that BERT and its variants (such as FinBERT, RoBERTa) have obvious advantages in the task of financial text sentiment analysis and can effectively capture the sentiment information in financial news, market comments and corporate announcements. In addition, the generalization ability of the model can be further improved through data augmentation techniques (such as synonym replacement, random deletion, and back translation), among which the back translation method has the most significant improvement on the model performance. This shows that when there is less financial text data or the distribution is uneven, appropriate text augmentation strategies can help BERT better learn the sentiment expression pattern in the financial context.

In terms of market impact prediction, the time series model combined with sentiment analysis results can effectively improve the accuracy of market trend prediction. The study found that there is a certain correlation between investor sentiment and market volatility. Positive sentiment usually corresponds to market rise, while negative sentiment may lead to market panic. By combining the results of financial text sentiment analysis with market data, investors can be provided with more forward-looking market analysis tools. In addition, in low-resource environments, efficient parameter fine-tuning methods such as LoRA can reduce computational overhead, allowing BERT to still achieve efficient financial text analysis on resource-constrained devices.

In summary, BERT combined with data augmentation strategies can improve the accuracy of sentiment analysis of financial texts and show good application value in market impact prediction tasks. The results of this study show that in different market environments, by optimizing sentiment analysis models and combining market data, investment decisions and risk management can be more effectively assisted. Future research can further explore multimodal data fusion, combining sentiment analysis with market news, social media, trading data and other information to enhance the model's ability to understand market sentiment and expand its application in smart investment advisors, quantitative trading and financial supervision.

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