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An Analysis of the Relationship Between Social Media Sentiment and the Stock Market Using the GloVe Model

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Abstract: Natural Language Processing (NLP) has found wide application across various fields in recent years. In this context, the GloVe model has been widely adopted and continuously optimized. Its application in the financial sector offers a promising approach for uncovering underlying patterns in financial markets. Therefore, this study investigates the relationship between social media sentiment and the stock market using the GloVe+Transformer model, analyzing the feasibility of using social media information to predict stock market fluctuations. The GloVe word embedding model used in this study preserves both global and local information of words, while the Transformer algorithm, utilizing the self-attention mechanism, effectively captures information at high training speeds. The study employs the GloVe+Transformer model for text classification on Twitter data, ultimately generating sentiment scores for each trading day by using the processed information from Twitter data as weights. The sentiment scores are analyzed against the NASDAQ Composite Index data using the Spearman correlation coefficient and the prediction success rate of direction. The results show that social media sentiment scores exhibit a certain correlation with trading volume and daily price fluctuations. The study discusses the underlying reasons for this result, further validating the feasibility of using social media sentiment scores for prediction. The findings ultimately suggest that social media sentiment holds potential for application and further investigation in predicting daily trading volume and daily price fluctuations.

Keywords: GloVe, Transformer, social media sentiment, stock market

1. Introduction

In recent years, Artificial Intelligence (AI) and Natural Language Processing (NLP) have garnered significant societal attention. Since the release of ChatGPT in November 2022, there has been rapid advancement in generative AI and large language model technologies. DeepSeek, an emerging AI model, has already gained industry prominence. The latest iteration, DeepSeek V3, has outperformed several leading international models in various benchmarks, while adopting a lightweight architecture. The rise of DeepSeek signals continued innovation and development in the field of NLP.

In the financial sector, NLP and machine learning technologies have become essential tools for addressing a variety of challenges. Some researches developed a financial risk detection model utilizing NLP to identify and predict potential risks in financial documents and communications, enhancing the efficiency of financial risk detection [1]. Others introduced eXplainable Lexicons (XLex), a novel method that expands the vocabulary coverage of the Loughran-McDonald (LM)

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lexicon, addressing the manual effort traditionally required in sentiment analysis tasks. The model's interpretability further enhances its value in financial sentiment analysis [2]. In the realm of financial sentiment analysis, it explored the optimization of sentiment classification using the BERT model, defining financial sentiment and evaluating it through Large Language Models (LLMs) [3]. These studies demonstrate the growing potential of NLP in finance, though the current application of NLP models in the sector remains largely focused on fundamental analysis, with limited exploration into other types of textual information. Social media texts, as a prevalent and natural form of textual data, inherently reflect the public's overall sentiment toward the market. This study seeks to examine whether social media sentiment correlates with fluctuations in stock prices and volumes, aiming to determine whether sentiment from social media can serve as a reliable predictor for stock price movements.

The study employs the GloVe model to generate daily sentiment scores from social media data, which are then compared with the NASDAQ Composite Index (IXIC). GloVe is a word embedding technique that utilizes term co-occurrence matrices and combines elements from both Latent Semantic Analysis (LSA) and the word2vec model, allowing it to capture both global and local semantic information. Twitter data with sentiment labels is used to train four models: GloVe+LSTM, GloVe+Transformer, GloVe+CNN, and GloVe+BiGRU. The model that demonstrates the best performance is selected for further analysis. The data spans non-trading hours (from 4 pm to 9 am the following day) on trading days between January 22, 2025, and March 7, 2025, as a representation of public sentiment toward the financial market. Each text's sentiment is analyzed using the trained GloVe model, and the results are aggregated into daily sentiment scores. The study then correlates these sentiment scores with stock performance data, specifically the NASDAQ Composite Index opening prices on each trading day within the period. The analysis investigates the potential of using sentiment scores as predictors for stock performance, drawing on relevant financial theories and research to interpret the observed relationships. This study explores the correlation between social media sentiment and stock performance, offering insights into the future potential of leveraging social media sentiment as a tool for predicting fluctuations in stock prices and volumes.

2. Literature review

The GloVe model is continuously being optimized and improved. This study references the following optimizations to the GloVe model and makes adjustments to the original model in line with the objectives of this research.

BiLSTM, a branch of recurrent neural networks, introduces bidirectional processing by combining forward and backward LSTM layers, thus enhancing the model’s ability to learn comprehensive contextual dependencies. It proposed an enhanced GloVe-CNN-BiLSTM model for sentiment analysis. In this architecture, GloVe are employed to vectorize textual input, convolutional neural networks (CNN) are utilized to extract local spatial features, and BiLSTM are applied to capture temporal dependencies. Experimental results demonstrate that the model achieves an accuracy exceeding 0.95, substantially outperforming existing baseline models [4].

Transformer utilizes the self-attention mechanism to capture global dependencies within the sequence, while employing multi-head attention to enhance the model’s generalization capability. Sanad Aburass *et al.* proposed an Electra+GloVe+LSTM model for question classification. In this architecture, Electra provides advanced language understanding capabilities based on the Transformer framework, GloVe offers global vector representations to capture word-level semantics, and LSTM is employed to model long-term dependencies. After training, the model achieved an accuracy of over 0.8 on the test set [5].

The Gated Recurrent Unit (GRU) is a branch of recurrent neural networks. It incorporates gating mechanisms designed to improve the model’s capability in capturing and long-term dependencies

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within sequential data. F. S. S. Purwanto *et al.* developed an information credibility detection system aimed at evaluating the trustworthiness of Twitter data. The system integrates techniques such as Bi-GRU, utilizes TF-IDF as the primary feature representation and GloVe embeddings as feature extension. Furthermore, the model is optimized using the Firefly algorithm. Experimental results demonstrate that the system achieved a high accuracy exceeding 0.9, confirming its effectiveness in enhancing information credibility assessment [6].

Motivated by prior GloVe-based optimization strategies and constrained by computational considerations, this study adopts four GloVe-integrated deep learning architectures, GloVe+LSTM, GloVe+Transformer, GloVe+CNN, and GloVe+BiGRU, to perform sentiment classification on the research dataset. The optimal model is determined based on four evaluation metrics: accuracy, recall, precision, and F1 score. This model is then used to predict social media sentiment, followed by a correlation analysis with the corresponding stock market data.

3. Methodology

GloVe (Global Vectors for Word Representation) is a word embedding model proposed by researchers at Stanford University in 2014. Its advantage lies in combining the global semantic analysis of LSA with the local window semantic analysis of word2Vec. This approach enables better text information capture while utilizing the matrix factorization technique from LSA to reduce the computational resource requirements of the model.

The basic concept of LSA is composed of term-document matrix, TF-IDF and Singular Value Decomposition (SVD). In TF-IDF, TF represents the term frequency of a word, while IDF, as the inverse document frequency, reflects the ubiquity of the word across the corpus. The product of TF and IDF represents the importance of the word within a specific document. The main goal of singular value decomposition (SVD) is to transform the high-dimensional term-document matrix into a lower-dimensional matrix that retains the most important information. Given a real matrix A, its SVD is given by $A=U\Sigma V^T$, where U and V^T are orthogonal matrix composed of the singular vectors of A and Σ is a matrix that contains the transformation information for features and text.

GloVe integrates key elements from both LSA and word2vec by considering global information as well as local information. The model incorporates the concept of a word frequency-based co-occurrence matrix, constructed by traversing the entire corpus. Building upon this, the model further calculates the co-occurrence probabilities between word pairs. After vectorizing each word in the text, the word vectors obtained from the model are assumed to capture the semantic and statistical regularities inherent in the co-occurrence matrix. The cost function of the model incorporates word frequency weights and applies constraints to prevent excessively high weights, leading to the following cost function and its associated weight term formula:

$$J = \sum_{i,j}^{N} f\left(X_{i,j}\right)\left(v_i^T v_j + b_i + b_j - \log\left(X_{i,j}\right)\right)^2 \tag{1}$$

$$f(x) = \begin{cases} \left(\frac{x}{x_{max}}\right)^{\alpha}, x < x_{max} \\ 1, x \geq x_{max} \end{cases} \tag{2}$$

v_i and v_j represents the vector representations of word i and its context word j, respectively, while b_i and b_j are the corresponding bias terms. $X_{i,j}$ denotes the co-occurrence frequency of words i and j in the corpus. Through research, the optimal choices for α and x_{max} are found to be 100 and 0.75, respectively. When the cost function is minimized, the GloVe model is able to learn the optimal word vector representations.

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4. Experimental study

4.1. Experimental dataset

The study utilized three datasets. Dataset 1 was obtained from kaggle on February 22, 2025. As of March 19, 2025, it had been downloaded 2,345 times. This dataset contains 18,301 Twitter texts annotated with binary sentiment labels, where 0 indicates negative sentiment and 1 indicates positive sentiment. For this study, a subset of these tweets was selected for training the sentiment analysis model.

Dataset 2 consists of Twitter text data collected using the keyword "stock market". The data was obtained through web scraping from Twitter over a 32-day period, from January 22 to March 7, 2025. A total of 1,050 tweets were collected per day during this period. Each tweet was posted between 4:00 PM and 9:00 AM the following day, representing social media sentiment during non-trading hours. In addition to the tweet content, the dataset also includes metadata such as the number of comments, retweets, likes, views, and the number of followers of the tweet's author. Dataset 3 contains the price fluctuations of the NASDAQ Composite Index from January 21 to March 7, 2025. The dataset includes daily open, close, high, and low prices, as well as trading volume data.

4.2. Data processing

The study first conducted data preprocessing on Dataset 1. Based on observations of the dataset, many Twitter texts contained noisy information such as URLs, email addresses, and social media handles. These noisy elements were removed from the original dataset during preprocessing. In addition, since Twitter posts are closely tied to individual expression habits, users often use informal language such as word abbreviations and elongated words (e.g., yeahhhh) to convey emotion. Plus, words frequently appear in various tenses. To address these issues, all words in the text were lemmatized to their base forms. Third, since users frequently use emojis to express emotions, the study replaced emojis with corresponding sentiment-related words whenever possible. Emojis that could not be interpreted were removed. Fourth, to ensure consistency and prevent erroneous learning, all words were converted to lowercase. The same preprocessing steps were applied to the Twitter text data in Dataset 2.

The study analyzed the text length in Dataset 1. The analysis revealed that the majority of texts fall between 10 to 20 words. Given that a masking operation is required for short texts during the subsequent text vectorization step, and to ensure model performance, the study used only the first 30 words of excessively long texts. The same operations were performed on Dataset 2's text data when conducting sentiment analysis.

The study applied one-hot encoding to the binary sentiment labels in Dataset 1 to prevent the model from incorrectly learning the sentiment. The study analyzed the word frequency of all words in the texts of Dataset 1. It was observed that most of the high-frequency words were stopwords, which frequently appear in text processing but carry no meaningful information. Therefore, the study removed stopwords from the text to prevent the model from learning irrelevant information.

After preprocessing Dataset 1, the study performed vectorization on all the words in the texts. Subsequently, after splitting the vectorized data into training, validation, and test sets, the study conducted an analysis of data imbalance in the training set. It was observed that the number of samples with label 1 in the training set was much lower than those with label 0. Therefore, the study applied random oversampling to balance the dataset in order to meet the requirements of model training.

4.3. Evaluation index

The study primarily uses accuracy, recall, precision, and F1 score as evaluation metrics for the model. For any given dataset, accuracy represents the proportion of correct predictions made by the model

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out of all possible outcomes. Recall indicates the proportion of actual positive instances that were correctly identified by the model. Precision represents the proportion of predicted positive instances that are truly positive. The F1 score is the harmonic mean of precision and recall. Based on these metrics, the study will select the model with the best overall performance as the sentiment analysis model.

4.4. Experimental parameter setting

Inspired by related work, the study decided to use four models: GloVe+LSTM, GloVe+Transformer, GloVe+CNN, and GloVe+BiGRU. After weighing the computational resources and the required model output, the study determined the specific parameters for each of the four models (see Table 1).

Table 1: Model parameters

Parameters	Value
dimensionality of attention heads in Transformer	512
number of attention heads in Transformer	128
dimensionality of hidden layer in Transformer	1024
units in LSTM layer	1024
activation in convolutional layer	ReLU
number of convolutional kernels in CNN	2048
size of the convolutional kernel in CNN	30
number of units in the Bi-GRU layer	2048
Loss	binary_crossentropy
dropout	0.2
Optimizer	Adam

4.5. Results and analysis

Using Python, four models were trained and evaluated based on multiple performance metrics, as shown in Figure 1. Among them, the GloVe+Transformer model achieved the best performance across all metrics and was therefore selected as the sentiment analysis model for this study.

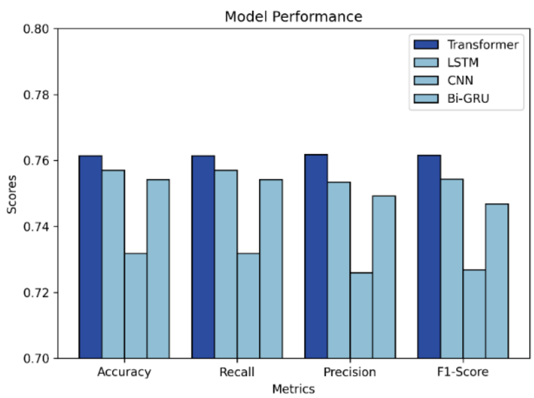

Figure 1: Model performance

The data from Dataset 2 were fed into the GloVe+Transformer model, yielding a binary sentiment label for each text instance in the dataset. Dataset 2 includes 1,050 daily texts, each with data such as the number of comments (C), shares (F), likes (U), views (V), and the author's followers (f). Since

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these numbers partly reflect the daily social influence of the texts, they were used to calculate weights for each text. This study did not compare the importance of the number of comments (C), shares (F), likes (U), views (V), and the author's followers (f). It only summed these daily data (S) as the source of the weight for a single day's text. Considering that the difference between the highest and lowest values after summing is too large, some text weights may be excessively high. Therefore, a logarithmic transformation is applied to the summation data from the previous step, and finally, Min-max normalization is used to generate the final weight (W) for a single day's text. Here, S represents the text's sentiment label, and Score denotes the daily emotional score. The specific formula is as follows:

$$w_i = \ln\left(C_i + F_i + U_i + V_i + f_i\right) \quad ,i = 1,2, \dots 1050 \tag{3}$$

$$x_i = \frac{w_i - \min(w)}{\max(w) - \min(w)} \tag{4}$$

$$W_i = \frac{x_i}{\sum_{i=1}^{1050} x_i} \tag{5}$$

$$\sum_{i=1}^{1050} W_i \times S_i \tag{6}$$

The study uses Dataset 3 to examine the volatility of the NASDAQ Composite Index from January 21, 2025, to March 7, 2025, as shown in Figure 2. To further explore the relationship between sentiment scores and index quantitative factors, the study introduces the following indicators: Potential to Rise, Potential to Drop, Real Rise, and Amplitude. The Potential to Rise indicator is the difference between the previous trading day's closing price and the current trading day's highest price. The Potential to Drop indicator is the difference between the previous trading day's closing price and the current trading day's lowest price. The Real Rise indicator is the difference between the current trading day's closing price and the opening price. The Amplitude indicator is the difference between the current trading day's highest price and the lowest price. Since the volatility of the index is affected by many factors, the sentiment score alone has a small impact and may shows a low correlation with other indicators. Therefore, the study introduces the Prediction Direction Success Rate (PDSR) as one of the metrics for correlation analysis. PDSR refers to the ability to predict whether another variable will rise on the current trading day when the sentiment score increases compared to the previous trading day, and whether the variable will fall when the sentiment score decreases. Finally, a probability indicator is generated to assess the relationship between the sentiment score and other variables.

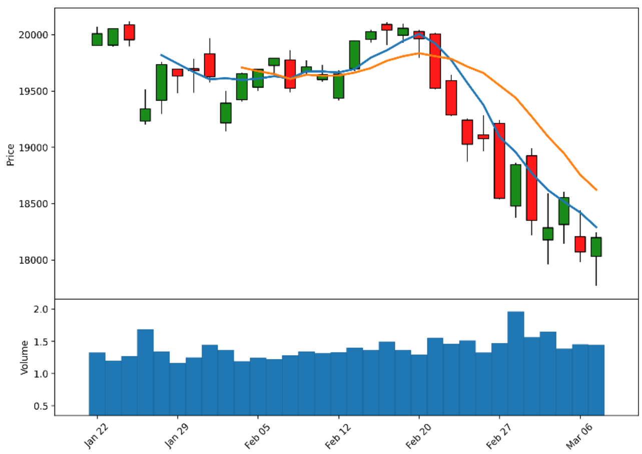

Figure 2: NASDAQ composite index volatility

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The study conducts a correlation analysis between the Potential to Rise indicator and the sentiment score indicator, as shown in Figure 3. Based on the characteristics of the variables, the study uses the Spearman correlation coefficient to measure the correlation between the Potential to Rise indicator and the sentiment score indicator. The correlation coefficient is -0.0432, indicating a very low correlation between the two. For the PDSR indicator, the success rate of predicting the direction of change in the Potential to Rise indicator based on the sentiment score is 0.4687. This also confirms that the correlation between the two is low. Therefore, using the sentiment score to predict the daily stock price's upward potential is unreasonable.

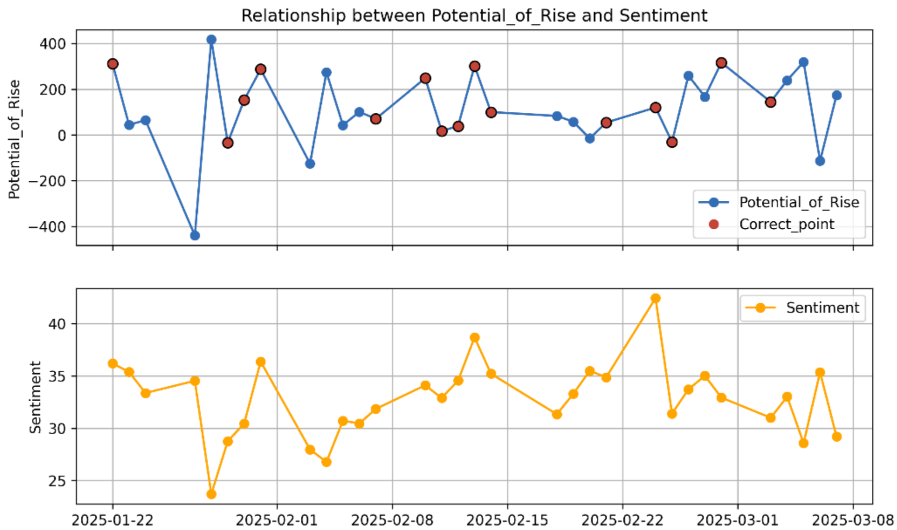

Figure 3: Potential to rise indicator and the sentiment score indicator

The study conducts a correlation analysis between the Potential to Drop indicator and the sentiment score indicator, as shown in Figure 4. The correlation coefficient between the Potential to Drop indicator and the sentiment score indicator is 0.0637, indicating a similarly very low correlation between the two. For the PDSR indicator, the success rate of predicting the direction of change in the Potential to Drop indicator based on the sentiment score is 0.5312. This also confirms that the correlation between the two is low. Therefore, using the sentiment score to predict the daily stock price's downward potential is unreasonable.

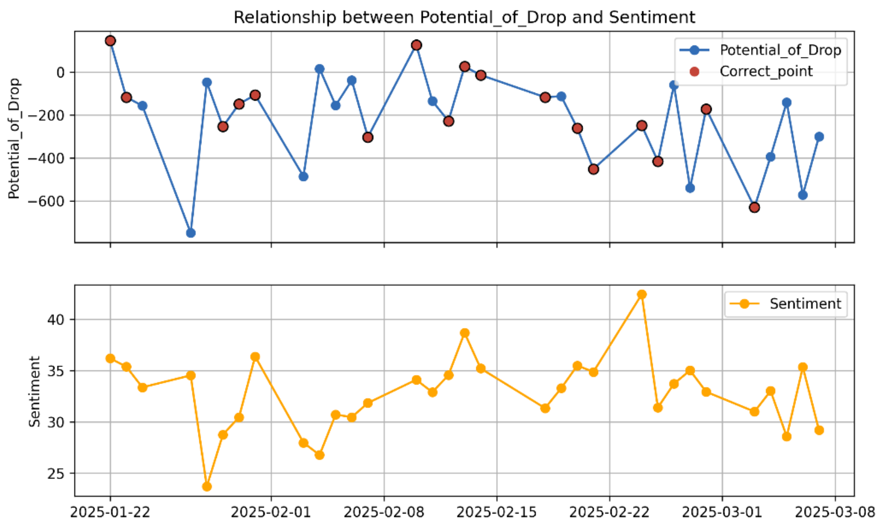

Figure 4: Potential to drop indicator and the sentiment score indicator

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The study conducts a correlation analysis between trading volume and the sentiment score indicator, as shown in Figure 5. The correlation coefficient between trading volume and the sentiment score indicator is 0.2265, indicating a relatively higher correlation between the two. For the PDSR indicator, the success rate of predicting the direction of change in the trading volume based on the sentiment score is 0.6562, indicating a moderate correlation between the two. Therefore, using the sentiment score to predict daily trading volume warrants further investigation.

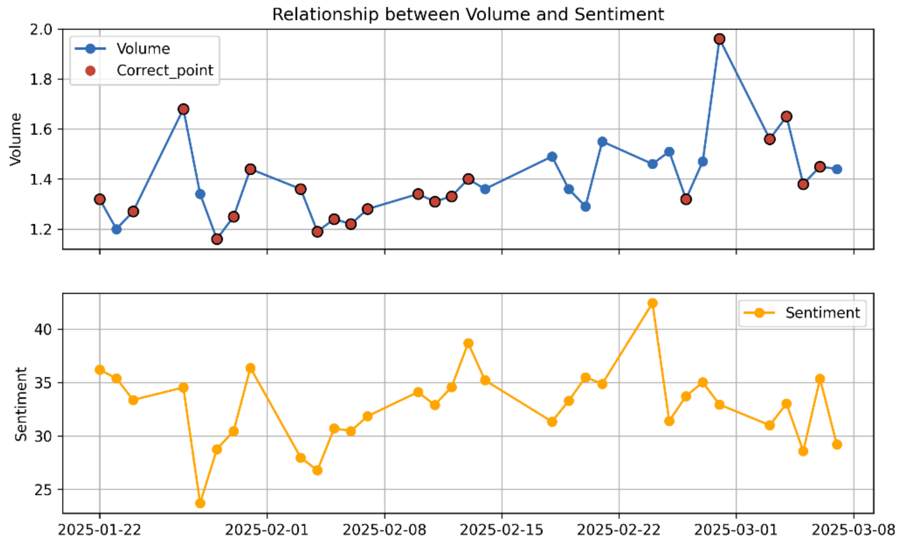

Figure 5: Volume indicator and the sentiment score indicator

The study conducts a correlation analysis between the Real Rise and sentiment score indicators, as shown in Figure 6. The correlation coefficient between the Real Rise and sentiment score indicators is -0.3148, indicating a moderate negative correlation between the two. For the PDSR indicator, the success rate of predicting the opposite direction of change in the Real Rise based on the sentiment score is 0.5, suggesting that the ability of the sentiment score to predict the direction of change in the Real Rise is relatively poor. Therefore, using the sentiment score to predict the Real Rise requires further investigation.

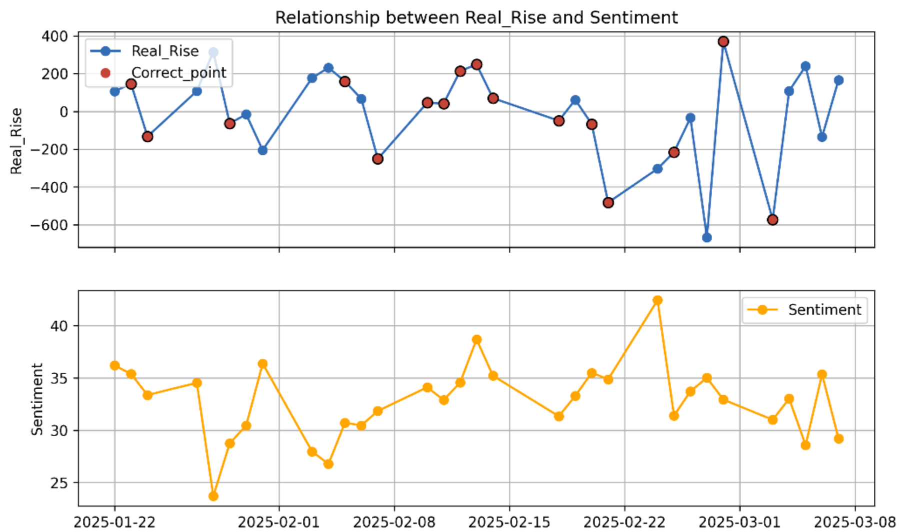

Figure 6: Real rise indicator and the sentiment score indicator

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The study conducted a correlation analysis between Amplitude and the sentiment score metric, as shown in Figure 7. The correlation coefficient between amplitude and sentiment score is -0.1125, indicating a very weak relationship between the two. For the PDSR indicator, the success rate of predicting the direction of amplitude change based on sentiment scores is 0.5312, further demonstrating the low correlation. Therefore, it is not reasonable to use sentiment scores to predict the direction of amplitude changes.

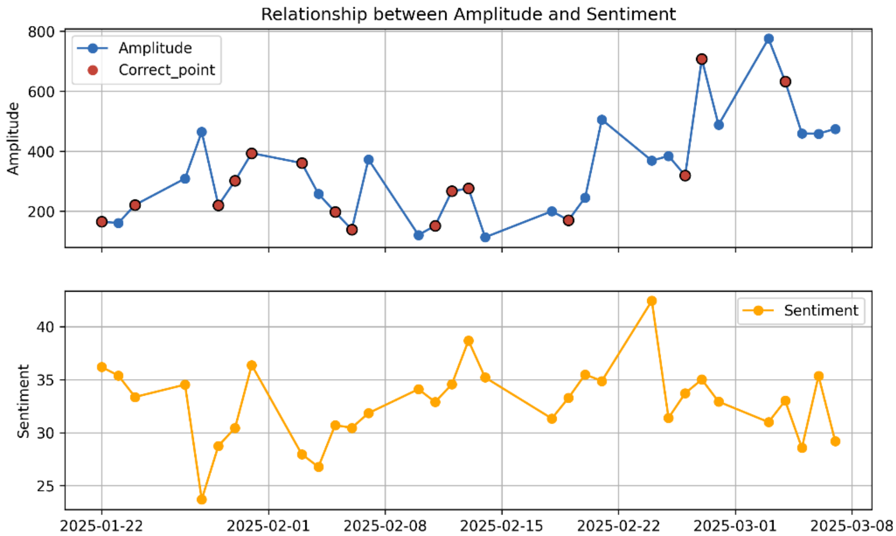

Figure 7: Amplitude indicator and the sentiment score indicator

4.6. Discussion

The study utilizes datasets from Kaggle and Twitter, which are based on real-world data and offer good interpretability. Additionally, these datasets contain relatively little noise and have a simple structure, making them easy to process. The binary sentiment labels provided in Dataset 1 have a simple structure, making them well-suited for text classification tasks using the LSTM, Transformer, CNN, and Bi-GRU algorithms referenced and employed in this study. The study references recent literature from the past three years on innovative applications of the GloVe model, ensuring that the employed model is not outdated. The selection of the sentiment scoring model was based on performance evaluation metrics under limited computational resources, demonstrating a high degree of objectivity. These aspects collectively reflect the scientific rigor of the research.

The study finds that the weak correlation between sentiment scores and the Potential to Rise/Potential to Drop indicators is because sentiment scores only reflect a small part of what affects the changes of stock performance. The intraday high and low prices are more significantly shaped by the ongoing game between the long and short sides of the market following the market opening. The occurrence of a stock's intraday high and low prices may be driven by individual trading strategies. These strategies mainly include two types: pushing up the price to sell at a higher level when lacking confidence in the future trend, and suppressing the price to accumulate low-cost shares when optimistic about future performance. When there is a significant imbalance in the number of individuals employing these two strategies in the market, the likelihood of candlesticks with long upper or lower shadows increases. However, the decision-making and execution of the above strategies require investors to consider factors such as the stock's long-term historical trends and the price-volume data observed after the market opens. Some researches, through monitoring, discovered that the Pump and Dump scheme in cryptocurrencies mainly originates from professional fraud teams. These teams set up social media groups and introduced a hierarchical system, where VIP clients

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receive information about target cryptocurrencies earlier. By enticing clients to buy, they can easily execute Pump and Dump operations [7]. Therefore, it can be concluded that the highest price and lowest price are likely the result of scams or other factors beyond emotional influences. Based on the above information, the study concludes that using a single sentiment score to predict the potential for stock price increases and decreases yields unreasonable results.

Regarding the correlation between sentiment score indicator and trading the volume indicator, the study suggests that it is due to the public accessibility of social media information. Social media sentiment can, to some extent, reflect investors' willingness to invest, while also influencing the investment intentions of other investors to a certain degree. Group behavior has an impact on global stock and financial markets. This behavior means that investors are making similar investment decisions to each other, either blindly following the decisions of a group or following the movements or actions of the group. Ayoub et al. proposed that the group effect refers to a situation where investors act irrationally as they go with the flow. They automatically follow the behavior or opinions of the group, meaning investors only follow and imitate the actions of others rather than relying on their own fundamental analysis or technical analysis. This can easily lead to phenomena such as a surge or sharp decline in stock market trading volumes [8]. Based on the above information, using sentiment score analysis to predict future changes in trading volume is reasonable to some extent, as the group effect is a common phenomenon in financial markets.

Regarding the negative correlation between the sentiment score indicator and the Real Rise indicator, the study suggests that the main reason can be explained from the perspective of how investors analyze and process market sentiment. It pointed out that small and medium individual investors in the market are more susceptible to the influence of market sentiment, leading to irrational investment behavior, while group behavior has a smaller impact on experienced investors [8]. At the same time, experienced investors are more adept at capitalizing on the irrational behavior of investors influenced by market sentiment to gain profits. The simplest strategy involves predicting an overheated market and selling in advance, or anticipating a sluggish market and buying in advance. The study suggests that the main reason for the PDSR indicator being only 0.5 is that sentiment during the trading period is difficult to obtain and is often overwhelmed by noise. However, it can still significantly influence the closing price. Based on the above information, using sentiment score indicators to predict actual price changes in the opposite direction is reasonable to some extent. However, it still requires the combination of other indicators to improve the accuracy of predicting [9].

The study suggests that the weak correlation between the sentiment score indicator and Amplitude indicator can be attributed to reasons similar to those for the Potential to Rise and the Potential to Drop indicators. The highest and lowest prices are the result of the ongoing game between the long and short sides of the market, and pre-market sentiment scores cannot capture or analyze this dynamic.

Using sentiment scores to predict trading volume and reverse-predict actual price changes is feasible to some extent. In future research and exploration, the study suggests that it is important to incorporate sentiment fluctuations during trading hours into the analysis of relevant indicators to improve the prediction of trading volume and actual price changes. At the same time, other formats of information can be obtained, or social media sentiment texts can be classified before being used to train corresponding models, which can improve the accuracy of sentiment analysis. In future applications, social media sentiment scores can be incorporated as part of a multi-factor model, helping to enhance the accuracy of predictions for trading volume and daily price changes, ultimately improving returns [10].

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5. Conclusion

The study, using the GloVe + Transformer algorithm, found a positive correlation between social media sentiment and market trading volume, while a negative correlation was observed between social media sentiment and the actual price changes. It is concluded that there is feasibility of using social media sentiment scores for prediction. Hoekstra et al. discovered a mediating effect of trading volume between investor sentiment and stock returns, suggesting that emotional factors influence stock returns through trading volume. This serves as one plausible explanation for the correlation between social media activity and trading volume.

The limitations of this study are as follows: First, the social media text data utilized may suffer from an insufficient volume. The analysis covered sentiment scores over a 30-day period, which may result in unclear correlations between the variables. A potential improvement would be to extend the data collection to 365 days, thereby enhancing the robustness of the findings. Second, due to limitations in computational resources, the study did not explore more complex algorithms for text analysis, preventing a comparison of the strengths and weaknesses of alternative models.

Liang Chang et al. considered the impact of cross-country differences on sentiment analysis when examining the relationship between sentiment and stock returns. They observed that U.S. media tend to emphasize negative information, while Chinese media display a preference for positive news, which may influence investor behavior. Abreu et al. differentiated between institutional and individual investor sentiment, noting interactions between the two, with institutional investors often viewed as a source of market instability. These studies suggest potential avenues for future research.

Building on the results of this study, investors can leverage social media sentiment to forecast market trading volume and daily price changes, enabling them to make more informed strategic decisions and potentially improve returns. For future research, further exploration of the underlying reasons behind the observed correlations could provide valuable insights into the mechanisms at play, helping to bridge existing theoretical gaps in the field.

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