***Modeling and Optimization of News-Stock Price Correlation Based on Topic Influence Selection***

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## Introduction

With the increasing complexity of financial markets and the rapid speed of information dissemination, the dynamic correlation between news texts and stock prices has gradually become a research hotspot in both academia and industry. A large body of research has shown that the sentiment orientation, topic distribution, and the influence of news events drive stock price fluctuations to some extent. News not only influences the stock market through sentiment but also, to a large extent, shapes market trends through the variation and dissemination of topics (Ren, 2023). However, existing studies mainly focus on sentiment analysis or time series modeling, with less in-depth exploration of the influence selection of news topics and their deeper correlations with stock prices. In particular, the lack of attention to the heterogeneous impact of different topics on stock prices limits the ability of existing models to understand market dynamics (Wang and Li, 2025; Minaee et al., 2021).

The core goal of this study is to explore the correlation between news topics and stock prices, and to analyze the impact of news sentiment and topics on the market. Specifically, this study aims to identify influential news topics through a staged modeling framework and then analyze the relationship between these topics, news sentiment, temporal factors, and stock price fluctuations. The significance of the study lies in three aspects: first, in the theoretical aspect, we propose a framework for quantifying "topic influence" based on topic-stock price causality, providing new perspectives for current research on topic heterogeneity analysis; second, in the methodological aspect, we combine natural language processing techniques, statistical methods (such as Granger causality test), and deep learning models (such as FinBERT and LSTM) to analyze news text and stock market data; finally, in the practical application aspect, this research helps to identify news topics and sentiment that have a significant impact on stock prices, providing valuable insights for understanding market dynamics. This study has the following innovations. First, in the quantification of topic influence, we propose a weight distribution method based on topic-stock price causality (using Granger causality test), overcoming the limitations of traditional topic modeling and enabling a more accurate identification of key topics related to stock price movements. Second, we utilize the FinBERT model for news sentiment analysis and combine it with time series analysis methods (such as CEEMDAN and SC-LSTM) to explore the potential links between sentiment, topics, temporal factors, and stock prices.This research aims to provide innovative theories and methods for financial text analysis and the study of its relationship with stock prices, especially in news topic selection and influence analysis, offering new perspectives in the field. We hope that this study will provide financial market participants with methods and tools to better understand the relationship between news information and stock prices, and provide a solid theoretical foundation for future financial market analysis.

## RELATED WORK

1. **Subject classification**

Subject Classification is a process of systematically organizing and categorizing information resources according to their subject or disciplinary field of content. Subject classification methods can be roughly divided into four categories according to the amount of data and explanatory needs: Rule based, Traditional machine learning, Topic model, and Deep learning (Table 1.).

The rule-based classification method uses manual rule making for text classification, which is highly interpretative when the data volume is small. However, a study that classified emotions using expert constructed word lexicons showed that the reliance on manual work led to the inefficiency of this method (Atmadja & Purwarianti, 2015). So, the research of this method nowadays starts to focus on combining other algorithms to reduce human resources. For example, Cui et al. (2019) constructed a classifier based on regular expressions to replace the work of experts and improve classification performance.

Traditional machine learning methods are more based on statistical methods to deal with medium-sized labeled data. Common algorithms for topic classification include: Naive Bayes (McCallum & Nigam, 1998), Support Vector Machine (SVM) (Joachims, 1998), Term Frequency-Inverse Document Frequency (TF-IDF) (Baeza-Yates & Ribeiro-Neto, 1999; Wang & Manning, 2012), Chi-Square Test (Yang & Pedersen, 1997), Mutual Information (MI) (Forman, 2003), and Maximum Entropy Model (Berger et al., 1996). These algorithms have different characteristics and different scenarios. In recent years, in order to optimize the algorithm structure to adapt to a wider range of scenarios, more and more research began to try to combine different algorithms to improve the classification ability. By combining Bayesian methods with mutual information, Nurfikri et al. (2018) proposed a news topic classification model that exhibits superior performance. There is also a study that combines SVM algorithm with information gain feature selection method to optimize traditional topic classification (Rizaldy & Santoso, 2017).

Topic modeling method is an algorithm applied to unsupervised topic discovery scenarios. This algorithm is mostly used to mine potential topics and can also be used for topic classification. LDA, as one of the currently popular topic modeling methods, Omrani et al. (2023) used it to classify true and false news. Their bilingual model demonstrated higher accuracy and F1 score than previous studies. Nonnegative Matrix Factorization (NMF), which was proposed by Lee and Seung in the 1999 issue of Nature, can directly extract themes from data. (2003). On the basis of NMF, Tang et al. (2011) proposed a new method for data clustering and classification, which is superior to traditional classification algorithms.

With the arrival of the era of big data, the amount of data is becoming larger and larger, and the data structure is becoming more and more complex. Deep learning is powerful in processing long sequence text, especially suitable for text analysis tasks in big data environment (Vaswani et al., 2017). Minaee et al. (2021) gave a comprehensive overview of the application of deep learning in text classification, including different model architectures such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Transformer, and discussed their advantages and challenges when dealing with large-scale text data. Faced with the drawback of low interpretability in deep learning (black box problem), there are currently many studies attempting to construct a more transparent machine learning system to alleviate it (Doshi Velez & Kim, 2017).

Table 1. Comparison of Common Topic Classification Algorithms.

|  |  |  |  |
| --- | --- | --- | --- |
| **Method Type** | **Data requirements** | **Interpretability** | **Applicable scenarios** |
| Rule based | low | high | simple structured data |
| Traditional machine learning | medium | medium | small and medium-sized labeled data |
| Topic model | low | medium | unsupervised subject discovery |
| Deep learning | high | low | large scale complex text |

Note: This table compares four common topic classification algorithms, highlighting their usage scenarios and features.

**B. Stock forecast**

Stock prediction holds significant importance for both retail investors and professional analysts. With the development of technologies such as machine learning, new methods for predicting stock prices have emerged. In algorithmic stock price forecasting, techniques are generally categorized into predictive technologies and clustering-based technologies.

Ticknor, J.L (2013) designed an ANN model to capture characteristics from input stock variables through variance networks. Rout, A.K et al (2014) developed a Computationally Efficient Functional Link ANN, enhancing generalization ability and incorporating technical indicators based on the previous work. Shrivas, A.K. and Sharma, S.K (2018) employed multiple machine learning algorithms including SVM, but faced significant limitations regarding datasets. Hadavandi, E. et al (2010) created a hybrid approach for stock price forecasting by combining Genetic Fuzzy Systems with ANN. Vargas, M.R et al (2017) utilized deep learning to predict market trends and directions. Xu, B et al (2018) developed a Convolutional Neural Network that captures critical information from stock data and used Long Short-Term Memory Networks (LSTM) to learn context relationships within financial news for predicting stock market trends. Hsieh, T.J et al (2011) proposed an integrated system ABC-RNN for forecasting, decomposing time series using wavelet transformation, processing selected input features with RNNs, and optimizing network weights and biases using the Artificial Bee Colony (ABC) algorithm, demonstrating promising research prospects for such methodologies. In the latest research of stock forecast. Rui Zhu et al.(2024) introduced a new hybrid neural network model based on LSTM, demonstrating the superiority of the proposed model over benchmark models. Wang Jing and Li Yunxia's study (2025) proposed a stock return prediction method named NS-FEDformer, which enhances the model’s ability to extract sequence features.

Numerous studies have already shown that specific themes or public sentiment can affect the stock prices of related companies. With the advancement of technology, methods for predicting stock prices by analyzing expert comments, public sentiment, and market news have been developing. For different themes, the model needs to identify information related to stocks within the text. In more recent research, Ren Kaiwen (2023) used the P-P algorithm which combines BERT (Bidirectional Encoder Representations) with a local sentiment word database to analyze the relationship between sentiment words and stock prices. Cui Ting and Huang Feiran (2024) proposed a method that uses lightweight language models to extract media news sentiment features and employs a GRU (Gated Recurrent Unit) deep learning network to predict stock prices based on historical data. Arya Chakraborty (2024) introduces a method combining a two-stage convolution-LSTM neural network with LLM (Large Language Model, designed to understand and generate human-like text)for comprehensive stock consultation analysis. The model leverages the advantages of LSTM in analyzing time-series data and LLM in handling and understanding textual information.

## DATA

Our study investigates the impact of news topics on stock market trends and combine each topics feature with news emotion features to optimize the strategy of predicting Dow Jones Industrial Average (DJIA) movement through a multimodal analysis framework, utilizing two complementary datasets spanning news headlines and financial markets from Kaggle.

**1.Daily Top 25 News Headline Dataset**

The primary news corpus (Sun, J, 2016) comprises 2,949 daily records from Reddit's WorldNews Channel (June 8, 2008 - July 1, 2016), featuring the top 25 most engaged news headlines per date and corresponding log return based on DJIA. This curated selection mechanism ensures our analysis focuses on news items with demonstrated public attention significance. In our research, we will use a topic classification model to classify the news in this dataset, and calculate the proportion of each news topic per date to investigate the impact of each news topic on the stock market.

TABLE 2. DAILY TOP 25 NEWS HEADLINES

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Date** | **DJIA** | **Top1** | **Top2** | **……** | **Top25** |
| 2015/1/13 | -0.00154079 | China has just banned the burqa in its biggest Muslim city | US and EU.. politicians use Charlie Hebdo attack to call for more Internet surveillance -- Fusion | …… | There is a.. lava flow in Iceland the size of Manhattan |
| 2015/1/14 | -0.01064998 | Cameroon.. Army Kills 143 Boko Haram Fighters | Air France.. hands out copies of Charlie Hebdo on flights | …… | Number 2 on Al-Qaeda's Most Wanted List Sells French Fries in a Florida Mall Food Court |
| 2015/1/15 | -0.00612299 | Saudi man.. sentenced 10 years jail and weekly public canings for 5 months. He is guilty of setting up a public online forum for debate and discussion. | Children.. caged to keep the streets clean for the Pope: Police round up orphans and chain them in filth during pontiff's visit to Philippines | …… | Fossil found.. by P.E.I. boy fills gap in reptile evolution |
| 2015/1/16 | 0.01095890 | Saudi Arabia.. publicly beheads a woman in Mecca | Boko Haram.. Appears to Be Using Abducted Girls as Suicide Bombers | …… | Nigeria:.. Satellite images show horrific scale of Boko Haram attack on Baga |

Note: *This table shows the structure and content of the aforementioned data.*

**2. News Topic Classification Dataset**

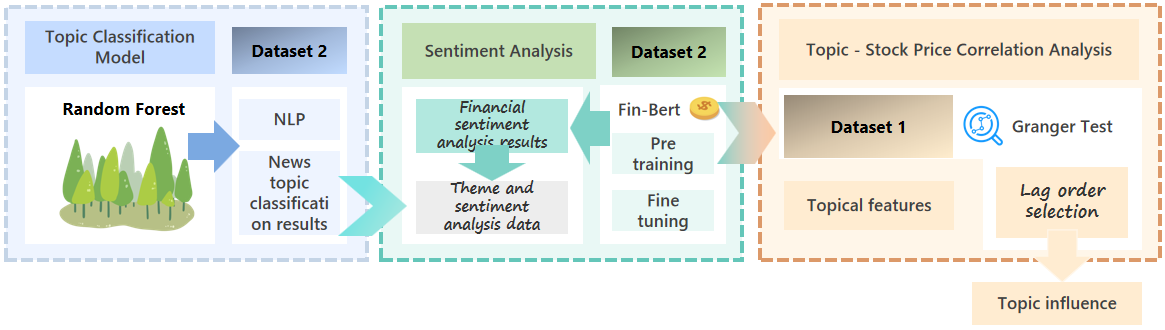
To obtain a reliable topic classification model, we employ a labeled dataset (Elkomy et al., 2024) containing 199,707 news instances across 17 distinct thematic categories (e.g., politics, technology, business). This comprehensive taxonomy, developed through expert annotation and NLP validation, serves as the training foundation for our topic classification model which is utilized to classify the Daily Top 25 News Headlines.

TABLE 3. NEWS TOPIC CLASSFICATION DATASET

|  |  |  |  |
| --- | --- | --- | --- |
| **Date** | **Headline** | **Content** | **News Categories** |
| 19-09-2023 | Assam CM Himanta Biswa Sarma gets Singapore's top fellowship | Assam CM Himanta Biswa Sarma has been bestowed with Lee Kuan Yew Exchange Fellowship of Singapore, an official release said on Sunday. Sarma was also extended an invitation to visit Singapore as a Lee Kuan Yew Fellow for his "dedicated leadership in public works and development", the statement added. He has become the first Assam CM to receive this fellowship. | ['politics', 'national'] |
| 19-09-2023 | Haryana CM announces ₹50 lakh for family of jawan killed in J&K | Haryana CM Manohar Lal Khattar on Sunday met with the family of Major Aashish Dhonchak, who lost his life in Anantnag encounter in J&K and announced ₹50 lakh compensation. "Major Aashish Dhonchak was a promising young man. He reached the rank of Major in 11 years of his service," CM Khattar said after meeting his family. | ['national'] |
| 19-09-2023 | Man caught on video having 'unnatural sex' with dog in Thane, FIR filed | A man in his mid-fifties was allegedly caught on video while having unnatural sex with a dog in Thane's Mumbra, near Mumbai. The accused, identified as Karim, has been booked, Mumbra Police said, adding that he is currently absconding. The incident came to light after a local citizen recorded the alleged act and shared it with animal activists. | ['national'] |
| 19-09-2023 | Man skydives in US with PM’s pic on Indian map on bday, video out | Union Minister Jyotiraditya Scindia has shared a video showing a man skydiving in US with a picture of PM Narendra Modi on the Indian map on the occasion of the PM's birthday. Sharing the video, Scindia said, "The love and admiration that Indians hold in their hearts for PM Shri Narendra Modi Ji is indeed special." | ['world', 'national'] |

Note: *This table shows the structure and content of the aforementioned data.*

## METHODOLOGY



To achieve these goals, this study proposes a staged modeling framework. First, in the topic influence selection stage, We use TF-IDF algorithm to extract potential topics from the news corpus and employ Random Forest model to classify daily news on various topics, and through topic-price correlation analysis (such as Granger causality test), select the topics with significant influence. The core of this stage is to quantify and select high-impact topics to lay the foundation for subsequent forecasting models. Next, in the multimodal modeling stage, we combine the selected topic features with news sentiment features (based on FinBERT-LSTM model) and temporal features (based on CEEMDAN-SC-LSTM model), constructing a hybrid neural network model that captures the cross-modal interaction effects between text and the market, improving prediction accuracy and model robustness. Finally, in the optimization stage, we adjust the model based on experimental results, optimizing the weight distribution of topic influence to ensure the model can make effective predictions based on market changes and verify its robustness in different market contexts.

1. **Topic Classification Modeling**

**1.1 Natural Language Processing**

First of all, we need to train models that can classify news headlines into topics, the first step is to process the textual data, which will become digital vectors through a series of conversion techniques in natural language, so that they can be processed by machine learning techniques. Some NLP processes are required.

**1.1.1 Text Cleaning**

The text data we have is garbled, missing removed, and each news headline is converted to lowercase, non-alphabetic characters are removed, and word splitting is done to make each sentence in the original text data into a list structure consisting of words, here for word splitting we use punkt tool which is based on the Moses word splitting algorithm. After that, the converted data are deactivated, deactivated words refer to words that are very common in natural language text, they usually do not carry specific meanings, such as “the”, “a”, “an “a”, ‘an’, ‘in’, and so on. In text categorization, these words may interfere with the training effect of the model, so they need to be removed from the text. After that, stemming is performed on the data to remove the affixes from the words so that the stem can be recognized as a variant of the same word. It aims to group the various variants of a word into the same stem to improve accuracy and reduce the size of the feature space.

**1.1.2 Feature Extraction**

After that, the text is transformed into numerical feature vectors by TF-IDF (Term Frequency-Inverse Document Frequency) which is a statistical method for evaluating the importance of a word in a document or corpus that takes into account the frequency of a word in a particular document and its It takes into account the frequency of a word in a particular document and its prevalence in the whole collection of documents, thus assigning to each word a weight value indicating its relative importance in distinguishing different categories. It consists of two parts: word frequency (TF) and inverse document frequency (IDF).

TF is calculated by the following formula:

Where denotes each document, denotes the number of times word appears in document , so the denominator of the formula is the sum of the number of words in the document, and denotes the number of times word appears in document . This formula solves for the value corresponding to word in its document.

IDF is calculated as follows:

Where denotes the number of documents in which word appears and denotes the total number of documents, this variant from the standard formula smoothes out the encoded value for each word to avoid 0.

Afterwards, the encoded value of each word in a document is obtained by multiplying these two values, thus making the whole text a numerical feature vector.

**1.2、Random Forest Classification**

**1.2.1 Principle**

Random Forest is an integrated learning method that is mainly used for classification, regression and other tasks. It improves the accuracy and stability of the model by constructing multiple decision trees and combining their results. The underlying model is the decision tree model, which forms a tree structure by recursively partitioning the dataset into different subsets. Each internal node represents a differentiation by a certain feature, each branch represents a different going direction after differentiation by the node, and each leaf node represents a category prediction.

In the classification task, the splitting criterion of the random forest is to choose the best splitting point so that the Gini impurity is minimized, which is defined as:

where is the number of categories and is the probability that the sample belongs to the ith category.

The model constructs different training sets to train multi-class decision trees by randomly drawing samples from the input data, i.e. Bootstrap sampling. For each decision tree in the forest, instead of considering all the features in the feature selection of the split node, the best features are selected from a subset of the extracted features to reduce the correlation between the trees. A decision tree algorithm is applied to each Bootstrap sample to generate a decision tree. Since different data samples and feature subsets are used for each construction, each tree is unique. Ultimately, the one with the most predictions from all trees in the forest is selected as the classification result by a voting mechanism that combines the predictions of all trees in the forest. For validation, about one-third of the untrained data is used for performance evaluation, i.e., OOB estimation, which is an unbiased estimation method.

1. **Time series analysis model**

**2.1 Data preparation**

Using a topic classification model, the top 25 news items are categorized into 15 different topics. We count each theme for the day and remove columns other than count, date, and label. Due to the label column in the dataset being the Dow Jones Industrial Average (DJIA) for the current day, it is clearly meaningless for our prediction target. So we move the data in the Label column up one unit so that the Label column is a prediction for the next day. And the last column will be deleted due to the lack of predictable labels.

**2.2 Granger Causal Relation Test**

**2.2.1 Basic principles**

The Granger causality test, proposed by Clive Granger, is used to determine causal relationships between time series variables. The basic assumption of Granger causality test is that if time series X has predictive ability for the future values of time series Y, then X is called the Granger cause of Y. This causal relationship does not imply a direct causal connection, but rather refers to the information contained in X that helps improve the accuracy of predicting Y. In our experiment, Y represents the rise and fall of DJIA (Label), while X represents the count of each news topic.

Granger's mathematical expression takes into account the following linear model form:

Autoregression :

Union-regression :

Where ,represent intercept terms; p,q represents the maximum lag order of Y and X respectively; , represent the parameters to be estimated; , represents the error term.

**2.2.2 Inspection standards**

By comparing the sum of squared residuals (RSS) of these two models, we further use an F-test to determine whether adding the lagged term of X significantly reduces the error variance.

The formula for F-test statistic is as follows:

is the sum of squared residuals of a model without X; is the sum of squared residuals of a model containing X; T is the sample size; K is the total number of parameters in the model containing X; q is the lag order of X.

If the calculated F value is greater than the critical value, reject the null hypothesis and accept the alternative hypothesis of Granger causality between X and Y. In addition, we also referenced the p-value of the results through the built-in functions of the statsmodels library. The P-value is calculated based on the F-statistic and its degrees of freedom, reflecting the probability of observing the current or more extreme result under the null hypothesis. If the P-value is less than the selected significance level (such as 0.1), the null hypothesis can be rejected and considered as the Granger cause of Y.

1. **Sentiment Analysis Framework**

The objective of this framework is to systematically quantify the sentiment polarity (positive/neutral/negative) and intensity associated with each financial news headline. This enables a granular examination of the interaction between emotional tone and news categorization in influencing market movements. By leveraging domain-specific natural language processing (NLP) models, the framework aims to enhance the accuracy of sentiment detection in financial contexts, thereby supporting the downstream task of assessing the correlation between news sentiment and stock price fluctuations.

**3.1 Model Selection and Customization**

**3.1.1 Model Architecture**

To address the challenges inherent in financial sentiment analysis, this study employs FinBERT, a transformer-based language model pre-trained on financial texts and fine-tuned on corpora such as earnings call transcripts, SEC filings, and Reuters financial news. FinBERT has demonstrated superior performance in interpreting domain-specific language compared to general-purpose sentiment models.

**3.1.2 Basic principles**

BERT uses a bidirectional Transformer encoder to pretrain text, which means it considers both the forward and backward context of a word during the training process. It uses a masking language model (MLM) to randomly mask some vocabulary in the input during the pre training stage and predict them, in order to learn the structure and semantic information of the language. In addition, Bert also performs the next sentence prediction, that is, given two sentences A and B, the model needs to determine whether B is the next sentence of A. This helps to understand the relationship between sentences.

**3.1.3 Model Adaptations**  
 To optimize FinBERT for headline-level sentiment analysis, the following customizations are introduced:

**Input Truncation**: Headlines are truncated or padded to a fixed length of 64 tokens, ensuring compatibility with FinBERT’s input limitations while preserving computational efficiency.

**Entity-Aware Attention Masking**: Named Entity Recognition (NER) is performed using SpaCy to identify and prioritize financial entities such as company names, stock indices, and monetary references. Attention masks are adjusted to emphasize these entities, enabling the model to focus on sentiment-bearing components of the headline.

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