FinGPT: Enhancing Sentiment-Based Stock Movement Prediction with Dissemination-Aware and Context-Enriched LLMs

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Abstract

Financial sentiment analysis is crucial for understanding the influence of news on stock prices. Recently, large language models (LLMs) have been widely adopted for this purpose due to their advanced text analysis capabilities. However, these models often only consider the news content itself, ignoring its dissemination, which hampers accurate prediction of short-term stock movements. Additionally, current methods often lack sufficient contextual data and explicit instructions in their prompts, limiting LLMs' ability to interpret news. In this paper, we propose a data-driven approach that enhances LLM-powered sentiment-based stock movement predictions by incorporating news dissemination breadth, contextual data, and explicit instructions. We cluster recent company-related news to assess its reach and influence, enriching prompts with more specific data and precise instructions. This data is used to construct an instruction tuning dataset to fine-tune an LLM for predicting short-term stock price movements. Our experimental results show that our approach improves prediction accuracy by 8% compared to existing methods.

Introduction

Financial markets are highly reactive to news, social media, and other public sentiment signals; these affect trading behaviors and, ultimately, stock prices. Understanding these sentiment shifts can provide valuable insights into price movement patterns, making sentiment analysis an essential component of modern financial forecasting.

Traditional sentiment analysis typically categorizes sentiment as positive, negative, or neutral. Advances in natural language processing (NLP) have significantly enhanced our ability to analyze and interpret sentiment data from vast text sources. Most prior research has focused on improving the accuracy of sentiment analysis for individual news items, rarely aggregating them to assess the overall market sentiment or integrating the results into downstream tasks such as stock prediction and risk management.

The emergence of Large Language Models (LLMs) has revolutionized financial sentiment analysis by providing not only sentiment-based classification but also explanations for stock movement predictions (Zhang et al. 2023b,a; Araci 2019; Wu et al. 2023). Recent works like FinRobot (Yang et al. 2024; Zhou et al. 2024; Han et al. 2024) demonstrate this capability through their "Market Forecaster" tool, which moves beyond single-news analysis to capture more breadth sentiment landscapes. Additionally, we are witnessing a growing body of research that extends beyond individual news analysis (Wang, Izumi, and Sakaji 2024), aiming to offer a more holistic view of stock market dynamics.

Despite the advancements brought by LLMs in financial sentiment analysis, existing methods often rely solely on the news content itself for predictions. This approach neglects the crucial factor of news dissemination, which significantly affects market reactions and stock price movements. Additionally, these methods often lack sufficient contextual data and explicit instructions, limiting the LLMs' ability to interpret news. Our proposed approach addresses these limitations by incorporating the breadth of news dissemination, detailed contextual data, and precise instructions, thereby enhancing the accuracy of short-term stock price movement predictions.

In this paper, we propose a novel approach to enhance LLM-powered sentiment-based stock movement predictions by incorporating news dissemination breadth, contextual data, and precise instructions. Our methodology clusters recent company-related news articles, using cluster attributes to evaluate the news's reach and influence. We operate under two key assumptions: *i)* The centroid article of each cluster encapsulates the most comprehensive information for LLM processing; *ii)* The cluster size indicates the topic's market impact, with larger clusters signifying more significant events. Additionally, we enhance the prompts with daily stock price and return data, along with instructions to consider the short-term or long-term impact of the news. Utilizing this information, we construct an instruction tuning dataset to fine-tune an LLM for short-term stock price predictions.

We summarize by our key contributions:

1. We propose a data-driven clustering-based method to capture the breadth of news dissemination, and incorporate it into the training dataset.
2. By enriching prompts with contextual data and instructions tailored to our proposed data format, we offer a more nuanced approach to financial sentiment analysis.

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3. Our experimental results demonstrate that our approach improves prediction accuracy by 8% compared to existing methods, offering a more robust and efficient framework for understanding the impact of news on stock prices.

The remainder of the paper is structured as follows: Section 2 reviews related work in sentiment-based financial prediction. Section 3 presents the problem statement. Section 4 describes our data-centric methodology, including high-granularity and news clustering methods. Section 5 discusses performance metrics, evaluation results, and a case study on Boeing. Section 6 concludes with findings and future directions.

Related Works

NLP for Financial Sentiment Analysis

Sentiment analysis has long been a key application of natural language processing (NLP), especially in finance, where it provides valuable insights into market trends and investor sentiment (Chan and Chong 2017; Atkins, Niranjan, and Gerding 2018). Various models and methodologies have been developed to enhance the accuracy and efficiency of sentiment analysis (Tai and Kao 2013; Hamilton et al. 2016; Day and Lee 2016; Sohangir et al. 2018; Mishev et al. 2020; Rizinski et al. 2024), ranging from lexicon-based techniques to machine learning and deep learning approaches.

Recent advances in large language models (LLMs) have demonstrated remarkable capabilities in understanding complex natural language, with promising applications in financial sentiment analysis (e.g. FinBERT (Araci 2019), Bloomberggpt (Wu et al. 2023), Fingpt (Wang, Yang, and Wang 2023; Yang, Liu, and Wang 2023)).

While these financial language models excel at individual news sentiment analysis, the systematic integration of related news for stock price prediction remains largely unexplored.

LLMs for Sentiment-based Stock Price Prediction

Leveraging text or news for stock prediction is not new; prior work has used tweets and historical data to forecast prices (Xu and Cohen 2018). Now, with the advent of LLMs, we can achieve more nuanced understanding and interpretation of financial text, allowing these models to capture complex relationships within news data and better inform stock price predictions.

Recent works demonstrate diverse applications of LLMs in stock prediction. LLMFactor (Wang, Izumi, and Sakaji 2024) targets short-term prediction through Sequential Knowledge-Guided Prompting, providing real-time interpretable insights. Similarly, (Elahi and Taghvaei 2024) addresses longer-term predictions by combining financial data and news through retrieval-augmented techniques for 3-6 month horizons.

Our work builds on this line of work, but are independent of the model itself: we focus exclusively on the data preparation process, incorporating the impact of news dissemination on stock price movements and providing LLMs with more precise instructions. In this paper, we follow the standard framework of instruction tuning LLMs for financial forecasting and used the data organization as the baseline (outlined in (Yang et al. 2024)) to show the significant improvement (Section 4), but we believe that our methodology has a much broader application, having the potential to be applied to all the existing models.

Problem Setting and Overall Framework

Our objective is to predict weekly stock price movements based on news sentiment. The movements are categorized into twelve labels: U1-U5 and U5+ for upward trends (0-1%, 1-2%, 2-3%, 3-4%, 4-5%, over 5%), and D1-D5+ for corresponding downward trends. Predictions are based on previous week's stock prices, recent news, and company fundamentals (updated quarterly and included three weeks after the quarterly report release). The model also generates reasoning for the prediction by identifying [Positive Developments] and [Potential Concerns]—highlighting the 2-4 most significant factors in each category—as well as providing [Prediction & Analysis].

Our overall framework is illustrated in Figure 1, following a standard framework of fine-tuning LLMs for financial analysis. Our work focuses on the Data Processing part and Prompt Engineering part in this flow.

Methodology

This section outlines our data-driven methodologies. Specifically, we 1) increase stock price granularity and implemented news clustering in the Data Processing part, and 2) incorporate contextual and more targeted instructions in Prompt Engineering part.

Data Processing

High Granularity in Stock Price Information (HG): The baseline method uses only weekly aggregate stock price movements (e.g. 3% weekly gain). To enhance prediction performance, we increase data granularity by incorporating daily closing prices and corresponding returns throughout each week. This granular approach serves two key purposes: 1) it reduces the uncertainty of the calculation within the LLMs by providing explicit daily price movements and 2) enables precise temporal alignment between price changes and news events, providing a basis for the differentiation of short- long-term impacts. We will refer to this method as **HG** in the following part.

News Clustering (HG-NC): Traditional stock market analysis often lacks systematic quantification of news dissemination. A more comprehensive approach requires analyzing the complete news landscape-often exceeding 200 articles weekly for active stocks. It presents significant challenges: redundant information processing, computational inefficiency, and potential token limitations in language models.

To address these challenges, built upon our HG method, we further developed a clustering approach that efficiently organizes high-volume news content while capturing news impact through two key dimensions: reporting frequency and temporal span. We will refer to this method as **HG-NC** in the following part. Our approach comprises the following steps:

1. **Data Collection**: We retrieve weekly financial news data, including titles and summaries, from the Finnhub API.
2. **Topic Clustering**: News articles are transformed into embedding representations using Sentence Transformers, followed by BERTopic-based topic modeling to identify and cluster thematically related news content.
3. **Cluster Quality Assessment**: We evaluate cluster cohesiveness through pairwise similarity analysis:
   - **High-Cohesion Clusters** (average pairwise similarity > 0.6): For these clusters, we select the centroid-proximate article as the cluster representative and preserve the metadata including cluster size and temporal span.
   - **Low-Cohesion Clusters** (average pairwise similarity ≤ 0.6): we again select the article closest to the centroid but limit the topic size to 2 and record the time range. This setting reflects lower clustering quality and lower confidence in these less cohesive groups.
4. **Topic Selection Strategy**: When high-cohesion clusters fall below six, we supplement with low-cohesion clusters (at most 4) to ensure sufficient information coverage. All parameters—similarity thresholds, cluster sizes, and topic quotas—are adjustable based on analysis needs and LLM constraints.

The clustering approach, leveraging BERTopic (Grootendorst 2022) and cosine similarity evaluation, efficiently condenses large volumes of news into representative samples while quantifying news dissemination, thereby enhancing stock movement prediction.

Prompt Engineering: Context-enhanced Instructions

To adapt to our proposed data format where we incorporate daily stock information and quantified news dissemination, context-enhanced instructions are needed for better analysis.

For HG: We instruct LLMs to differentiate between short-term and long-term impacts of news, as daily stock prices and returns can reveal immediate market reactions. This distinction is crucial because the influence of short-term news is often already reflected in stock movements within the same week. For a prompt template, see Figure 4.

For HG-NC: Built upon HG, we construct the news component using selected representative articles and their associated metadata (topic size and temporal coverage). Then, we enhance the instructions by describing the news component and providing guidelines for analyzing the impact of news dissemination on stock movement. For a prompt template, see Figure 5.

Instruction-tuning

The training dataset pairs our structured input prompts (including company introduction, historical stock prices, related news, company fundamentals, and instructions for utilizing sentiment analysis for prediction) with GPT-4o-generated analysis based on known future movements. Then, removing the ground truth stock price in the prompt, we use this dataset to fine-tune Llama3-8B for weekly stock movement prediction and evaluate both numerical accuracy and reasoning quality (see Appendix A for details.)

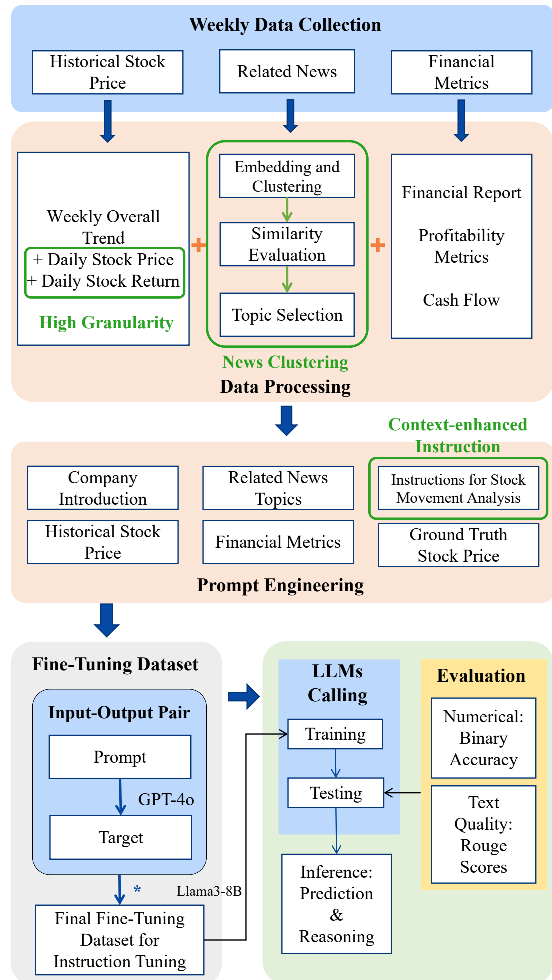

Figure 1: Overall framework. In Data Processing part, we increase granularity in the historical stock price data and employ news data clustering. In Prompt Engineering part, we incorporate context-enhanced instructions for stock movement analysis. The operation we mark with "*" is removing future movement label.

Performance Evaluation

We evaluate our models' performance using two key metrics: binary accuracy for stock prediction and ROUGE scores for reasoning quality. Our analysis compares three progressive methods: the **baseline**, the **HG** method with increased stock price granularity, and the **HG-NC** method.

Binary Accuracy in Stock Movement Prediction

We assess each model's ability to predict directional stock price movements (up/down) using binary accuracy metrics. Our comprehensive dataset comprises 380 observations across 20 companies, spanning multiple market sectors to ensure robust evaluation. The results demonstrate a consistent improvement pattern across our model iterations:

Method	Avg Acc	Long term	Short term
Baseline	55.0%	15.0%	7.5%
HG	59.2%	69.8%	56.6%
HG-NC	63.0%	58.5%	50.9%

Table 1: Our methods show a significant increase in the binary accuracy. Also, the increase in "long-term" word frequency and "short-term" word frequency provides evidence for attention to temporal aspects, which may account for the accuracy improvement.

With high granularity stock price and targeted instructions, accuracy improves from 0.550 to 0.592. A detailed analysis reveals increased attention to temporal aspects in the **Prediction & Analysis** component, with the frequency of "long-term" rising from 15.0% to 69.8% and "short-term" from 7.5% to 56.6%. This indicates that the LLM effectively follows the instructions to differentiate between short-term and long-term news impacts, balancing them in stock price predictions, leading to improved accuracy.

The further increase to 63% with NC validates our hypothesis that incorporating news clustering results enhances the LLM's capacity to capture market dynamics and the impact of news dissemination on stock movements.

ROUGE Scores for Reasoning Quality Evaluation

Given the large size of our training and test datasets, obtaining ground-truth sentiment-based analysis for every instance is impractical. Therefore, we rely on automated evaluation metrics to assess the quality of model outputs. We use ROUGE (Recall-Oriented Understudy for Gisting Evaluation) scores (Lin 2004) to assess the reasoning quality as they measure the overlap of key words and phrases between LLM-generated outputs and reference summaries. Higher ROUGE scores indicate closer alignment with the reference text and broader coverage of news content as the basis for reasoning. However, precise and comprehensive evaluation still requires human judgment.

We evaluate three metrics: ROUGE-1, ROUGE-2, and ROUGE-L (longest common subsequences), with ROUGE-N representing N-gram co-occurrence statistics. Across all metrics, the HG-NC method consistently outperforms both the baseline and HG approaches.

Specifically, we analyze ROUGE scores for the **Prediction & Analysis** component in the output, which integrates positive and negative factors to justify the model's directional predictions. This critical component highlights the LLM's ability to weigh competing factors from sentiment analysis and articulate its decision-making process. As shown in Table 2, the HG-NC method better captures and articulates the complex interactions between various market factors in its analysis.

Method	ROUGE-1	ROUGE-2	ROUGE-L
Baseline	0.450	0.121	0.224
HG	0.469	0.131	0.224
HG-NC	0.472	0.140	0.234

Table 2: ROUGE scores for different methods

Case Study: Boeing Company

We use The Boeing Company (NYSE: BA) as a representative case study and compare the prediction performance of the HG method and HG-NC method. Overall, the HG-NC method has accuracy (63.2%) compared to the HG method (52.63%). For prediction results see Figure 6 in Appendix.

We examine the ratio of news articles in high-coherence clusters (those with average pairwise similarity > 0.6) to the total number of news articles as an indicator of clustering performance. In general, we observe a strong correlation between clustering performance and prediction performance. Specifically, as shown in Figure 2, in 7 instances where our HG-NC method outperforms HG (Case 1), we observe relatively high ratios of high-coherence clusters (mostly exceeding 50%). Conversely, performance declines when this ratio falls below 40% (Case 2), suggesting insufficient capture or preservation of significant market information.

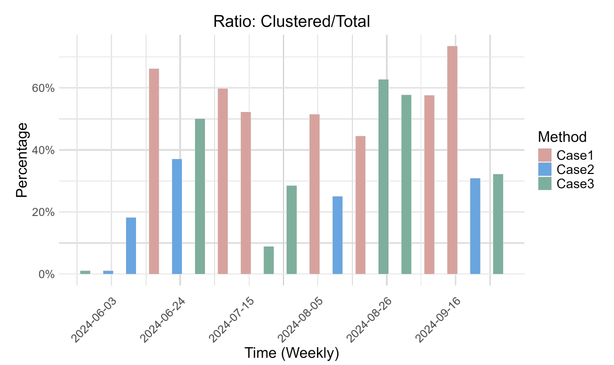

Figure 2: The ratio of news articles in high-coherence clusters to the total number of news articles. We classify prediction comparisons into three cases: Case 1: HG-NC correct vs. NC incorrect; Case 2: HG correct vs. HG-NC incorrect; Case 3: Both methods yield identical predictions.

Conclusion

In this paper, we proposed an approach to enhance LLM-powered sentiment-based stock movement prediction. By increasing granularity for stock price and providing instructions for short-term or long-term analysis, we enhance the contextual understanding of news. Further, we evaluate news dissemination through clustering and incorporate its market impact to improve predictions. We developed an instruction tuning dataset to fine-tune LLMs for more accurate short-term stock movement predictions. Experimental results validate our approach, achieving 63% binary accuracy compared to the 55% baseline, with better predictions at high clustering ratios ($> 50\%$). These findings highlight the importance of enriched contextual data and dissemination-aware methods in improving prediction accuracy.

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Appendix A: Model Training

The training parameters are given in Table. For our model, we initialize it with LLAMA-3-8B model and perform instruction tuning over 5 epochs. The training process utilizes the AdamW optimizer, with a batch size of 32, an initial learning rate of 1×10^{-5}, and a weight decay of 0.01. In order to be able to input the normal amount of news in a week, we set a maximum input text length of 8000 tokens. We utilize DeepSpeed for the fine-tuning process on A100 (40GB) GPU, resulting in a total training time of 162 minutes.

Parameter	Value
Learning rate	1×10^{-5}
Weight Decay	0.01
Batch size	32
Training epochs	5
Num warmup Steps	0
Max Token Length	8000
GPUs	A100 (40GB)

Table 3: Training parameters.

Appendix B: Prompt Templates

Prompt Template 1: Baseline

[Company Introduction]
Apple Inc is a leading entity in the Technology sector...
Apple Inc operates primarily in the US, trading under the ticker AAPL ...

[Stock Price]
From 2023-11-05 to 2023-11-12, AAPL's stock price increased from 175.75 to 185.70.

[News]
News during this period are listed below:
[Headline]: Apple Vision Pro Spatial Video arrives for iPhone in iOS 17.2 beta 2
[Summary]: At a glance, there don't appear to be many new features in the second beta of iOS 17.2 — with the exception of Spatial Video recording for Apple Vision Pro.

[Headline]: ...
[Summary]: ...

[Basic Financials]
No basic financial reported.

[Instruction]
Based on all the information before 2023-11-12, let's first analyze the positive developments and potential concerns for AAPL. Come up with 2-4 most important factors for each category and keep them concise. Most factors should be inferred from company related news. Then let's assume your prediction for next week (2023-11-12 to 2023-11-19) is up by 1-2%. Provide a summary analysis to support your prediction. The prediction result need to be inferred from your analysis at the end, and thus not appearing as a foundational factor of your analysis.

Figure 3: Baseline Prompt Template. This template contains company introduction, stock price weekly trend, news headlines and summaries, basic financials, and analytical instruction for prediction.

Prompt Template 2: High Granularity

[Company Introduction]
Apple Inc is a leading entity in the Technology sector...
Apple Inc operates primarily in the US, trading under the ticker AAPL ...

[Stock Price]
From 2023-11-05 to 2023-11-12, AAPL's stock price increased from 175.75 to 185.70. The daily stock price during this period is [178.31, 180.89, 181.95, 181.48, 185.69], and the corresponding daily return is given by [0.0146, 0.0144, 0.0058, -0.0026, 0.0232].

[News]
News during this period are listed below:
[Headline]: Apple Vision Pro Spatial Video arrives for iPhone in iOS 17.2 beta 2
[Summary]: At a glance, there don't appear to be many new features in the second beta of iOS 17.2 — with the exception of Spatial Video recording for Apple Vision Pro.

[Headline]: ...
[Summary]: ...

[Basic Financials]
No basic financial reported.

[Instruction]
Based on all the information before 2023-11-12, let's first analyze the positive developments and potential concerns for AAPL. Note that some of the factors only influence the price for the following 1 or 2 days while some others may have longer-term effects. Come up with 2-4 most important positive factors and 2-4 most significant negative effects and keep them concise. Most factors should be inferred from company related news. Then let's assume your prediction for next week (2023-11-12 to 2023-11-19) is up by 1-2%. Provide a summary analysis to support your prediction. The prediction result need to be inferred from your analysis at the end, and thus not appearing as a foundational factor of your analysis.

Figure 4: HG Prompt Template. This template includes daily stock prices with corresponding returns and context-enhanced analytical instructions emphasizing temporal effects.

Prompt Template 3: HG-NC

[Company Introduction]
Apple Inc is a leading entity in the Technology sector...
Apple Inc operates primarily in the US, trading under the ticker AAPL ...

[Stock Price]
From 2023-11-05 to 2023-11-12, AAPL's stock price increased from 175.75 to 185.70. The daily stock price during this period is [178.31, 180.89, 181.95, 181.48, 185.69], and the corresponding daily return is given by [0.0146, 0.0144, 0.0058, -0.0026, 0.0232].

[News]
News Topics during this period are listed below:
[Topic]: Apple product upgrade.
[Duration]: 2023-11-07 to 2023-11-10
[News Headline]: Apple Vision Pro Spatial Video arrives for iPhone in iOS 17.2 beta 2
[News Summary]: At a glance, there don't appear to be many new features in the second beta of iOS 17.2 — with the exception of Spatial Video recording for Apple Vision Pro.
[Topic Size]: 12

[Basic Financials]
No basic financial reported.

[Instruction]
Based on all the information before 2023-11-12 and the following guidelines, let's analyze the positive developments and potential concerns for AAPL. Apart from stock price information and basic financials, several news topcis are given and they are derived from news clustering. Each topic contains its duration, a key news headline and summary, and a topic size, indicating the number of related news items within that cluster. First, note that some of the factors only influence the price for the following 1 or 2 days while some others may have longer-term effects. Second, the topics that are closer to 2023-11-12 are likely to have a stronger influence on the upcoming stock price forecast. Third, take into account the topic size: larger clusters represent greater market attention and, consequently, likely exert more influence on the stock price. Following these instructions, please come up with 2-4 most important positive factors and 2-4 most significant negative effects and keep them concise. Most factors should be inferred from company related news. Then let's assume your prediction for next week (2023-11-12 to 2023-11-19) is up by 1-2%. Provide a summary analysis to support your prediction. The prediction result need to be inferred from your analysis at the end, and thus not appearing as a foundational factor of your analysis.

Figure 5: HG-NC Prompt Template. This template enhances the HG format by incorporating clustered news topics with topic size and temporal span, along with guidelines for analyzing news dissemination on price predictions.

Appendix C: Experimental results for Boeing Company

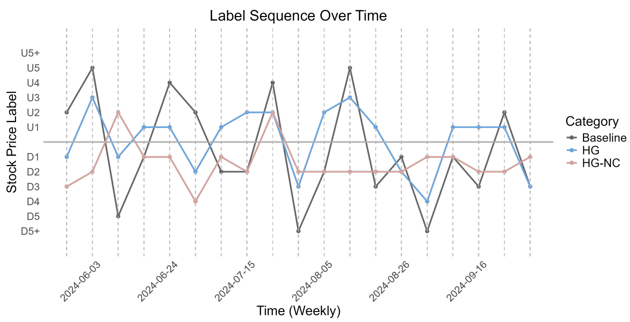

Figure 6: BA prediction labels during test period.

Start Date	News Count	Clusters	Good Clusters	Clustered News	Ration
5/26	74	2	0	0	0
6/2	76	4	1	3	0.04
6/9	77	5	1	14	0.18
6/16	118	9	5	78	0.66
6/23	135	6	3	50	0.37
6/30	110	6	2	55	0.50
7/7	87	7	4	52	0.60
7/14	69	7	3	36	0.52
7/21	102	2	1	9	0.09
7/28	109	4	2	31	0.28
8/4	70	4	2	36	0.51
8/11	68	4	1	17	0.25
8/18	63	2	1	28	0.44
8/25	67	9	5	42	0.63
9/1	78	3	2	45	0.58
9/8	139	8	5	80	0.58
9/15	124	9	9	91	0.73
9/22	120	7	3	37	0.31
9/29	84	2	1	27	0.32

Table 4: Weekly news clustering statistics (2024/5/26 - 2024/9/29) showing total news count, number of clusters, good (high-cohesion) clusters, clustered news (news in high-cohesion clusters), and the ratio of clustered to total news.

Prediction Result Example: BA, 2024/6/16 to 2024/6/23

[Positive Developments]:
1. Arajet, a carrier expanding international routes, has taken delivery of its 10th Boeing 737 MAX, indicating ongoing demand and successful sales of Boeing's fuel-efficient aircraft.
2. Despite concerns, there is a sustained strong demand for new planes as travel has surged post-pandemic, which supports Boeing's longer-term sales prospects.

[Potential Concerns]:
1. Boeing is facing an investigation into quality issues with undelivered 787 Dreamliners, related to incorrect installation of fasteners, which can hurt the company's reputation and future deliveries.
2. The FAA is investigating potential issues with the authenticity of titanium documentation in newly manufactured Boeing jets. This adds regulatory scrutiny and could delay production approvals.
3. Boeing and the FAA are subjected to a congressional probe initiated by Senator Chuck Grassley, further intensifying scrutiny and potentially impacting operational efficiency and decision-making.

[Prediction & Analysis]:
Prediction: **Down by 0-1%**
Analysis: In light of recent developments, Boeing is confronting multiple headwinds that may overshadow its positive sales developments. The recent investigations, both by the FAA and a congressional probe, could lead to regulatory delays or production setbacks, which could dampen investor confidence in the short term. Furthermore, the concerns regarding quality control in the 787 Dreamliner line emphasize operational challenges that Boeing needs to address swiftly to prevent damage to its reputation and future sales. Despite strong demand for aircraft, these issues are likely to pose a significant risk to Boeing's immediate stock performance. Given the news topics predominantly reflecting negative sentiment recently and the fact that scrutiny often results in market skepticism, I predict a slight decline of 0-1% in Boeing's stock price in the upcoming week (2024-06-16 to 2024-06-23).

Figure 7: The prediction outcome of HG-NC method: Boeing Company, 2024/6/16-2024/6/23.