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Multimodal Data-Driven Factor Models for Stock Market Forecasting

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Abstract: This study proposes a multimodal factor mining method that integrates market data, financial texts, and social emotions to improve the accuracy and interpretability of stock market forecasts. Traditional factor models often rely on a single data modality and are difficult to fully describe market dynamics. This study introduces multimodal data integration to not only extract traditional factors from market fundamentals and technical indicators but also extract sentiment and topic factors from financial texts using natural language processing technology and generate investor influence and social sentiment factors by modeling social media data through graph neural networks. Experimental results show that the integration of multimodal factors significantly improves the prediction ability of the model, and the benchmark model shows superiority in indicators such as mean square error, directional accuracy, and prediction R2. At the same time, factor contribution analysis further verifies the complementary effects of market factors, text factors, and social factors, reflecting the practicality of multimodal methods. The research results provide an important reference for the application of multimodal data in financial markets and provide new ideas for building more intelligent factor models.

Keywords: Multimodal factor mining; stock market prediction; natural language processing; graph neural network.

1. Introduction

In today's financial markets, information is becoming increasingly complex and diverse. Traditional factor investment strategies mainly rely on fundamental data and technical indicators, but these methods have limitations in capturing market sentiment and unstructured data. With the rapid development of artificial intelligence technology, researchers have begun to try to introduce multimodal information such as text data, social media sentiment, and market data in order to improve the predictive power and robustness of factor models [1]. There is a potential intrinsic connection between investor sentiment on social media platforms, market interpretation of financial news, and real-time trading data in the stock market [2]. After the fusion of this information, it can more comprehensively portray the trend of stock price changes. Therefore, exploring how to effectively integrate and utilize these heterogeneous data to provide a new perspective for stock market factor mining has become a research direction with important academic value and application prospects [3].

Traditional financial factors are mainly based on structured information such as historical price data, trading volume, and corporate financial data. In recent years, more and more studies have shown that the sources of market information are no longer limited to these traditional data. The impact of unstructured data such as investor behavior, market news, and social media sentiment on stock prices cannot be ignored. For example, investor discussions on social media can reflect the fluctuations in market sentiment, while financial news reports may significantly affect market expectations in a short period of time. It is often difficult to describe market dynamics using a single type of data. Therefore, a multimodal method that combines text, social data, and market data can more accurately identify potential factors that affect stock prices and improve the explanatory power and prediction accuracy of factor models. At the same time, the development of machine learning and deep learning technologies has provided new methods for the fusion of multimodal data, making the construction of factor models more intelligent and precise [4].

At present, the volatility of financial markets is increasing, the factors affecting stock prices are more complex, and investors' feedback on market sentiment is also more rapid. In this context, multimodal data fusion methods can dig out more nonlinear and dynamic market laws and make up for the shortcomings of traditional financial factor models. For example, financial news reports can often affect investors' market expectations, while discussions and investment sentiment on social media can also boost short-term market fluctuations. By extracting semantic information from text data through natural language processing (NLP) technology and combining it with the structured characteristics of market data, we can more comprehensively understand the potential trends of stock market changes. In addition, social media data usually contains a large amount of investor interaction information. Through technologies such as graph neural networks (GNN) [5], we can further analyze the network structure of investors and the influence of opinion leaders, thereby enhancing the factor model's ability to portray market sentiment. The application of these technologies lays the foundation for building more accurate and explanatory financial factors.

The study of the fusion of multimodal data is not only of academic value but also of important practical application significance. In actual investment decisions, the core of quantitative investment strategies is to build a factor system that can stably predict market returns. However, traditional factor construction methods often ignore market sentiment and text information, while multimodal factor mining can make up for this defect and improve the robustness of stock selection strategies. Especially in the market environment where high-frequency trading and algorithmic trading are becoming increasingly popular, investment institutions need to rely on more comprehensive market information to make faster and more accurate decisions. Through multimodal data fusion, the adaptability of factor models can be improved, enabling them to respond to market changes more quickly, thereby improving investment returns and risk control capabilities. In addition, this research can also provide new tools for financial supervision, helping regulators to better identify market risks, warn of abnormal fluctuations, and formulate more reasonable market intervention strategies.

In summary, the study of multimodal stock factors that integrate text, social data and market data is an important extension of traditional financial factor models. With the development of big data technology and the growing demand for intelligent investment strategies in the financial market, this research direction will have broad application prospects and a far-reaching impact. Future research can further optimize the fusion method of multimodal data [6], explore more effective factor selection mechanisms, and combine technologies such as reinforcement learning to improve the adaptability and stability of factor models, providing more advanced technical support for quantitative investment, risk management, and market forecasting.

2. Related Work

The evolution of stock market prediction models has increasingly focused on multimodal data fusion techniques, which integrate structured financial data with textual narratives and social sentiment to capture the full complexity of market dynamics. Early approaches primarily relied on historical prices and corporate fundamentals, but recent advances have shown that combining heterogeneous data sources can significantly improve both prediction accuracy and model robustness.

Several studies have emphasized the integration of market and sentiment data through deep learning architectures. One such approach leverages convolutional neural networks (CNN) to extract spatial dependencies from financial data, while gated recurrent units (GRU) preserve the sequential structure of sentiment time series, effectively capturing the interplay between news sentiment and price movements [7]. Another framework enhances feedforward neural networks by integrating multimodal data from historical prices, financial reports, and investor sentiment, demonstrating the benefits of fusing structured and unstructured information for stock prediction [8]. These studies highlight how combining numerical indicators with sentiment signals enriches traditional factor models.

Incorporating advanced sequence modeling techniques has also strengthened the predictive performance of financial models. Transformer networks, originally designed for natural language processing, have been adapted to financial markets due to their ability to model long-range dependencies across financial indicators and external factors [9]. Beyond supervised learning, reinforcement learning methods have been applied to dynamic portfolio management, where nested decision-making processes adjust strategies in response to evolving market conditions, improving adaptability in non-linear environments [10]. Additionally, ensemble learning strategies, where multiple deep models are combined, have been shown to improve the robustness of risk assessments in financial derivatives markets, particularly when fusing price movements, external news, and derivatives-specific factors [11].

With the rise of social media influence on markets, graph-based modeling techniques have gained attention for their ability to capture relationships between investors, assets, and opinion leaders. Graph neural networks (GNN), which propagate information across complex relational structures, have been applied to credit risk analysis, demonstrating how relational modeling captures latent dependencies across financial entities [12]. The same principle is increasingly applied to investor sentiment modeling, where influence networks from social media discussions are integrated into stock prediction pipelines.

Another persistent challenge in financial modeling is data imbalance, particularly in scenarios where rare but high-impact events (e.g., financial fraud, sudden price crashes) dominate predictive performance. To mitigate this, generative adversarial networks (GAN) have been applied to synthetic data generation, improving model robustness by enriching training data with realistic minority samples [13]. Complementary techniques such as Markov network classification with adaptive weighting have also been used to emphasize underrepresented classes, ensuring that predictive models allocate appropriate weight to rare but critical events [14]. These methods are especially relevant in multimodal settings, where structured and unstructured data may have different imbalance characteristics.

Beyond domain-specific methods, foundational deep learning architectures originally designed for other fields have also contributed to financial data mining and multimodal fusion. The ResNeXt architecture, known for its modular design and parallel pathways, has been repurposed to enhance feature extraction in financial data mining tasks, demonstrating the versatility of advanced convolutional networks for structured and unstructured financial data [15]. Building on this, an improved ResNeXt50 variant has further optimized convolutional pathways to handle the high-dimensional, multi-source data typical of financial markets, improving feature discrimination and classification accuracy [16]. Similarly, temporal convolutional networks (TCN), originally introduced for speech processing and time series analysis, have been adapted to high-frequency trading (HFT) signal prediction, where modeling rapid price fluctuations requires efficient extraction of short-term temporal dependencies [17]. These cross-domain applications illustrate the adaptability of modern deep learning models for complex financial data. The importance of anomaly and fraud detection in financial systems has also driven the application of specialized deep learning models. Convolutional networks optimized for financial statement analysis have been used to detect anomalies indicative of corporate fraud, automating the discovery of irregular patterns that may be missed in manual audits [18]. Further, EfficiencyNet, a streamlined neural network architecture combining separable convolutions and self-attention, has been applied to audit fraud detection, balancing efficiency and interpretability in financial anomaly detection [19]. Complementing these efforts, specialized transaction sequence models have been developed for money laundering detection, where sequential patterns across transactions indicate potential illicit activities [20]. These techniques underscore the importance of combining pattern recognition, temporal modeling, and attention mechanisms in financial anomaly detection.

The scalability and efficiency of multimodal financial systems are further supported by advancements in computational infrastructure and scheduling mechanisms. Dynamic distributed scheduling algorithms have been introduced to optimize data stream processing, balancing load and minimizing latency in real-time analysis environments [21]. Additionally, stable diffusion models, originally developed for generative image synthesis, have been adapted into a unified framework for classification and anomaly detection, demonstrating the flexibility of diffusion-based generative techniques for structured financial data [22]. These computational advances provide the backbone for scalable and adaptive multimodal data processing pipelines.

Collectively, these studies contribute to a broad technical foundation for multimodal factor mining in stock market prediction, blending structured financial data with unstructured textual and social signals, while leveraging cutting-edge deep learning, graph modeling, and anomaly detection techniques. By integrating these approaches, multimodal factor models are positioned to more comprehensively capture the non-linear, dynamic, and sentiment-driven nature of modern financial markets, improving both predictive performance and model interpretability.

3. Method

In this study, we proposed a multimodal factor mining method that integrates text, social data, and market data, aiming to build a more explanatory and predictive stock market factor model. Its network architecture is shown in Figure 1.

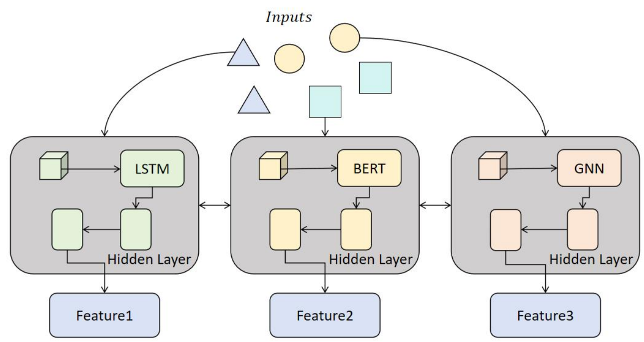

Figure 1. Overall model architecture

Assume that the state variable of the stock market is S_t, and its evolution is affected by multiple heterogeneous data sources, including market data M_t, text data T_t, and social sentiment data $S_t^{(social)}$. Our goal is to construct a factor function $f(S_t)$ that can effectively characterize the future return r_{t+1} of the stock, that is:

$$r_{t+1} = f(S_t) + \varepsilon_t$$

Among them, ε_t is the random error term. In order to extract effective factors, we first learn the feature representation of each data source and then use deep learning methods to perform multimodal fusion to obtain the optimal factor combination.

First, for market data M_t, we use time series modeling methods, such as LSTM or Transformer, to learn the historical patterns of stock price sequences. Assuming that the historical market data of stock i is $M_l^i = \{m_{t-k}^i, ..., m_t^i\}$, where k is the length of the lookback window, the representation of market features can be calculated by LSTM:

$$h_t^M = LSTM(m_t^i)$$

The text data T_i mainly comes from financial news and company announcements. We use pre-trained language models, such as BERT to convert text into vector representations and use sentiment analysis models to extract market sentiment scores. Let the original input of the text data be T_t^i, and the representation after BERT encoding is:

$$h_t^T = BERT(T_t^i)$$

For social media data, we use graph neural networks (GNN) to model investor relationships in social networks.

Let the adjacency matrix of the social network be A and the social sentiment information be $S_t^{(social)}$, then the propagation formula of GNN is as follows:

$$h_t^S = \sigma(A h_{t-1}^S W + b)$$

Among them, W and b are model parameters, and σ is a nonlinear activation function (such as ReLU). Finally, we use the multimodal attention mechanism to fuse the feature representations of different data sources to obtain the final factor representation:

$$h_t = \alpha_M h_t^M + \alpha_T h_t^T + \alpha_S h_t^S$$

Among them, $\alpha_M, \alpha_T, \alpha_S$ is the weight adaptively learned through the attention mechanism. Finally, we input the fused features into the factor selection module and use methods such as XGBoost and LASSO regression to select the factors with the most predictive ability.

Finally, we evaluate the predictive power of the selected factors in a factor regression framework and use Fama-MacBeth regression to estimate the factor return β_t.

$$r_{t+1} = \beta_t F_t + \varepsilon_t$$

Through the above methods, we are able to build a multimodal stock factor system covering market, text and social data, effectively improving the robustness and predictive ability of the factors.

4. Experiment

4.1 Datasets

The dataset used in this study covers market data, financial news texts, and social media information to comprehensively construct multimodal stock factors. Market data comes from Yahoo Finance and contains standard historical stock trading data, such as opening price, closing price, highest price, lowest price, trading volume, etc., which are usually used to construct technical factors and fundamental factors. In addition, we also introduce the stock market volatility index (VIX), company financial report data, and macroeconomic indicators such as interest rates and inflation rates to enrich the multidimensional information of market data. These data are updated daily, and different stocks are processed synchronously to ensure the integrity and consistency of the time series.

In order to enhance the interpretability of market factors, we integrate financial reports from financial news websites (Reuters and Bloomberg) and use natural language processing (NLP) methods to extract information such as text sentiment and topic distribution [23]. In addition, social media data comes from platforms such as Twitter and Reddit, including investors' emotional expressions, market discussions, and hot topics related to stocks. We use sentiment analysis models (such as FinBERT) to calculate the sentiment score of text and combine social network structures (such as likes and forwarding relationships) to construct investor influence indicators. By integrating data from different modalities, we can build a more comprehensive and accurate stock factor system to improve the robustness and explanatory power of market forecasts. To further illustrate the situation of the data set, this paper first gives the distribution of financial news sentiments, as shown in Figure 2.

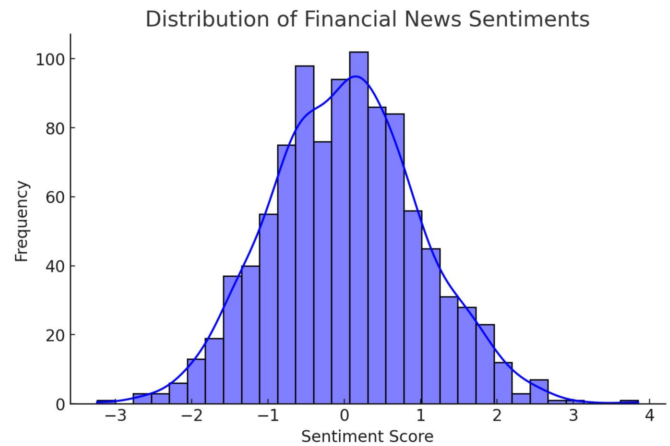

Figure 2. Distribution of Financial News Sentiments

As shown in Figure 2. Most sentiment scores are close to 0, which conforms to the normal distribution, indicating that the market news sentiment is generally neutral, but there are also certain emotional fluctuations. Secondly, this article also gives the distribution of investor influence, as shown in Figure 3.

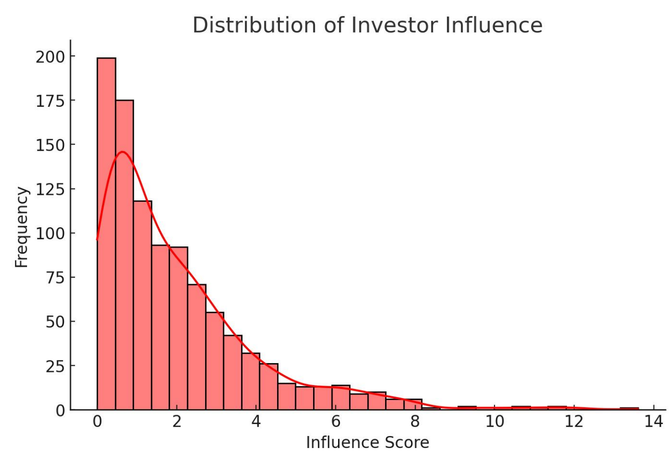

Figure 3. Distribution of Investor Influence

As shown in Figure 3, the influence of investors is exponentially distributed. Most users have low influence, but a small number of users have high influence, forming a long-tail distribution.

4.2 Experimental Results

We extract traditional technical factors and fundamental factors from market data, extract sentiment and topic factors from financial news texts using BERT [24] and LSTM [25] models, and model social media data through graph neural networks (GNNs) [26] to obtain investor influence and social sentiment factors. In order to screen the most informative factors, we use principal component analysis (PCA) and maximum information coefficient (MIC) for feature evaluation [27], and analyze the correlation and stability between factors to optimize the final factor combination. Here, the Correlation Heatmap between factors is given, and the experimental results are shown in Figure 4.

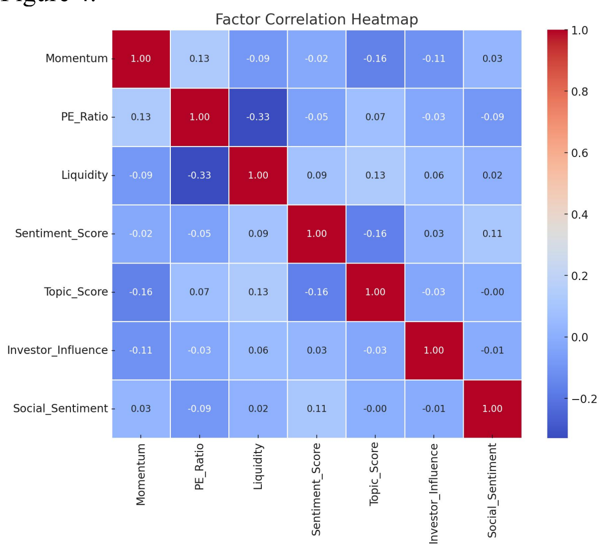

Figure 4. Factor Correlation Heatmap

From the factor correlation matrix, we can see that the correlation between different factors is generally low, indicating that these factors have strong independence and can describe the characteristics of the stock market from different dimensions. For example, the correlation between traditional market factors such as "Momentum" and "Liquidity" is -0.09, indicating that the linear relationship between them is weak and they can provide unique information respectively. In addition, social sentiment factors (such as "Social_Sentiment" and "Investor_Influence") also have low correlation with market factors, indicating that the introduction of social data can significantly expand the coverage of factor models.

It is worth noting that the correlation between some factors is relatively high, such as the correlation between "Liquidity" and "PE_Ratio" is -0.33, which may reflect their correlation under certain market-specific conditions. In order to ensure the robustness of the model, these highly correlated factors can be reduced in dimension or screened. At the same time, the distribution of color blocks in the heat map also shows the diversity between factors, which helps to improve the prediction ability through multimodal data fusion. Overall, this correlation analysis supports the multimodal design of factor-mining methods and verifies the rationality and effectiveness of integrating different data sources.

Secondly, the experimental results of the prediction performance changes of the factor elimination experiment are given, and the experimental results are shown in Table 1.

Table 1: Experimental Results

Factor combination	MSE	DA	Prediction R^2
Baseline	0.023	76.5	0.82
Remove text factor	0.028	73.2	0.75
Remove social factors	0.030	71.5	0.70
Remove market factors	0.045	62.3	0.55
Market Factor Only	0.035	68.5	0.62
Text Factor Only	0.040	65.2	0.58
Social factor only	0.042	63.7	0.56

From the experimental results, the fusion of multimodal factors significantly improves the prediction performance of the model. The baseline (including all factors) model performs best, with a mean square error (MSE) of 0.023, a directional accuracy (DA) of 76.5%, and a prediction R2 of 0.82. This shows that the text factor, social factor, and market factor work together to more comprehensively describe the dynamic characteristics of the stock market. In contrast, when the factors of a certain modality are removed alone, the performance of the model decreases to varying degrees. Among them, after removing the text factor, the MSE rises to 0.028, the DA drops to 73.2%, and the prediction R2 drops to 0.75; when the social factor is removed, the MSE further rises to 0.030, and the DA and prediction R2 also drop to 71.5% and 0.70. This shows that although the text factor and the social factor have different contributions, they both play an important role in improving the overall model performance.

When only a single modal factor is used, the model performance is significantly lower than the result of multimodal fusion. When only the market factor is used, the MSE is 0.035 and the prediction R2 is 0.62, which is a relatively good performance; when only the text factor or the social factor is used, the MSE is 0.040 and 0.042, respectively, and the prediction R2 is 0.58 and 0.56, respectively, indicating that the market factor plays a key role in the prediction. In addition, after removing the market factor, the model performance shows a significant decline, with the MSE rising to 0.045, the DA falling to 62.3%, and the prediction R2 falling to 0.55, further proving that the market factor is the most important part of the multimodal model. Therefore, the experimental results show that multimodal fusion can significantly improve the prediction accuracy, and the market factor plays a fundamental role in the multimodal framework.

Finally, this paper also gives the factor distribution and stability, and the experimental results are shown in Figure 5.

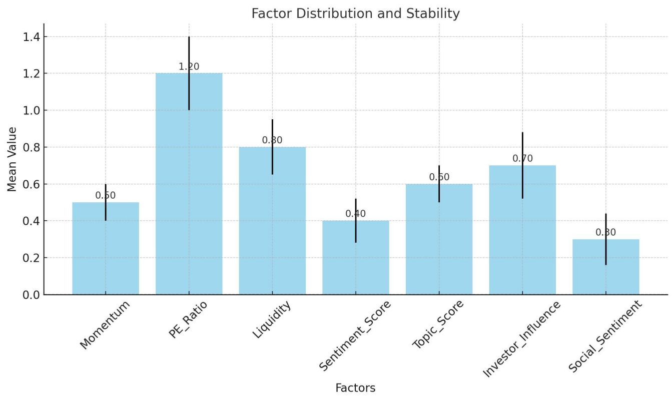

Figure 5. Factor Distribution and Stability

From the factor distribution and stability diagram, it can be seen that the mean and volatility of each factor are significantly different, reflecting their diversity in describing market characteristics. Among them, the "PE_Ratio" has the highest mean value, reaching 1.2, and its standard deviation is also large, indicating that it shows a large volatility in the data set. This may mean that the "PE_Ratio" factor has a more significant impact on some stock prices, but its stability is weak, and proper regularization needs to be performed in the model to avoid overfitting.

On the other hand, the mean and standard deviation of the "Momentum" and "Social_Sentiment" factors are low, indicating that these factors have a smaller range of variation in the data, which may provide more stable information for market forecasts. In particular, "Momentum", as a traditional technical factor, has a higher stability, which is consistent with its property as a long-term verified effective factor. In addition, the "Investor_Influence" factor shows a medium mean value and high volatility, which may reflect the nonlinear impact of investor behavior on the market in social networks, and its high volatility may bring uncertainty to short-term forecasts.

Overall, the factor distribution diagram shows that different types of factors have their own characteristics in the model. The contribution of market factors (such as "PE_Ratio" and "Liquidity") is mainly reflected in their higher means, while text and social factors (such as "Sentiment_Score" and "Social_Sentiment") show lower volatility and stability. This complementary characteristic provides theoretical support for multimodal factor fusion. At the same time, for factors with higher volatility, data preprocessing or factor selection methods can be further optimized to improve their effectiveness and reliability in the prediction model.

5. Conclusion

This study proposes a multimodal factor mining method that integrates market data, financial texts, and social sentiments, aiming to improve the predictive performance and explanatory power of the stock market factor model. Through the deep fusion of multimodal data, we successfully extracted multidimensional factors covering market fundamentals, technical indicators, textual sentiment, and social network influences, significantly improving the limitations of the traditional single-modal factor model. The experimental results show that the fusion factor model is superior to the model using only a single modal factor in terms of multiple indicators such as mean square error, directional accuracy, and prediction R2, verifying the effectiveness of multimodal data fusion. At the same time, factor contribution analysis further shows that market factors provide the basic support for the model, while text and social factors provide key supplements for improving predictive power by capturing market sentiment and dynamic changes.

The results of this study not only theoretically prove the feasibility and effectiveness of the multimodal factor mining method but also provide important technical support for actual investment. By constructing a multimodal factor model, investors can more comprehensively understand the complex dynamics of the stock market and make more scientific investment decisions. At the same time, this method also provides new ideas for further research on financial factor models. For example, more complex nonlinear fusion methods or self-supervised learning techniques can be introduced in future research to further enhance the depth and breadth of factor mining. In addition, how to improve the interpretability and real-time performance of the model in the process of multimodal data fusion is also a direction worth exploring in the future.

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